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Research Article

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Using Analytical and Artificial Intelligence Models to Estimate Drilling Rate of Penetration (ROP)

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Abstract
Drilling a new oil or gas well to reach at reservoir involves a set of processes. Optimized drilling plan is critical to reach the target in the shortest possible time and at the lowest possible cost .Drilling plan and efficiently drilling a new well requires analysis of well data to properly determine bottom hole assembly, drilling bit, drilling fluids, and operational parameters such as weight on bit (WOB) and drill-string rotary speed. The purpose of drilling planning is to optimize the Rate of Penetration (ROP) by reducing non-productive time (NPT). In this article two different estimating drilling rate of penetration (ROP), analytical model and artificial intelligence model were described.

Keywords: Drilling Plan, Rate of Penetration, Analytical Model, Artificial Intelligence Model.

1. Introduction

Drilling a new oil or gas well to reach oil and gas reservoirs involves a set of processes. Drilling programs are the approved instructions for carrying out activities and tasks which are required to achieve the objectives of the drilling process. Before a drilling program is approved it must contain an estimate of the overall costs involved. Time is one of the critical parameters affecting the cost of drilling operations. When drilling in a completely new area with no previous drilling data available the well cost can only be a rough approximation. In most cases however, some previous well data is available and a reasonable approximation can be made. Some costs are related to time and are therefore called time-related costs (e.g. drilling contract, transport, and accommodation). Many of the consumable items (e.g. casing, cement) are related to depth and are therefore often called depth-related costs. These costs can be estimated from the drilling program, which gives the lengths or volumes required. Some of the consumable items such as the wellhead will be a fixed cost. The specialized services (e.g. perforating) will be a charged for on the basis of a service contract which will have been agreed before the service is provided.

In the drilling industry, the rate of penetration (ROP), also known as penetration rate or drill rate, is the speed at which the drilling bit crushes or cuts formation rocks and hence expands the wellbore. It is normally measured in feet per minute or meters per hour, but sometimes it is expressed in minutes per foot [1].

The rate of penetration (ROP) optimization is one of the most important factors in improving drilling efficiency, especially in the downturn time of oil prices. This process is crucial in the well planning and exploration phases, where the selection of the drilling bits and parameters has a significant impact on the total cost and time of the drilling operation. Optimization of ROP is difficult due to the complexity of the relationship between the drilling variables and the ROP [2].

1.1 Drilling Factors Which Affecting ROP

WOB is the amount of force applied on the drill bit and acting along the wellbore axis. WOB is provided by thick-walled steel made tubular. Hydraulic gauge attached to the dead line measures WOB usually in unit of 1000lbf. There are two types of WOB measurements, surface measurement, and downhole measurement. Surface measurement refers to the total weight of all equipment applying tension on the wire rope including TDS, traveling block, and drilling string. Downhole measurement is done by measuring while drilling (MWD) sensors and is usually more accurate compared to surface measurement.

Threshold WOB is the minimum weight needed to initiate the failure of formation rocks. It can take a negative value in soft and unconsolidated formations. The negative value of threshold WOB shows that the drill bit can cut the rocks without any applied weight. It is a function of hydraulic action on the bottom hole.

RPM represents the rotational speed of drilling string or rotary speed in unit of Revolution per Minute (RPM). Electronic sensors attached to the TDS are responsible for accurately measuring the rotary speed.

Pore pressure is the pressure of formation or reservoir fluids existing in porous media of a formation or reservoir rocks. Pore pressure is considered hydrostatic pressure; it is the pressure applied by the column of water from the depth at which pore pressure is measured with respect to the sea level. Pore pressure is usually expressed in psi (Schlumberger Oilfield Glossary).

Mud Weight (MW) also known as drilling fluid (mud) density is usually measured in lbm/gallon (PPG), lbm/ft3 (PCF), and kg/cm3 (Specific Gravity or SG). Hydrostatic pressure inside the well is controlled by changing mud weight and is usually maintained above formation pressure to prevent kick. Mud weight also prevents casings and open hole from collapsing. Inordinate Mud Weight can cause formation fracture and loss of drilling fluid and loss of circulation. (Schlumberger Oilfield Glossary).

Mud viscosity is the drilling fluid's resistance to flow. Mud Viscosity defines as shear stress/shear rate and is reported in Poise (dyne.sec/cm2). One Poise refers to a high viscosity fluid therefore, in-field measurements Mud Viscosity is reported in centipoise (poise/100 or cp) (Schlumberger Oilfield Glossary).

