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Determination of constant coefficients of Bourgoyne and Young drilling rate model using a novel evolutionary algorithm

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Abstract

Achieving minimum cost and time in reservoir drilling requires evaluating the effects of the drilling parameters on the penetration rate and constructing a drilling rate estimator model. Several drilling rate models have been presented using the drilling parameters. Among these, the Bourgoyne and Young (BY) model is widely utilized in order to estimate the penetration rate. This model relates several drilling parameters to the penetration rate. It possesses eight unknown constants. Bourgoyne and Young have suggested the multiple regression analysis method in order to define these constants. Using multiple regressions leads to physically meaningless and out of range constants. In this work, the Cuckoo Optimization Algorithm (COA) is utilized to determine the BY model coefficients. To achieve this goal, the corresponding data for two wells are collected from one of the oilfields located in SW of Iran. The BY model constants are determined individually for two formations in one of the wells. Then the determined constants are used to estimate the drilling rate of penetration in the other well having the same formations. To compare the results obtained for COA, first, the two mathematical methods including progressive stochastic and multiple regressions were implemented. Comparison between these methods indicated that COA yields more accurate and reliable results with respect to the others. In the following, Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) as meta-heuristic algorithms were applied on the field data in order to determine BY model's coefficients. Comparison between these methods showed that the COA has fast convergence rate and estimation error less than others.

Keywords: *Bourgoyne and Young Model, Drilling Rate Estimation, Cuckoo Optimization, Drilling Parameters.*

1. Introduction

The penetration rate is a key parameter in drilling optimization and drilling cost reduction. Numerous factors including the formation characteristics, weight on bit, drilling fluid properties, hydraulics, bit type, and rotary speed affect the drilling rate of penetration [1], and there are perhaps other undetected important factors involved up to the present time [2]. Presence of various factors complicates building the rate of penetration predictor model [3]. However, many efforts have been made for presenting simple rate of penetration estimator models. The Bourgoyne and Young (BY) model is a successful one for estimation of the drilling rate [4-6] and it has been widely used by the researchers [7]. In this model, there are some unknown constants that should be determined using the previous drilling reports in the understudied field. The accuracy of the BY model highly depends on the coefficient values; in other words, it depends on how these constants are computed.

Bourgoyne and Young (1974) have suggested the multiple regression method to determine the unknown coefficients [8]. The results of the previous studies have shown that using the multiple regressions method for determining the model constants does not lead to reliable and physically meaningful results. Thus numerous efforts have been made in order to utilize other techniques. The techniques used in this regard could be divided into two groups including the mathematical methods and meta-heuristic algorithms. Bahari and Baradaran Seyed (2007) have determined the coefficients of the BY model using the mathematical trust-region method [9]. Their results have demonstrated that the results obtained for the trust-region technique are more precise and reliable than those for the multiple regressions method. Bahari et al. (2008) have compared the results of genetic algorithm, trust-region, and multiple regressions in determining the coefficient of the BY model using the data obtained for several wells [5]. The results of their work have exhibited that the genetic algorithm outperforms other methods. Bahari and Bradran Seyed (2009) have optimized the drilling parameters using the BY model [10]. To achieve this, they determined the BY model constants using the genetic algorithm. Rahimzadeh et al. (2011) have implemented the progressive stochastic, trust-region, and regression methods to determine the model coefficients [11]. A comparison between the results of these methods have shown that the progressive stochastic method presents more accurate and reliable results with respect to other methods. Nascimento et al. (2015) applied the BY model to a Presalt case study [12]. They computed unknown coefficients of the BY model using regression method combined with normalization factor. Formighieri and Filho (2015) used Markov Chain Monte Carlo for determining BY model's coefficients [13]. They did not compare their suggested method with other methods. However, their results were not satisfactory.

In this paper, firstly, the BY drilling rate model is discussed in details, and then the corresponding constants of this model are determined using COA to estimate the penetration rate for two wells in an oilfield. In continuation, the proposed model is validated using the mathematical and meta-heuristic methods.

