RGNZ/MGPB

Prediction of Rate of Penetration (ROP) in Petroleum Drilling Operations using Optimization Algorithms

Rudarsko-geološko-naftni zbornik
(The Mining-Geology-Petroleum Engineering Bulletin)
UDC: 622.3
DOI: 10.17794/rgn.2024.3.9

Original scientific paper

Arash Ebrahimabadi[1]; Alireza Afradi[2]

[1] *Department of Petroleum, Mining and Material Engineering, Central Tehran Branch, Islamic Azad University, Tehran, Iran.*
https://orcid.org/0000-0002-1996-2731

[2] *Department of Mining and Geology, Qaemshahr Branch, Islamic Azad University, Qaemshahr, Iran.*
https://orcid.org/0000-0002-1071-3990

Abstract

In drilling operations, by choosing the proper tools and also incorporating more accurate and reliable parameters, this operation can be performed in less time and cost manner. Among drilling parameters, Rate of Penetration (ROP) is viewed as the main parameter in drilling operation evaluation. Field data investigations can be considered the most fruitful approaches to evaluate drilling performance, or ROP, as well as development of predictive models although laboratory tests and experimental formulas are vastly used to identify the drilling problems. In this research, intelligent modeling was used to predict the penetration rate of drilling operations through analyses of an established comprehensive data base from drilling operations in one of Iranian oilfields, Shadegan oilfield, in which novel artificial intelligence techniques such as Grey Wolf Optimization (GWO), Particle Swarm Optimization (PSO), and Grasshopper Optimization Algorithm (GOA) were applied. Since the database includes 400 data, these techniques were utilized due to their effectiveness on a large set of data. In this research, using drilling data compiled from Shadegan oilfield, a precise model was developed to predict the ROP. Results showed that determination coefficient (R^2) and Root mean squared error (RMSE) parameters for Particle Swarm Optimization (PSO) are found to be as R^2=0.977 and RMSE=0.036, for Grey Wolf Optimization (GWO) R^2=0.996 and RMSE=0.014, for Grasshopper Optimization Algorithm (GOA) R^2=0.999 and RMSE=0.003, respectively. Ultimately, it can be concluded that all predictive models lead to acceptable results but GOA yields more precise and realistic outcome.

Keywords:

drilling operation; Rate Of Penetration; Grey Wolf Optimization; Particle Swarm Optimization; Grasshopper Optimization Algorithm

1. Introduction

Drilling operation plays a crucial role in petroleum industry to reduce unnecessary expenses and therefore to enhance profitability of the operation. Rate of penetration (ROP) relies upon on different issues consisting of formation characteristics, depth of wellbore, drilling fluid attributes, weight on bit, rotational speed of drill string, mud loss conditions, bit type and project hydraulics, bit consumption and cleaning. These elements have various impacts on rate of penetration. With this respect, drilling performance prediction can be viewed as an essential factor to decrease drilling costs. Some researchers investigated the effect of various factors on ROP. **Maurer (1962)** suggested a model to evaluate the rate of penetration for roller-cone bits. **Galle and Woods (1963)** proposed an analytical approach to evaluate ROP based on parameters such as Revolution per Minute (RPM), Weight on Bit (WOB), formation properties and bit metallurgical characteristics. **Mechem and Fullerton (1965)** presented a model using drilling fluid pressure, RPM, bit weight, hydraulics and formation attributes. **Bourgoyne and Young (1973)** proposed a model for predicting ROP using statistical approach. Using available drilling data, **Bourgoyne and Young (1974)** presented an approach to appropriate selection of input parameters affecting ROP prediction. **Tanseu (1975)** optimized some drilling data like cost, bit life and ROP and some equations were developed to predict the ROP and bit life. It was tried to minimize costs considering predicted ROP and bit life. **Al-Betairi et al. (1988)** investigated the effect of several factors on rate of penetration utilizing multiple regression analysis. They applied sensitivity analysis to choose major parameters affecting ROP and then proposed optimum values of these parameters under controllable and uncontrollable conditions. **Maidla and Ohara (1991)** presented a software programming in order to optimum selection of drilling bits with the special emphasis of reducing cost per foot.

Corresponding author: Arash Ebrahimabadi
e-mail address: A.Ebrahimabadi@iauctb.ac.ir

Table 1: Drilling rate of penetration models

Maurer (1962)	$R=K(N(W-W_0)^2/60D^2S^2)$ For $w<w_0$ $R=K(NW^2/60D^2S^2)$ Where R: rate of penetration in m/h; D: bit diameter in mm; k: a constant for drillability; N: rotational speed in rpm; W_0: weight on bit threshold prior to initiation of cratering in kN; W: weight on bit in kN; and S: rock strength in MPa.
Bauer and Calder (1967)	$R= [61-28\log_{10} (s)]$ W/D. N/300 Where N: rotational speed in rpm; W: weight on bit in lbf; D: bit diameter in inch; S: rock strength in psi; and R: rate of penetration in ft/h.
Cunningham (1978)	$DR=NW^a/0.424\sigma_d^{1.5}+\sqrt{NWa}\,(\Delta P)^{0.75}$ Where N: rotational speed in rpm; W: weight on bit in 1,000 lb/in of diameter; ΔP: the differential pressure between pore pressure and drilling fluid pressure at the bit in 1,000 psi; σ_d: drilling strength in 1,000 lb/in.^{2}; *a*: constants (achieved from tests); DR: drilling rate in ft/hr.
Warren (1981)	$R=(aS^2D^3/N^bw^2+C/ND)^{-1}$ Where R: penetration rate in ft/hr (m/h); *a*, *b*, and *c*: bit constants; D: bit diameter in cm; N: rotational speed in rev/s; S: drilling strength in psi (kPa); and W: weight on bit in N.
Bourgoyne and Young (1984)	ROP=f1×f2×f3×f4×f5×f6×f7×f8 where ROP: rate of penetration; f_1: effect of drillability of rock formation; f_2: effect of compaction; f_3: under-compaction due to differential pressure; f_4: effect of differential pressure; f_5: effect of rate of penetration due to any change in weight on bit; f_6: effect of rotational speed on rate of penetration; f_7: effect of bit wear on rate of penetration; and f_8: effect of bit hydraulics on rate of penetration.
Walker et al. (1986)	$R=14+54W-56p+31\varphi-10g-16\sigma_c+46p-31pW$ Where W: weight on bit in lbs; p: bore hole pressure in psi; φ: porosity in percentage; g: average grain size in inch; σ_c: in-situ compressive strength in psi; and R: rate of penetration in ft/hr .
Bourdon et al. (1989)	R=KWf(v) Where R: penetration rate in ft/hr (m/h); W: weight on bit in N; f: function of rotary speed; K: drilling-model coefficient; and *υ*: rotary speed in rpm.
Wijk (1991)	$B= \overline{B}\, n\, S_c^{1/4}\, [F/D\sigma_{RD}]^{3/2}$ Where B: rate of penetration; $\overline{B}$: a non-dimensional constant; n: rotary speed; *Sc*: button density; F: weight on bit; D: hole diameter; and *σRD*: stamp test strength index.
Autio and Kirkkomäki (1996)	$R=AW^B$ Where R: rate of penetration or net advance rate in m/h; W: weight on bit; A and B: adjustment coefficients.
Kahraman (1999)	$PR=1.05\,(W^{0.824}RPM^{1.69}/D^{2.321}\sigma_c^{0.610})$ Where PR: penetration rate in m/min; W: weight on bit in kg; RPM: rotational speed in rpm; D: bit diameter in cm; and σ_c: uniaxial compressive strength in MPa.
Shirkavand et al. (2009)	$R=W_f(14.14W.N^b.\cos\alpha/S.D_B\,.\tan\theta)$ Where R: rate of penetration; *Wf*: wear constant that varies between 1 (for new drill bit) and 0 (for cutters totally worn); S: confined compressive strength; W: weight on bit; N: rotational speed; α and θ: cutter rake angles; and D_B: bit diameter.
Kowakwi et al. (2012)	$R=(0.082\sigma^2\, D^3/N^{0.6}\, W^2+5.034/ND)^{-1}.f(x).f_c(P_e).W_f$ Where σ: rock strength in kPa; N: rotational speed in rev/s; R: rate of penetration in ft/h; (*x*): hydraulic energy function; $f_c(P_e)$: effect of chip hold down; and *Wf*: effect of bit wear; D: bit diameter in cm; and W: weight on bit in N.
Chen et al. (2014)	$R= 13.33\mu_b N/D_B(CCS/E_m We^{-\mu\gamma b} -1/A_B)$ Where R: rate of penetration in ft/h; μ_b: friction coefficient of bit; N: rotational speed in rpm; D_B: bit diameter in inch; CCS: confined compressive strength in psi; E_m: mechanical efficiency of a new bit, W: weight on bit in lbf; μ: friction coefficient of drill string; γ_b: bottom hole inclination in rad; and A_B: bit area in square inch.
Deng et al. (2015)	$v=2\pi nM/\tfrac{1}{4}\pi D^2a-P$ Where *υ*: rate of penetration; n: rotational speed; M: torque; D: bit diameter; *a*: specific energy, and P: weight on bit.
Ataei et al. (2015)	$R=2.31(W^{0.094}N^{0.95}RDi^{0.099}/\, P^{0.075}D^{3.04})$ Where R: rate of penetration in m/min; W: weight on bit in kg; N: rotational speed in rpm; RDi: rock mass drillability index; P: air pressure for flushing the blast hole in psi; and D: bit diameter in mm.
He et al. (2016)	$R=W_f\, G(W^aN^b/SD_b)$ Where W: weight on bit; W_f: bit wear function; R: rate of penetration; N: rotational speed; S: confined rock compressive strength; G, a and b: constants; and *Db*: drill bit diameter.

