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Drilling parameters optimization :application of modern optimization method

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To the soul of the late sakli boussad , To Our mothers, sources of tenderness and love for their support throughout our university life. Our fathers, who have always supported us and who have done everything possible to help us. Our brothers and sisters, whom we love very much. Our big family. Our dear friends, and teachers. All that collaborated from near or far in the development of this work.

This for all of you

First and foremost, we thank Allah for endowing us with health, patience, and knowledge to complete this work.

We would like to express our deep and sincere gratitude to our advisor Dr.Hachana Ouassam. The doors to him were always open whenever we ran into a trouble or had questions. It was a great privilege and honor to work and study under his guidance.

Finally, we are extremely grateful to our parents for their love, prayers, caring and sacrifices for educating and preparing us for our future. Also we are very much thankful to our sisters, brother, and lovers for their support and valuable prayers.

Abstract

Rate of penetration (ROP) is one of the most critical parameters affecting virtually all drilling characteristics including technical, operational, economical, safety and other aspects of it. ROP evaluation may provide important information which can be applied to improve drilling efficiency, For this, good ROP model is required. Several ROP models are available in the industry which is derived based on both mechanistic and empirical methods. However, each model has its strengths and shortcomings, also The choice of ROP for every is dependent on variety of drilling parameter . All these parameter must be considered while choosing the proper ROP for drilling of every oil well so the objective of our study is to focus on the Optimization of the Drilling Parameters

so in this thesis , we talk about some important ROP model and we chose in our study widely utilized method for drilling rate prediction that called Bourgoyne and Young's Model and we try to predict the best optimal ROP by using some metaheuristic optimization techniques like PSO, MPSO and ABCO and we compare all the result founded to see the best technique .

by the final results, we have find by many different tests and comparisons between PSO, M PSO and ABCO also by using some relative error , We final that ABCO achieves optimal convergence, optimum performance and optimum values.

Key words: rate of penetration , bourgoyne an young's model , drilling optimization metaheuristic technique ,relative error

ملخص

يعد معدل الاختراق واحد من أهم العوامل المؤثرة في عملية الحفر خاصة في الجوانب الفنية والتشغيلية والاقتصادية والسلامة والجوانب الأخرى لذلك. و التقييم الجيد لسرعة الاختراق يوفر معلومات مهمة يمكن تطبيقها لتحسين كفاءة الحفر ، ولهذا ، فإن نموذج الجيد مطلوب. تتوفر العديد من نماذج في الصناعة المشتقة من الأساليب الميكانيكية والتجريبية. ومع ذلك ، كل نموذج له نقاط القوة وضعف , كما يعتمد اختيار ROP على مجموعة متنوعة من المعلمات الحفر. يجب أخذ كل هذه المعلمات في الاعتبار عند اختيار ROP المناسب لحفر كل بئر نفطية ، لذا فإن هدف دراستنا هو التركيز على تحسين هاته المعلمات

في دراستنا ، نتحدث عن بعض نماذج ROP المهمة و لقد اخترنا في دراستنا الطريقة المستخدمة على نطاق واسع للتنبؤ بمعدل الحفرللباحثين بورغوين و يونغ و حاولنا التنبؤ بأفضل ROP الأمثل باستخدام بعض افضل الخوارزميات مثل PSO ، MPSOو ABCO ومقارنة جميع النتائج التي تم تأسيسها لمعرفة أفضل التقنيات.

من خلال النتائج النهائية ، وجدنا من خلال العديد من الاختبارات والمقارنات المختلفة بين PSO و M PSO و ABCO و باستخدام بعض الأخطاء النسبية ، اكتشفنا أن ABCO تحقق التقارب الأمثل والأداء الأمثل والقيم المثلى

الكلمات المفتاحية :معدل الاختراق , نموذخ الباحثين بورغوين و يونغ, تحسين نموذج الحفر ,خوارزميات ,الخطأ النسبي.

Résumé

Le taux de pénétration est l'un des paramètres les plus critiques affectant pratiquement toutes les caractéristiques de forage, y compris leurs aspects techniques, opérationnels, économiques, de sécurité et autres. L'évaluation de la ROP peut fournir des informations importantes qui peuvent être appliquées pour améliorer l'efficacité du forage. Pour cela, un bon modèle de ROP est nécessaire. Plusieurs modèles de ROP disponibles dans l'industrie sont dérivés des méthodes mécanistes et empiriques. Cependant, chaque modèle a ses points forts et ses points faibles. Le choix du ROP pour chaque modèle dépend de la variété des paramètres de forage. Tous ces paramètres doivent être pris en compte lors du choix de la ROP appropriée pour le forage de chaque puits de pétrole. L'objectif de notre étude est donc de se concentrer sur l'optimisation des paramètres de forage.

Ainsi, dans ce document, nous parlons d'un modèle important de ROP et nous avons choisi dans notre étude une méthode largement utilisée pour la prédiction de la vitesse de forage appelée modèle de Bourgoyne et Young. Nous essayons de prédire la meilleure ROP optimale en utilisant certaines techniques d'optimisation métaheuristique telles que PSO, MPSO. et ABCO et nous comparons tous les résultats obtenus pour voir la meilleure technique.

par les resultat final , nous avons trouvé par de nombreuse tests et comparaison entre PSO ,MPSOet ABCO en utilse egalement une erreur relative , nous avons decouvret que ABCO atteint une convergence optimale , des performances optimales et des valeurs optimales

mot clés : taux de penetration ,modèle de bourgoyne et young , optimisation de paramétre de forage , technique d'optimisation métaheuristique erreur relative

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NOMENCLATURE

A_n	The total nozzle area	in.
A_V	The ratio of jet velocity	
a_1	Effect of formations strength	
a_2	Exponent of the normal compaction trend	
a_3	Under-compaction exponent	
a_4	Pressure differential exponent	
a_5	Bit weight exponent and bit diameter	
a_6	Rotary speed exponent	
a_7	Tooth wear exponent	
a_8	Bit hydraulic exponent	
a, b and c	Bit constants in the penetration model	
a_c, b_c and c_c	Lithology coefficients	
D	The depth	ft (m).
dD/dt	Rate of penetration	ft. /hr.
d	Exponent in general drilling equation	
d_b	The bit diameter	in.
d_n	Nozzle diameter	in
d_s	Diamond cutter diameter in inches	in
e	Exponent related to rotary speed	
$F_{jm})$	Modified jet impact force	
F_j	The jet impact force	
f_1	The effect of rock drill ability	
f_2	The depth effect	
f_3	Pore pressure effect on ROP	
f_4	The differential pressure effect	
f_5	The effect of changing the weight on ROP	
f_6	The effect of rotary speed	
f_7	The effect of bit wears on ROP	
f_8	The effect of bit hydraulics	
fit_i	The fitness value	
G	Coefficient determined by bit geometry, cutter size and design	

gp	The pore pressure gradient of the formation	lb/gal
H	The fractional bit tooth wear	
K	Constant related to formation.	
M	Number of insert penetrations per Revolution	
N	Rotary speed	rpm
N_{cut}	Number of cutter	
N	Number of inserts in contact with rock at the bottom	
n	Number of inserts in contact with rock at the bottom	
P_c	The equivalent mud density	lb/gal
P_e	The differential pressure	
P_g	Represents the global previous best from the entire swarm	
P_i	Represents the previous best of the current particl	
Q	Flow rate	gpm
r_1 and r_2	Random values that are taken from the uniform distribution [0,1].	
S_i	Rock compressive strength	
t	Time (usually bit rotating time)	[T], hours
V_i	Represents the velocity of a particle	
V_n	Nozzle velocity	ft/sec
V_f	Return fluid velocity	
v_{ij}	New food position	
$\left(\frac{w}{d_b}\right)_t$	The threshold it weight at which bit begins to drill	1000lbf/in.
W	Weight on bit	lbf
W_f	The wear function (bit wear)	
W_{mech}	Weight on bit per diamond cutter	lbs
ω	Weighted inertia constant [0.4 to 1.4]	
X_c	The calculated value	
X_i	Represents the current position of the particle	
X_m	The average value of X_r and X_c	
X_r	The reference value	
x_{min}^j and x_{max}^j	Are bounds	
x_i	Represents the current position of a bee	
x_k	Randomly choose bee.	

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	
γ_f	Function of the fluid density	
ψ	Chip formation angle	
μ	Drilling fluid viscosity	
$\emptyset$	Consisting of the cone offset coefficient	
ϕ_1 and ϕ_2	Acceleration constants, respectively	
ϕ_{ij}	Random number between [–1, 1].	
$\phi_{ij}\ (x_{ij} - x_{kj})$	Called step size	
ε	Rock ductility	
ε_r	The relative error	
σ_c	Uniaxial compressive strength	[Pounds per square inch]
ΔBG	The change in bit tooth wear	

ABBREVIATIONS

ABC	Artificial Bee Colony
CCS	Confined Compressive Strength
ECD	Equivalent Circulating Density
M_PSO	Modified version of Particle Swarm Optimization
MR	Multiple Regression
ROP	Rate Of Penetration
RPM	Rotations Per Minute
PDC	Polycrystalline Diamond Compact
PDMs	Positive Displacement Motors
PSO	Particle Swarm Optimization
WOB	Weight On Bit

General introduction

Drilling may be summarily defined as the operation of making a hole, to connect the reservoir to the surface installations. The main objectives are the realization of a hole in the best technical and safety conditions by minimal cost.

According to the field data, there are several methods to reduce the drilling cost of future well. One of these methods is the optimization of drilling parameters to obtain the maximum rate of penetration (ROP) in each bit run. Many parameters affect ROP so there is a lot of experimental work has been done to study the effect of these variables on drilling rate.

This factor can be listed under two general classifications such as controllable and environmental. Controllable factors are the factors which can be instantly changed or selected by people such as weight on bit, rotary speed, bit hydraulics. Environmental factors on the other hand are not controllable such as formation properties, drilling depth, 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.

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. To achieve this goal we divide our study in three essential parts:

1) Literature study on ROP models, in this part we take abstract about the different ROP modeling, after that we will base on the dominant and the widely utilized ROP model that called Bourgoyne and Young’s Model;
2) Develop a new techniques to model the ROP; our study aims to propose some of the best metaheuristic optimization techniques ; Particle Swarm Optimization (PSO), Modified Particle Swarm Optimization (MPSO) and Artificial Bee Colony Optimization (ABCO) algorithm;
3) Analyze the results of the proposed optimization techniques to identify their validity and performance, and also to compare the quality of solution found among them.

This technique of optimization can be implemented by any programming language and we have chosen MATLAB software 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 that we are used (ABCO), 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 be achieved in the drilling operation.

Chapter I:

Rate Of Penetration Modeling

I.1. Introduction

ROP models are one of the key elements of drilling parameters control. As to avoid excessive sources, in this study we will make a state of the art for different models used in drilling parameters optimization. Through our research we found several mathematical ROP models were developed in the last five decades in the petroleum industry as: Bingham's, Bourgoyne & Young's, Warren and modified Warren, Hareland's drag bit, Hareland's roller bit, and Motahhari's, departing from rather simple but less reliable (drilling rate, weight on bit, and rotary speed) formulations until the arrival to more comprehensive and complete approaches such as the Bourgoyne and Young ROP model widely used in the petroleum industry.

I.2. Drilling Optimization History

The concept of rotary drilling originated in the beginning of the year 1900 [1]. The development of rotary drilling can be divided into four distinct periods: conception period 1900 to 1920, development period 1920 to 1950, scientific period 1950 to 1970, and automation period which began in 1970. The conception period the rotary drilling principle marked the usage of cementing methods, rotary bits, drilling fluids and casing installations. In 1950s the scientific period took place with expansion in drilling research, better understanding of the hydraulic principles, significant improvements in bit technology, improved drilling fluid technology and most important of all optimized drilling. 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 [2].

Figure I-1 gives the time line of drilling optimization history. One of the first attempts for the drilling optimization purpose was presented in the study of Graham and Muench in 1959 [3]. They analytically evaluated the weight on bit and rotary speed combinations to derive empirical mathematical expressions for bit life expectancy and for drilling rate as a function of depth, rotary speed, and bit weight. In 1963 Galle and Woods [4] produced graphs and procedures for field applications to determine the best combination of drilling parameters. One of the most important drilling optimization studies performed was in 1974 by Bourgoyne and Young [5]. They proposed the use of a linear drilling penetration rate model and performed multiple regression analysis to select the optimized drilling parameters. They used minimum cost formula, showing that maximum rate of penetration may coincide with minimum cost approach if the technical limitations were ignored.

In the mid 1980s operator companies developed techniques of drilling optimization in which their field personnel could perform optimization at the site referring to the graph templates and equations. In 1990s different drilling planning approaches were brought to surface [6,7]. New techniques identified the best possible well construction performances. Later on "Drilling the Limit" optimization techniques were also introduced [8]. Towards the end of the millennium real-time monitoring techniques started to take place, e.g. drilling parameters started to be monitored from off locations. A few years later real-time operations/support centers started to be constructed. Some operators proposed advanced techniques in monitoring of drilling parameters at the rig site.