2. BY drilling rate penetration model

Bourgoyne and Young (1974) presented Eq. (1) as the drilling rate of the penetration model for the roller cone bits.

$$ROP = f_1 \times f_2 \times f_3 \times f_4 \times f_5 \times f_6 \times f_7 \times f_8 \quad (1)$$

where ROP is the penetration rate in ft/h. Function f_1 represents the effects of formation strength, bit type, mud type, and solid content, which are not considered in the drilling model. The corresponding unit is similar to that of ROP, and is called the formation drillability. Functions f_2 and f_3 express the effect of formation compaction on the penetration rate. Function f_4 denotes the effect of overbalance on the drilling rate. Functions f_5 and f_6 model the effects of weight on the bit and the rotary speed on the penetration rate, respectively. Function f_7 expresses the effect of tooth wear and function f_8 presents the effect of bit hydraulic on the penetration rate. These functions are defined as follow:

$$f_1 = e^{2.303a_1} = K \quad (2)$$

$$f_2 = e^{2.303a_2(10000-D)} \quad (3)$$

$$f_3 = e^{2.303a_3D^{0.69}(g_p-\rho_c)} \quad (4)$$

$$f_4 = e^{2.303a_4D(g_p-\rho_c)} \quad (5)$$

$$f_5 = \left[\frac{\frac{W}{d_b} - \left(\frac{W}{d_b}\right)_t}{4 - \left(\frac{W}{d_b}\right)_t}\right]^{a_5} \quad (6)$$

$$f_6 = \left(\frac{N}{60}\right)^{a_6} \quad (7)$$

$$f_7 = e^{-a_7h} \quad (8)$$

$$f_8 = \left(\frac{F_j}{1000}\right)^{a_8} \quad (9)$$

where:

a_1 to a_8 = Bourgoyne and Young model constant coefficients

D = True vertical depth (ft)

d_b = Bit diameter (in)

F_j = Jet impact force (lbf)

g_p = Pore pressure gradient (lbm/gal)

h = Fractional bit tooth wear

ρ_c = Equivalent mud density (lbm/gal)

N = Rotary speed (rpm)

W = Weight on bit (1000 lbf)

$\left(\frac{W}{d_b}\right)_t$ = Threshold bit weight per inch of bit diameter at which the bit begins to drill

The coefficients a_1 to a_8 depend on the local drilling condition and for each formation, should be individually determined using the previous drilling reports data [14]. Implementing the BY drilling rate model requires the existence of at least eight data points for each formation because of eight unknown constants. Based on several case studies in different area, Bourgoyne and Young presented the lower and upper limits of these eight constants to achieve meaningful results. These ranges are given in Table 1.

Table 1. Suggested ranges for constants by Bourgoyne and Young.

Coefficient	Lower bound	Upper bound
a_1	0.5	1.9
a_2	0.000001	0.0005
a_3	0.000001	0.0009
a_4	0.000001	0.0001
a_5	0.5	2
a_6	0.4	1
a_7	0.3	1.5
a_8	0.3	0.6

3. Studied wells

The Studied wells were two vertical wells from one of the oilfields in SW Iran. These wells are named as wells A and B, which consist of 616 and 210 data points, respectively. In this work, the constant coefficients of the BY model were determined using the data for well A. Then using the data for well B, the BY model together with the determined coefficients were validated. The range of the studied depth for both wells was in the ASMARI and PABDEH formations, and the diameter of the wells in this range was 8.5 in. Figure 1 depicts the corresponding diagram for the collected data from well A. The ranges of the parameters for both wells implemented in the BY model are given in Table 2.

4. Determination of constant coefficients of BY model using COA

COA was inspired by the life of a bird called cuckoo. This meta-heuristic algorithm is appropriate when dealing with non-linear continuous optimization problems. Like other evolutionary algorithms, COA begins with an initial population of the cuckoos. These initial cuckoos have some eggs to be laid in some host bird's nests. Some of these eggs that are more similar to the host bird's eggs have this opportunity to grow up and become a mature cuckoo. Host birds discern and kill the remaining eggs. The more the number of survived eggs, the more profit is gained. Thus the position at which more eggs are survived would be the term that COA is going to optimize. When cuckoos become mature, they leave their own society. At the time of egg laying, the young cuckoos immigrate to new environments, where there is more similarity of eggs to the host birds. After the cuckoo groups are formed in different areas, the society with the best profit value is selected as the target point for other cuckoos to immigrate [15]. All groups of cuckoos immigrate towards the current best area. Each group locates near the current best position. Egg-laying radius is computed regarding to the number of eggs each cuckoo lays, and the distance of cuckoos from the current best area. Then cuckoos start randomly-produced egg laying in the nest within the egg-laying radius area. This process continues to achieve the best area for egg-laying (area with maximum profit). This optimal area is where the maximum number of cuckoos is gathered. After some iterations, all the cuckoo population moves to the best habitat with maximum similarity of eggs to the host birds and also with the maximum food resource. This habitat will produce a maximum profit, and there will be the least egg losses in this best habitat. this process will continue until achieving the best position with the maximum profit and most cuckoo populated area [15]. Figure 2 illustrates the COA diagram.

