www.czasopisma.pan.pl PAN www.journals.pan.pl

DE GRUYTER OPEN

Arch. Min. Sci. **62** (2017), 1, 131-144

Electronic version (in color) of this paper is available: http://mining.archives.pl

DOI 10.1515/amsc-2017-0010

SINA NOROUZI BEZMINABADI*[1], AHMAD RAMEZANZADEH*,
SEYED-MOHAMMAD ESMAEIL JALALI*, BEHZAD TOKHMECHI*, ABBAS ROUSTAEI**

EFFECT OF ROCK PROPERTIES ON ROP MODELING USING STATISTICAL AND INTELLIGENT METHODS: A CASE STUDY OF AN OIL WELL IN SOUTHWEST OF IRAN

BADANIE WPŁYWU WŁAŚCIWOŚCI SKAŁ NA PRĘDKOŚĆ WIERCENIA PRZY ZASTOSOWANIU METOD STATYSTYCZNYCH I INTELIGENTNYCH: STUDIUM PRZYPADKU: SZYB NAFTOWY W POŁUDNIOWO-ZACHODNIEJ CZĘŚCI IRANU

Rate of penetration (ROP) is one of the key indicators of drilling operation performance. The estimation of ROP in drilling engineering is very important in terms of more accurate assessment of drilling time which affects operation costs. Hence, estimation of a ROP model using operational and environmental parameters is crucial. For this purpose, firstly physical and mechanical properties of rock were derived from well logs. Correlation between the pair data were determined to find influential parameters on ROP. A new ROP model has been developed in one of the Azadegan oil field wells in southwest of Iran. The model has been simulated using Multiple Nonlinear Regression (MNR) and Artificial Neural Network (ANN). By adding the rock properties, the estimation of the models were precisely improved. The results of simulation using MNR and ANN methods showed correlation coefficients of 0.62 and 0.87, respectively. It was concluded that the performance of ANN model in ROP prediction is fairly better than MNR method.

Keywords: ROP, rock properties, MNR, ANN

Prędkość wiercenia jest jednym z podstawowych parametrów charakteryzujących tempo prac wiertniczych. Oszacowanie prędkości wiercenia jest zagadnieniem kluczowym dla inżynierów wiertnictwa, gdyż pozwala na dokładne określenie czasu trwania prac, a co za tym idzie także kosztów operacyjnych. Szacowanie prędkości wiercenia odbywa się na podstawie modelu uwzględniającego parametry pracy oraz parametry środowiskowe. Pierwszy krok obejmuje pozyskanie danych o fizycznych i mechanicznych właściwościach skał na podstawie profilowania geofizycznego otworu. Zastosowano korelację odpowiednich par danych dla pokreślenie wpływu głównych czynników warunkujących prędkość wiercenia. Nowy model obliczania prędkości wiercenia opracowany został w okręgu naftowym Azadegan w południowo-zachodniej części Iranu. Symulacje prowadzono w oparciu o metodę wielokrotnej regresji nieliniowej a także przy wykorzystaniu sztucznych sieci neuronowych. Poprzez dodanie danych o właściwościach

* DEPARTMENT OF MINING, PETROLEUM AND GEOPHYSICS, SHAHROOD UNIVERSITY, SHAHROOD, IRAN
** EXPERT, PETROLEUM ENGINEERING & DEVELOPMENT COMPANY(PEDEC), TEHRAN, IRAN
[1] CORRESPONDING AUTHOR. E-MAIL ADDRESSES: Sina.Norouzib@yahoo.com

skał, model został znacznie udoskonalony. Wyniki symulacji prowadzonych w oparciu o powyższe metody wykazały współczynniki korelacji na poziomie 0.62 i 0.87. Stwierdzono, że metoda wykorzystująca sztuczne sieci neuronowe daje dokładniejsze szacunki prędkości wiercenia niż podejście bazujące wyłącznie na metodzie obliczania regresji nieliniowej.

Słowa kluczowe: prędkość wiercenia, właściwości skał, metoda wielokrotnej regresji nieliniowej, sztuczne sieci neuronowe

Nomenclature

ROP – Rate of Penetration (m/h),
D – Depth (m),
WOB – Weight on Bit (Klbf),
RPM – Revolution per Minute (rpm),
FR – Flow Rate (gal/min),
MW – Mud Weight (pcf),
BWC – Bit Wear Coefficient,
NPHI – Neutron Porosity Hydrogen Index (dec),
RHOB – Density (gm/cc),
FA – Friction Angle (Degree),
RT – Resistivity Logs (Ohmm),
GR – Gamma Ray (api),
DT – Sonic Travel Time Compressional (uSec/Ft),
UCS – Uniaxial Compressive Strength (Mpa),
DP – Differential Pressure (Pcf),
P_p – Pore pressure (MPa),
K – Drillability index.