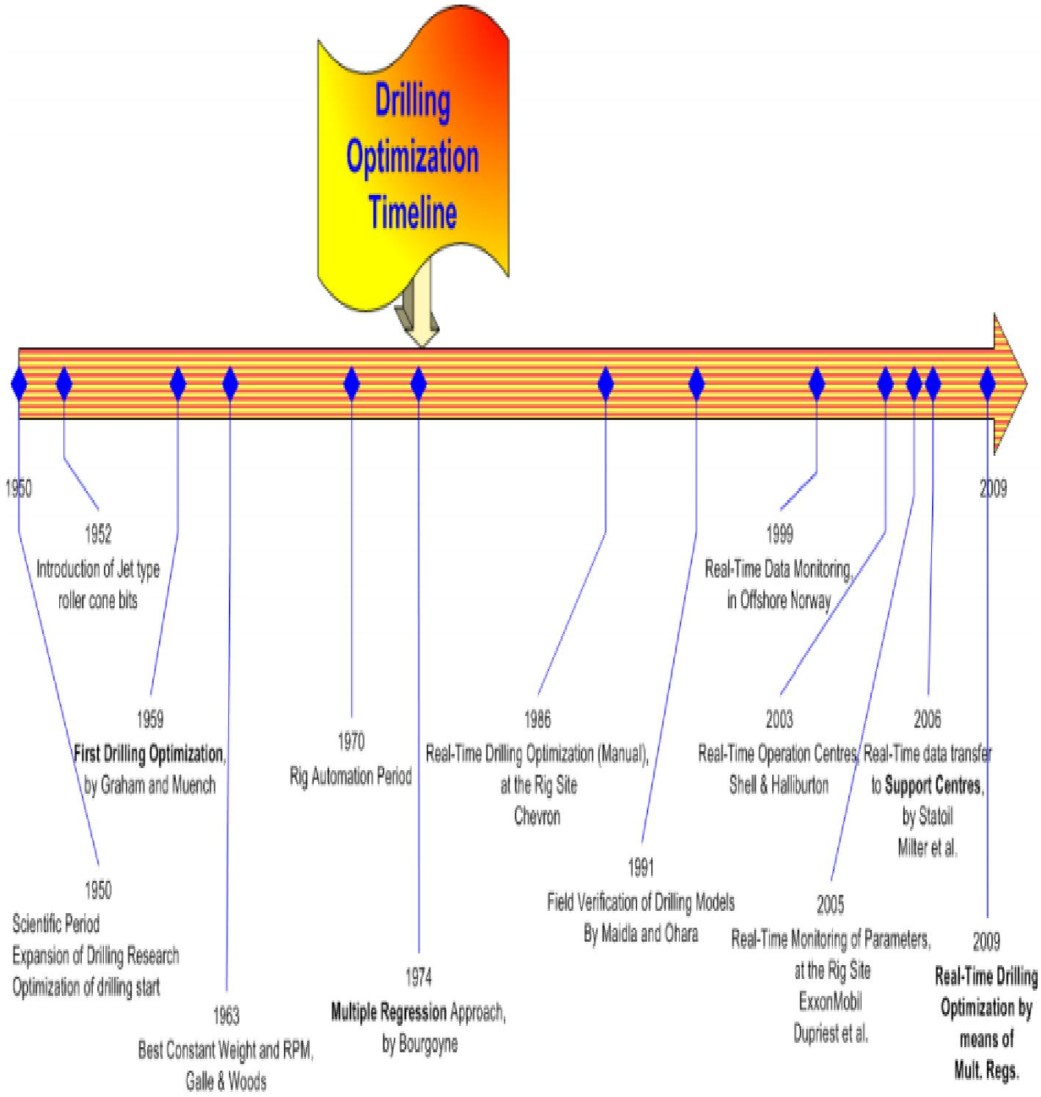


Figure I.1: the time line of drilling optimization history.

Following the early developments in rotary drilling system, ground-breaking developments in the latter years of the century took place. Highly inclined wells were drilled using rotary steerable; pressure controlled drilling techniques with acquisition of drilling parameters. In recent years drilling parameters are easily acquired, stored and also transferred in real-time basis. Following the invent of the sophisticated and automated rig data acquisition microelectronic systems linked to computers, a range of drilling optimization and control services started to take place [9]. Drill-off tests performed to optimize drilling penetration rate and bit life [10] are now able to be conducted with advanced techniques using smart computer systems. The test is applied by the driller by means of applying a little bit of excessive weight, locking the brake to keep the string from running into the hole [11, 12, 13]. In this study we will perform a statistical synthesis of some modern drilling parameters optimization techniques.

I.3 Factors affecting ROP

The drilling factors can be divided into two groups as dependent and independent variables. The dependent variables are determined by the drilling conditions whereas the independent variables may be controlled and changed before and during drilling. A similar dividing can classified by controllable and environmental variables, where also formation related factors are included.

The controllable variables are like the independent variables directly and instantly adjustable. These include:

- ❖ Weight on bit (WOB)
- ❖ Rotations per minute (RPM)
- ❖ Bit type
- ❖ Hydraulics

The environmental variables are similarly to the dependent variables not controllable; however also include the formation factors. Although the drilling fluid may be directly changed, it is included as an environmental variable as it is dependent on the drilling conditions and there is a certain fluid required for the drilling operation. The environmental variables include:

- ❖ Drilling fluid
- ❖ Torque
- ❖ Formation properties

Additionally Equivalent Circulating Density (ECD) and cuttings transport affects the ROP. Observations indicate that the ROP increases with decreased ECD. Ozbayoglu et al. analyzed effects of cuttings transport on drilling parameters [14]. Efficient hole cleaning is essential during drilling, this is controlled by a number of factors:

- Hole angle
- Fluid velocity
- Fluid properties (rheological properties and density)
- Cuttings size, shape, and concentration
- Annular size
- Rate of pipe rotation and pipe eccentricity
- Fluid flow regime (laminar or turbulent)

I.4. 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 modeled 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 like Motahhari's model should be used for drag bits [15], and Winters, Warren, and Onyia's for roller bits [16]. Using other models is dependent on availability of data, well complexity, and desire to expand on design or confirm calculations.

I.4.1. Bingham model

One of the earliest papers on rate of penetration modeling, Bingham's 1965 paper suggested a model that predicted ROP by using it as simply a function of rotary speed, weight on bit, and bit diameter [17]. The literature on ROP has grown extensively since Bingham's (1965) paper and so have methods of quantification and the overall understanding of what affects ROP. Despite all this, his model is still a very good rough starting point for ROP quantification. It is identified by the following equation:

$$ROP = K \times RPM^{e} \times \left(\frac{W}{D}\right)^{d} \quad \text{(I.1)}$$

where D is bit diameter, RPM is rotary speed, W is weight on bit, *d* is exponent in general drilling equation, *e* is exponent related to rotary speed, K is a constant related to formation.

I.4.2. Bourgoyne & Young model

Bourgoyne and young developed a model in 1974 that simplifies the rotary drilling process into one single model [5]. This model depends on statistical past drilling data and is done by multiple regression analysis for the past drilling data. It is considered as the most suitable model for real-time drilling optimization [5, 2]. Bourgoyne and Young introduced the penetration rate as a function of various drilling variables that are considered to have an effect on the ROP which are: formation strength, formation depth, formation compaction, the pressure differential across the hole bottom, bit diameter, bit weight, rotary speed, bit wear and bit hydraulics.

This rate of penetration model predicts the effect of the included eight drilling variables (x_j) on the penetration rate (dD/dt). In a given formation, the modeling is done by determining the eight constants (a_j). The model is mathematically given by:

$$\frac{dD}{dt} = EXP(a_1 + \sum_{j=2}^{8} a_j X_j) \quad (I.2)$$

The model can also be expressed clearer, with the exponential function integrated:

$$ROP = f_1 \times f_2 \times f_3 \times f_4 \times f_5 \times f_6 \times f_7 \times f_8 \quad (I.3)$$

Note: $f_n = \exp(a_n \times x_n)$. (I.4)

While, f_{1-8} represents the various normalized effects on ROP [18]. Where f_1 is the effect of rock drill ability, f_2 is the depth effect, f_3 is pore pressure effect on ROP, f_4 is the differential pressure effect, f_5 is the effect of changing the weight on ROP, f_6 is the effect of rotary speed, f_7 is the effect of bit wear on ROP, f_8 is the effect of bit hydraulics, a_1 models the effect of formations strength, a_2 and a_3 model the effect of compaction, a_4 models the effect of pressure differential across the hole bottom on ROP, a_5 models the effect of bit weight and bit diameter, a_6 models the effect of rotary speed, a_7 models the effect of tooth wear, a_8 models the effect of bit hydraulics, D is depth in feet, gp is the pore pressure gradient of the formation in lb/gal, P_c is the equivalent mud density in lb/gal, N is rotary speed in revolutions per minute, W is weight on bit in lbf, d_b is the bit diameter in inches.

Modeling of the drilling process is accomplished by determining the constants (a_1 through a_8) in the above equation by means of an optimization technique such as multiple regression analysis of field data used by the authors. Thus, the eight drilling variables are defined as follows:

- **Effect of formation strength**: The constant (a_1) represents the effect of formation strength and drill ability on penetration rate. It also includes the effects of drilling parameters that have not been mathematically modeled.
- **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 :

$$X_2 = (10000 - D) \quad (I.5)$$

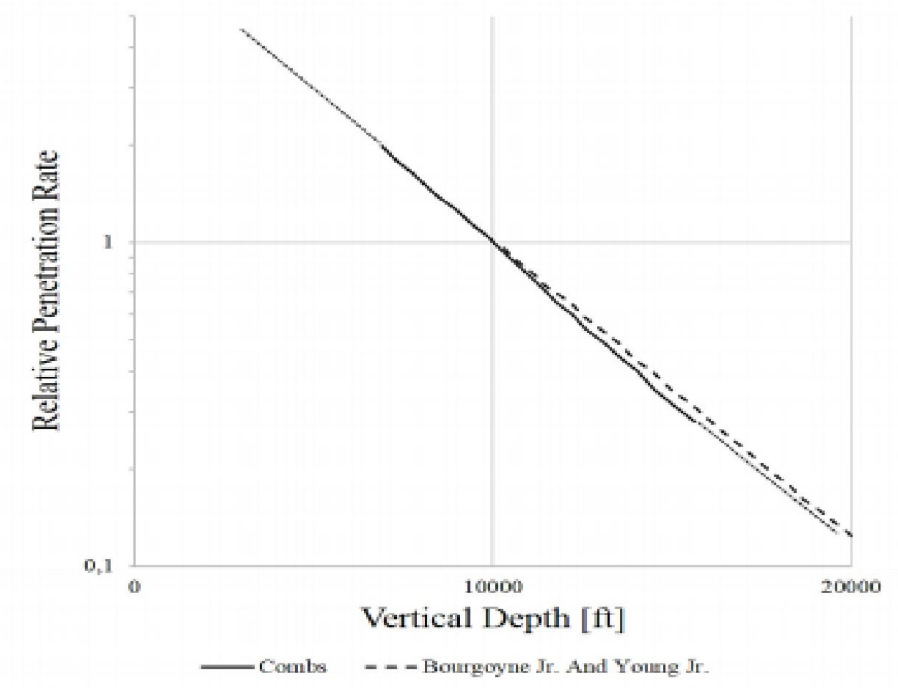


Figure. I.2: Effect of normal compaction on penetration rate.

And this assumes an exponential decrease penetration rate with depth (D) in a normally compacted formation. X_3 is defined by:

$$X_3 = D^{0.69} \times (gp - 9) \quad \text{(I.6)}$$

Indeed, this assumes an exponential increase in penetration rate with pore pressure gradient (gp).

- **Effect of Differential Pressure**: The term (a_4X_4) models the effect of differential pressure across the hole bottom on penetration rate. X_4 is defined by:

$$X_4 = D \times (gp - P) \quad \text{(I.7)}$$

And this assumes an exponential decrease in penetration rate with excess bottom- hole pressure. Field and laboratory data presented by Vidrine and Benit [19] and and laboratory data presented by Combs [20], all indicate an exponential relation between penetration rate and excess bottom-hole pressure up to about 1000psi (see Figure.I.3.). Vidrine and Benit also noted an apparent relation between the effect of differential pressure on penetration rate and weight on bit [19]. However, no consistent correlation could be obtained from the available data, so no bit weight term was included in Eq. I.7.