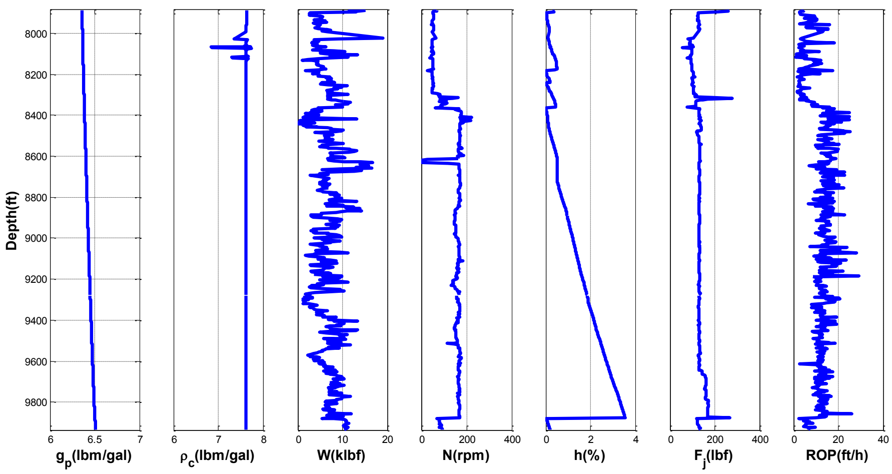

Figure 1. Diagrams of the parameters used for well A.

Table 2. Range of each input and output parameter used in BY model for studied wells.

Well Name	Formation	Statistical indicators	Depth (ft)	g_p (lbm/gal)	ρ_c (lbm/gal)	W (klbf)	N (rpm)	h (%)	F_j (lbf)	ROP (ft/h)
Well A	ASMARI	Minimum	7887.139	6.357	6.838	0.161	0.0	0.0	55.911	0.828
		Mean	8595.099	6.401	7.624	6.687	126.325	0.650	124.979	12.121
		Maximum	9278.215	6.450	7.752	18.996	222.750	1.850	278.983	29.085
	PABDEH	Minimum	9281.496	6.450	7.625	1.093	69.441	0.025	117.087	2.441
		Mean	9607.940	6.478	7.625	7.195	156.531	2.436	141.403	12.087
		Maximum	9934.383	6.509	7.626	13.435	176.097	3.545	266.207	25.970
Well B	ASMARI	Minimum	8489.501	7.5072	9.094	3.255	40.446	0.197	41.551	2.549
		Mean	8576.115	7.5076	9.159	16.244	58.315	0.217	59.398	9.770
		Maximum	8662.73	7.5078	9.254	22.558	69.974	0.237	71.120	26.853
	PABDEH	Minimum	9924.541	7.5075	9.016	18.460	192.341	0.312	193.968	5.106
		Mean	9957.021	7.5076	9.324	24.155	196.595	0.320	198.196	8.316
		Maximum	9989.501	7.5078	10.354	29.539	199.310	0.328	200.870	17.554

