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Optimisation of Drilling Parameters for Directional and Horizontal Wells Using Genetic Algorithm

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Authors' contributions

This work was carried out in collaboration between both authors. Author OAF designed the study, wrote the protocol. Author CJA wrote the first draft of the manuscript. Author OAF managed the literature searches. Author CJA did analyses of the study, performed the genetic algorithm modelling and analysis. Both authors read and approved the final manuscript.

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ABSTRACT

In this paper, a modification of Bourgoyne and Young ROP model has been derived. Bourgoyne and Young recommend multiple regression method to determine unknown coefficients. However, applying multiple regressions leads to physically meaningless values in some situation. Although some new mathematical model methods have recently been developed to reach meaningful results. In order to reach a more accurate prediction and physically meaningful coefficient, genetic algorithm was used to determine the eleven unknown drilling parameters of the proposed model. The model was validated with field data obtained from randomly selected wells drilled in the offshore locations at Khangiran Iranian field. The proposed model was found to estimate the rate of penetration with an error of ±10%.

In this study, a robust model has been developed, tested and found to give realistic penetration rate for roller cone bits in directional and horizontal wells. The model is a veritable tool that can be used to investigate the synergistic effect of several drilling parameters on the rate of penetration.

Keywords: ROP; regression; genetic algorithm; drilling; directional well; horizontal well.

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NOMENCLATURES

A_{bed} : *Area of cuttings bed, ft^2*
A_{well} : *Area of wellbore, ft^2*
C_c : *Cuttings concentration by volume in the annulus*
D : *Well depth, ft*
GR : *Genetic algorithm*
H : *Hole or bit diameter, in*
MR : *Multiple regressions*
N : *Rotary speed, RPM*
ROP : *Rate of penetration, ft/hr*
V_{actual} : *Critical transport velocity, ft/sec*
$V_{critical}$: *Actual transport velocity, ft/sec*
W : *Bit weight, 1,000 lbf*
a_1 : *Formation strength*
a_2 : *Normal compaction*
a_3 : *Under compaction*
a_4 : *Pressure differential*
a_5 : *Weight on bit*
a_6 : *Rotary speed*
a_7 : *Tooth wear*
a_8 : *Jet impact force*
a_9 : *Horizontal hole cleaning*
a_{10} : *Inclined hole cleaning*
a_{11} : *Vertical hole cleaning*
d_b : *Bit diameter, in*
g_p : *Pore pressure gradient of the formation, : lb/gal*
t : *Rotating time, hours*
ρ_c : *Equivalent circulating mud density at the bottom hole, lb/gal*

1. INTRODUCTION

Geological studies and seismic surveys can point the way to a hydrocarbon prospect. However, the only way to know if that prospect contains oil or gas is to drill a well. Drilling is the most *expensive* component of the entire exploration and field development process.

The oil and gas industry pays a lot of attention to optimize the drilling process such that oilfield development is carried out in cost efficient manners [1]. In a drilling project, two goals are governing all aspects of it. The first is to drill the well in a safe manner and the second is to complete it with minimum cost [2,3].

Drilling is a complex and multidisciplinary phase of the upstream oil industry. In order to drill a safe and cost effective well especially in difficult terrains, techniques from several disciplines such as physics, engineering and geology are usually combined and employed [4]. Communication and computer technologies are among the most important disciplines which can contribute to drilling optimization. Large amount of data could be piped through different locations on the planet in reliable and time efficient manners. Advanced computer technologies are now being used in storing large amounts of data, and solving complex problems.

Companies that lack accurate, timely and integrated information cannot adequately control and optimize well production, leverage a centralized repository of data for real-time and historical analysis, or monitor and enhance field production strategies-leading to sub-optimal performance. Today's industry challenges are impacting drilling success and overall system cost. Drilling optimisation is the logical process of analyzing effects and interactions of drilling variables through mathematical modeling to achieve maximum drilling efficiency [5]. The process involves the post appraisal of offset well record to determine the cost effectiveness of selected control variables [6]. Drilling optimisation could help reduce drilling time and cost of operation, increase performances and reduce the probability of encountering problems thus increases the profit.