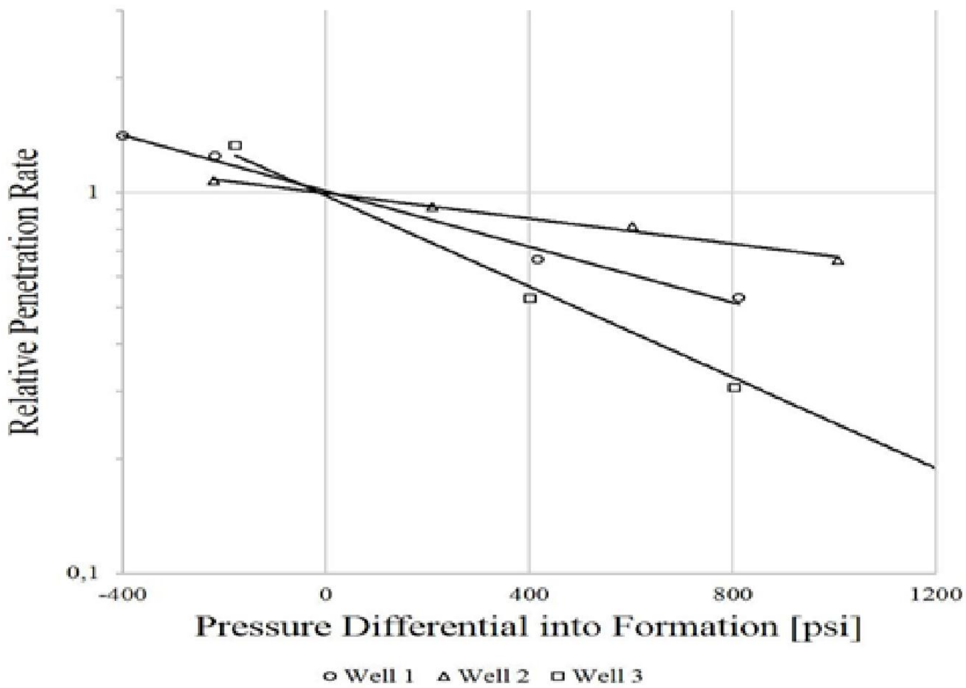


Figure.I. 3: Effect of differential bottom-hole pressure on ROP.

- **Effect of Bit Weight and Bit Diameter**: The term (a_5X_5) models the effect of bit weight and diameter on penetration rate.X_5 is defined by:

$$X_5=\ln\left[\frac{\left(\frac{W}{d_b}\right)-\left(\frac{w}{d_b}\right)_t}{4.0-\left(\frac{w}{d_b}\right)_t}\right] \qquad (I.8)$$

$\left(\frac{w}{d_b}\right)_t$ is the threshold at which bit begins to drill in 1000 lbf/in. And this assumes that the penetration rate is directly proportional to $\left(\frac{W}{d_b}\right)^{a_5}$.

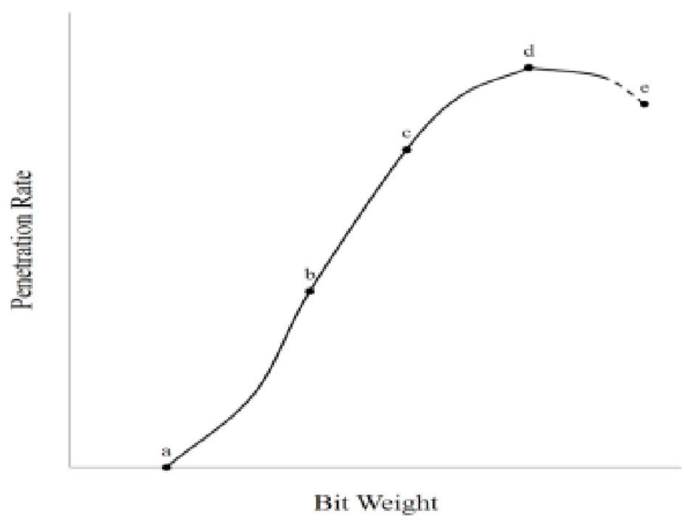


Figure.I. 4: Effect of bit weight on ROP.

❖ **Effect of Rotary Speed**: The term (a_6X_6) models the effect of rotary speed on penetration rate. X_6 is defined by :

$$X_6 = \ln\left(\frac{N}{100}\right) \quad (I.9)$$

It is assumed that the penetration rate is directly proportional to N^{a_6}.

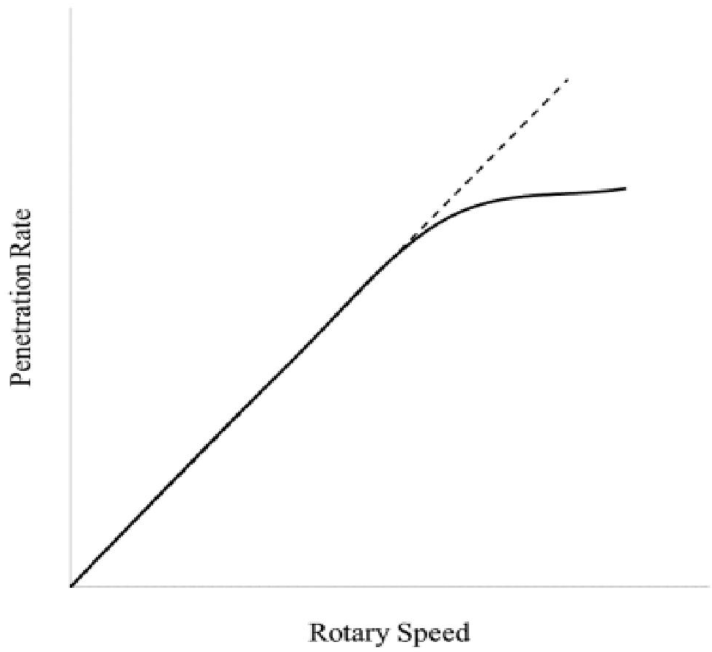


Figure.I. 5: Effect of rotary speed on ROP.

❖ **Effect of Bit Tooth-Wear**; The term (a_7X_7) models the effect of tooth-wear on penetration rate. X_7 is defined by :

$$X_7 = -H \quad (I.10)$$

Where, H is the fractional bit tooth wear. And this assumes an exponential decrease in penetration rate with increasing tooth wear.

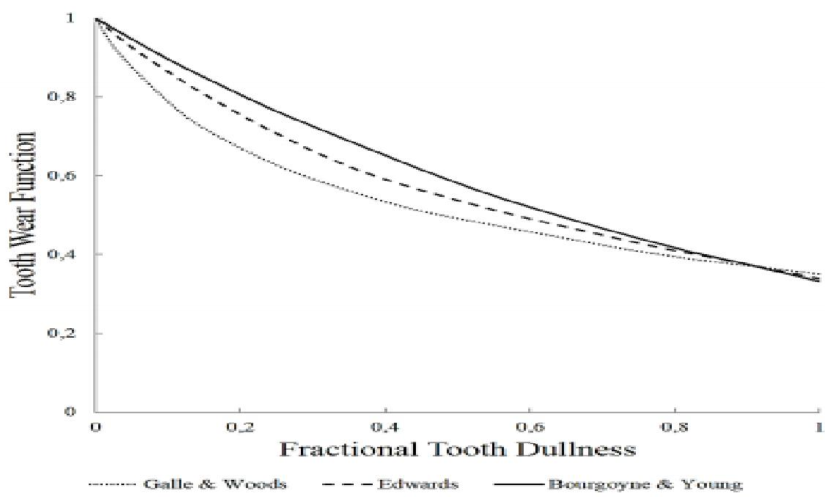


Figure.I.6: Effect of tooth wear on ROP (chipping-type tooth wear).

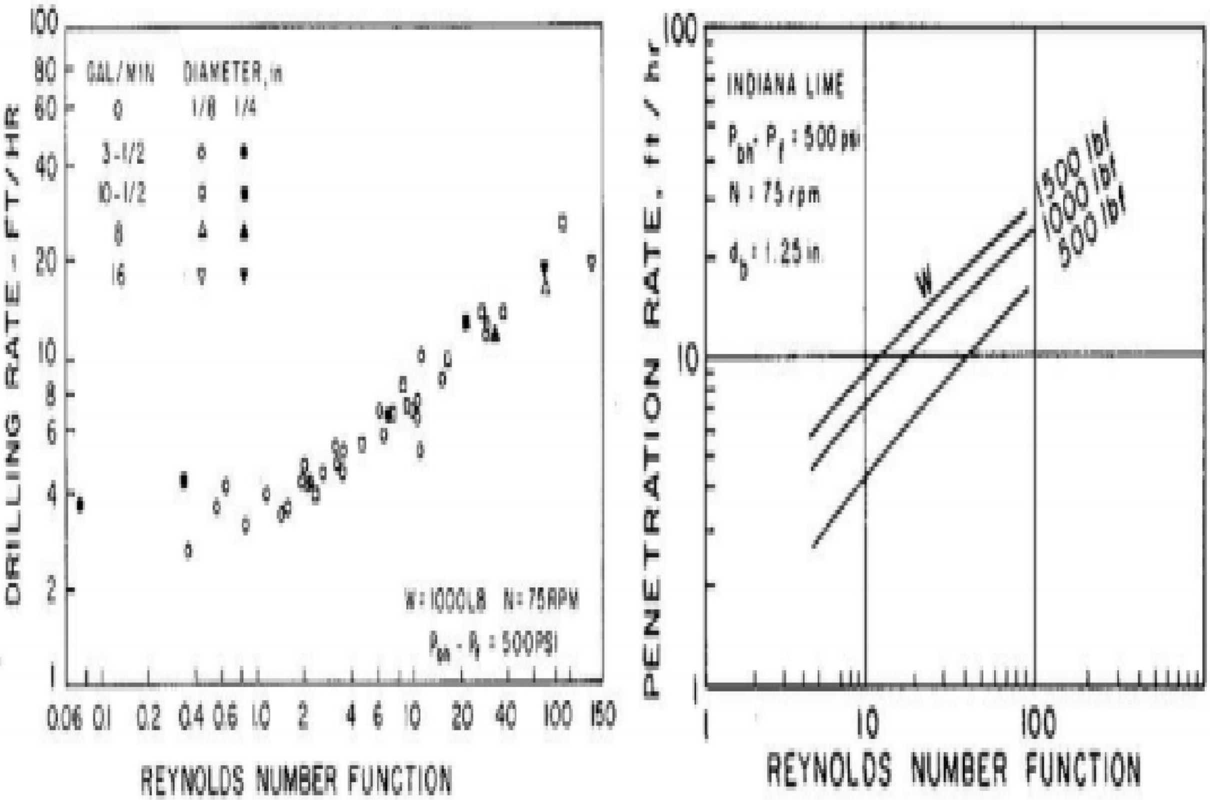
- **Effect of Bit Hydraulics**: The term (a_8X_8) models the effect of bit hydraulics on penetration rate. X_8 is defined by :

$$X_8 = \frac{\rho q}{350\mu d_n} \quad \text{(I.11)}$$

X_8 is based on micro bit experiments performed by Eckel [21]. 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 1/sec, is not routinely measured and recorded it must be estimated using the relation:

$$\mu = \frac{\mu_p + \tau_p}{20} \quad \text{(I.12)}$$

The constants a_1 through a_8 can be determined by using an optimization technique such as multiple regression analysis. This statistical technique is used to model sets of data points by a suitable equation with the best possible accuracy. At first, the parameters X_2 through X_8 must be calculated with Eq. (I.5) through Eq. (I.11) for each data points, then multiple regression analysis can be applied to determine these constants.



(a) **(b)**

Figure.I.7: ROP as a function of bit Reynolds number.

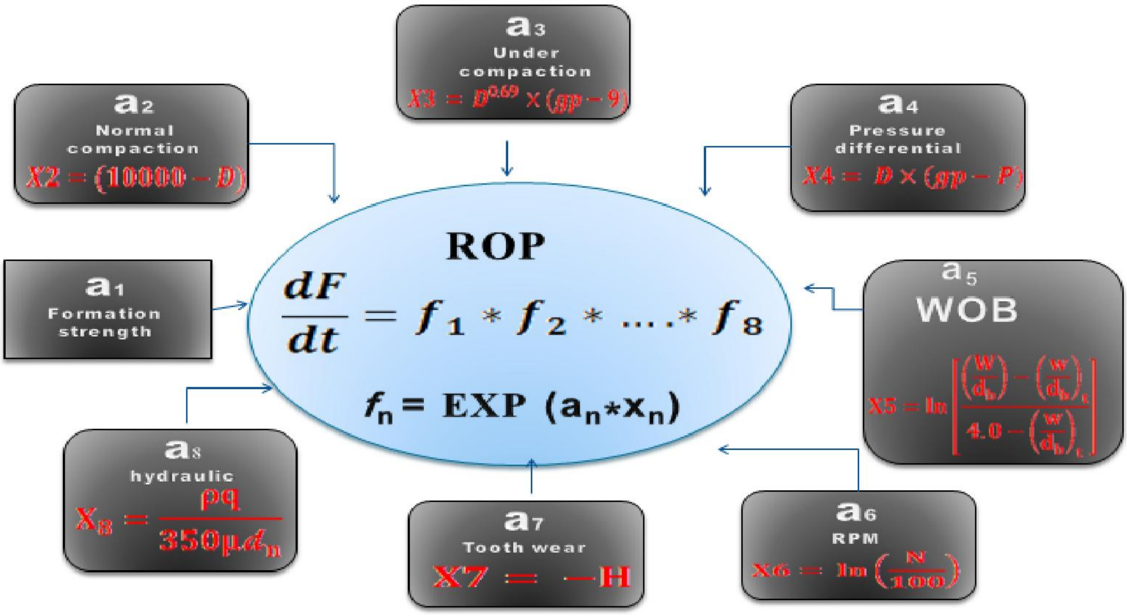


Figure.I.8: All the effect on ROP used in modeled of Bourgoyne and Young.

I.4.3 Warren model

Warren developed models to predict the rate of penetration for soft formation bits. The models are generated from laboratory work, by combining rotary speed, bit type, bit size, rock strength and weight on bit to calculate the rate of penetration. A large-scale drilling rig was used to obtain experimental data. The main intention of the models is to describe the relationship between the variables that control the rate of penetration. The initial model assumes perfect cleaning conditions. Warren then modified his own model to account for more realistic, imperfect cleaning conditions.