Hemphill and Clark (1994) evaluated the effect of drilling fluid chemistry on rate of penetration through full scale drilling tests using nine types of muds and two PDC bits. **Fear (1999)** developed an approach to choose key elements affecting on ROP via analyses of several bit runs. The study involved bit properties, geological data and mud logging. **Motahhari et al. (2009)** investigated the relationship between ROP and optimum weight on bit. **Ritto et al. (2010)** optimized ROP considering rotational speed at the top, initial reaction force of bit as well as fatigue, stress and vibration limit of the dynamical system. **Alum and Egbon (2011)** presented some models to predict ROP through developing equations. **Ping et al. (2014)** suggested an evolutionary algorithm for optimizing the drilling parameters in an effective manner. This optimization process consisted of flow rate, weight on bit and rotation of bit. **Hankins et al. (2015)** proposed a procedure for predicting operational factors and equipment through simulation of operational drilling data of nearby wells in Louisiana field. They demonstrated that optimum criteria can be achieved via applying variation in combinations of bit characteristics, hydraulics, rotary speed of bit and weight on bit to evaluate the economic and operational merits for drilling projects. **Shishavan et al. (2015)** studied several drilling case studies and found out the combination of bottom hole pressure control and rate of penetration could contribute to a decrease in project's risks as well as operator and drilling costs. **Wang and Salehi (2015)** used artificial neural network (ANN) technique for prediction of optimum drilling fluid hydraulics.**Elkatatny et al. (2017)** proposed an ANN model to predict ROP based on mud properties and drilling parameters. **Soares and Gray (2019)** used machine learning (ML) techniques using real-time optimization of drilling parameters in order to predict ROP. **Elkatatny (2021)** used ANN approach to predict real-time ROP in complex lithologies. **Kazemi et al. (2023)** presented a prediction of blast-induced air overpressure using a hybrid machine learning model and gene expression programming. **Kazemi et al. (2023)** investigated the Application of XGB-based metaheuristic techniques for prediction time to failure of mining machinery. **Nabavi et al. (2023)** proposed A Hybrid Model for Back-Break Prediction using XGBoost Machine learning and Metaheuristic Algorithms in Chadormalu Iron Mine. **Kazemi et al. (2024)** proposed A novel Hybrid XGBoost Methodology in Predicting Penetration Rate of Rotary Based on Rock-Mass and Material Properties. **Nabavi et al. (2024)** used Reliable novel hybrid extreme gradient boosting for forecasting copper prices using meta-heuristic algorithms. As cited before, several models have been proposed for predicting ROP. **Table 1** listed some of these models.

The technology revolution in conjunction with the deep learning algorithms provide the capability for researchers to appropriately analyze the gathered information and conclude significant results. Predictive data analysis is begun by statistical analyses, intelligent approaches and ultimately hybrid methods. Many research works have been carried out to measure the precision these techniques. The findings represented that hybrid methods are considered the best, then intelligent approaches are better than statistical analyses **(Acharjya and Anitha, 2017)**. In current study, in order to enhance the accuracy of results of statistical analysis, a novel method for ROP prediction is introduced in which the artificial intelligent (AI) techniques are utilized. The aim of this paper is to develop new models to predict drilling rate of penetration in one of Iranian oilfields, Shadegan oilfield, using some new AI techniques such as Particle Swarm Optimization (PSO), Grasshopper Optimization Algorithm (GOA) and Grey Wolf Optimization (GWO) approaches. The reason for using optimization algorithms in this research is to find a solution according to the constraints applied and the need of a problem. The number of solutions to the problem may be large, but optimization algorithms try to find the most optimal solution.

2. Materials and Methods

Meta-heuristic algorithms are new methods in solving petroleum engineering problems that can be used to solve complex problems that conventional methods are not able to solve accurately **(Sobhi et al.,2022)**. In these methods, all effective parameters can be considered without any restrictions, while in other methods, this is not possible and they are always accompanied by assumptions and limitations. These methods are easy to use, and the results can be used before or during drilling **(Brenjkar et al., 2021)**. In conventional computational methods, the computational steps are predetermined and have logical sequences; in comparison with meta-heuristic algorithms, they are neither sequenced nor necessarily predetermined **(Riazi et al., 2022)**. Because the estimation of the penetration rate depends on many different parameters, their calculation is always faced with uncertainty. The information obtained from most of the above methods cannot be used during drilling and is in fact considered dead information. No method has been proposed for in-situ measurement **(Khosravanian and Aadnøy, 2022)**. Although laboratory tests are the best way to estimate, they only measure at a few discrete points; Experimental relationships that have the necessary continuity are not accurate enough and should also be presented according to the conditions and characteristics of the reservoir of these relationships. Mathematical models designed due to limitations and incorrect hypotheses often have problems in describing and expressing the effects of these factors. One way that is fundamentally different from past mathematical methods is to use an artificial grid to model the behavior of the material directly from the data obtained from experiments and operations **(Alsaihati et al., 2021)**. Neural network technology can be used to model the behavior of materials due to its ability to learn and find relationships between different parameters. Optimization is very important in many branches of science. Optimization algorithms inspired by nature have exhibited remarkable outcomes as intelligent optimization approaches in parallel with conventional methods. Methods such as Particle Swarm Optimization (PSO), Grasshopper Optimization Algorithm (GOA) and Grey Wolf Optimization (GWO) can be of these techniques. These methods have been utilized to solve numerous optimization processes in different issues such as determining the optimal path of automated agents, optimal controller design for industrial processes, solving major problems in improving the effective parameters in the drilling industry **(Saremi et al., 2017)**.