The philosophy of optimisation is to use the records of one or more wells as a basis for calculation and applying optimum techniques to the next and other wells, which is using the record of the first drilled wells as a basis and applying optimisation techniques on those records to reduce drilling costs for the next wells being drilled. As drilling progresses in a new area, the drilling crew becomes familiar with the area and drilling can be optmised to reduce the cost of drilling subsequent wells [4].

Drilling optimisation program is designed to optimise controllable drilling variables including weight on bit and bit rotation speed in order to obtain maximum drilling rate since rock drillability decreases with increasing depth of the hole [4,7]. The increase in complexity for drilling operation causes many problems which lead to critical cost consideration [8,9].

Optimisation of drilling operation can be obtained by increasing drilling speed [10]. Major drilling variables considered to have effect on drilling rate of penetration are not fully understood and complex to model.

To effectively remove drill cuttings during drilling, a number of factors must be put in place to achieve optimal bottom hole cleaning. To efficiently transport cuttings out of the hole, there must be enough energy to push the solids out of the hole and the drilling fluid must be able to suspend the solid particles. Some of the factors that affect hole cleaning are drill pipe rotation, drill pipe eccentricity, rheology, drilling Rate, Cutting Bed Properties, and hydraulics [11].

Drilling cost reductions have been achieved using mathematical models that were developed to combine known relations of drilling parameters to optimise drilling operation by selecting the best bit weight and rotary speed [4,12,13].

There are mainly two optimization methodologies; using analytical models such as the method of Galle and Woods, [13] drill-off tests, and use of the numerical (statistical) models such as multiple regression analysis [14]. One of the most important early studies performed in regards to optimal drilling detection was by Bourgoyne and Young [14]. They constructed a linear penetration rate model and performed a multiple regression analysis of drilling data in order to select the bit weight, rotary speed, and bit hydraulics.

1.1 Problem Statement

The efficiency of any drilling program depends on several variables that are likely to affect it positively or negatively. These variables are interrelated and depend on one another. The effect of these variables during vertical drilling on one another and the combined effect on the drilling efficiency have been investigated by several authors. However, during horizontal or directional drilling, variables such as hole cleaning becomes important and can affect ROP, hydraulics, torque and drag, etc have not been accounted for. This study is designed to incorporate the effect of such parameters on drilling efficiency.

1.2 Objective of Study

The aim of this study is to propose a modified Bourgoyne and Young model in optimization of drilling parameters. However to achieve this aim the following objectives are set:

i. Derive the of ROP model for directional and horizontal wells.
ii. Determine proposed model constants coefficient using genetic algorithms.
iii. Test the performance of the proposed model using actual field data obtained from Khangiran field, and Genetic Algorithm to determine constants that represents several drilling parameters for the field data.

2. LITERATURE REVIEW

2.1 Drilling Optimisation

Optimization of drilling activities for oil and gas wells is an area for which numerous detailed research studies have been performed. Optimized drilling is a system of pre-selecting the magnitude of controllable drilling variables to maximize footage or minimize drilling cost [10]. It is considered that with the increasing demand to drill wells, the area of research on the optimization of the drilling operations is going to be one over which scientist will be working on.

The rate of penetration is considered one of the prime factors in drilling a hydrocarbon well and it is therefore given a prime consideration when drilling an oil well. However, a lot of extensive analysis on ways of increasing the rate of penetration from both theoretical and experimental standpoint has been carried out till date, [13-24]. During drilling, one major goal during the design of any drilling program is to remove the cuttings from the hole efficiently. Inefficient hole cleaning can lead to serious drilling problems, such as increase in torque and drag, stuck pipe, loose control on density, difficulty when running and cementing casing, etc [25,26]. In order to alleviate these problems, the drilling fluid must be designed to have carrying capacity sufficient to lift and suspend the cuttings during transport to the surface. Studies have shown that the key factors that affect the carrying capacity of a drilling fluid include cuttings properties, hole geometry, drill pipe rotation speed, fluid annular velocity, pipe/hole eccentricity, hole inclination, drilling fluid properties and penetration rate. Among these factors, fluid flow velocity appears to be the dominant drilling variable that affects hole cleaning because it is directly related to the shear stress acting on the cuttings bed [26-29]. Also, it has been documented in literature that gel formation can arise in the cuttings bed as a result of the interaction between the drilling fluids and cuttings, which significantly increases the shear force needed to erode the bed, and lift the cuttings up from the bed [26,27].