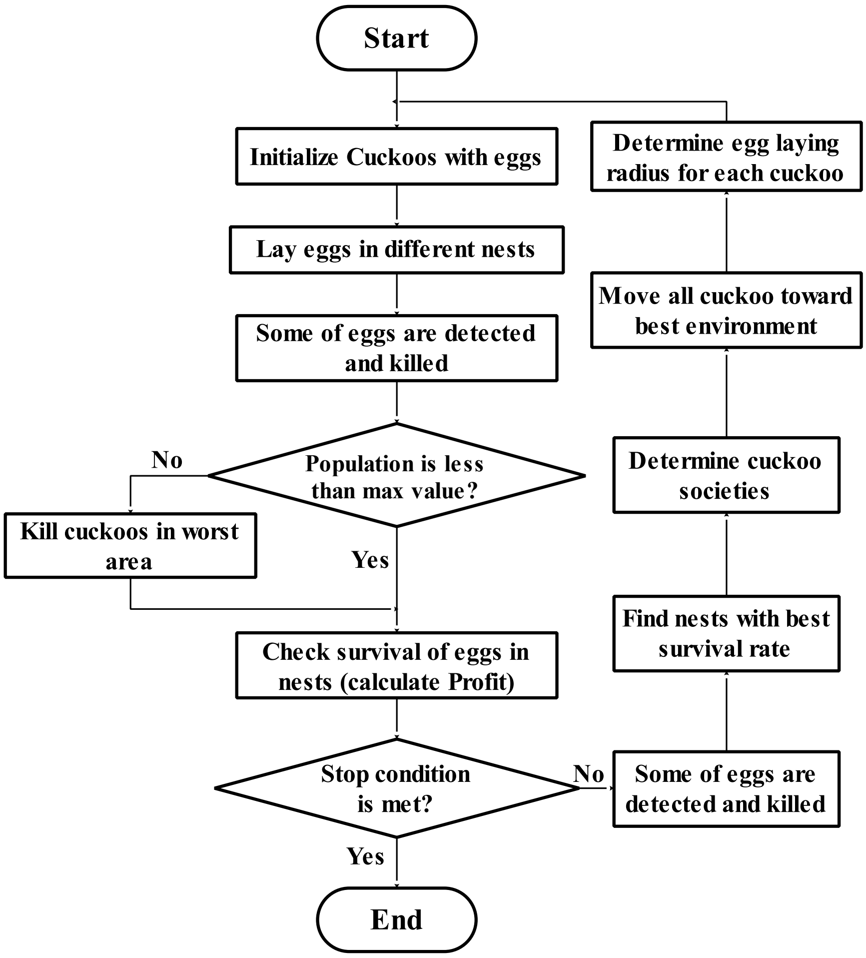

Figure 2. Flowchart of COA [15].

In order to determine the optimum values of BY model coefficients, it is necessary to have the values for the problem variables formed as an array. In GA and PSO terminologies, these arrays are called "chromosome" and "particle position", respectively. However, here, in COA it is called "habitat". In an N_{var}–dimensional optimization problem, a habitat is an array of $1 \times N_{var}$ dimension, representing the current living position of cuckoos. The array for computing the unknown constants of the BY model is defined as follows:

$$habitat = [x_1, x_2, x_3, x_4, x_5, x_6, x_7, x_8] \tag{10}$$

Each one of the variable values $(x_1, x_2, \dots, x_8)$ is a floating point number. The profit of a habitat is obtained by evaluation of the profit function. Since the BY model optimized constants are obtained when the BY model yields a minimum error, the objective function should be minimized. As it can be seen, COA is an algorithm that maximizes a profit function. To use COA in cost-minimizing problems, one could easily maximize the negative of the profit function. The objective function is considered as the Root Mean Square Error (RMSE). In this problem, RMSE is computed using the real values for the rate of penetration (ROP_{real}) and the predicted rate of penetration ($ROP_{predicted}$) for a total number of n data points in each formation (Eq. (11)):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(ROP_{real_i} - ROP_{predicted_i})^2} \tag{11}$$

If the number of cuckoos (their population) isN_{pop}, to start the optimization algorithm, a candidate habitat matrix should be generated with the size of$N_{pop} \times N_{var}$. Then some randomly-produced numbers of eggs are devoted for each one of these initial cuckoo habitats. In nature, each cuckoo lays between 5 to 20 eggs. These values are used as the upper and lower limits of eggs, which are dedicated to each cuckoo at different iterations. The maximum distance within which cuckoos lay their eggs is called the Egg Laying Radius (ELR). ELR is determined using the lower limit (var_{low}) and upper limit (var_{hi}) of variables, total number of eggs, and current number of cuckoo's eggs (Eq. (12)).

$$ELR = \alpha \times \frac{Number\ of\ current\ cuckoo's\ eggs}{Total\ number\ of\ eggs} \times (\text{var}_{hi} - \text{var}_{low}) \tag{12}$$

where α is a number that handles the maximum ELR value. First its value is taken unity, and then it is reduced by 1% per each iteration. Convergence of COA increases by this technique.

After the egg-laying process, 10% of all eggs with less profit values are killed. These eggs have no chance to grow. The rest of the eggs grow in host nests, hatch, and are fed by the host birds. When the young cuckoos grow and become mature, they live in their own area and society for a while. However, when the time for egg-laying approaches, they immigrate to the new and better habitats with more similarity of eggs to the host birds and also with more food for new youngsters. After the cuckoo groups are formed in different areas, the society with best profit value is selected as the target point for other cuckoos to immigrate. When the mature cuckoos live all over the environment, it is difficult to recognize which cuckoo belongs to which group. To solve this problem, the grouping of cuckoos is done by means of the K-means clustering method. The number of clusters was set as 4 based on the sensitivity analysis. Now that the cuckoo groups are constituted, their mean profit value is calculated. Then the maximum value for these mean profits would determine the goal group, and consequently, the group's best habitat would be the new destination habitat for the immigrant cuckoos.

When all the cuckoos immigrated toward the goal point and the new habitats were specified, each mature cuckoo is given some eggs. Then considering the number of eggs dedicated to each bird, an ELR is calculated for each cuckoo. Afterwards, the new egg-laying process restarts.

Due to the fact that there is always an equilibrium in the birds' population a number of N_{max} controls and limits the maximum number of cuckoos in the environment. This balance is due to food limitations, being killed by predators and also inability to find the proper nest for eggs.