2.1 Particle Swarm Optimization (PSO)

The particle swarm optimization algorithm is regarded as one of the newest evolutionary optimization methods. This algorithm is an algorithm that imitates the behaviors of animal communities in the processing of society knowledge and is rooted in two areas, first artificial life (such as birds, fish) and second evolutionary calculations. The principle of the PSO algorithm is that the achieved results from optimization process are viewed to be birds without volume and qualitative attributes, referred to as particles, these birds fly in a next **N** space and their path in space **(Kennedy and Eberhart, 1995)**. They change the search in accordance with their previous experiences and those of their neighbors. In groups comprising **N** components, the position of the **i** component is influenced by a dimensional **N** spatial vector which is summarized in the following equation **(Joćko et al., 2022)**:

$$X_i = (x_{i1}, x_{i2}, ..., x_{in})^T \in S \tag{1}$$

Where **S** is the search space.

The best previous position obtained for component **i** is represented using **Equation 1**.

$$V_i = (v_{i1}, v_{i2}, ..., v_{in})^T \in S \tag{2}$$

$$P_i = (p_{i1}, p_{i2}, ..., p_{in})^T \tag{3}$$

Ultimately, the new position of the category components is achieved via **Equations 2 and 3**.

$$V_i(t+1) = V_i(t) + cr_1(P_i(t) - X_i(t)) + cr_2(P_g(t) - X_i(t)) \tag{4}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{5}$$

The velocity of each particle has a maximum value determined by the user. This factor controls the speed of the handle and prevents the handle from exploding. Although the PSO algorithm is able to find the optimal response region very quickly, but when it reaches this region, its convergence speed is greatly reduced. To solve this problem, relations are corrected as follows:

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 (P_i(t) - X_i(t)) + \\ + c_2 r_2 (P_g(t) - X_i(t)) \tag{6}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{7}$$

In the above equations: **g** denotes the index used for the particle that has the best position and **t** is the number of repetitions. $\mathbf{r_1}$ and $\mathbf{r_2}$ are random numbers between 0 and 1. **ω** is the weight coefficient of inertia. $\mathbf{C_1}$ is a positive parameter called the cognitive parameter and $\mathbf{c_2}$ is a positive parameter called the social parameter, which accelerates the motion of the particle towards the optimal value. **Equation 4** shows that the new velocities for each particle are updated in accordance with their prior velocity $V_i(t)$, the best local particle position $P_i(t)$ and the foremost global position of $P_g(t)$. The particle velocity in each dimension is maintained at a maximum speed of V_{max}, and the maximum velocity V_{max} is set for a specific fraction of the search space range in any dimension. **Equation 5** represents how the position of each particle $X_i(t)$ is updated during the search in the solution space. To reach the end criterion. The use of the inertia weight parameter creates a compromise between the ability to explore the category nationally and locally. In fact, the lower the weight, the more accurate the search in areas that have been experienced in the past. Choosing the right size for **ω** ensures the desired balance between local and global exploration capability and thus increases the algorithm efficiency. Experimental findings demonstrate that the selection of large values for **ω**, at the beginning of the search, causes the priority of global exploration to be higher than local exploration, and with a gradual decrease of **ω**, the search in local spaces is pursued more seriously. As a result, the value of **ω** is selected as 1 at the beginning of the search and gradually tends to zero **(Joćko et al., 2022)**.

2.2. Grey Wolf Optimizer (GWO)

The grey wolf is a member of the Canid family. Grey wolves are viewed as predatory predators which means they are at the top of the food chain. Grey wolves are mostly willing to live in a herd. Each group includes nearly 5 to 12 wolves. These wolves have a seriously social hierarchy. Leaders are male or female and known as alpha. Alpha has mainly the responsibility for decision-making on sleeping location, hunting, waking time, etc **(Mirjalili et al., 2014)**. Alpha intentions are given to the group. Nevertheless, some democratic behaviors have also been identified in which an alpha grey conforms the other wolves in the group. When all members are gathered, the whole group confirms alpha via holding their tail. Since the whole group must follow the instructions of the alpha wolf (male or female). Dominant wolf is another expression for the alpha wolf. In the group, alpha wolf is only allowed to have mate. In an interesting manner, alpha is not definitely the most powerful member, but is the foremost member for group management. It means the discipline and organization of a group is far more essential than its strength. The next category of the grey wolf hierarchical order are the beta wolves. Beta wolves are subject to alpha decision **(Mirjalili et al., 2014)**. Beta wolves can also be male or female, and are the best candidates to replace alpha wolves that have been outgrown or aged. The wolf beta must show respect to alpha ones, but also command other low-level wolves. This type of wolf acts as a consultant for an alpha and a helper for the group. Beta boosts alpha commands. The lowest rating is for omega grey wolves. Omega serves as a protector. Omega wolves should always be sent with whole dominant wolves. They are the last wolves which have permission to eat. It may be perceived that omega does not play a major role in the group, but it has been concluded that if omega is lost in the whole group, there will be problems. This is because of the decreased violence and frustration of whole wolves via omega. This helps to satisfy the whole group and maintain the hierarchical order. In a number of instances, Omega also works as a babysitter in the package. If a wolf is not alpha, beta, or omega, it is called a function or (delta in some sources). Delta wolves must be sent to alpha and beta but dominate omega. Supervisors, guards, the elderly, hunters and supervisors are members of this category. Supervisors have the responsibility for observing the boundaries of the territory and warning the group in case of any danger. Guards provide the protection and safety of the group. Hunters help alpha and beta wolves when hunting and preparing food for the group. At last, caregivers have the responsibility for caring for injured, sick and weak wolves **(Kalita et al., 2022)**.

2.2.1 Mathematical Models and Algorithms

In this section, mathematical forms of social hierarchy structure, attacking, siege, and tracking grey wolves are expressed. Then, the grey wolf algorithm is presented.

2.2.2 Social Hierarchical Structure

To describe mathematical design of social hierarchical structure in GWO, alpha (α) is supposed to be the solution. Thus, the other (second and third) solutions are considered as beta (β) and delta (δ), respectively. Through this algorithm, the hunt (optimization) is driven by α, β, δ. ω wolves follow these three wolves.

2.2.3 Siege of Prey

As cited above, grey wolves surround prey during hunting. The equations of the mathematical model of grey wolf siege behavior are proposed as below:

$$\vec{D} = |\vec{C}.\vec{X}P(t) - \vec{X}(t)| \tag{8}$$

$$\vec{X}(t+1) = \vec{X}P(t) - \vec{A}.\vec{D} \tag{9}$$

Where t denotes the current iteration, $\vec{A}$ and $\vec{C}$ represent the vector coefficients, $\vec{X}P$ represents the hunting location vector and X shows the vector of grey wolf location position. The vectors $\vec{A}$ and $\vec{C}$ are defined **as Equations 10 and 11**:

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \tag{10}$$

$$\vec{C} = 2.\vec{r_2} \tag{11}$$

The component $\vec{a}$ decreases linearly from 2 to 0 during the iterations, and $\vec{r_1}$ and $\vec{r_2}$ are random values between 0 and 1.

2.2.4 Hunt

Grey wolves are able to detect hunting grounds and surround them. Hunting is generally led by alpha wolves. Beta and delta wolves sometimes participate in hunting. However, there is no idea regarding the optimum position (hunting) in an abstract search space. To simulate the hunting behavior of grey wolves from mathematical point of view, it is assumed that the alpha (best candidate solution), beta and delta have information on the potential hunting position. Hence, we store the first three best solutions ever obtained and need other search agents (including omega) to update their position in accordance with the position of the best search agents as follows **(Meidani et al., 2022)**:

$$\vec{D}\alpha = \left|\vec{C}1.\vec{X}\alpha - \vec{X}\right|,\ \vec{D}\beta = \left|\vec{C}2.\vec{X}\beta - \vec{X}\right|,\ \vec{D}\delta = \left|\vec{C}3.\vec{X}\delta - \vec{X}\right| \tag{12}$$

$$\vec{X}1 = \vec{X}\alpha - \vec{A}1.(\vec{D}\alpha),\ \vec{X}2 = \vec{X}\beta - \vec{A}2.(\vec{D}\beta),\ \vec{X}3 = \vec{X}\delta - \vec{A}3.(\vec{D}\delta) \tag{13}$$

$$\vec{X}1(t+1) = \frac{\vec{X}1 + \vec{X}2 + \vec{X}3}{3} \tag{14}$$

2.3 Grasshopper Optimization Algorithm (GOA)

Stochastic, optimization and evolutionary search approaches are emerging techniques utilized to achieve optimum global results. The randomness of such optimization methods prevents trapping in local optimization points. Access to global optimal solutions to practical optimization and engineering optimization problems is of paramount importance. Many of these optimization algorithms are nature-inspired. Grasshopper Optimization Algorithm (GOA) also belongs to this group of optimization methods and has a high optimization speed. The proposed algorithm is modeled mathematically and

 pp. 119-130, DOI: 10.17794/rgn.2024.3.9

presented to mimic the natural behavior of Grasshoppers in order to solve optimization problems. Grasshopper is insect. They are considered a pest due to the harm they do to agricultural products **(Saremi et al.,2017)**.