Development of new models for soft formations was needed, as there was a lack of an adequate existing model. Galle and Woods had at the time the most commonly used model for soft formation drilling [22]. However, Randall and Estes explains the inadequacy of that model [23], where applying the model in real conditions violates an assumption of the model. Maurer's [24] 'perfect cleaning' model was found not applicable in general for soft formation bits. Deviation occurred constantly in the results from experimental data in soft-formation conditions used with the Maurer model.

Warren presented the perfect-cleaning model in 1981 [25]. In the "Drilling Model for Soft Formation Bits" paper, it is described that developing the drilling model was done with dimensional analysis and generalized response curves. A model by Ward law [26] was modified to better comply with experimental data acquired from a laboratory test. The model modified to best comply with the experimental data is given by equation I.13.

$$ROP = \left(\frac{aS^2 {d_b}^3}{N\,WOB^2} + \frac{c}{Nd_b}\right)^{-1} \quad \text{(I.13)}$$

Here the constants a and c are bit constants in the penetration model, this constants do not need to change when the variables alter to retain adequate ROP prediction. The first term describes the maximum rate that a bit can crush rock into cuttings by: $\left(\frac{aS^2 {d_b}^3}{N\,WOB^2}\right)$.

The second term of the model adjusts the model to consider the distribution of the applied WOB to more teeth as the WOB is increased and the teeth penetrates deeper into the rock [19, 27]. This happens due to the fact that the first term is predominant at low ROP values and the second term is predominant at higher ROP values. Where S is rock compressive strength, d_b is bit diameter, N is rotary Speed, and WOB is weight on bit.

The negative of this model is not taking into account hydraulic effects, and assumed perfect cleaning. In 1987, Warren presented the imperfect cleaning model [28]. To simplify the complex modeling required to give a good ROP prediction, Warren understood that a basic model had to be developed first. The perfect cleaning model is this basic model, the starting point. Refining the basic model is done by adding new terms. If the physics of the process is controlled correctly, the new terms will not dismiss the initial model.

Warren explained that under steady state conditions, the cuttings removal rate from the bit is equivalent to the rate new chips forms. This infers that the rate of penetration is affected by cuttings generation process or cuttings removal process, or a combination of them both. As the basic model does not account for cuttings removal, this term had to be added.

To account for cuttings removal, Warren used dimensional analysis to isolate variables consisting of the impact force and mud properties. These were incorporated into equation I.14to express the imperfect cleaning model by:

$$ROP = \left(\frac{aS^2 {d_b}^3}{N\,WOB^2} + \frac{b}{Nd_b} + \frac{cd_b\gamma_f\mu}{F_{jm}}\right)^{-1} \quad \text{(I.14)}$$

The constants a, b and c are bit constants in the penetration model. This term is a function of the fluid density (γ_f), drilling fluid viscosity(μ), and modified jet impact force (F_{jm}).

The modified jet impact force is defined by the following equation:

$$F_{jm} = \lfloor 1 - {A_v}^{-0.122} \rfloor * F_j \quad \text{(I.15)}$$

Where A_V is the ratio of jet velocity, F_j is the jet impact force. This last is defined by the following equation:

$$F_j = \frac{Q \times V_n \times P_c}{1930} \quad \text{(I.16)}$$

Where Q is flow rate in gpm and V_n is nozzle velocity in ft/sec. A_V can be calculated, assuming three jets, from the equation:

$$A_v = \frac{v_n}{v_f} = \frac{0.15D^2}{3d_n^2} \quad (I.17)$$

Where d_n is nozzle diameter, V_n is nozzle velocity, V_f is return fluid velocity.

And V_n can be calculated from the equation:

$$V_n = \frac{0.321 \times Q}{A_n} \quad (I.18)$$

Where A_n is the total nozzle area in in^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 [16], consisting of the cone offset coefficient ($\emptyset$), rock compressive strength (S), and rock ductility (ε).

$$ROP = \left(\frac{aS^2 d_b{}^3}{N\,WOB^2} + \frac{b}{Nd_b} + \frac{cd_b\gamma_f\mu}{F_{jm}} + \frac{\emptyset S d_b{}^2}{N\varepsilon} \right)^{-1} \quad (I.19)$$

I.4.4 Modified Warren Model

There are many processes and actions that occur during the drilling operation with a significant impact on the penetration rate. It's difficult to completely model the ROP with all the factors and conditions affecting the penetration process. However, an attempt was made to improve the model presented by Warren by addressing more quantifiable conditions and effects in the model.

❖ **Addressing chip hold down effect**

"Chip hold down effect" was not addressed in the ROP model presented by Warren (1987) in spite of its importance and impact on the ROP [29, 20]. In 1993, Hareland and Hoberock [29] modified Warren's model by addressing chip hold down effects. This was done using data from laboratory full-scale drilling tests. The tests were performed by varying the bottom-hole pressure while other conditions remained constant. The resultant "chip hold down function" P_e is given by:

$$f_c(P_e) = c_c + a_c(P_e - 120)^{b_c} \quad (I.20)$$

Where (a_c, b_c and c_c) are lithology dependent constants and P_e is the differential pressure. Units on (a_c, bc and c_c) where chosen such that P_e is dimensionless [19]. The resultant modified equation including "chip hold down effect" is given by:

$$ROP = \left[f_c(P_e) \left(\frac{aS^2 d_b{}^3}{N\,WOB^2} + \frac{b}{Nd_b} \right) + \frac{cd_b\gamma_f\mu}{F_{jm}} \right]^{-1} \quad (I.21)$$

❖ **Addressing bit wear effect**

Hareland and Hoberock [29] also included bit wear effect to strengthen Warren's model. Bit wear has a negative impact on drilling process by reducing the rate of penetration. Hareland and Hoberock modified Warren's ROP model to account for bit wear effect by introducing a wear function (W_f) into the model [19]:

$$ROP = \mathrm{W}_f\left[f_c(P_e)\left(\frac{aS^2 d_b{}^3}{N\,WOB^2} + \frac{b}{N d_b}\right) + \frac{c d_b \gamma_f \mu}{F_{jm}}\right]^{-1} \quad (I.22)$$

The wear function, W_f, is given by:

$$W_f = 1 - \frac{\Delta BG}{8} \quad (I.23)$$

Where ΔBG represents the change in bit tooth wear and is given as:

$$\Delta \mathrm{BG} = W_c \sum_{i=1}^{A} \mathrm{WOB_i} \times \mathrm{RPM_i} \times \mathrm{Ar_{abr_i}} \times \mathrm{S_i} \quad (I.24)$$

Here $\mathrm{S_i}$, is the rock compressive strength which is a function of rock lithology and confining pressure, given by:

$$\mathrm{S_i} = S_0\left(1 + a_s P_e{}^{bs}\right) \quad (I.25)$$

I.4.5 Harland's Drag Bit

Hareland's (1994) model proposed a new way to predict ROP for drag bits. The model expands on previous ones by introducing equivalent bit radius, dynamic cutter action, lithology coefficient, and cutter wear. The model apart from helping with optimization of drilling parameters, also aids in solids control.

Due to the model not accounting for certain theoretical properties that affect ROP, such as bit cleaning, imperfections in bit and cutter geometry, and microscopic variations in rock strength, the paper includes a correlation factor. Here is Hareland's ROP equation for drag bits and the correlation factor:

$$ROP = \frac{14.14 \times N_{cut} \times RPM}{d_b} \times \left[\left(\frac{d_s}{2}\right)^2 \times \cos^{-1}\left(1 - \frac{4 \times W_{mech}}{N_{cut} \times d_s{}^2 \times \pi \times \sigma_c}\right) - \left(\frac{2 \times W_{mech}}{N_{cut} \times \pi \times \sigma_C} - \frac{4 \times W_{mech}{}^2}{(N_{cut} \times d_s \times \pi \times \sigma_c)^2}\right)^{0.5} \times \left(\frac{d_s}{2} - \frac{2 \times W_{mech}}{(N_{cut} \times d_s \times \pi \times \sigma_c)}\right)\right] \quad (I.26)$$

$$COR = \frac{a}{(RPM^b \times W^C)} \quad (I.27)$$

where d_b is bit diameter in inches, N_{cut} is number of cutters, RPM is rotary speed in revolutions per minute, d_s is diamond cutter diameter in inches, W_{mech} is weight on bit per diamond cutter in lbs, σ_c is uniaxial compressive strength in pounds per square inch, W is weight on bit, a, b, c are cutter geometry correction factors.

I.4.6 Hareland's Roller Bit

G. Hareland's (2010) model proposed a different approach to predict ROP for roller cone bits. The paper analyzed the existing drilling models, including Bourgoyne and Young's, and expanded on them by including bit-rock interaction. The added complexity derives itself by relating the roller cone bit and rock interaction to rock failure by a wedge. The model is as follows:

$$ROP = K \times \left(\frac{80 \times n \times m \times RPM^{a}}{d_b{}^{2} \times tan^{2}\psi}\right) \times \left(\frac{W}{100 \times n \times CCS}\right)^{b} \times W_f \qquad (I.28)$$

where K is the comprehensive coefficient, m is number of insert penetrations per revolution, n is number of inserts in contact with rock at the bottom, RPM is rotary speed, d_b is bit diameter, ψ is chip formation angle, W is weight on bit, CCS is confined compressive strength, W_f is bit wear, a and b are model coefficients.

I.4.7 Motahhari's PDC Bit

Motahhari's (2010) model proposed a new method to accurately predict ROP for Polycrystalline diamond compact (PDC) bits and positive displacement motors (PDMs). This model is incredibly useful for directional and horizontal drilling operations with PDMs, as previous models do not as accurately enhance preplanning, reduction of drilling time with ROP optimization According to Motahhari (2010), PDM performance/selection in the drilling planning phase will help perform a safe and cost-effective operation by preventing motor stalls and maintaining highest average ROP for the section". The model is as follows:

$$ROP = G \times \left(\frac{W^{a} \times RPM^{y}}{d_b \times CCS}\right) \times W_f \qquad (I.29)$$

where G is a coefficient determined by bit geometry, cutter size and design (namely back rake and side rake angles) and cutter-rock coefficient of friction, RPM is rotary speed, d_b is bit diameter, W is weight on bit, CCS is confined compressive strength, W_f is bit wear, α and y are model coefficients.

I.5 Conclusion

In this chapter we have described the several factors effecting on ROP which are divided on two groups, and the history of ROP modeling from 1965 until these days, and we mentioned all the equations that are used in every model. Then, we have detailed in the model of Bourgoyne and Young which is the selected one in our study.

Chapter II:

Description Of The Optimization Approach

II.1. Introduction

In this next study, we will present and discuss about some important techniques used in the field of optimization like be multiple regressions, particle swarm and specially artificial bee colony, and we will determine the phases of each of them to reach the desired global optimum which will be in our case the feasible drilling parameters.

II.2. Optimization Techniques

The word optimum, meaning “best”, the term optimize means to achieve the Optimum, and optimization refers to the act of optimizing.

Optimization problem are becoming increasingly important in decision-making processes, and there is a several techniques to solve this problem, these techniques divide into two broad approaches. One of these approaches is called deterministic and on which the search algorithms always use the same routing to arrive at the desired solution. The other approach is the random or non-deterministic approach, on which the algorithm will not necessarily follow the same routing to the final solution and may even propose different solutions following the initial conditions proposed.

It is towards this approach that we will focus and more particularly towards a very specific type of evolutionary random search algorithms with solution populations.

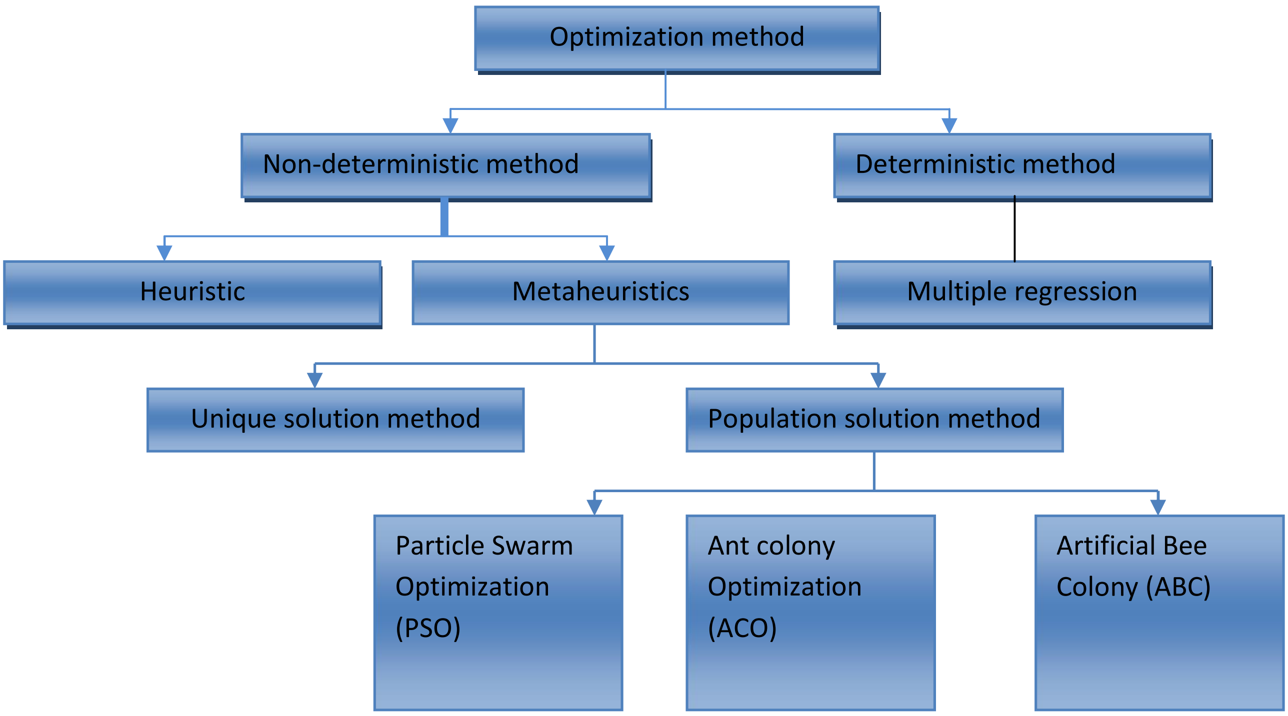


Figure. II. 1. Flowchart of optimizations methodes

There are several techniques as shown in Figure II.1. Among these algorithms, we will be particularly interested in the algorithm of artificial bee colonies (ABC).