2.2 Genetic Algorithm

Genetic algorithm is a tool that can be used for solving both constrained and unconstrained optimisation problems. It was developed by John Holland in early 1970's and is based on Darwin's theory of natural selection, the process that drives biological evolution [30-32]. Genetic algorithm repeatedly modifies a population of individual solutions. The algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. The population "evolves" toward an optimal solution within successive generations. Genetic algorithm can be applied to solve a variety of optimisation problems that cannot be handled by standard optimisation algorithms, including discontinuous functions, non-differentiable, stochastic, or highly nonlinear. In addition, genetic algorithm can be used to solve the problems of mixed integer programming, where some components are restricted to be integer-valued.

Genetic algorithm employs three main rules at each step to create the next generation from the current population:

i. Selection rules: These rules select the individuals (parents) that contribute to the population at the next generation.
ii. Crossover rules: These rules combine two parents to produce children for the next generation.
iii. Mutation rules: These rules apply random changes to individual parents to form children.

2.3 Terminology of Genetic Algorithms

2.3.1 Fitness function

The fitness function is the function you want to optimize. For standard optimization algorithms, this is known as the objective function. The toolbox software tries to find the minimum of the fitness function. Write the fitness function as a file or anonymous function, and pass it as a function handle input argument to the main genetic algorithm function.

2.3.2 Individuals

An individual is any point to which you can apply the fitness function. The value of the fitness function for an individual is its score. For example, if the fitness function is the vector (2, -3, 1), whose length is the number of variables in the problem, is an individual. The score of the individual (2, –3, 1) is f (2, –3, 1) = 51. An individual is sometimes referred to as a *genome* and the vector entries of an individual as *genes*.

2.3.3 Populations and generations

A population is an array of individuals. For example, if the size of the population is 100 and the number of variables in the fitness function is 3, you represent the population by a 100-by-3 matrix. The same individual can appear more than once in the population. For example, the individual (2, -3, 1) can appear in more than one row of the array.

At each iteration, the genetic algorithm performs a series of computations on the current population to produce a new population. Each successive population is called a new generation.

2.3.4 Diversity

Diversity refers to the average distance between individuals in a population. A population has high diversity if the average distance is large; otherwise it has low diversity. In Fig. 1, the population on the left has high diversity, while the population on the right has low diversity. Diversity is essential to the genetic algorithm because it enables the algorithm to search a larger region of the space.

2.3.5 Fitness values and best fitness values

The fitness value of an individual is the value of the fitness function for that individual. Because the toolbox software finds the minimum of the fitness function, the best fitness value for a population is the smallest fitness value for any individual in the population.

2.3.6 Parents and children

To create the next generation, the genetic algorithm selects certain individuals in the current population, called parents, and uses them to create individuals in the next generation, called children. Typically, the algorithm is more likely to select parents that have better fitness values.

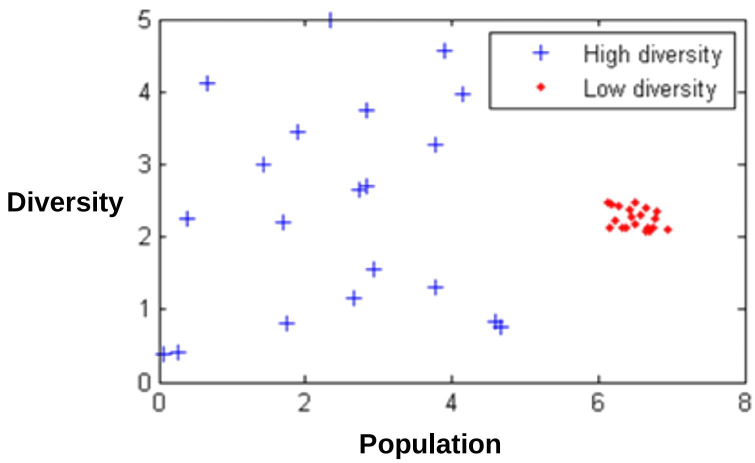

Fig. 1. Population diversity in genetic algorithm

2.3.7 Formalization of gas

The mathematicians Michael Vose and Gunar Liepins developed a formal model based on the following simple GA [28].