A mathematical model is used for simulating the group behavior of Grasshoppers, as below **Equation 15**:

$$X_i = S_i + G_i + A_i \tag{15}$$

Where Xi denotes the position of the i Grasshopper, S_i is social interaction, G_i is the gravitational force acting on the i Grasshopper, and A_i is the horizontal force of the wind. Where Xi defines the position of the i Grasshopper, S_i is social interaction, G_i is the gravitational force acting on the i Grasshopper, and A_i is the horizontal force of the wind. It should be noted that in order to show random behavior, this equation can be rewritten as $X_i = r_1 S_i + r_2 G_i + r_3 A_i$ where r_1, r_2 and r_3 are random numbers between 0 and 1.

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s(d_{ij})\widehat{d_{ij}} \tag{16}$$

Where $\mathbf{d_{ij}}$ shows the distance between Grasshopper **i** and **j**, which is calculated as $d_{ij} = |x_j - x_i|$, **S** is a function to represent the power of social forces, and is $\widehat{d_{ij}} = \frac{x_j - x_i}{d_{ij}}$ a single vector from Grasshopper **i** to Grasshopper **j**. The s function, represent social forces, is expressed as follow:

$$s(r) = fe^{\frac{-r}{l}} - e^{-r} \tag{17}$$

Where f indicates the intensity of gravity and l is the measure of the length of gravity.

Table 2: Input parameters and output parameter

Input parameters	Weight on Bit (WOB), Revolution Per Minute (RPM), Mud Weight (MW) and Torque
Output parameter	Rate of Penetration (ROP)

Table 3: Descriptive statistic of database for Shadegan oilfield

Parameter	Unit	Range	Mode	Average	Median	St. Dev	Max.	Min.
WOB	klbf	44.5	8.60	13.4	10.8	7.46	45.6	1
RPM	1/min	144	169	158	161	18.25	201	56
MW	pcf	75.39	73.35	79.26	74.10	12.63	140.46	65.07
Torque	lbf.ft	9144	6800	7183	7072	1568	12463	3319
ROP	m/hr	4.46	2.60	5.6	4.2	4.14	46.7	0.3

*SI unit : WOB(kN); RPM(rpm); MW(kg/m3); Torque(kN×m); ROP(m/hr)

Table 4: Particle swarm optimization parameters

Parameters	Value
Population size	400
Number of iterations	200
Interia factor	0.5,0.05
Social rate	0.9

Table 5: Grey wolf optimizer parameters

Parameters	Value
Population size	400
Number of iterations	200
Number of appliances	24
Random vectors r_1 and r_2	0.1

Table 6: Grasshopper optimization algorithm parameters

Parameters	Value
Population size	400
Number of iterations	200
Random vectors r_1, r_2 and r_3	0 and 1

3. Description of study area

The Shadegan oilfield, the case study, is an Iranian oilfield located in Khuzestan province, in the south west of Ahvaz city. A database was compiled from drilling parameters in this field. The data were then analyzed through intelligent approaches introduced within this paper. The input and output parameters are listed in **Table 2**. **Table 3** shows descriptive statistics of the database for Shadegan oilfield. **Table 4** shows Particle Swarm Optimization (PSO) parameters. **Table 5** shows Grey Wolf Optimizer (GWO) parameters. **Table 6** shows Grasshopper Optimization Algorithm (GOA) parameters. In this study, the accuracy and efficiency of the models were assessed using the coefficient of determination (R^2) and root mean square error (RMSE) factors, as described by equations 18 and 19. A value of one indicates the optimal performance for these criteria, while a value of zero represents the best outcome for RMSE. Furthermore, distribution diagrams and comparative graphs of observational-computational values were employed to facilitate a comprehensive analysis and comparison of the results, in addition to the aforementioned criteria.

The Coefficient of Determination (R^2) is also equal to the square of the correlation between x and y scores. R^2 is attained as:

$$R^2 = \frac{\sum_{i=1}^{N}(Xi-\overline{X})(Yi-\overline{Y})}{\sqrt{\sum_{i=1}^{N}(Xi-\overline{X})^2\sum_{i=1}^{N}(Yi-\overline{Y})^2}} \quad (18)$$

The Root Mean Square Error (RMSE) and the connecting factor between the guessed and measured amounts are considered as the efficiency amounts. The RMSE is attained as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Xi-Yi)^2} \quad (19)$$

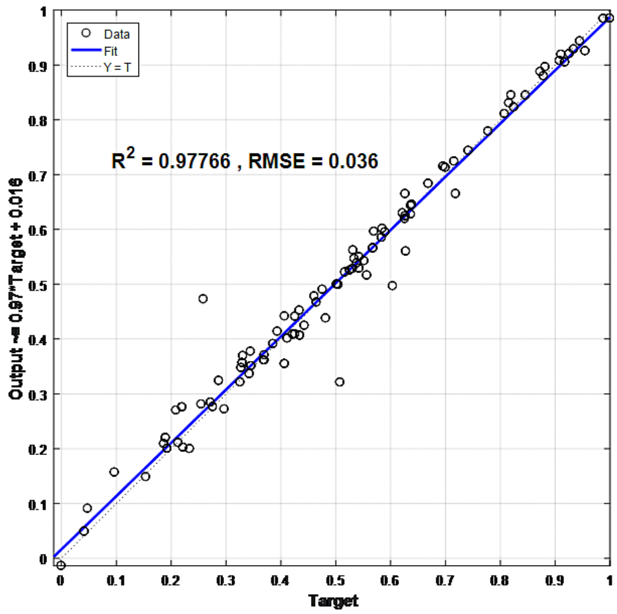

Figure 1: Distribution diagram by particle swarm optimization

Xi and Yi are the computational and observational values of the time step i, N is the number of time steps. $\overline{X}$ and $\overline{Y}$ are the average of computational and observational values, respectively.

4. Results

4.1. Penetration Rate Prediction in Shadegan Oilfield by PSO

PSO (Particle Swarm Optimization) is one of the metaheuristic methods. Despite its simplicity, it has high power. It is inherently a continuous algorithm and therefore more applicable to continuous domain optimization problems. Of course, with some precautions, it can also be used for discrete problems. It is in the branch of swarm intelligence or collective intelligence (crowd). It is sometimes classified as an evolutionary algorithm because the recovery mechanism is repeating itself, introducing a new model based on information sharing. While in crowd intelligence, information flow is one of the main prerequisites that leads to cooperation. The next point is that when we want to create purposeful cooperation in a group, we need a concept called self-organization or self-organization and must control the style and rules of the population. In the discussion of crowd intelligence, we try to create the concept of self-regulation using a series of simple rules that everyone is required to follow, and wherever there is a flow of information and self-regulation, collective intelligence will emerge. Distribution diagram and matching diagram of the measured values of the penetration rate, or target and predicted values of the penetration rate, are represented by the predictive model, as illustrated in **Figure 1 and Figure 2**, respectively.