II.2.1. Metaheuristic Optimization Technique

The word Metaheuristic is derived from two Greek words:

- Heuristic that comes from the verb "heuriskein" and which means to 'find';
- Meta which is a suffix meaning "beyond", in a higher level.

From the onset of optimization problems, research has turned to the proposition of exact algorithms for solving these problems. But with the increasing complexity of these, it has become very difficult to find an exact solution. A new class of heuristics, named "Metaheuristics", has emerged in order to better solve these problems. The Metaheuristics are strategies that guide the search for an optimal solution.

Metaheuristics are a set of optimization algorithms to solve difficult optimization problems. They are often inspired by natural systems, whether taken in physics (if simulated annealing) in evolutionary biology (genetic algorithms cases) or in ethology (case algorithms ant colony) or particle swarm optimization.

Metaheuristics can be classified into two groups: population-based methods known as evolutionary algorithms such as genetic algorithms, ant colonies, bee colonies ..., as well as single-solution methods such as annealing simulated, taboo research, and else.

II.2.2. Multiple Regression

Regression analysis is used to estimate the relationships among one dependent and two or more independent variables. This method of data analysis is useful when examining a quantitative variable in relation to other factors. The Multivariate analysis describes an observation factor by having several variables, taking into consideration all changes of properties that may happen simultaneously.

The equations (Eq. I.5 through Eq. I.11) 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 [3] 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. I.2). A derivation of the multiple regression-analysis procedure is presented in detail in the section (II.2.2.1).

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. I.2) 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. I.2) but also on the range of values of the drilling parameters x_2 through x_8.

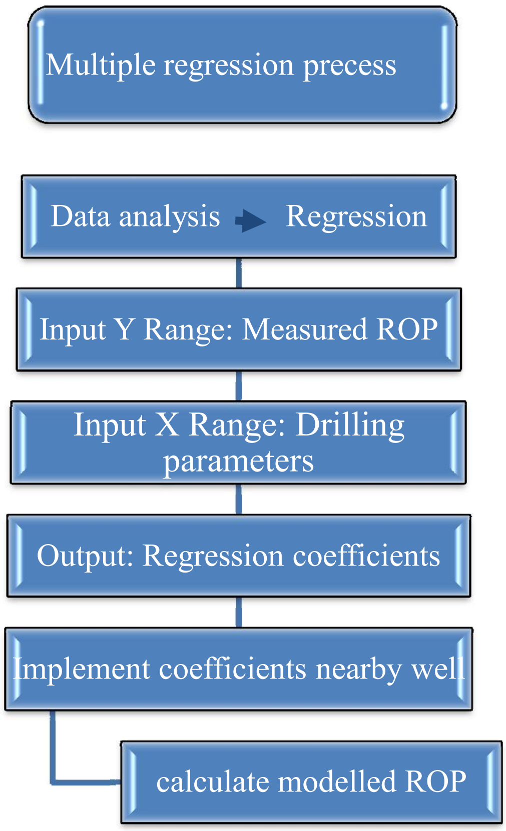


Figure. II. 2. Flowchart of multiple regressions.

Table.II.1 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[30].. As the number of drilling parameters included in the analysis is decreased, the minimum number of data points required to calculate the remaining regression constants is also decreased (see Table. II.1) [5]. In many applications, data from more than one well had to be combined in order to calculate all eight regression constants.

II.2.2.1. Multiple regression Analysis Procedure

Table. II.1. Recommended minimum data ranges for regression analysis

Parameter	Minimum rang	Number of parameter	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	0.5	4	10
X_7	0.2	3	7
X_8	0.5	2	4

The equation of the proposed model is:

$$\mathrm{ROP} = \frac{dD}{dt} = Exp\left(\mathrm{a}_{1+}\sum_{j=2}^{8}\mathrm{a_j x_j}\right) \qquad \text{(II.31)}$$

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

$$ln\frac{dD}{dt} = \left(\mathrm{a}_{1+}\sum_{j=2}^{8}\mathrm{a_j x_j}\right) \qquad \text{(II.32)}$$

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

$$r_i = \left(\mathrm{a}_{1+}\sum_{j=2}^{8}\mathrm{a_j x_j}\right) - ln\frac{dD}{dt} \qquad \text{(II.33)}$$

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 $\sum_{i=1}^{n} r_i^2$.

$$\frac{\partial \sum_{i=1}^{n} r_i^2}{\partial a_j} = \sum_{i=1}^{n} 2r_i\frac{\partial r_i}{\partial a_j} = \sum_{i=1}^{n} 2r_i x_j \qquad \text{(II.34)}$$

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 : $\sum_{i=1}^{n} 2r_i x_j$; for j=1, 2, 3… 8.

The expansion of $\sum_{i=1}^{n} r_i x_j$ yields:

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

$$a_1 \sum x_2 + a_2 \sum x_2^2 + a_3 \sum x_2 x_3 + \cdots \dots\dots\dots\dots\dots + a_8 \sum x_2 x_8 = \sum \ x_2 \ ln \frac{dD}{dt} \qquad \text{(II.35)}$$

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

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

After that in order to calculate the constants a_1 throught a_8 by using multiple regressions – analysis the following linear equation system can be obtained by matrix:

$$\begin{bmatrix} n & \sum_{i=1}^{n} X_{2i} & \sum_{i=1}^{n} X_{3i} & \sum_{i=1}^{n} X_{8i} \\ \sum_{i=1}^{n} X_{2i} & \sum_{i=1}^{n} {X_{2i}}^2 & \sum_{i=1}^{n} X_{2i} X_{3i} & \sum_{i=1}^{n} X_{2i} X_{8i} \\ . & . & . & \cdot\cdot \ \cdot\cdot \quad . \\ . & . & . & \cdot\cdot \ \cdot\cdot \quad . \\ \sum_{i=1}^{n} X_{8i} & \sum_{i=1}^{n} X_{8i} X_{2i} & \sum_{i=1}^{n} X_{8i} X_{3i} & \sum_{i=1}^{n} {X^2}_{8i} \end{bmatrix} \times \begin{bmatrix} a_1 \\ a_2 \\ . \\ . \\ a_8 \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} Y_i \\ \sum_{i=1}^{n} X_{2i} Y_i \\ . \\ . \\ \sum_{i=1}^{n} X_{8i} Y_i \end{bmatrix} \qquad \text{(II.36)}$$

II.2.3. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is an evolutionary computational technique originally developed by Kennedy, Eberhart and Shi [31] [32]. It was intended for simulating social behavior, which is inspired by the movement dynamics of organisms in insects, birds and a bird flock or fish school as they searching the food source. The algorithm was simplified and it was observed to be performing optimization.

The PSO is stochastic, population-based computer algorithm modeled on swarm intelligence. Basically, PSO optimizes a problem by having a population of candidate which known as the particles and moving these particles around in the search-space. Each particle's movement is influenced by its local best known position and is also guided toward the best known positions in the search-space which are updated as better positions are found by other particles. This is expected to move the Swarm toward the best solutions [33]. Each particle will produce two parameter and both parameters were communicate each other, which are the velocity of particle and the position of particle. All the particles can share their information about the search space, so there is a global best solution.

The analogy of the particle and swarm is depending to the problem, and it can represent whatever name and value that suitable from the problem according to the formulae shown below.

The velocity of particle i, is calculated as :

$$v_i^{k+1} \leftarrow \omega v_{i+}^{k} + \phi_1 r_1^k \left(p_i^k - x_i^k\right) + \phi_2 r_2^k \left(p_g^k - x_i^k\right) \qquad \text{(II-37)}$$

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].

The position of particle i is calculated as :

$$x_i^{k+1} \leftarrow x_i^k + v_i^{k+1} \qquad \text{(II-38)}$$

The velocity equation, (Eq. II.37), 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. All 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 .

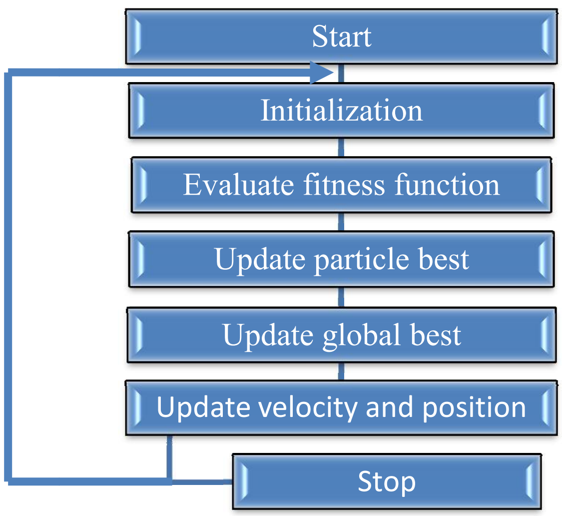


Figure. II. 3. Flowchart of PSO procedure.

II.2.4. 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.37.and II.38) with modified in ϕ_1 and ϕ_2, and W as follows:

$$\lambda = \frac{2\alpha}{\left|2-b-\sqrt{b^2-4b}\right|} \qquad \text{(II-39)}$$

$$\Phi_1 = \lambda.\,b_1 \qquad \text{(II-40)}$$

$$\Phi_2 = \lambda.\,b_2 \qquad \text{(II-41)}$$

where, $\alpha = 1$, $b_1 = 1.5$, $b_2 = 2$ and $b = b_1 + b_2$.

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 [31].

II.2.5. Artificial bee colony optimization

ABC optimization algorithm is a recent addition in swarm intelligence proposed by Karaboga in 2005 and the performance of ABC is analyzed in 2007 [35]. ABC algorithm is simple and very flexible when compared to other algorithms and there are many possible applications of ABC. Like any other population-based optimisation algorithm, ABC consists of a population of potential solutions. With reference to ABC, the potential solutions are food sources of honey bees. The fitness is determined in terms of the quality (nectar amount) of the food source. There are three types of bees in the colony: onlooker bees, employed bees and scout bee. Numbers of employed bees or onlooker bees are equal to the food sources. Employed bees are associated with food sources while onlooker bees are those bees that stay in the hive and use the information gathered from employed bees to decide the food source. One of the employed bees, whose food source is exhausted, becomes scout bee and she searches the new food source randomly.

Similar to the other swarm-based algorithms, ABC is an iterative process. There are two fundamental processes which derive the evolution of an ABC population: the variation process, which enables exploring different areas of the search space and the selection process, which ensures the exploitation of the previous experiences. However it has been shown that ABC may occasionally stop proceeding toward the global optimum even though the population has not converged to a local optimum (Karaboga and Akay, 2009) (36). ABC process requires cycle of four phases: initialisation phase, employed bees phase, onlooker bees phase and scout bee phase, each of which is explained below.

II.2.5.1. Initialisation of the population

Initially, ABC generates a uniformly distributed population of SN solutions where each solution x_i (i = 1, 2... SN) is a D-dimensional vector. Here D is the number of variables in the optimisation problem and x_i represents the i^{th} food source in the population. Each food source is generated as follows:

$$x_i^j = x_{min}^j + \text{rand}(0,1)\,(x_{max}^j - x_{min}^j),\ \forall_{j=1,2,\ldots,D} \qquad \text{(II.42)}$$

Where x_{min}^j and x_{max}^j are bounds of x_i in j^{th} direction.

II.2.5.2. Employed bees phase

In this phase, employed bees modify the current solution based on the information of individual experiences and the fitness value (nectar amount) of the new solution. If the fitness value of the new food source is higher than that of the old food source, the bee updates her position with the new one and discards the old one. The position update equation for j^{th} dimension of i^{th} candidate in this phase is shown in following equation:

$$v_{ij} = x_{ij} + \phi_{ij}\,(x_{ij} - x_{kj}) \qquad \text{(II.43)}$$

Where $\phi_{ij}\,(x_{ij} - x_{kj})$ is called step size, k ∈ {1, 2... SN}, j ∈ {1, 2... D} are two randomly chosen indices. K must be different from i so that step size has some significant contribution and ϕ_{ij} is a random number between [–1, 1].