Start with a random population of binary strings of length l and follow these steps:

1. Calculate the fitness f(x) of each string x in the population.
2. Choose (with replacement) two parents from the current population with probability proportional to each string's relative fitness in the population.
3. Cross over the two parents (at a single randomly chosen point) with probability p_c to form two offspring. (If no crossover occurs, the offspring are exact copies of the parents.) Select one of the offspring at random and discard the other.
4. Mutate each bit in the selected offspring with probability p_m, and place it in the new population.
5. Go to step 2 until a new population is complete.
6. Go to step 1.

3. MATERIALS AND METHODS

The drilling model selected for predicting the rate of penetration, ROP, by considering the effect of the various drilling parameters is described as:

ROP = $(f_1)(f_2)(f_3)(f_4)(f_5)\ldots.(f_n)$

where f_1, f_2,f_3. . . . . . f_n represent the functional relations between penetration rate and various drilling variables. Each of these functions contains constants which are shown as a_1 through a_n. Determination of these constants is accomplished by using a multiple regression analysis and genetic algorithm of collected drilling data. In this study, Bourgoyne and Young's model is improved and enhanced for roller cone bits, as well as for horizontal and directional wells. The major improvements are the consideration of additional drilling parameters (hole cleaning) occurring due to inclination.

$$f_1 = e^{a_1}, \tag{1}$$

$$f_2 = e^{a_2 x_2} = e^{a_2(10{,}000 - D)}, \tag{2}$$

$$f_3 = e^{a_3 x_3} = e^{a_3 D^{0.69}(g_p - 9.0)}, \tag{3}$$

$$f_4 = e^{a_4 x_4} = e^{2.303 a_3 D (g_p - \rho_c)}, \tag{4}$$

$$f_5 = e^{a_5 x_5} = \left[\frac{\left(\frac{W}{d_b}\right) - \left(\frac{W}{d_b}\right)_t}{4 - \left(\frac{W}{d_b}\right)_t}\right]^{a_5}, \tag{5}$$

$$f_6 = e^{a_6 x_6} = \left[\frac{N}{100}\right]^{a_6}, \tag{6}$$

$$f_7 = e^{a_7 x_7} = e^{a_7(-h)}, \tag{7}$$

$$f_8 = e^{a_8 x_8} = \left[\frac{F_j}{1{,}000}\right]^{a_8} \tag{8}$$

Effect of hole cleaning (f_9) (f_{10})(f_{11})

$$f_9 = \left[\frac{A_{bed}/A_{well}}{0.2}\right]^{a_9} \tag{9}$$

$$f_{10} = \left[\frac{V_{actual}}{V_{critical}}\right]^{a_{10}} \tag{10}$$

$$f_{11} = \left[\frac{C_c}{100}\right]^{a_{11}} \tag{11}$$

Table 1 is a description of the drilling parameter constants.

Table 1. Constants a_1 to a_{11}

Variable	Constant
Formation strength	a_1
Normal compaction	a_2
Under compaction	a_3
Pressure differential	a_4
Weight on bit	a_5
Rotary speed	a_6
Tooth wear	a_7

3.1 Determining Proposed Model Constant Coefficients Using Genetic Algorithms

As mentioned, GA is employed to determine optimal value for constant parameters of the proposed model. Since GA handles bound constraints, using it guarantees to find optimum values of coefficients in recommended bounds (not out of bounds). Therefore GA does not only provide meaningful result but also is not limited to the number of data points. Table 2 is a sample of required data obtained from khanigran gas field.

To find constant parameters of the aforementioned model for each formation, GA was run in the following steps:

i. Set the initial parameters for GA: population size, crossover type and probability and mutation probability.
ii. Set all bounds recommended by the proposed model for each of the 11 parameters.
iii. Generate the initial population randomly.
iv. Reckoning of a fitness function is standard deviation of distances between real ROP and Estimated ROP by predictor system.
v. Selection of the subjects that will mate according to their share in the population global fitness.
vi. Apply the genetic operators (crossover and mutation)
vii. Repeat steps 3 to 6 until the generation number is reached.