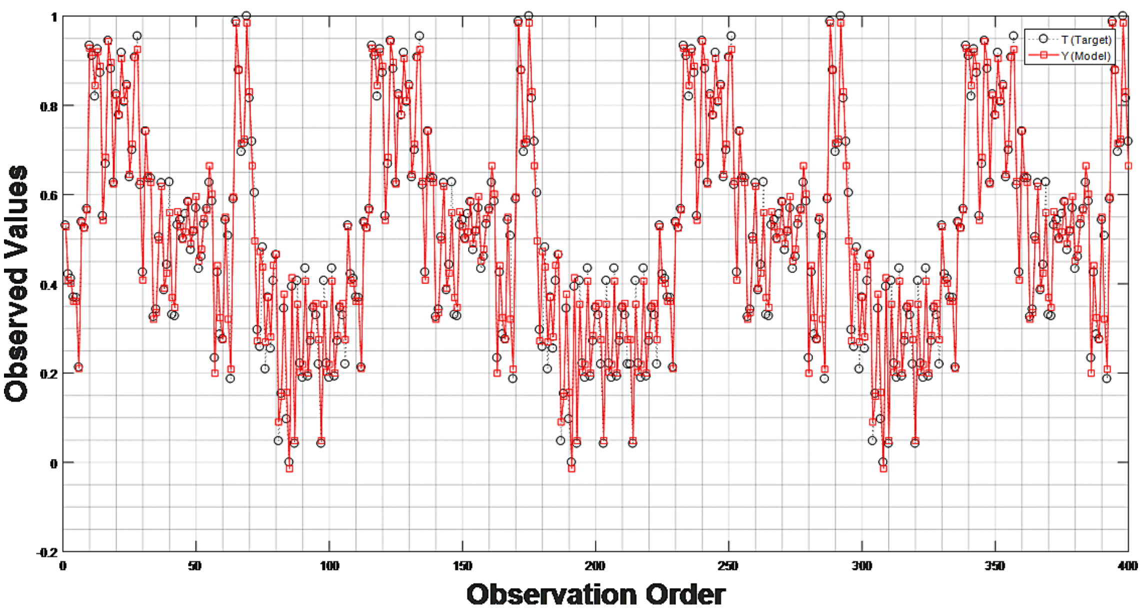

Figure 2: Matching diagram by particle swarm optimization

4.2. Penetration Rate Prediction in Shadegan Oilfield by GWO

The grey wolves' meta-heuristic algorithm is proposed to solve optimization problems, as mentioned before. In the proposed algorithm, the weakest wolves are removed from the group. These wolves are replaced with other wolves from the primary population. The choice of placed wolves will be random or based on fitness. Through this approach, the fit of the location of particle is checked in every iteration, and if the fit goes forward, the wolves proceed towards the target, otherwise they remain in the previous appropriate position. This algorithm is presented in order to enhance the search performance in coping with different problems, improving the speed of convergence and impede getting stuck in the local optimization. The simulation in MATLAB software is performed on 23 standard mathematical optimization functions. By examining the performance and statistical comparison of the results obtained from the new algorithm with the basic Grey wolf algorithm and several other algorithms, we conclude that by properly adjusting the parameters, the improvements have a significant impact on the performance of the algorithm on various functions. Distribution diagram and matching diagram of the measured values of the penetration rate, or target and predicted values of the penetration rate, are represented by the predictive model, as shown in **Figure 3 and Figure 4**, respectively.

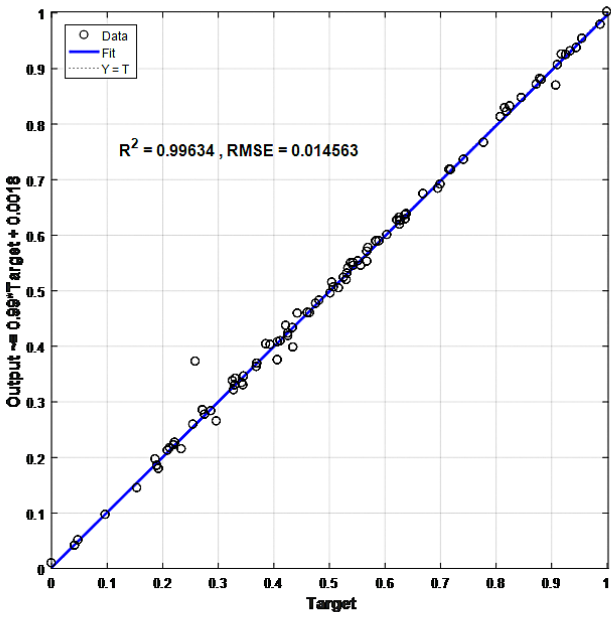

Figure 3: Distribution diagram by grey wolf optimization

4.3. Penetration Rate Prediction in Shadegan Oilfield by GOA

The Grasshopper optimization algorithm uses an equilibrium coefficient that the relationship between them changes linearly and causes a proper balance between the time to reach convergence and finding the global optimal, ie by choosing a large coefficient of early convergence occurs and The probability of getting stuck in the local optimization increases and if a small coefficient is selected, the convergence time will be long and in the limited time the global optimum will not be obtained. In this paper, by using geometric coefficient appropriate to time and new methods for calculating it, the balance between the two characteristics of exploration and exploitation to prevent early and late convergence on the one hand and achieve global optimization on the other hand is provided. Also, ten different fitting functions have been investigated as fitting functions in the basic algorithm and the proposed scheme. The results of comparing different aspects including best, worst and average fit as well as their standard deviation and execution time in 50 different runs demonstrate that the performance of the proposed approach is ten times better than the basic algorithm in all fitting functions. Due to the

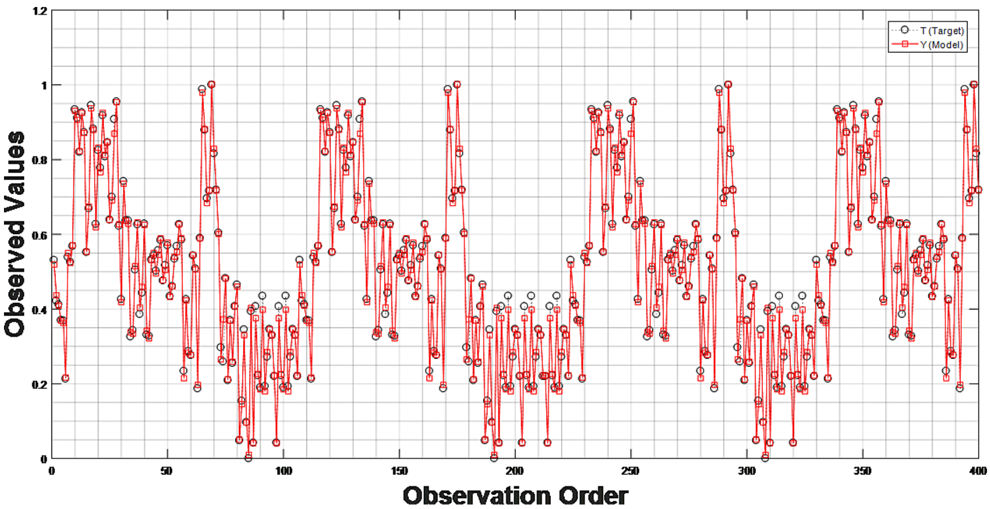

Figure 4: Matching diagram by grey wolf optimization

 pp. 119-130, DOI: 10.17794/rgn.2024.3.9

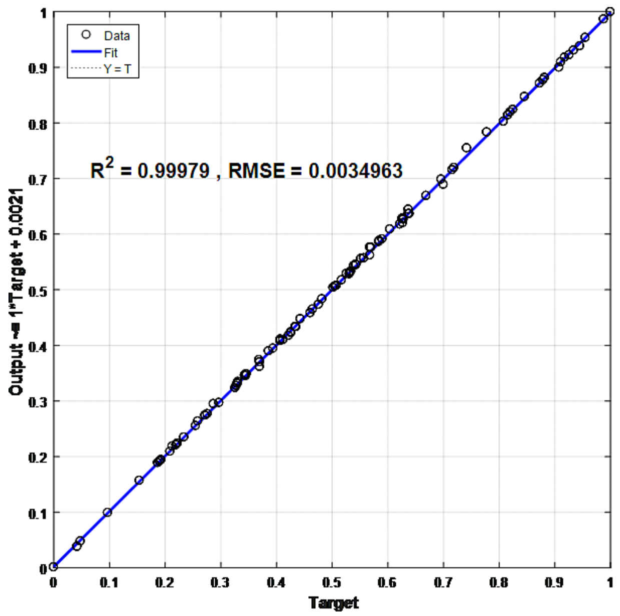

Figure 5: Distribution diagram by grasshopper optimization algorithm

of different sources (in absolute environment or uncertainty) on a mathematical model **(Afradi et al, 2024)**. This method is applied for domains that tackle one or more input variables and tend to measure the behavior of a function or relation according to them. Sensitivity analysis parameters are shown in **Figure 7**. As it can be seen, torque and WOB are more sensitive than other input parameters, therefore need to be managed properly.