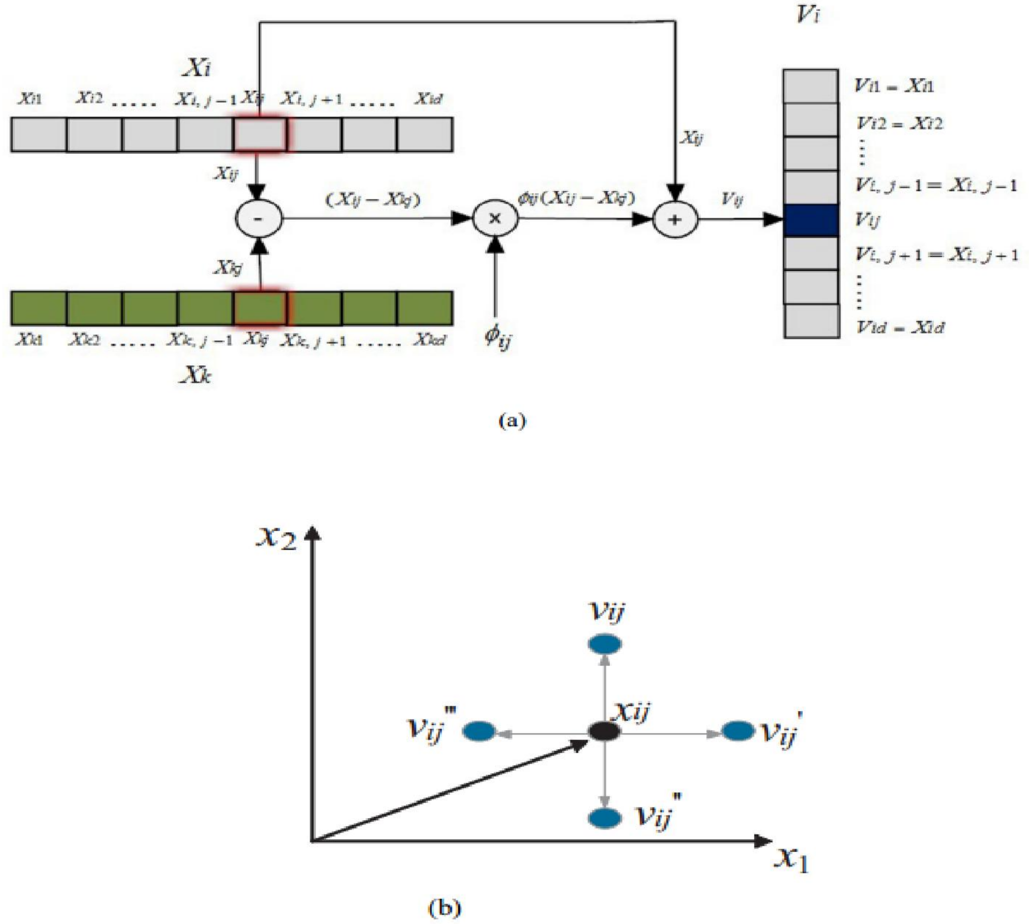


Figure.II.4: (a) A simple position update equation execution, (b) Different possible new vectors formed in neighbourhood of x_{ij} due to position update equation in 2-D

Position update process in employed bee phase is shown in Figure.II.4 (a). Here x_i represents the current position of a bee and highlighted box represents the randomly choosen direction j. x_k is the randomly choosen bee. In this step the direction j of a random bee k ≠ i is subtracted from same direction of i^{th} bee then this difference is multiplied by a random number $\phi_{ij} \in [-1, 1]$. Finally this quantity is added to j^{th} dimension of x_i to get j^{th} dimension of new food position v_{ij} . This v_{ij} is represented by vertical vector in the figure whose all other dimensions are same as of x_i and is generated in the neighbourhood of x_i. If we consider only 2−D search space then possible positions for this new food source v_{ij} can be seen in Figure.II.4 (b).

II.2.5.3. Onlooker bees phase

After completion of the employed bees phase, the onlooker bees phase is started. In this phase, all the employed bees share the fitness information (nectar) of the updated solutions (food sources) and their position information with the onlooker bees in the hive. Onlooker bees analyse the available information and select a solution with a probability,p_i, related to its fitness.

The probabilityp_i may be calculated usingfollowing expression (there may be some other but must be a function of fitness):

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \quad \text{(II.44)}$$

Where fit_i is the fitness value of the i^{th} solution. As in the case of the employed bee, onlooker bee produces a modification in the position in her memory and checks the fitness of the candidate source. If the fitness is higher than that of the previous one, the bee memorises the new position and forgets the old one.

II.2.5.4. Scout bees phase

If the position of a food source is not updated for a predetermined number of cycles, then the food source is assumed to be abandoned and scout bees phase is started. In this phase the bee associated with the abandoned food source becomes scout bee and the food source is replaced by the randomly chosen food source within the search space. In ABC, the predetermined number of cycles is a crucial control parameter which is called limit for abandonment. Assume that the abandoned source is x_i then the scout bee replaces this food source with new x_i as follows:

$$x_i^j = x_{min}^j + \text{rand}(0, 1)\,(x_{max}^j - x_{min}^j),\ \forall j = 1,2,\ldots,D \quad \text{(II.45)}$$

Where x_{min}^j and x_{max}^j are bounds of x_i in j^{th} direction.

The general algorithmic structure of the ABC optimization approach is given as Follows:

Step 1: (Initialization)

- The initial swarm by using equation (II.42).
- Calculate the fitness value (fit_i) of each food source by using equation.

Reset the abandonment counter.

Step 2: (Move the employed bees) For each employed bee :

- Select a neighbor employed bee randomly.
- Calculate the new solution by using equation (II.43).
- Calculate the fitness value (fit_i) of each food source by using equation:

$$fit_i = \begin{cases} \frac{1}{1+F} & if\ F \geq 0 \\ 1 + abs(F) & if\ F < 0 \end{cases} \quad \text{(II.46)}$$

- If the fitness value of the new solution is better than the fitness value of the old solution then replace the old solution with new one and reset the abandonment counter of the new solution, else increase the abandonment counter of the old solution by 1.

Step 3: (Move the onlooker bees) For each onlooker bee:

- Select an employed bee as neighbor randomly.
  An onlooker bee selects a food source by evaluating the information received from all of the employed bees based on the equation of probability (II.44).
- Improve the solution of the employed bee by using equation and the neighbor (II.43).
- Calculate the fitness value (fit_i) of each food source by using equation (II.45).
- If the fitness value of the new solution is better than the fitness value of the old solution then replace the old solution with new one and reset the abandonment counter of the new solution, else increase the abandonment counter of the old solution by 1.

Step 4: (Move the scout bees) :

- Fixe the abandonment counter with the highest content.
- If the content of the counter is higher than the predefined limit then reset the abandonment counter and by using equation (II.44) generate a new solution for the employed bee to which the abandonment counter belongs. Else continue.

Step 5: If a termination condition is met, the process is stopped and the best food source is reported, otherwise the algorithm returns to Step 2 [37].

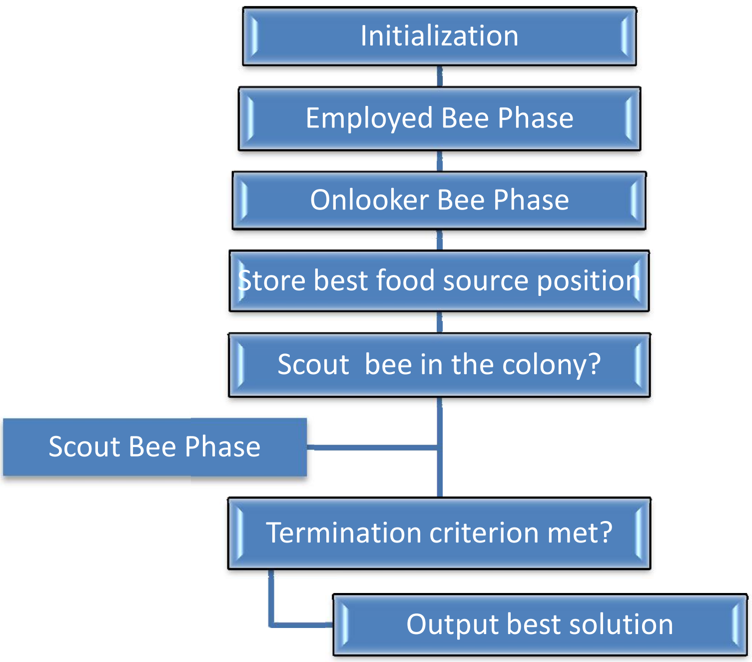


Figure. II.5: Flowchart of ABCO procedure.

II .3.Conclusion

In this chapter, we have discussed some proposed techniques known in the field of optimization, whether those derived from nature or mathematics, like the technique of particle swarms, modified version of this last and artificial bees colony. And we have described the mechanisms and steps and the principle work of each one, also we mention every equations that correspond to the process of the technique. In the next chapter we will exploit these techniques to solve our optimization problem.

Chapter III:
Simulation And Results Analysis

III.1. Introduction

In this final chapter we will describe our results after using the concept of the following metaheuristique methods: Particle Swarm Optimization, Modified Particle Swarm Optimization and artificial bee colony in order to get the best optimal solution for the objective function represented in the difference between ROP experimental and ROP simulated found by the proposed optimization technique. We will make several tests to assess the best adopted metaheuristique technique.

III.2. Experimental Data

The field data is taking from the Louisiana offshore well that are showing in Table.III.1 [5]. The parameters X_2 through X_8 must be calculated using Eq. I.5 through Eq. I.11 for each data entry, to calculate the best value soft model constants A_1 through A_8 using the experimental data. So that's the primary drilling variables required for the proposed techniques 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.

III.3. Result Analysis

III.3.1. Initial settings

III.3.1.1 PSO

Based on the general working principal of PSO and its standard settings where the personal acceleration constant: $\Phi_1 = \Phi_2 = 2$ and the weighted inertia constant w = 1. During the programming of this technique, a new factor is integrated which is called damping ratio of inertia coefficient where w_{damp} = 0.4, the test results are shown in the **tables (III. 2 through III. 7) and figures (III. 1 through III. 6)** bellow for three different swarm population (n) test.

III.3.1.2. MPSO

Some modification has been made to the previous technique in which the internal factor and the weighted inertia factor are variable form an iteration to another one. The weighted inertia constant has been calculated by the following equation:

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

While, $\alpha = 1$, $b_1 = 1.5$, $b_2 = 2$ and $b = b_1 + b_2$.

Therefore $\Phi_1 = \lambda . b_1$. And $\Phi_2 = \lambda . b_2$, w = 0.7 .

Table.III.1. ROP data for different factors (Taken in shale, Offshore Louisiana area).

Data entry	Depth (ft)	Bit number	Drilling rate (ft/hr)	Bit weight (1000lb/in)	Rotary speed (rpm)	Tooth Wear	Reynolds number Function	ECD (lb/gal)	Pore Gradient (lb/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	0.938	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	11757	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	12575	24	42.7	3.48	77	0.17	1.221	16.7	16.1
18	13055		38.6	3.29	75	0.29	1.61	16.8	16.2
19	16250		43.4	2.82	76	0.43	1.161	16.8	16.2
20	16795	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	0.417	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

III.3.1.3. ABCO

C: recognition parameter, C_{min}= 0.02 and C_{max} =0.2;

W: inertia weight parameter, W_{min} =0.1 and W_{max} =0.9;

All remaining initial settings are the steps and mechanism of the technique described in Chapter 2.

III.3.1.4. 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. Result

To assess the feasibility of the proposed techniques, we have checked the convergence quality by means of varying the iteration number (it) from 100 to 300. For each variation of the iteration number, we have modified the population number (n) three times, 30, 50 and for 100. The evolution factor, between the techniques, is the objective function value and the speed of convergence required.

1. Iteration variation test

1.1. For iteration =100

Table III. 3. Test results using PSO, MPSO and ABCO with n=30.