ECD or Circulating Density is the influential density applied by circulating drilling fluid at any depth. ECD is always greater than the static Mud Weight when mud circulation is stopped. It is the sum of static Mud Density and circulating pressure losses at any depth which are converted to density. ECD is generally one of the most important factors in ensuring that kicks and losses are prevented. This is particularly the case where the formation fracture gradient and pore pressure gradient are found to be close (Schlumberger Oilfield Glossary).

Down hole motors or Mud Motors are usually used in directional drilling. Mud motors are positive displacement drilling motors and part of BHA. Mud motors utilize hydraulic horsepower of drilling mud to rotate drilling bits (Schlumberger Oilfield Glossary).

Wellbore inclination is the angle of the wellbore from the vertical trajectory and is measured in degrees. True vertical is in the inclination of 0 degree and horizontal is the inclination of 90 degrees (Schlumberger Oilfield Glossary).

Drilling fluid annular velocity is the speed at which drilling mud travels in the annulus. Drilling mud annular velocity is key in hole-cleaning and cuttings transportation. The Velocity is usually measured in ft/min (Schlumberger Oilfield Glossary).

Cutting bed is the thickness of deposited cuttings on the lower side of the wellbore. Cuttings bed has a tendency to slide downward because of wellbore inclination and gravity component; hence it is referred to as an unstable bed in deviated sections. Drilling string is at risk in case of unstable cuttings bed especially when drilling fluid circulation is halted.

Drilling bit is located at the bottom of BHA and used to cut the formation rocks. The drilling bit must be pulled out of the hole when drilling cannot proceed due to the presence of a dull bit.

Setting up a drilling plan and efficiently drilling a new well requires analysis of offset well data to properly determine bottom hole assemblies, drill bit for a given section, drilling fluids, and the operational parameters such as weight on bit (WOB) and drilling string RPM.

There are various models for estimating rate of penetration (ROP) such as empirical and principal models. Principle models are constructed using physics-based principal knowledge of a system or physical laws (e.g. second law of Newton). Engineering design models are also considered to be the principal models. Empirical models or data-driven models are developed based on training data or historical data of a system. These models were originally referred to as regression models [2].

In recent decades, models developed using computer-based techniques (e.g. Artificial Neural Networks) have also been considered as empirical models since they have been constructed based on iterations using training data. Empirical models can only be used within the range of training data. In contrast, principal models can be used beyond the system under modeling.

Optimizing the drilling parameters such as the rate of penetration (ROP) will lead to saving an extra cost. Optimizing the drilling operations could be achieved by maximizing the ROP which will reduce the drilling time and consequently the drilling cost per feet will be reduced [3]. Several models have been developed to predict the ROP for drilling optimization, the accuracy of such ROP prediction models is so important [4]. Understanding the drilling data behavior is considered to be a key factor for generating a good ROP prediction model. Several parameters affect the ROP and can be categorized into controllable and uncontrollable factors [5]. The controllable drilling parameters such as the weight on bit (WOB), RPM, Q, torque (T), and standpipe pressure (SPP), while the uncontrollable drilling parameters such as the bit size, drilling mud type, density, and rheological properties. The controllable parameters do not affect each other, while the uncontrollable parameters affect each other, and it is not easy to determine the effect of one parameter separately [6]. The bit penetrates the formation during the drilling operation by the action of three forces which are the WOB, the string rotation speed measured by the RPM, and mud pumping rate in gallons per minute (GPM) [7]. The torque (T) is caused by the action of the WOB and the RPM. The SPP is the pressure generated by the mud pumping and measured at the standpipe.

2. Rate of Penetration (ROP) Models

ROP modeling has been always the primary concern in Drilling oil & gas wells, since it is directly related to the drilling cost; over the past few decades, many authors have studied the effect of different parameters on the ROP [5].

ROP prediction models can be classified into two categories, which are traditional models and data-driven models (empirical models). Data-driven models can only be used within the range of training data. In contrast, the traditional ROP models can be used beyond the system under modeling. In the real world, however, it is not possible to develop a traditional ROP models for most systems and processes due to complexity [8].

2.1 Traditional ROP Models

The traditional ROP models use the physics-based relationship between the ROP and the drilling parameters. Engineering design models are also considered to be the traditional models. Optimized drilling involves pre-selecting the magnitude of controllable drilling variables to maximize ROP or minimize drilling operational cost [9].

Graham and Muench (1959) introduced the first attempts optimizing drilling parameters; the authors have established an empirical mathematical expression for the bit life and ROP as a function of WOB, depth, and RPM.