4.5. Comparison of models

In this section, the models used in this research were compared, which shows that GOA has relative superiority over other models.

Table 7: Comparison of models

Models	PSO	GWO	GOA
R^2	0.977	0.996	0.999
RMSE	0.036	0.014	0.003

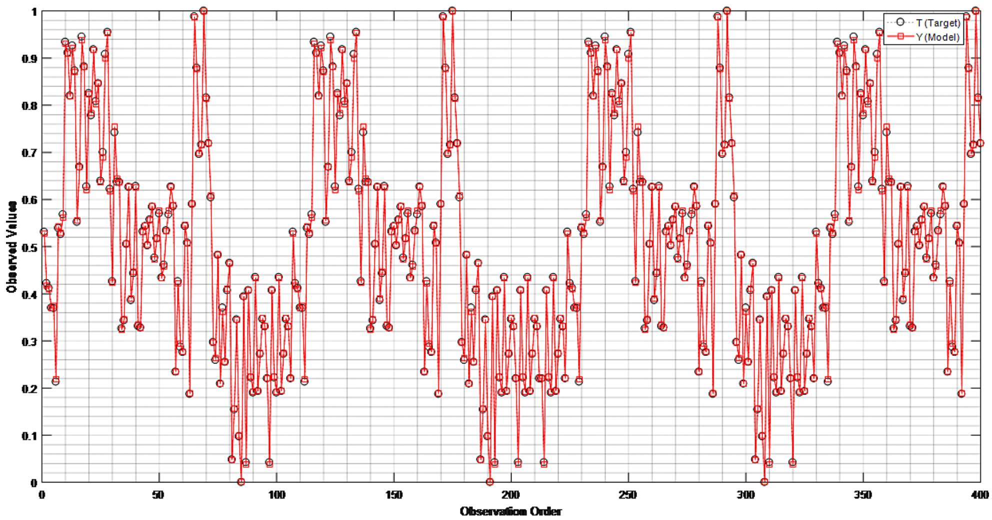

Figure 6: Matching diagram by grasshopper optimization algorithm

uniform number of repetitions in the implementation of optimizations, the convergence time is the same in all. Distribution diagram and matching diagram of the measured values of the penetration rate, or target and predicted values of the penetration rate, are represented by the predictive model, as illustrated in **Figure 5 and Figure 6**, respectively.

4.4. Sensitivity Analysis

Sensitivity Analysis shows how various values of an independent variable affect a dependent variable under some assumptions. On the other hand, sensitivity analysis is an approach to examine and study how the impact

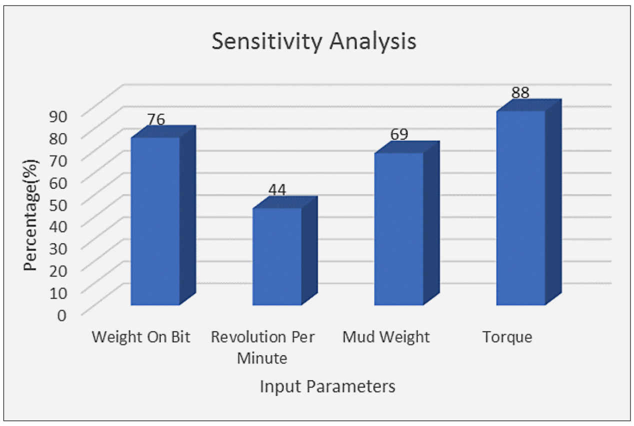

Figure 7: Sensitivity analysis for input parameters

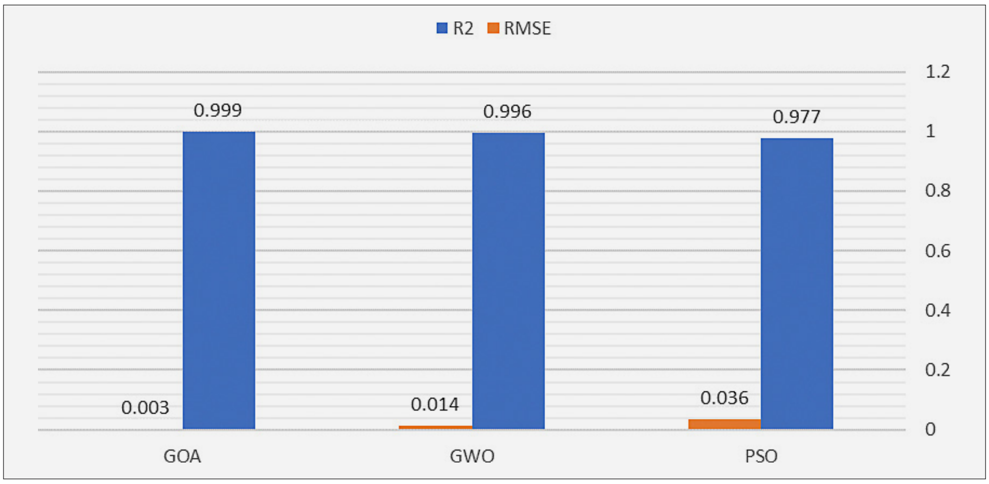

Figure 8: Comparison chart of models

5. Conclusions

Optimization algorithms are trained through operational and environmental data and report the simultaneous effect of all effective parameters. Accurate and more detailed studies on this information can be a good alternative to experience-based engineering judgments. Various artificial intelligence (AI) techniques are considered powerful approaches to predict rate of penetration (ROP) in petroleum drilling industry. In this study, among AI techniques, Particle Swarm Optimization (PSO), for Grey Wolf Optimization (GWO) and Grasshopper Optimization Algorithm (GOA) were used to predict ROP. Through the analyses, Weight on Bit (WOB), Revolution per Minute (RPM), Mud Weight and Torque compiled from drilling operations in Iranian Shadegan oilfield were included as input parameters. The coefficients of determination of optimization algorithms are acceptable after adding such sensitive drilling parameters and due to the low values of the obtained RMSE, the use of these algorithms is reliable. The mentioned methods applied to the database and R^2 and RMSE for each approach were obtained. Results showed that these parameters for Particle Swarm Optimization (PSO) are found to be as $R^2 = 0.977$ and RMSE = 0.036, for Grey Wolf Optimization (GWO) $R^2 = 0.996$ and RMSE = 0.014, for Grasshopper Optimization Algorithm (GOA) $R^2 = 0.999$ and RMSE = 0.003, respectively, showing high accuracy of used approaches but GOA yielded more precise results than other methods. For future work, we suggest using other heuristic algorithms such as shark smell optimization and artificial bee colony algorithm to prediction of rate of penetration (ROP) in petroleum drilling operations.

6. References

Acharjya, D., Anitha, A. (2017): A comparative study of statistical and rough computing models in predictive data analysis. International Journal of Ambient Computing and Intelligence, 8,32–51. https://doi.org/10.4018/IJACI.2017040103.