4. RESULTS AND DISCUSSION

The proposed model was use to predict the ROP for the khangiran field and Table 3 show the data and relative error that was calculated for both genetic algorithm (GA) and multiple regression (MR). Where, absolute error GA = Actual ROP – GA ROP/ Actual ROP.

Rate of penetration vs well data are plotted in Fig. 2 for actual, genetic algorithm and multiple regression using the proposed model, to show the differences between the both predicted and actual ROP performances for certain formation and wellbore diameters. The achieved results gave consistent outputs for the actual rate of penetration and GA for proposed model than multiple regressions. Data point 3,5,7, and 8 had a match with the actual ROP and GA when compared to actual ROP and multiple regressions which had only a match on 5 and 7. The absolute error for GA and MR is shown in Fig. 3. It can be observed that the proposed model can estimate rate of penetration with an error of ±10% when compared with the field data.

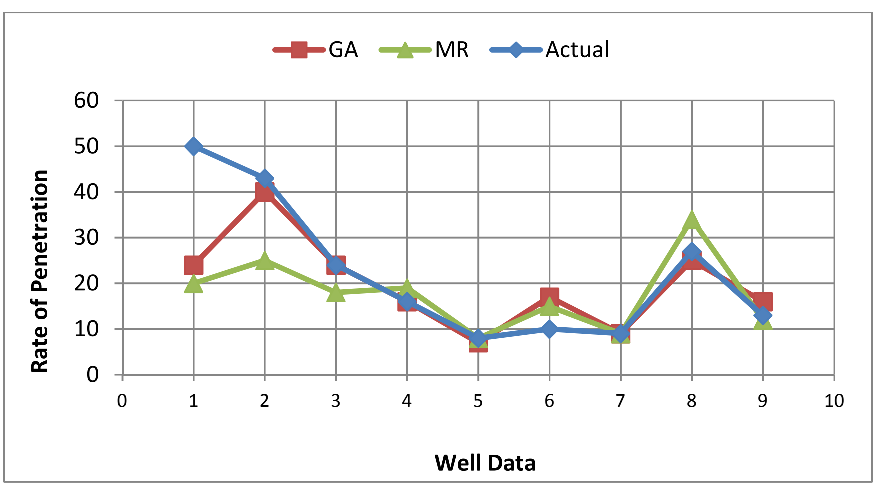

Fig. 2. Rate of penetration vs well data for actual, genetic algorithm and multiple regression

Table 2. A sample of required data obtained from khangiran gas field

Well no	Rop (ft/h)	D (ft)	W (1000 lbf)	d_b (in)	N (Rpm)	ρ_c (lbm/gal)	H (%)	g_p (lbm/gal)	F_j (lbf)	C_c	$\frac{V_{actual}}{V_{critical}}$	$\frac{A_{bed}}{A_{well}}$
1	50.6	354	17.5	26.0	130	08.82	0.25	7.48	960	0.045	0.71	0.26
2	42.5	1411	15.0	17.5	130	09.96	0.25	8.62	1776	0.130	0.68	0.28
3	24.3	359	15.0	26.0	130	08.95	0.25	7.62	1611	0.170	0.92	0.24
4	16.2	1519	10.0	17.5	110	10.20	0.38	8.82	2123	0.094	1.10	0.31
5	07.3	1772	07.5	17.5	110	10.30	0.25	8.95	1185	0.300	1.15	0.28
6	09.5	1969	10.0	17.5	110	10.80	0.50	9.49	1324	0.450	0.83	0.30
7	08.9	1900	09.0	17.5	100	10.50	0.50	9.15	1186	0.260	0.93	0.29
8	26.9	1575	15.0	17.5	90	10.40	0.38	9.09	2196	0.550	1.35	0.33