For n=30	A1	A2	A3	A4	A5	A6	A7	A8	It.s	OF	T
PSO	2.0337	0.1953	0.6762	0.1258	0.1503	0.4300	0.9263	0.8840	78	0.01051	08.66 s
MPSO	5	0.3539	1	0.1563	0.6543	0.7194	0.2816	1.7443	77	1.359e-04	07.57 s
ABCO	4.1434	0.0824	0.1220	7.9226e-4	0.2504	0.4271	0.9063	0.3448	99	1.7692e-08	58.79 s

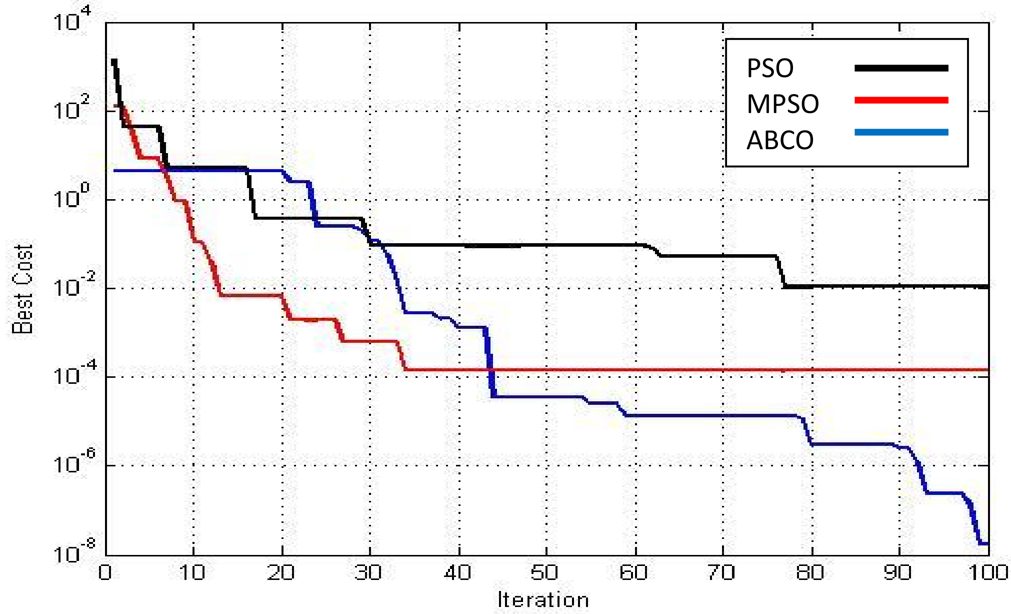


Figure.III.1: Comparison between the three techniques by using n=30 and it=100.

Table III. 4. Test results using PSO, MPSO and ABCO with n=50.

For n=50	A1	A2	A3	A4	A5	A6	A7	A8	It.s	OF	T
PSO	0.8644	0.1443	0.6362	0.1364	0.3467	0.0789	1.2601	0.1565	95	1.3828 e-5	14.30s
MPSO	3.5899	0.3072	0.7860	0.1093	0.5455	0.5648	0.6755	0.6012	78	1.8976e-07	12.50s
ABCO	0.7122	0.1660	0.2448	0.0014	0.2132	0.7540	0.8073	0.3145	100	4.4159e-09	64.11s

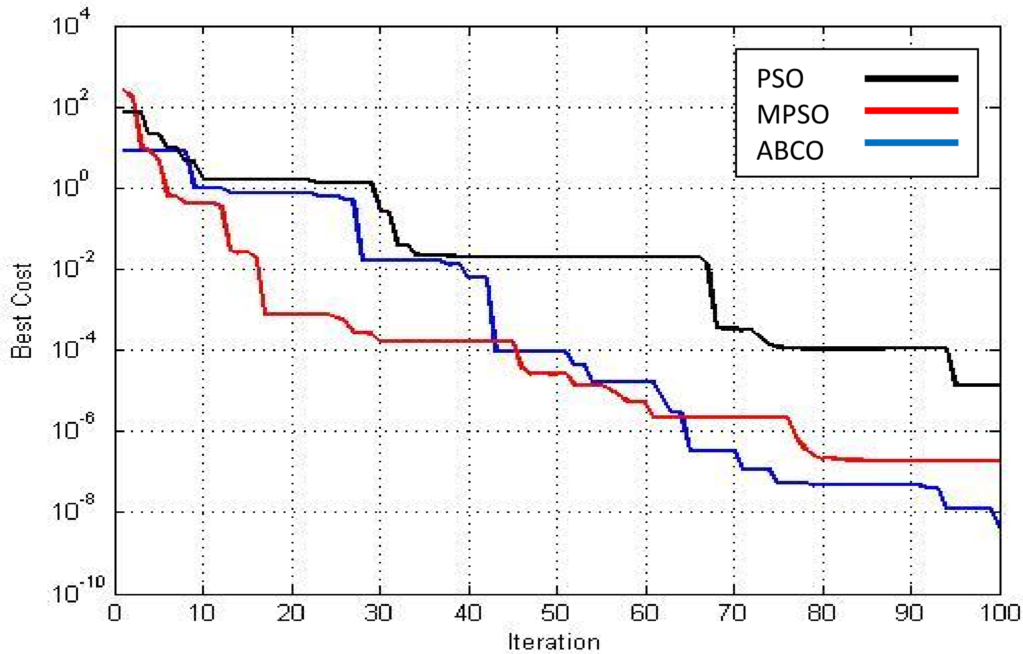


Figure III.2: Comparison between the three techniques using n=50 and it=100

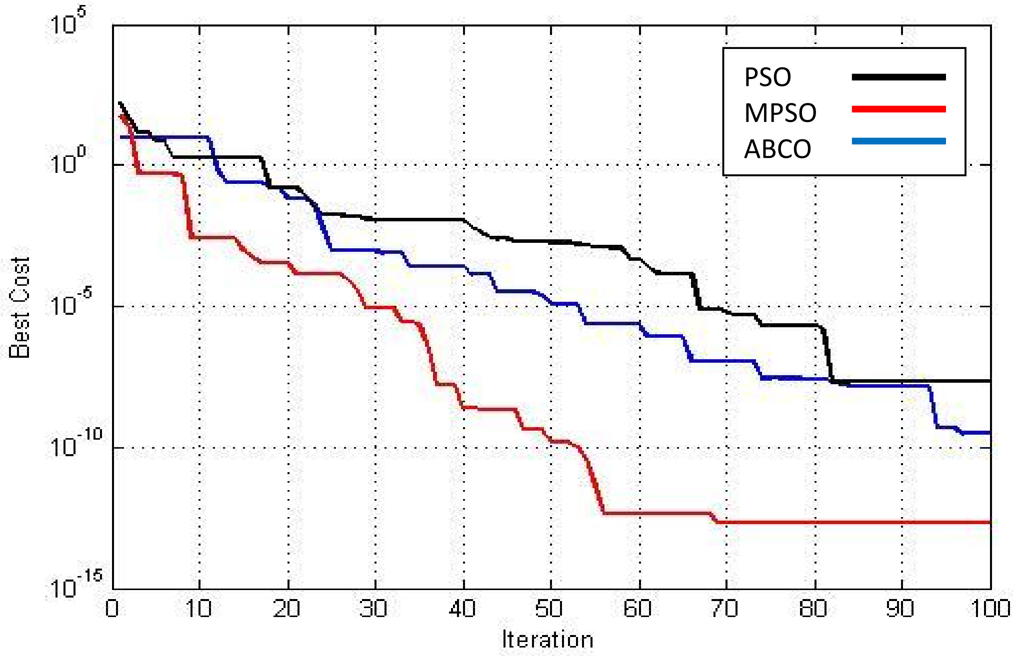


Figure.III.3. Comparison between the three techniques using n=100 and it=100.

Table.III.5. Test results using PSO, MPSO and ABCO with n=100.

For n=100	A1	A2	A3	A4	A5	A6	A7	A8	It.s	OF	T
PSO	3.1458	0.1385	0.6328	0.1381	0.2197	0.3232	1.0431	1.5390	82	2.0902 e-8	29.73 s
MPSO	2.8713	0.2756	0.4048	0.0033	0.7091	0.7091	0.6474	1.0016	78	2.0961e-13	33.45 s
ABCO	0.1220	0.0714	0.2212	0.0374	0.2556	0.4571	0.2084	0.5144	100	2.9293e-10	80.79 s

3.2. Iteration = 300

Table III. 6. Test results using PSO, MPSO and ABCO with n=30.

For n=30	A1	A2	A3	A4	A5	A6	A7	A8	It.s	OF	T
PSO	1.4738	0.2191	0.3282	0.0036	0.7462	0.6044	0.7225	1.4049	201	9.1028e-06	020.63 s
MPSO	2.0200	0.2096	0.3143	0.0035	0.5189	0.7593	0.9630	0.5412	299	8.8818e-15	021.78 s
ABCO	1.1795	0.3286	0.7067	0.0740	0.9384	0.5929	0.3076	1.0339	167	5.3291e-15	117.72 s

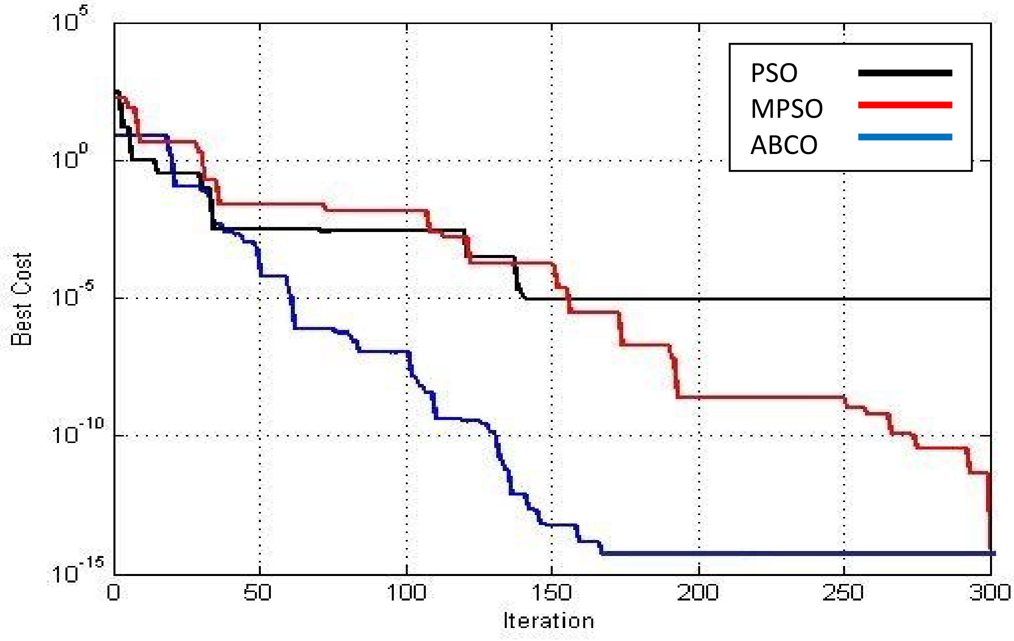


Figure III.4: Comparison between the three techniques using n=30 and it=300.

Table III. 7. Test results using PSO, MPSO and ABCO with n=50.

For n=50	A1	A2	A3	A4	A5	A6	A7	A8	It.s	OF	T
PSO	0.5915	0.3620	0.6477	0.0398	0.6866	0.6670	1.1347	1.5676	278	7.851e-09	38.45 S
MPSO	3.5028	0.4744	0.7667	0.0262	0.8610	0.0845	0.8861	0.9039	299	8.1075e-9	39.24 s
ABCO	3.3117	0,1362	0,3575	0,0511	0,5448	0,0774	0,7314	0,4437	189	1.7764e-15	145.997 s

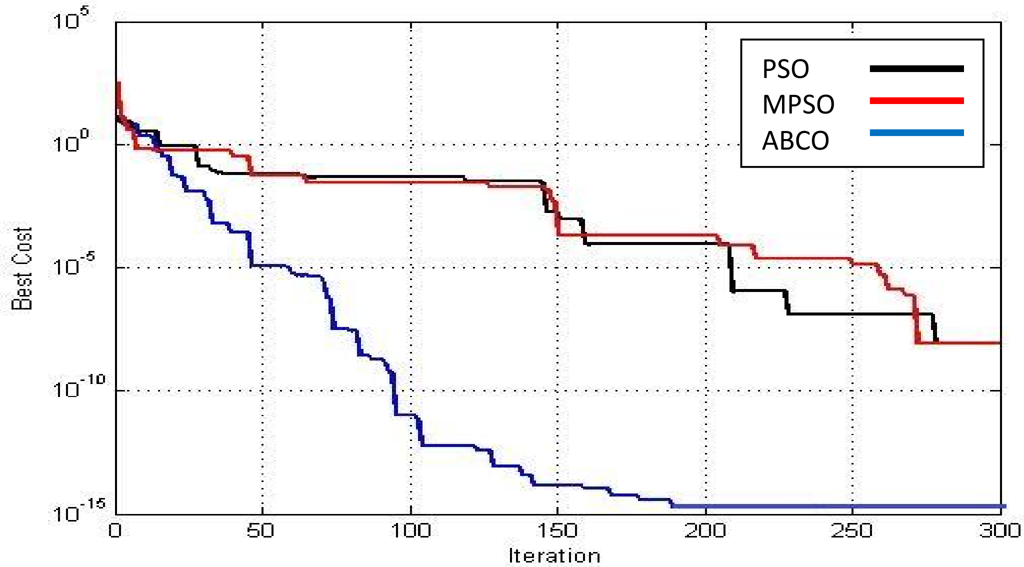


Figure III.5: Comparison between the three techniques using n=50 and it=300.

Table III. 8. Test results using PSO, MPSO and ABCO with n=100.