In this work, the number of population, maximum number of population and maximum number of iterations were chosen using the sensitivity analysis. For this purpose, the optimal values for these parameters were selected based on two criteria including the accuracy and the process time. According to the results of the sensitivity study, the number of population, maximum number of population, and maximum number of iterations were set as 50, 50, and 20, respectively.

5. Results and discussion

The aforementioned constant coefficients of the BY model should be determined separately for each formation. Thus COA was run to determine the constants in the BY model for each formation of well A, independently. To evaluate the performance of COA, multiple regression and progressive stochastic as mathematical methods and GA and PSO as evolutionary algorithms were applied to determine the unknown constants of BY drilling rate model.

5.1. Comparison among COA, progressive stochastic and multiple regressions

Table 3 shows the constant values obtained implementing the three methods on the data of well A. As it can be seen, in some cases, the values obtained using the multiple regressions are negative, and it may yield zero values for the penetration rate, which is logically meaningless.
Figure 3 shows the calculated drilling rate using COA, progressive stochastic, and regression in the ASMARI and PABDEH formations for well A. As it can be seen, COA produced better results with respect to the other two methods. In the ASMARI formation, for depths less than 8400 ft, the BY model obtained using the progressive stochastic, analogous to the BY model obtained using the regression, the drilling penetration rate was underestimated. Depths more than 8400 ft, the progressive stochastic results were close to those of COA, whereas the created BY model using the regression method underestimated the drilling rate for depths more than 8700 ft. As it can be seen in Figure 3(b), the created BY models using the regression and progressive stochastic methods overestimated the penetration rate for depths less than 9400 ft, but for depths between 9420 and 9600 ft, both methods estimated the drilling rate close to the real value. In both formations, the model built using COA precisely estimated the trend of the penetration rate changes. Table 4 depicts the RMSE obtained for each model built in estimating the drilling rate for each individual formation of well A. The corresponding error for COA was less than that for the other two methods in both formations.
The computed constant coefficients in each formation of well A were used to estimate the penetration rate in the same formation of well B (Figure 4). As it can be seen in this Figure, the estimated drilling rate values using the built model by the regression method are highly scattered with respect to the two other methods. It yielded zero values for the predicted penetration rate in some data points of the ASMARI formation. The other methods (i.e. COA and progressive stochastic) yielded similar results. However, the estimated drilling rate values using the progressive stochastic method were slightly scattered. Table 5 shows the corresponding computed errors of the estimated penetration rate using the three different methods implemented for the well B formations. The model built using COA outperforms the other models. Coefficient of determination for COA is higher than progressive stochastic and regression technique (Table 6).

Table 3. Coefficients values obtained for BY model using three different methods in well A.

Formation	Method	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
ASMARI	COA	1.899	0.00019	0.00016	0.0001	0.725	0.722	0.310	0.336
	Progressive stochastic	1.719	0.000001	0.00021	0.000095	0.659	0.814	0.310	0.219
	Regression	4.372	0.0017	-0.00401	0.000075	0.0001	-2.639	0.0754	1.378
PABDEH	COA	1.792	0.000179	0.000075	0.0000435	0.824	0.815	0.610	0.514
	Progressive stochastic	1.659	0.000116	0.00029	0.000001	0.801	0.951	0.560	0.490
	Regression	3.453	-0.00192	0.00156	-0.527	0.513	-4.351	1.428	0.336

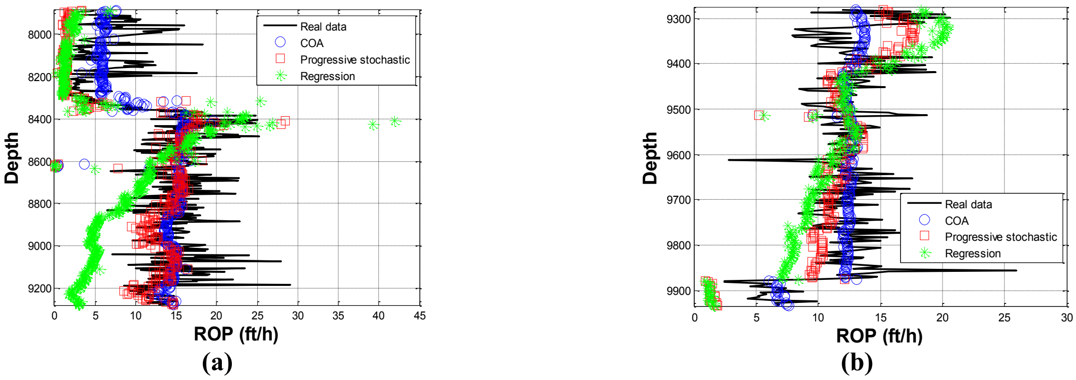

Figure 3. Comparison between estimated and real rate of penetration values in well A: (a) ASMARI and (b) PABDEH formations.