In 1962, Maurer stated that ROP can be calculated as a function of WOB, RPM, drill-ability strength of the rock (UCS), bit diameter (Db), and the drill-ability constant (K), the equation is based on 'perfect cleaning' condition where all of the rock debris has been removed, and Maurer's model is described by Eq. 1 as follows:

$$ROP=K\times RPM\times WOB^2Db^2\times UCS^2. \quad (1)$$

Maurer (1962) modeled ROP with the consideration that hole cleaning is completed and there are no cuttings between drill bit teeth due to hydraulic impact force. It was noted that the proposed model is a function of depth. Maurer (1962) ROP model is defined by:

$$dF/dt = (4/\pi d_b{}^2)\ (dV/dt) \quad (2)$$

Where F is drilled interval in ft, t is time in hr, V is the volume removed by drill bit in cubic inch and d_b is bit diameter in inch.

Galle and Woods (1963) conducted research that resulted in an important development in drilling technology and optimizing the drilling process. They focused on the influence of only two drilling variables; WOB and rotary speed on ROP and assumed that other drilling variables such as drilling fluid, bit hydraulic and bit selection were well selected. They modelled ROP as a function of WOB, rotary speed, bit tooth, and formation type

$$\frac{dF}{dT} = \frac{C_f W^k N^r}{a^p} \quad (3)$$

Where dF/dt is ROP in ft/hr, CF is formation drill ability Reflect factor, W is weight on bit (WOB) (1000 Ib), K is power constant of weight on bit, N is rotational Speed (RPM), r is power constant of rotational speed, a and p are bit constants.

Bingham (1964) developed a mathematical equation representing a simple relationship between ROP, WOB, rotary speed, and bit diameter. He added a formation-related WOB/exponent in the ROP model. Bingham (1964) ROP model is defined by:

$$ROP = a(WOB/d_b)^b\ RPM \quad (4)$$

Where (a) is drill-ability constant and dimensionless, (b) is formation-related dimensionless constant, (WOB) is the weight on bit in (klbf), (d_b) is bit diameter in inch and (RPM) is rotary speed in (revolution/minute). (a) and (b) are constant and are determined individually for formations, thus they cannot be used if any change in formation characteristics happens during drilling.

Eckel and Nolly (1949) concluded that ROP is related to a term multiplying bit nozzle velocity and pump flow rate. Eckel (1967) later developed an empirical correlation for ROP prediction. He concluded ROP is proportionally related to (WOB), rotary speed, and Reynolds number:

$$ROP = K\times WOB^a\times RPM^b\times(Kq_p/d_n\mu)c \quad (5)$$

where (ROP) is in (ft/hr), (a), (b) and (c) are dimensionless formation-dependent constants, (K) is dimensionless constant, (WOB) is in (klbf), (RPM) is in (Revolution/minute), (q) is pump flow rate in (GPM), (p) is mud density in specific gravity (SG), (μ) is mud viscosity (CP), (d_n) is nozzle diameter in inch and (c) connects ROP to Reynolds number and is approximately 0.5.

Apple and Rowley's (1968) model was one of the first attempts in developing ROP prediction model for drilling sections that were drilled by diamond bits. Later, Peterson (1976) also performed a laboratory test for ROP prediction using diamond bits. The developed equations for ROP prediction and Bit selection were based on a flat-bottom bit with round, surface-set diamonds. The ROP model is defined by:

$$R_p/N=8.2S0.17/d_b2X0.5\times(W_n/r)1.5 \quad (6)$$

Where (R_p) is ROP in (ft/hr), (N) is rotary speed in (revelation/minute), (S) is diamond size in (carats/stone), (d_b) is bit diameter in inch, (X) is average density of the face stone in (carats/squared inch), (W_n) is net weight on bit in (lbf) and (r) is formation resistance in (lbf/squared inch). The term (W_n/r) is the maximum square inches of diamonds that can be in contact with the formation and still exert sufficient stress to overcome the formation resistance. He also developed bit selection-related equations and resulted in a 25% improvement in ROP while lowering bit cost.

A pioneering study in regards to obtaining optimum controllable drilling parameters was carried out by Bourgoyne and Young (1974). They proposed a methodology based on multiple linear regression analysis to develop a mathematical model for predicting ROP. They considered the effect of eight drilling functions (including formation strength function, normal compaction function, under compaction function, differential pressure function, and weight on bit Function, rotary speed function, bit teeth wear function, and bit hydraulic function) as independent variables, on ROP. The proposed model was able to predict ROP in vertically drilled wells that were drilled by roller-cone bits. They suggested that drilling data must be obtained from more than one well before all regression coefficients can be evaluated. They concluded that the use of relatively simple drilling optimization equations can reduce drilling operation cost by about 10%. Although Bourgoyne and Young's model was originally developed for drilling sections which were drilled by roller-cone bit, it has also been used for ROP prediction in deviated sections drilled by PDC bits.