1. Introduction

A great portion of cost at exploration and exploitation of oil and gas well is being allocated to drilling operations. In order to time management and drilling process optimization, obtaining a model which could accurately define the relationship between ROP and affecting environmental factors is very important. Various parameters have influence on ROP simultaneously which could be classified into operational and environmental parameters (Bourgoyne & Young, 1974). Operational or controllable factors are manipulated by human factors. While uncontrollable or environmental factors are related to formations properties especially the rock mechanical parameters. Drilling process could be improved by adding the rock properties to drilling operation simulation (Andrews et al., 2007).

Since nearly five decades ago, the necessity of optimizing the drilling operations was felt and several ROP models have been proposed (Bourgoyne & Young, 1974; Hareland & Rashidi, 2010; Walker et al., 1986; Winters et al., 1987). This models were widely used, however, only some affecting factors have been considered in the mentioned models. Besides the existing models, various laboratory (Babatunde et al., 2011; Hoover & Middleton, 1981) and field studies (Bataee et al., 2010; Shirkavand & Hareland, 2009) have been conducted to determine the effect of parameters on ROP. In addition to the use of mathematical models, in some studies neural networks were suggested due to their ability to solve nonlinear problems in the ROP modeling (Bataee & Mohseni, 2011; Esmaeili et al., 2012). Due to lack of access to database in these studies, often less attention have been paid to the rock properties. Studies indicated that among the operational parameters, weight on bit, rotational speed, bit wear, wellbore depth, mud weight and flow rate were crucial parameters (Bielstein, 1950; Cunningham and Eenink, 1959; Duklet & Bates, 1980; Paiaman et al., 2009). In this line, it was found that ROP increased with increasing weight on bit, rotational speed and mud flow rate. Also, ROP decreased when depth, bit wear and mud weight increased. This parameters is closely related to other drilling factors and it cannot be studied apart from other effective factors.

Geomechanical parameters have a significant role on ROP (Gstalder & Raynal, 1966, Somerton, 1969; Walker et al., 1986). The most accurate method was obtained through laboratory testing available cores (Andrews et al., 2007). Due to sample preparation limitations and high cost of core sampling, the indirect methods were used to make a relationship between ROP and well log curves (Ma, 2011; Onyia, 1988). The well log curves were widely used to estimate the geomechanical properties at different depths. Consequently, well log data including porosity, density, gamma, resistivity and sonic were used to estimate these properties (Chang et al., 2006; Onyia, 1988). Studies showed that there is a close relationship between rock parameters including compressive strength, density and porosity with ROP. It is obvious that porous rocks as sandstone and shale have lower strength than the carbonate rocks. The conducted researches indicated the direct relationship between porosity and ROP (Howarth, 1987; Onyia, 1988). The rock density indicates rock minerals percentage and the specific weight of them. As the density of the carbonate rocks increases, the energy for a rotary drilling system will be increased; therefore, the drilling speed is reduced (Kahraman et al., 2000; Ma, 2011).

The compressive strength of the rock can be regarded as one of the most versatile mechanical properties of rocks. By increasing the strength, the volume of the crushed rock below the bit was reduced which decreases ROP (Shirkavand & Hareland, 2009). Despite the widespread use of the strength parameters in prediction of ROP, these parameters should not be used in this process merely. For example the Berea sandstone had the lower uniaxial compressive strength but because of the high internal friction angle, it had a high confined compressive strength (Prasad, 2009).

Pore pressure is one of the stresses in rock which cause breakout. Generally the term of differential pressure was used to analyze the effect of this parameter on ROP. Differential pressure is the difference of drilling fluid pressure and the pore pressure in formation (Warren & Smith, 1985). This factor was introduced as the effective stress at the bottom of the well. Differential pressure by influencing on rock failure mechanism and fragments detachment, affected ROP (Akbari et al., 2014; Bourgoyne et al., 1986).

Other physical and mechanical parameters of rock like hardness, erosion, toughness and so on are important in the breakout process and drilling penetration rate (Al-muhailan et al., 2013; Gstalder & Raynal, 1966; Nauroy, 2011); but due to difficult access to the cores, more study is required to analyze the effect of these parameters.

The parameters used in this study were collected from the reservoir information of one of the wells in southwestern Iran. In order to complete the database factors affecting ROP, the geomechanical parameters were estimated using the petrophysical logs. Then, all parameters which had influence on ROP were classified in two classes of operational and environmental parameters and the effects of each one were measured, accordingly. Finally for estimating ROP, multivariate regression and neural networks methods were used due to their high performance in data modeling and model recognition.

2. The introduction of the field and estimation of the geomechanical parameters

Azadegan oil field in southwestern Iran is one of the largest oil fields with carbonate reservoirs. Figure 1 shows the location of the mentioned field. Also the Lithostratigraphic column and the composition formations of the well are presented in figure 2. The shale part under the Ilam formation is known as Lafan Formation (Jadbavi, 2012).