Table 4. RMSE obtained for three different methods in well A.

Method	ASMARI	PABDEH
COA	4.185	2.786
Progressive stochastic	5.130	3.803
Regression	8.159	4.737

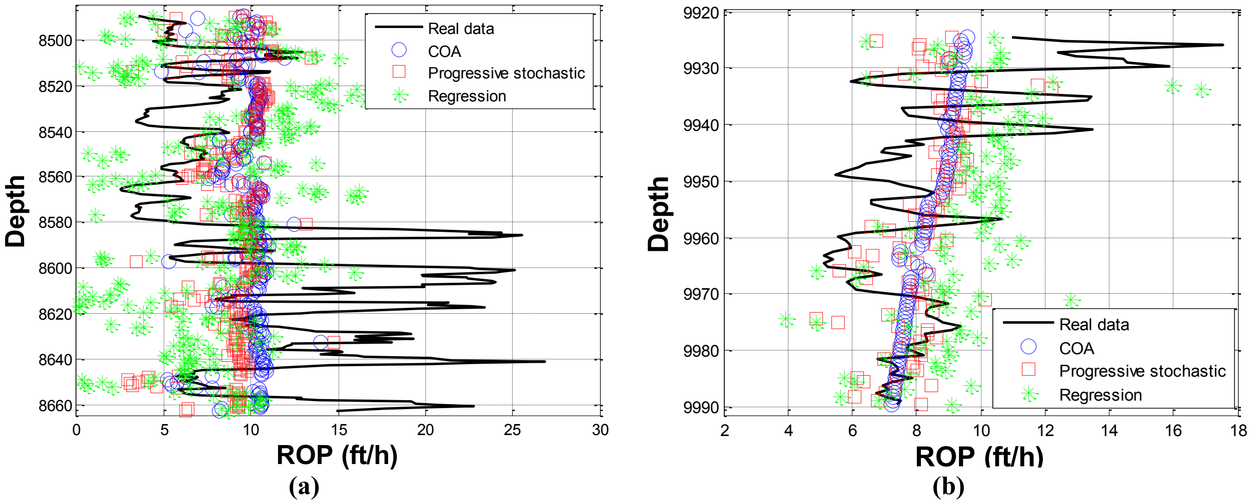

Figure 4. Comparison between estimated and real penetration rate values in well B: (a) ASMARI and (b) PABDEH formations.

Table 5. Computed RMSE for three different models in well B.

Method	ASMARI	PABDEH
COA	5.796	2.285
Progressive stochastic	6.127	2.591
Regression	7.874	3.598

Table 6. Computed coefficient of determinations for three methods in well A.

Method	ASMARI	PABDEH
COA	0.711	0.643
Progressive stochastic	0.619	0.582
Regression	0.401	0.362

5.2. Comparison among COA, PSO and GA in determining BY model's coefficients

In this comparison; the crossover and mutation coefficients in the GA were adopted as 0.6 and 0.4, respectively. The mutation rate was considered as 0.3. The number of initial population in GA and PSO was 50 and maximum iteration of the algorithms was selected equal to 300. These values were selected using trial and error method.

The rate of error reduction for both formations of the training well is given in Figure 5. As one could see in Figure 5, COA has higher convergence rate than other two evolutionary algorithms. Furthermore, the estimation error of the COA in both formations of two wells is less than other meta-heuristic algorithms (Table 7). Even after 300 iterations, PSO and GA did not reach to the estimation error of COA. It indicates that the COA is more reliable and precise. As can be seen from Table 8, the determination coefficient of the COA is higher than other two algorithms. It means that more percent of ROP data is predictable using the COA.

Figure 6 shows the estimated values of ROP through the studied ranges of depth in two wells. As can be seen, the predicted values of ROP using PSO is more accurate than GA. However, comparison between COA and PSO results indicates superiority of COA. Table 9 contains the calculated values of BY model's coefficients using data of well A.