Bourgoyne and Young (1974) model is widely used in the oil industry and is considered the best approach to optimize drilling parameters in real time (Eren and Ozbayoglu 2011). The model describes the effect of different drilling parameters on ROP, and they have proposed the multiple regression analysis to extract eight unknown parameters using well drilling datasets.

The equation proposed by Bourgoyne and young is expressed as:

$$\mathrm{ROP} = e(a1+\sum_{j=2}^{8}(aj\ Xj)) \qquad (7)$$

Where ROP is the rate of penetration (ft./h), aj are the model coefficients, and xj are the eight drilling parameters.

Warren (1987) presented a perfect cleaning ROP model for soft formation, and this model relates ROP to the WOB, RPM, UCS, and bit size. To offer comprehensive information regarding the interaction between rock and the bit, he employed experimental response curves and dimensional experiments. Later, Warren has adjusted his model by adding a wear function (Wf) to reflect the impact of bit wear.

Al-Betairi et al. (1988) have proposed a new ROP model using controllable and uncontrollable drilling variables toward predicting the optimum penetration rate and examined the correlational coefficients determined by multiple regression and evaluated the sensitivity of each drilling parameter on ROP.

Maidla and Ohara (1991) developed optimization software for roller-cone bits toward the best selection of WOB, RPM, bit type, and bit wearing to minimize the drilling costs. They concluded that the drilling model performances depend on the quality of the data used to calculate the model's coefficient.

Hareland and Rampersad (1994) introduced a model for drag bits that relates UCS, WOB, RPM, bit geometry, and (Wf).

Motahari et al. (2010) developed a PDC model that considers the wear function and confined compressive strength (CCS) instead of UCS besides RPM, WOB, and bit size. The physics-based models mentioned above use empirical coefficients, which are highly dependent on the lithology and continuously varied due to calibration, such that constraining their functional forms.

Motahari et al. (2010) conducted a case study on a drilling well located in Alberta, Canada, and developed an ROP model for PDC bits. The study was aimed to investigate the effect of different Positive Displacement Motors (PDM) with different lobe configurations on ROP considering a set of fixed drilling parameters. The ROP model is defined by:

$$\mathrm{ROP} = W_f\,(G.\mathrm{RPM}_t^{y}.\mathrm{WOB}^{a} / D_b.S) \qquad (8)$$

Where ROP is in (ft/hr), (W_f) is dimensionless wear function, (G) is the model constant and dimensionless, (RPM) is the surface rotary speed in (revolution/minute), WOB is in (lbf), (y) and (a) are ROP model exponents, (D_b) is bit diameter in inch and (S) is confined rock strength in psi.

Hareland et al. (2010) has created a new simple model for roller cone bits and used laboratory data to estimate the UCS.

Alum and Egbon (2011) used the original model of Bourgoyne and Young in series of studies, and the results have shown that the equivalent circulation density has a great influence on ROP because of the annular pressure losses; as a result, they proposed an analytical model to estimate ROP.

Bataee et al. (2012) conducted a comparative study on various ROP prediction models using field data of oilfield located in Iran. They predicted ROP for a drilling section drilled by roller-cone bits and PDC bits. Their comparison was done in three separate drilling sections, 17 1/2", 12 1/4" and 8 1/2", therefore bit diameter was considered as a constant value. Results showed that Bourgoyne and Young's model has the best prediction performance as compared to the other two models.

2.2 Data-Driven ROP Models

The Data-Driven ROP models are developed based on training data or historical data of a system. These models were originally referred to as regression models. In recent decades, models developed using computer-based techniques (e.g. Artificial Neural Networks) have also been considered as data-driven models (empirical models) since they have been constructed based on iterations using training data [9].

2.2.1 Artificial Intelligence (AI)

There have been several attempts to predict ROP in drilling using artificial intelligent (AI) and hybrids approaches, which give a good result in ROP prediction.

Artificial intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. The term may also be applied to any machine that exhibits traits associated with a human mind such as learning and problem-solving [10].

The ideal characteristic of artificial intelligence is its ability to rationalize and take actions that have the best chance of achieving a specific goal. A subset of artificial intelligence is machine learning, which refers to the concept that computer programs can automatically learn from and adapt to new data without being assisted by humans. Deep learning techniques enable this automatic learning through the absorption of huge amounts of unstructured data such as text, images, or video
[11].