Afradi, A., Ebrahimabadi, A., & Hedayatzadeh, M. (2024): Performance Prediction of a Hard Rock TBM using Statistical and Artificial Intelligence Methods. Journal of Mining and Environment, 15(1), 323-343. doi: 10.22044/jme.2023.13370.2460

Al-Betairi, E. A., Moussa, M. M., Al-Otaibi, S. (1988): Multiple regression approach to optimize drilling operations in the Arabian gulf area. SPE Drilling Engineering,3 ,83-88. https://doi.org/10.2118/13694-PA

Alsaihati, A., Elkatatny, S., Gamal, H. (2021). Rate of penetration prediction while drilling vertical complex lithology using an ensemblelearning model. Journal of Petroleum Science and Engineering, 208: 109335. https://doi.org/10.1016/j.petrol.2021.109335

Alum, M. A., Egbon, F. (2011): Semi-analytical models on the effect of drilling fluid properties on rate of penetration (ROP). Paper presented at the Nigeria Annual International Conference and Exhibition, Abuja, Nigeria, July 2011. doi: https://doi.org/10.2118/150806-MS

Ataei, M., KaKaie, R., Ghavidel, M., Saeidi, O. (2015): Drilling rate prediction of an open pit mine using the rock mass drillability index. International Journal of Rock Mechanics and Mining Sciences, 73, 130–138. https://doi.org/ 10.1016/j.ijrmms.2014.08.006.

Autio, J., Kirkkomäki, T. (1996): Boring of full-scale deposition holes using a novel dry blind boring method. Helsinki: Posiva.

Bauer, A., Calder, P. N. (1967): Open Pit Drilling - Factors Influencing Drilling Rates. presented at the 4th Rock Mechanics Symposium, Ottawa.

Brenjkar, E., Biniaz Delijani, E. & Karroubi, K. (2021): Prediction of penetration rate in drilling operations: a comparative study of three neural network forecast methods. Journal of Petroleum Exploration and Production Technology, 11, 805–818. https://doi.org/10.1007/s13202-020-01066-1

Bourgoyne, Jr. A.T., Young, Jr. F. S. (1973): A multiple regression approach to optimal drilling and abnormal pressure detection. In: SPE-AIME Sixth Conference on Drilling and Rock Mechanics, January. SPE, Austin, TX, 4238.

Bourgoyne, A. T., Young, F. S. (1974): A multiple regression approach to optimal drilling and abnormal pressure detection. Society of Petroleum Engineers Journal, 14, 371-384. https://doi.org/10.2118/4238-PA

Burgoyne, D. J., Young, T. C. (1984):Applying a genetic Neuro-model Reference Adaptive Controller in Drilling Optimization. World Oil Magazine, 228, 29-38.

Bourdon, J.-C., Cooper, G. A., Curry, D. A., McCann, D., and Peltier, B. (1989): Comparison of Field and Laboratory-Simulated Drill-Off Tests. SPE Drilling Engineering,4, 329–334. https://doi.org/10.2118/16162-PA

Chen, X., Fan, H., Guo, B., Gao, D., Wei, H., Ye, Z. (2014): Real-Time Prediction and Optimization of Drilling Performance Based on a New Mechanical Specific Energy Model. Arabian Journal for Science And Engineering, 39,8221-8231 https://doi.org/10.1007/s13369-014-1376-0.

Cunningham, R. A. (1978): An Empirical Approach for Relating Drilling Parameters. Journal of Petroleum Science and Engineering, 30, 987–991. https://doi.org/10.2118/6715-PA

Deng, Y. et al. (2015): A New Prediction Model of Energy Consumption on Rock Fragmentation and Rate of Penetration Based on Fractal Theory," presented at the 49th US Rock Mechanics/Geomechanics Symposium, San Francisco, CA, Jun.

Elkatatny, S.M, Tariq, Z., Mahmoud, M.A., Al-AbdulJabbar, A. (2017):Optimization of Rate of Penetration using Artificial Intelligent Techniques. Paper presented at the 51st U.S. Rock Mechanics/Geomechanics Symposium, San Francisco, California, USA, June.

Elkatatny, S. (2021): Real-time prediction of rate of penetration while drilling complex lithologies using artificial intelligence techniques. Ain Shams Engineering Journal, 12, 917-926. https://doi.org/10.1016/j.petrol.2018.08.083

Fear, M.J. (1999): How to improve rate of penetration in field operations. SPE Drilling & Completion, 14, 42-49. https://doi.org/10.2118/55050-PA

Galle, E. M., Woods, H. B. (1963): Best Constant Weight and Rotary Speed for Rotary Rock Bits, API Drilling and Production Practice, 1 January. New York, API- 63-048.

Hankins, D., Salehi, S., Saleh, F. K. (2015): An Integrated Approach for Drilling Optimization Using Advanced Drilling Optimizer. Journal of Petroleum Engineering. https://doi.org/10.1155/2015/281276.

He, J., Chen, Y., Zhengchun, L., Samuel, R. (2016): Global Correlation of Rock Brittleness Indices with Petrophysical and Geomechanical Properties and its Application to the Prediction of Rate of Penetration (ROP)," presented at the IADC/SPE Asia Pacific Drilling Technology Conference, Singapore, https://doi.org/ 10.2118/180518-MS

Hemphill, T., Clark, R. K. (1994): The effects of pdc bit selection and mud chemistry on drilling rates in shale. SPE Drilling & Completion,9,176-184. https://doi.org/10.2118/22579-PA

Joćko, P., Ombuki-Berman, B. M. & Engelbrecht, A.P. (2022): Multi-guide particle swarm optimisation archive management strategies for dynamic optimisation problems. Swarm Intelligence, 16,143–168. https://doi.org/10.1007/s11721-022-00210-3

Kahraman, S. (1999): Rotary and percussive drilling prediction using regression analysis. International Journal of Rock Mechanics and Mining Sciences, 36, 981-989.

Kalita, K., Pal, S., Haldar, S. et al. (2022): A Hybrid TOPSIS-PR-GWO Approach for Multi-objective Process Parameter Optimization. Process Integration and Optimization for Sustainability. https://doi.org/10.1007/s41660-022-00256-0

Kazemi, M.M.K., Nabavi, Z. &, Khandelwal, M. (2023): Prediction of blast-induced air overpressure using a hybrid machine learning model and gene expression programming (GEP): A case study from an iron ore mine. AIMS Geosciences, 9(2), 357-381. doi: 10.3934/geosci.2023019

Kazemi, M.M.K., Nabavi, Z., Rezakhah, M., & Masoudi, A. (2023): Application of XGB-based metaheuristic techniques for prediction time-to-failure of mining machinery. Systems and Soft Computing,5, 200061. https://doi.org/10.1016/j.sasc.2023.200061

Kazemi, M.M.K., Nabavi, Z. & Armaghani, D.J. (2024): A novel Hybrid XGBoost Methodology in Predicting Penetration Rate of Rotary Based on Rock-Mass and Material Properties. Arabian Journal for Science and Engineering,49, 5225–5241. https://doi.org/10.1007/s13369-023-08360-0

Kennedy, J., Eberhart, R. (1995): Particle swarm optimization, Proceedings of ICNN'95 - International Conference on Neural Networks, 4: 1942-1948, doi: 10.1109/ICNN.1995.488968.

Khosravanian R, Aadnøy B S. (2022): Chapter Seven - Data-driven machine learning solutions to real-time ROP prediction. Methods for Petroleum Well Optimization Automation and Data Solutions.249-301. https://doi.org/10.1016/B978-0-323-90231-1.00001-7

Kowakwi, I., Chen, H., Hareland, G., and Rashidi, B. (2012): The Two-Term Rollercone Rate of Penetration (ROP) Model with Integrated Hydraulics Function," presented at the 46th U.S. Rock Mechanics/Geomechanics Symposium.