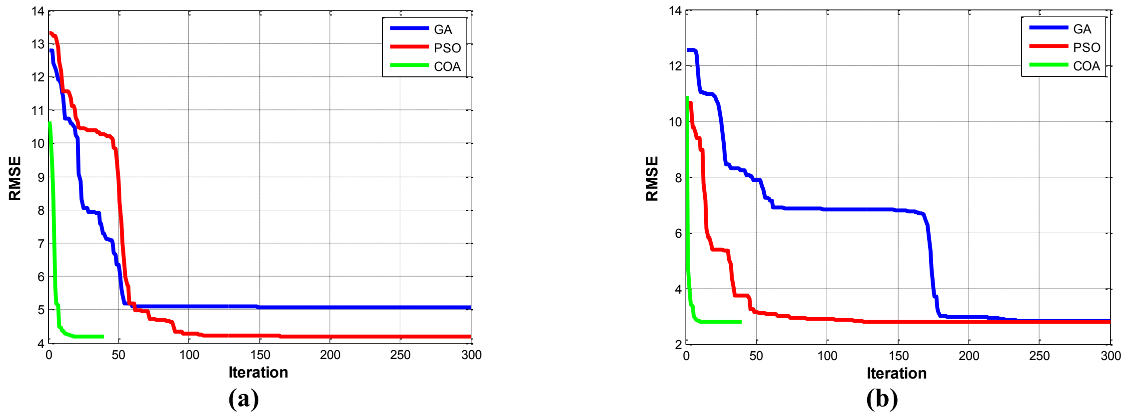

Figure 5. RMSE reduction rate for COA, PSO and GA in (a) ASMARI and (b) PABDEH formations of well A.

Table 7. Computed RMSE for three different meta-heuristic algorithms in two wells.

Well name	Method	ASMARI	PABDEH
Well A	COA	4.185	2.786
	PSO	4.197	2.792
	GA	5.063	2.811
Well B	COA	5.796	2.285
	PSO	5.913	2.301
	GA	6.492	2.383

Table 8. Computed coefficient of determinations for three evolutionary algorithms in well A.

Method	ASMARI	PABDEH
COA	0.711	0.643
PSO	0.694	0.628
GA	0.678	0.610

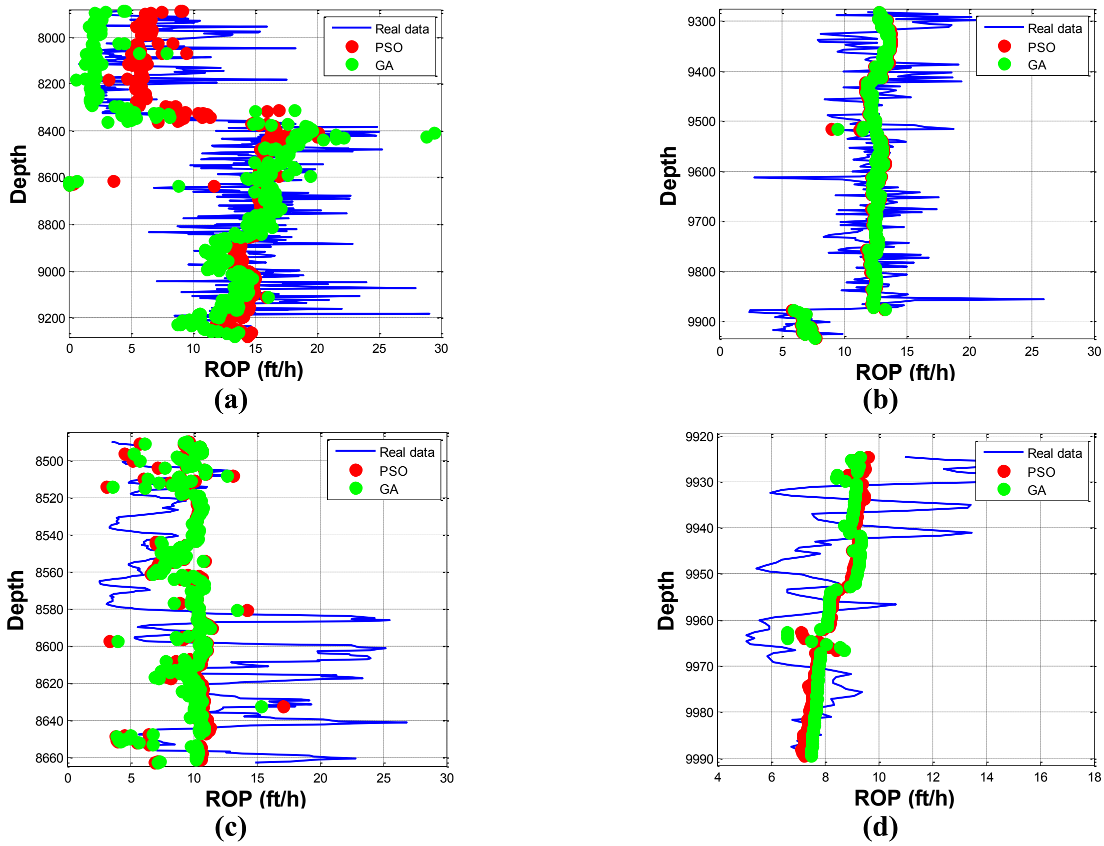

Figure 6. Comparison between estimated and measured rate of penetration in well A ((a) ASMARI and (b) PABDEH) and well B ((c) ASMARI and (d) PABDEH).