For n=100	A1	A2	A3	A4	A5	A6	A7	A8	It.s	OF	T
PSO	1.4703	0.1041	0.6712	0.1661	0.9671	0.6664	0.3127	1.2203	236	1.9158e-13	049.58 s
MPSO	1.2389	0.1780	0.9320	0.2154	0.4321	0.6613	0.9300	1.0702	291	302493e-11	051.96 s
ABCO	2.0221	0.0581	0.2073	0.0391	0.2162	0.4323	1.3826	0.4080	163	1.7764e-15	167.99 s

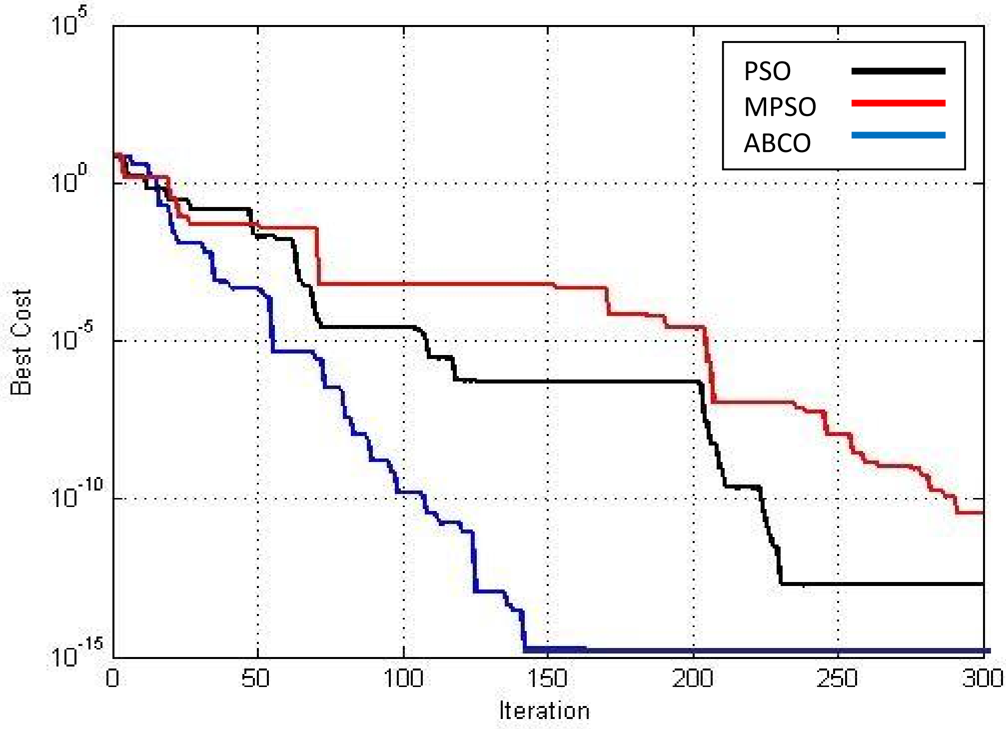


Figure III.6: Comparison between the three techniques using n=100 and it=300.

III.4. Discussion

As it is illustrated by the above tables and figures, and after several tests we have deduced the following points:

- The best value of the objective function in PSO (OF = 1.9158e-13) is obtained in the sixth test with n=100 and it=300, after 236 iteration and it takes 49.58 second;
- For the second technique (MPSO) we get an optimal objective function value (OF=8.8818e-15) in the fourth test with (n=30 and it=300), it is stabilized after one iteration before the end of the test (it=299), in addition to that we noted that the simulation time in MATLAB took about from 21.78 sec to 23.5 sec.
- Finally in the last technique (ABCO) we have observed that the optimal solution (OF=1.7764e-15) we found it in both test (fifth and sixth), we consider the fifth test to be optimal because it takes less number of population size (n=50) with 300 iteration, it needs only 189 iteration to be fixed.

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

Table III.9. Relative error test results for the proposed techniques (with n =100 and it =300).

Relative error Tests		ε_{a1}	ε_{a2}	ε_{a3}	ε_{a4}	ε_{a5}	ε_{a6}	ε_{a7}	ε_{a8}
PSO	Test1	28.70%	39.20%	15.02%	41.20%	68.74%	96.58%	48.98%	38.24%
	Test2	44.68%	40.15%	18.54%	54.97%	35.14%	98.01%	46.24%	44.02%
MPSO	Test1	06.89%	36.23%	30.14%	45.21%	24.57%	72.35%	34.15%	31.25%
	Test2	25.63%	35.14%	20.19%	36.15%	33.14%	66.21%	46.14%	18.12%
ABCO	Test1	04.55%	22.10%	13.66%	30.05%	29.89%	19.87%	13.25%	5.92%
	Test2	03.78%	26.50%	12.57%	32.21%	32.57%	13.24%	14.97%	9.49%

From the observations and the table above we conclude that artificial bee colony ABCO is the best technique to find the constant modeled values no matter of number of iteration and population size because it already takes the optimal objective function. To confirm that, we will proceed to another test to check the techniques quality to find the same result in each execution. So, we are going to do relative error test by using the following equations:

$$X_m = \frac{X_r + X_c}{2} \qquad \text{(III.2)}$$

$$\varepsilon_r = \frac{X_m - X_c}{X_m} \qquad \text{(III.3)}$$

Where, X_r is the reference value, X_c is the calculated value, X_m is the average value of Xr and X_c, and ε_r is a the relative error. The reference values is shown in table III.9.

From table III.8, it's easy to find out that the percentage error of ABCO is smaller than the one of PSO and MPSO in all tests, and that's an indication of how good the constants A_1 through A_8 are when we used ABCO. Otherwise, this means that the bees in our technique have searched for optimal solution with good precision, this explain why ABCO takes relatively more time than the others.

III.5. Conclusion

At the end of this study, which is based on drilling parameters optimization and after the execution of many tests, approximately 40 tests with using MATLAB software tool. We have found the best possible solutions, especially those related to ABCO, we notice that the quality of the solutions is affected by the number of population and directly proportional of the number of iteration. We have shown that the ABCO has a better performance in terms of stability to find the global optimum.

General Conclusion

In the industry, there are several software, practices and methods used to optimize drilling operation. Among others, ROP is one of the optimization considerations. The primary objective of this thesis work was to know all the model ROP from 1965 until now, and to assess the difference between them. Several parameters effecting on ROP, those parameters should be well modeled to express their influence on ROP. Bourgoyne and Young's model is one the feasible and effective models. We have chosen it to understand and calculate the optimal ROP for a nearby well to be drilled according to on existing well data. This model contains eight unknown parameters should be solved by means of an optimization technique. As there are more two unknown parameters we have selected some well used metaheuristique techniques to find them, which are: PSO, MPSO and ABCO.

Firstly, we have confirmed the feasibility of each one of them compared with multiple regression technique used by Bourgoyne and Young. After that we have performed several tests to check which one among them is the most effective in sight of convergence quality to reach the global optimum.

According to the found results, we can deduce that ABCO technique is well suited to be a good optimization technique in sight of an implementation in real time.

REFERENCES

[1] Lummus J.L., "Drilling Optimization," SPE 2744, SPE 40th Annual California Fall Meeting, San Francisco, November 1969.

[2] Eren, T. "Real-time-optimization of drilling parameters during drilling operations," PhD Thesis, METU, Ankara, February 2010.

[3] Graham J.W. and Muench N.L., "Analytical Determination of Optimum Bit Weight and Rotary Speed Combinations," SPE 1349-G, Fall Meeting of the Society of Petroleum Engineers, Dallas, October 1959.

[4] Galle E.M and Woods A.B., "Best Constant Weight and Rotary Speed for Rotary Rock Bits," Drill. And Prod. Prac., pp 48-73, API 1963.

[5] Bourgoyne Jr., A. T. and Young Jr., F. S., "A multiple regression approach to optimal drilling and abnormal pressure detection," Society of Petroleum Engineers Journal, August, 371-384. doi:10.2118/4238-PA, 1974.

[6] Carden, R.S., Grace, R.D., and Shursen, J.L., "Drilling Practices," Petroskills OGCI, Course Notes, Tulsa, OK, pp 1-8, 2006.

[7] Bond D.F., Scott P.W., Page P.E., and Windham T.M., "Applying Technical Limit Methodology for Step Change in Understanding and Performance," SPE 51181, IADC/SPE Drilling Conference, New Orleans, April 1998.

[8] Schreuder J.C. and Sharpe P.J., "Drilling The Limit – A Key to Reduce Well Costs," SPE 57258, Asia Pacific Improved Oil Recovery Conference, Malaysia, October 1999.

[9] Bradley H.B., "Petroleum Engineering Handbook," Society of Petroleum Engineers, Richardson, TX, Chapter 52 (Mud Logging), pp- 52-1, 1987.

[10] Devereux S., "Practical Well Planning and Drilling Manual," PennWell Publishing Company, Tulsa, OK, pp 412, 1998.

[11] Baker Hughes Inteq: "Drilling Engineering Workbook", Training Development, Houston, TX, pp 9-18, 1995.

[12] Lyons W.C., "Standard Handbook of Petroleum & Natural Gas Engineering," Gulf Professional Publishing, Houston, Texas, VOLUME-I, pp 1022, 1996.

[13] Lyons W.C., and Plisga G.J., "Standard Handbook of Petroleum & Natural Gas Engineering," Gulf Professional Publishing, pp 4 (363 - 366), 2005.

[14] Ozbayoglu M.E., Miska S.Z., Reed T., and Takach N., "Analysis of the Effects of Major Drilling Parameters on Cuttings Transport Efficiency for High-Angle Wells in Coiled Tubing Drilling Operations," SPE 89334, SPE/IcoTA CT Conf. and Exhb., Houston, TX, March 2004.

[15] Motahhari, H.R."Improved Drilling Efficiency Technique Using Integrated PDM and PDC Bit Parameters". MS thesis, University of Calgary, Calgary, Alberta. 2008.

[16] Winters, W. J., Warren, T. M., and Onyia, E. C., "Roller bit model with rock ductility and cone offset," in SPE Annual Technical Conference and Exhibition, SPE, January 1987.

[17] Bingham, M. G.. A New Approach to Interpreting Rock Drillability. October 1965

[18] B. Rashidi, G. Hareland, R. Nygaard, "Real-Time Drill Bit Wear Prediction by Combining Rock Energy and Drilling Strength Concepts", International Petroleum Conference and Exhibition, Abu Dhabi, UAE, 3rd–6th November 2008.

[19] M. Rastegar, G. Hareland, R. Nygaard, and A. Bashari, "Optimization of multiple bit runs based on ROP models and cost equation: a new methodology applied for one of the Persian Gulf carbonate fields," in IADC/SPE Asia Pacific Drilling Technology Conference and Exhibition, Society of Petroleum Engineers, 2008.

[20] H. Darley, "Designing fast drilling fluids," Journal of Petroleum Technology, vol. 17, no. 04, pp. 465-470, 1965.

[21] Eckel, J. J., "Micro bit Studies of the Effect of Fluid Properties and Hydraulics on Drilling Rate," Pet. Tech., pp 541-546; Trans., AIME, Vol. 240, April 1967.

[22] Galle, E. M. and Woods, H.B., "Variable Weight and Rotary Speed for Lowest Drilling Cost," AAODC Annual Meeting, New Orleans, Sept. 27, 1960.

[23] Estes, Jack C. and Randall, B.V., "Practical Application of Optimized Drilling Operations, " IADC Drilling Technology Conf., New Orleans, March 16-18, 1977.

[24] Maurer, W.C., "The Perfect Cleaning Theory of Rotary Drilling", J. Pet. Tech., 1270-1274; Trans., AIME, Vol. 225, Nov. 1962.

[25] Warren, T.M., "Drilling Model for Soft-Formation Bits," JPT, pp 963-70, June 1981.

[26] Wardlaw, H.W.R., "Optimization of Rotary Drilling Parameters," PhD dissertation, U. of Texas, Austin, Aug. 1971.

[27] T. Warren, "Penetration rate performance of roller cone bits," SPE Drilling Engineering, vol. 2, no. 01, pp. 9-18, 1987.

[28] T.M. Warren, "Penetration-Rate Performance of Roller Cone Bits", SPE, Amoco Production Co. 1987.

[29] G. Hareland and L. Hoberock, "Use of drilling parameters to predict in-situ stress bounds," in SPE/IADC Drilling Conference, SPE, 1993.

[30] Akik akrem, Chelouche aissa and Abd esselam mohammed'' Optimization of drilling parameters using metaheuristic technique'' Master's thesis in drilling 2017/2018

[31] J. Kennedy, R. C. Eberhart, "Particle Swarm Optimization", *Proc. IEEE* International Conference on Neural Networks*, vol*. IV, pp. 1942-1948, 1995

[32] R. C. Eberhart, J. Kennedy, "A New Optimizer Using Particles Swarm Theory", Proc. Sixth International Symposium on Micro Machine and Human Science (Nagoya Japan), pp. 39-43, 1995.

[33] Handbook of Genetic Algorithms, NY, New York:Van Nostrand Reinhold, 1991

[34] Nur Azia azwani binti ismail''particle swarm optimization (PSO) for CNC route probleme'' Bachelor of Electrical Engineering (Electronics) in Faculty of Electrical & Electronics Engineering

Universiti Malaysia Pahang JUNE, 2012.

[35] Karaboga D, Akay B Artificial bee colony (abc) algorithm on training artificial neural networks. In:2007 IEEE 15th signal processing and communications applications, vols 1-3, IEEE, pp 818–821

[36] Karaboga D, Akay B A survey: algorithms simulating bee swarm intelligence. Artif Intell Rev 31:61–85 (2009c).

[37] Samiha Aichouche "Improvement of Performance of Certain Numerical Computational Methods using Swarm Intelligence Algorithms'' PhD in Mathematics University of Biskra, Algeria 2016