Maurer, W. C. (1962): The perfect-cleaning theory of rotary drilling. Journal of Petroleum Technology, 14, 1270-1274. https://doi.org/10.2118/408-PA

Maidla, E. E., Ohara, S. (1991): Field verification of drilling models and computerized selection of drill bit, WOB, and drillstring rotation. SPE Drilling Engineering, 6 ,189-195. https://doi.org/10.2118/19130-PA

Meidani, K., Hemmasian, A., Mirjalili, S. et al. (2022). Adaptive grey wolf optimizer. Neural Computing and Applications ,34,7711–7731. https://doi.org/10.1007/s00521-021-06885-9

Mechem, O.E., Fullerton, Jr. H.B. (1965): Computers invade the rig floor. Oil and Gas Journal.

Mirjalili, S., Mirjalili, S.M., Lewis, A. (2014): Grey wolf optimizer. Advances in Engineering Software .69,46–61

Motahhari, H.R., Hareland, G., Nygaard, R., Bond, B.(2009): Method of optimizing motor and bit performance for maximum ROP. Journal of Canadian Petroleum Technology, 48, 44–49. https://doi.org/10.2118/09-06-44-TB

Nabavi, Z., Mirzehi, M., Dehghani, H., & Ashtari, P. (2023): A Hybrid Model for Back-Break Prediction using XGBoost Machine learning and Metaheuristic Algorithms in Chadormalu Iron Mine. Journal of Mining and Environment, 14(2), 689-712. doi: 10.22044/jme.2023.12796.2323

Nabavi, Z., Mirzehi, M., Dehghani, H. (2024): Reliable novel hybrid extreme gradient boosting for forecasting copper prices using meta-heuristic algorithms: A thirty-year analysis. Resources Policy,90,104784. https://doi.org/10.1016/j.resourpol.2024.104784

Ping, Y., Aniket, K., Robello, S. (2014). Realtime rate of penetration optimization using the shuffled frog leaping algorithm.

Journal of Energy Resources Technology, Transactions of the ASME, 137. https://doi.org/ 10.2118/167824-MS

Riazi, M., Mehrjoo, H., Nakhaei, R. et al. (2022): Modelling rate of penetration in drilling operations using RBF, MLP, LSSVM, and DT models. Scientific Reports ,12,11650. https://doi.org/10.1038/s41598-022-14710-z

Ritto, T.G., Soize, C., Sampaio, R. (2010): Robust optimization of the rate of penetration of a drill-string using a stochastic nonlinear dynamical model. Computational Mechanics, 45, 415-427. https://doi.org/10.1007/s00466-009-0462-8

Saremi, S., Mirjalili, S., Lewis, A. (2017): Grasshopper Optimisation Algorithm: Theory and application. Advances in Engineering Software ,105,30–47.https://doi.org/10.1016/j.advengsoft.2017.01.004.

Shirkavand, F. Hareland, G., Aadnoy,B. S. (2009): Rock Mechanical Modelling for a Underbalanced Drilling Rate of Penetration Prediction," in 43rd Rock Mechanics Symposium and 4th US-Canada Rock Mechanics Symposium, Asheville, NC, Jun.

Shishavan, A.R, Hubbell, C., Perez, H., Hedengren, J., Pixton, D. (2015): Combined rate of penetration and pressure regulation for drilling optimization by use of highspeed telemetry. SPE Drilling & Completion, 30 ,17–26. https://doi.org/10.2118/170275-PA

Soares, C., Gray, K. (2019). Real-time predictive capabilities of analytical and machine learning rate of penetration (ROP) models Journal of Petroleum Science and Engineering, 172,934–59. https://doi.org/10.1016/j.petrol.2018.08.083.

Sobhi, I., Dobbi, A. & Hachana, O. (2022):Prediction and analysis of penetration rate in drilling operation using deterministic and metaheuristic optimization methods. Journal of Petroleum Exploration and Production Technology, 12,1341–1352.

Tansev, E. (1975): A Heuristic Approach to Drilling Optimization. Paper presented at the Fall Meeting of the Society of Petroleum Engineers of AIME, Dallas, Texas, September. https://doi.org/10.2118/5546-MS

Walker, B. H., Black, A.D., Klauber, W. P., Little, T., Khodaverdian, M. (1986): Roller-Bit Penetration Rate Response as a Function of Rock Properties and Well Depth. Paper presented at the SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, October. https://doi.org/10.2118/15620-MS

Wang, Y., Salehi, S. (2015): Application of real-time field data to optimize drilling hydraulics using neural network approach. Journal of Energy Resources Technology, 137, 062903. https://doi.org/10.1115/1.4030847

Warren, T. M. Drilling Model for Soft-Formation Bits. Journal of Petroleum Technology, 1981, 33 (06), 963–970. https://doi.org/10.2118/8438-PA

Wijk, G. (1991):Rotary Drilling Prediction. International Journal of Rock Mechanics and Mining Sciences & Geomechanics, 28, 35–42. https://doi.org/10.1016/0148-9062(91)93231-T

SAŽETAK

Predviđanje mehaničke brzine bušenja u operacijama bušenja nafte korištenjem optimizacijskih algoritama

Odabirom odgovarajućih alata te primjenom precizno i pouzdano određenih parametara operacija bušenja može se izvesti brže i uz manje troškove. Mehanička brzina bušenja (engl. ***Rate of Peneration***, ROP) smatra se glavnim parametrom u procjeni operacije bušenja. Iako se rezultati laboratorijskih istraživanja i eksperimentalno dobivene formule uvelike koriste za identifikaciju problema u operacijama bušenja, korištenje terenskih podataka smatra se najboljim pristupom za procjenu parametara bušenja ili ROP-a, kao i za razvoj modela predviđanja. U ovome je istraživanju primijenjeno inteligentno modeliranje, u kojemu su korištene nove tehnike umjetne inteligencije kao što su optimizacija ***Gray Wolf*** (engl. ***Gray Wolf Optimization,*** GWO), optimizacija ***Particle Swarm*** (engl. ***Particle Swarm Optimization,*** PSO) i optimizacijski algoritam ***Grasshopper*** (engl. ***Grasshopper Optimization Algorithm,*** GOA) za predviđanje mehaničke brzine bušenja na temelju analize podataka iz sveobuhvatne baze podataka prikupljenih tijekom operacija bušenja na jednome od iranskih naftnih polja, naftnome polju Shadegan. S obzirom na to da navedena baza sadržava 400 podataka, navedene tehnike umjetne inteligencije korištene su zbog učinkovitosti na velikome skupu podataka. U ovome je radu korištenjem podataka bušenja prikupljenih s naftnoga polja Shadegan razvijen precizan model za predviđanje ROP-a. Rezultati provedenoga istraživanja pokazuju da su parametri koeficijenta determinacije (R^2) i korijen srednje kvadratne pogreške (RMSE) za optimizaciju ***Particle Swarm*** (PSO) R^2 = 0,977 i RMSE = 0,036, za optimizaciju ***Gray Wolf*** (GWO) R^2 = 0,996 i RMSE = 0,014, a za algoritam ***Grasshopper*** (GOA) R^2 = 0,999 odnosno RMSE = 0,003. U konačnici se može zaključiti da svi prediktivni modeli daju prihvatljive rezultate, ali da GOA daje precizniji i realniji ishod.

Ključne riječi:
operacije bušenja, mehanička brzina bušenja, Gray Wolf optimizacija, Particle Swarm optimizacija, optimizacijski algoritam ***Grasshopper***

Author's contribution

Arash Ebrahimabadi (1) (PhD., Professor) formed the object and the subject of the research; proposed the idea; development of the idea of work and the methodology for achieving results; analysis of research; provided technical suggestions; Project administration; Supervision; Conceptualization and wrote the article. **Alireza Afradi (2)** (PhD) wrote the article; Software; development of approaches and the presentation of the results.