Table 9. Coefficients values obtained for the BY model using three different meta-heuristic algorithms.

Formation	Method	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
ASMARI	COA	1.899	0.00019	0.00016	0.0001	0.725	0.722	0.310	0.336
	PSO	1.892	0.00019	0.00018	0.0001	0.725	0.722	0.310	0.341
	GA	1.803	0.00015	0.00017	0.000092	0.723	0.722	0.309	0.349
PABDEH	COA	1.792	0.000179	0.000075	0.0000435	0.824	0.815	0.610	0.514
	PSO	1.792	0.000179	0.000072	0.0000437	0.824	0.816	0.621	0.514
	GA	1.763	0.000178	0.000073	0.0000441	0.822	0.831	0.627	0.513

6. Conclusions

Inability of the multiple regression techniques in determining meaningful and reliable constant values in the BY drilling rate model requires application of other methods. In this work, therefore, the COA evolutionary algorithm was utilized for determining the unknown constants in the BY model. Also four other methods, i.e. progressive stochastic and multiple regressions as mathematical methods and GA and PSO as meta-heuristic algorithms were applied to validate the results of the proposed model. For this purpose, first the BY model constants were determined using the five methods for the two formations in one of the wells. Then the determined constants were incorporated for computing the penetration rate in the similar formations of the other well. The results obtained showed that the BY model was extremely sensitive to the values for these constant coefficients. Unlike the other four methods, the constant values determined using the regression method did not lay in the meaningful and recommended range. Consequently, it yielded dispersed values for the penetration rate in the test well, and even, in some cases, it estimated a zero value for the penetration rate. COA converged rapidly and reached the optimal value at the 8th iteration. While GA and PSO did not reach the optimum value at the 300th iteration and they trapped in local minimum.

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تعیین ضرایب ثابت مدل نرخ حفاری بورگوین و یانگ با استفاده از الگوریتم تکاملی نوین

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چکیده:

دستیابی به حداقل هزینه و زمان در حفاری مخزن نیازمند ارزیابی تأثیرات پارامترهای حفاری روی نرخ نفوذ و ساخت یک مدل تخمینگر نرخ حفاری است. چندین مدل نرخ حفاری با استفاده از پارامترهای حفاری ارائه شده است. از میان آن‌ها، مدل بورگوین و یانگ (BY) به صورت گسترده برای تخمین نرخ نفوذ به کار برده شده است. این مدل چندین پارامتر حفاری را به نرخ نفوذ مرتبط می‌سازد و دارای هشت ضریب نامعین است. بورگوین و یانگ تحلیل رگرسیون چندگانه را برای تعیین این ضرایب پیشنهاد دادند. استفاده از رگرسیون چندگانه منجر به جواب‌های بی‌معنی و خارج از محدوده این ضرایب می‌شود. در این تحقیق، الگوریتم بهینه‌سازی فاخته (COA) برای تعیین ضرایب مدل بورگوین و یانگ به کار برده شد. برای نیل به این هدف، داده‌های مرتبط از دو چاه واقع در یکی از میادین جنوب غربی ایران جمع‌آوری شد. ثابت‌های مدل بورگوین و یانگ به صورت مجزا برای هر کدام از سازندهای یکی از چاه‌ها تعیین شد. سپس این ضرایب محاسبه شده برای تخمین نرخ نفوذ در سازندهای مشابه چاه دیگر استفاده شد. برای مقایسه نتایج COA، ابتدا، دو روش ریاضی شامل روش تصادفی فزاینده و رگرسیون چندگانه به کار برده شد. مقایسه بین این روش‌ها نشان داد که نتایج COA از دقت و قابلیت اطمینان بالاتری نسبت به روش‌های ریاضی برخوردار است. در ادامه، الگوریتم‌های بهینه‌سازی ازدحام ذرات (PSO) و ژنتیک (GA) به عنوان الگوریتم‌های فرا ابتکاری به منظور تعیین ضرایب مدل روی داده‌های میدان به کار برده شد. مقایسه بین این روش‌ها نشان داد که COA از سرعت همگرایی بالاتر و مقدار خطای تخمین کمتری نسبت به دو روش دیگر برخوردار است.

کلمات کلیدی: مدل بورگوین و یانگ، تخمین نرخ حفاری، بهینه‌سازی فاخته، پارامترهای حفاری.