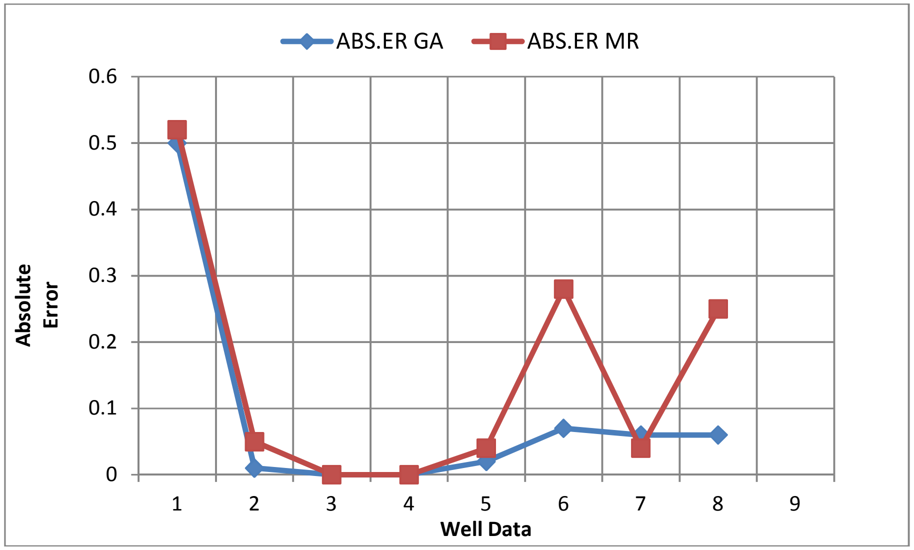

Fig. 3. Absolute error for genetic algorithm and multiple regression

Table 3. The actual and predicted ROP for both GA and MR for well (Khangiran field)

Well data	Actual ROP	GA ROP	MR ROP	Absolute error GA	Absolute error MR
1	50.6	25.1	24.3	0.50	0.52
2	42.5	43.0	40.2	0.01	0.05
3	24.3	24.3	24.2	0.00	0.00
4	16.2	16.1	16.2	0.00	0.00
5	07.3	07.5	7.00	0.02	0.04
6	09.5	10.2	12.2	0.07	0.28
7	08.9	09.4	8.5	0.06	0.04
8	26.9	25.2	20.1	0.06	0.25

Table 4. Constants for both proposed model and Bourgoyne and Young using genetic algorithm

Variable	Constant	Proposed model constants	B & Y model constants
Formation strength	a_1	0.8008	1.5348
Normal compaction	a_2	0.000292	0.0001
Under compaction	a_3	0.000146	0.00000116
Pressure differential	a_4	0.0001	0.0000917
Weight on bit	a_5	0.4881	1.9999
Rotary speed	a_6	0.2019	0.9835
Tooth wear	a_7	0.8154	0.4864
Jet impact force	a_8	0.5704	0.3000
Horizontal hole cleaning	a_9	0.4919	-
Inclined hole cleaning	a_{10}	0.9799	-
Vertical hole cleaning	a_{11}	0.196	-

The data available from Bourgoyne and Young were used to check the accuracy of the computer program. The results are shown in above Table 4. When GA analysis is conducted using the field data, all the model coefficients were positive which is mathematically correct, and physically make sense.

5. CONCLUSION AND RECOMMENDATION

In this study, a robust model based on genetic algorithm has been developed and successfully applied to realistically predict the penetration rate for a roller cone bit for drilling inclined and horizontal wells. The model would serve as a tool for predicting the synergistic effect of several variables on the rate of penetration of drilling in inclined wells. The model has been tested using data from an Iranian field and the following conclusions have been reached.

i. An improved model that takes into account additional drilling parameters (hole cleaning) occurring due to inclination in inclined wells has been developed. The model can predict the rate of penetration with a reasonable accuracy.
ii. Genetic Algorithm procedure can be applied to determine the constant coefficients present in the rate of penetration equation.
iii. The annular cuttings concentration, C_c, dimensionless equilibrium bed area, A_{bed}/A_{well}, and dimensionless velocity, $V_{actual}/V_{critical}$ can be predicted using dimensional analysis.

The results of this study show that excluding parameters that accounts for inclination can greatly underestimate the rate of penetration predicted when drilling horizontal and directional wells. Also, genetic algorithm is a cost effective optimisation technique and can be adopted in industry. It is recommended that the accuracy of the present model can be improved using more data from other fields. In addition, the drilling cost variable can be considered in future work.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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