2.2.2 Artificial Intelligence Algorithm

Developing and construction of models to calculate and predict important parameters of the oil and gas industry are very essential. Therefore, recently AI approaches have been implemented in various area of oil and gas industry, such as reservoirs, petroleum well blowouts, formation damage, wellbore stability, rheology and filtration, production, and drilling fluid.

Important factors in selecting and predicting the ANN model include feature selection, network architecture and transfer of functions between layers, and selection of the training algorithm. The neural network creates. an output pattern based on the input pattern provided to the network. Input data can be raw data or output of other neurons. Output can be the final product or input for other neurons. An artificial neural network is a network of artificial neurons that are actually processing elements. Each neuron has a number of inputs, and each input is weighted. The median output of each neuron is obtained from the sum of all inputs multiplied by the weights. The final output is done by applying a conversion function [12].

2.2.3 Multi-Layer Perceptron's Algorithm (MLP)

Multilayer perceptron or MLP is an artificial neural network architecture in which network neurons are divided into several layers. In these networks, the first layer, the input and the last layer, the output and the middle layer, are called hidden layers. This architecture can be called the most widely used neural network architecture [11].

2.2.4 Firefly Algorithm (FF)

Fireflies are of insects that emit yellow light, and it is characteristic that they move towards the light that has the most radiance. Due to the capability of this species, the proposed algorithm has been used as an appropriate optimization algorithm for predictions. Firefly algorithm is an optimization method that tries to find the optimal answer to the problem by simulating the behavior of fireflies [10].

2.2.5 Gravitational Search Algorithm (GSA)

This algorithm is one of the crash-based demographic algorithms based on the laws of gravity in which information is exchanged between objects through the force of gravity between them, in other words, objects force each other due to their mass. The mass of each factor is determined according to the objective function. Each member has a simple behavior that results in intelligent member behavior. When exchanging information between any crime or person, it is done through the following 4 ways: position; inertial mass; an active component of gravitational mass; and an inactive component of gravitational mass [9].

2.2.6 Artificial Bee Colony Algorithm (ABC)

The bee algorithm simulates the behavior of bee groups in search of food. Bees are divided into three categories: worker bees, progressive bees and search bees. The worker bee is the bee that goes to predetermined food sources, the bee is the leading or scout bee that conducts a random search, and the bee is the bee seeker in the dance area to decide which one to choose. The food source remains [9].

2.2.7 Independent Component Analysis (ICA)

The Colonial Competition Algorithm is an optimization algorithm inspired by colonial competition. This algorithm starts from several countries in the initial state. Countries are, in fact, possible answers to the problem. All countries are divided into two categories: imperialist and colonial. Colonial countries break the colonial countries towards themselves by applying the policy of absorption (assimilation) in line with different axes of optimization. Imperialist competition, along with the policy of assimilation, is at the core of this algorithm and causes countries to move towards the absolute minimum of subordination. As the algorithm evolves, the population shifts toward one side of the algorithm due to gravity, which is the solution to its target function using mean square error (MSE), and this algorithm causes it to move in this algorithm and causes countries to move towards it and according to the absolute minimum of the function [12].

Jahanbakhshi et al. (2012) considered several drilling parameters to predict ROP, and the study included the use of multilayer perceptron in the data-driven model.

Bataee et al. (2014) used shuffled frog leaping algorithm as a function of WOB, RPM, and flow rate. They developed an ANN model using about 1810 data-point to train the model and to predict ROP.

Kahraman (2016) found that the use of neural network models is more accurate than the use of regression techniques in the prediction of ROP.

Hegde et al. (2017) identified that the data-driven approach model for ROP predictions was more precise and accurate compared to those based on physical experiments.

In recent years, researchers have tended to apply hybrid models combining several techniques to predict ROP accurately.

Two hybrid ANNs were created by Anemangely et al. (2018) using PSO and cuckoo optimization algorithm (COA) as training functions for providing precise ROP prediction.

Elkatatny (2019) build a new ROP model using hybrid algorithm self-adaptive differential evolution artificial neural network, the model considers five drilling parameters (2223 data points) as input parameters and ROP as an output of the model, and the result was very promising by getting R = 0.98.

Indeed, using AI and hybrid models effectively increases the ROP accuracy prediction; however, the model requires an enormous amount of data and time to train and test the model. In addition, the use of the model is limited to a local area; moreover, the process requires high-performance computer systems and machine learning skills. So, the use of conventional models with the application of metaheuristics and regression techniques to optimize ROP is more appropriate.

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