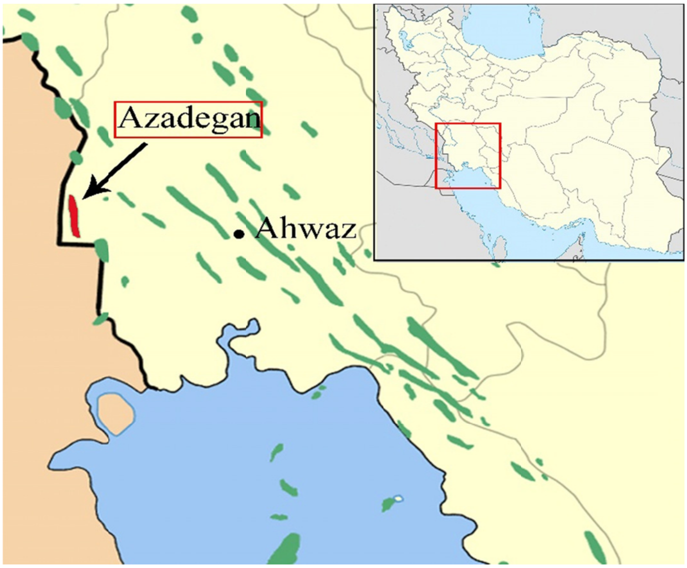

Fig. 1. Geographical location of the study area

After identifying the geological structures, geomechanical studies are necessary. One of the effective ways to improve and accelerate the drilling process is to have sufficient knowledge about the geomechanical conditions (Villalobos et al., 2005). Geomechanical parameters are important in the optimization methods of well stability and hydraulic fracturing analysis in reservoir (Zoback, 2007); However, these parameters are seldom used in estimating ROP and drillability.

Limited procedures have been developed to measure or calculate the mechanical properties of rocks. The most common of these methods is conducting the geomechanical tests on cores (Qiu et al., 2013) or estimating the mechanical properties of the rock from the petrophysical logs (Ameen et al., 2009; Fjaer et al., 2008; Yasar & Erdogan, 2004). Regarding limitations of this study, petrophysical logs were used to calculate the mechanical properties of the rock. The various steps of estimating geomechanical parameters and calibration of them are discussed below.

Uniaxial compressive strength is essential parameter in determining the safe mud weight window and drillability (Afsari et al., 2009; Spaar et al., 1995). For estimating the uniaxial compressive strength from the logs data, usually three types of logs including sonic, neutron and density were used (Chang et al., 2006; Yasar & Erdogan, 2004). It should be noted that empirical relationships were provided for specific geological conditions and they should be calibrated with laboratory tests (Fernandez-ibanez et al., 2010). According to (Li et al., 2012) the average uniaxial compressive strength of the rock in Sarvak formation in the North Azadegan field is about 27.5-34.5 MPa. Therefore, the equation 1 is the most appropriate correlation for the mentioned well.

$$UCS = \frac{\left(\frac{7682}{DT}\right)^{1.82}}{145} \tag{1}$$

Internal friction angle of rock is another strength parameter. This parameter is one of the most important parameters in geomechanical applications like wellbore stability (Collins, 2002). Gholami et al (2014) used the equation 2 to estimate this parameter in carbonate formations of Iran.

$$\varphi = 26.5 - 37.4\left(1 - NPHI - V_{shale}\right) + 62.1\left(1 - NPHI - V_{shale}\right)^2 \tag{2}$$

$$V_{shale} = \frac{GR - GR_{\min}}{GR_{\max} - GR_{\min}} \tag{3}$$

In this equation V_{shale} is the volume of the shale which is defined by the equation 3 at under 8000 depths feet. In equation 3, $GR_{\min}$ is the gamma ray log in non-shaly sandstone and $GR_{\max}$ is the gamma ray log in shaly zone (Tiab & Donaldson, 2011).

Pore pressure as a geomechanical properties is another important parameter which has a considerable role in design, control, safety and omission of the drilling process problems of well (Zhang, 2011). The most commonly used method to predict the pore pressure is the Eaton equation (Eaton, 1975). The equation is as follow:

$$P_{pg} = OBG - \left(OBG - P_{ng}\right)\left(\frac{NCT}{DT}\right)^3 \tag{4}$$

In the equation 4, *NCT* is the normal compacted trend line obtained by fitting a linear or non-linear curve to compressional wave log data, *OBG* is the overburden pressure gradient, P_{ng} is hydrostatic pore pressure gradient and P_{pg} is the pore pressure gradient of formation. In order to determine the pore pressure, the calculated values in Eaton equation were calibrated by the values obtained from the *DST* test including the well tests. Fig. 2

3. Data base

Factors database affecting *ROP* was formed based on gathered data from the mud logging, petrophysical logs and the daily drilling reports. Finally, the analysis was performed on 604 data that include operational and environmental parameters. The operating and controllable parameters included depth, weight on bit, rotation speed, flow rate, mud weight, bit wear coefficient and the environmental parameters included porosity, density, uniaxial compressive strength, internal friction angle and differential pressure. Since the geomechanical parameters are an indicator of petrophysical logs including sonic, resistivity and gamma, the relationship of these logs were analyzed as well. The data graph used in the study is presented in Figure 2.

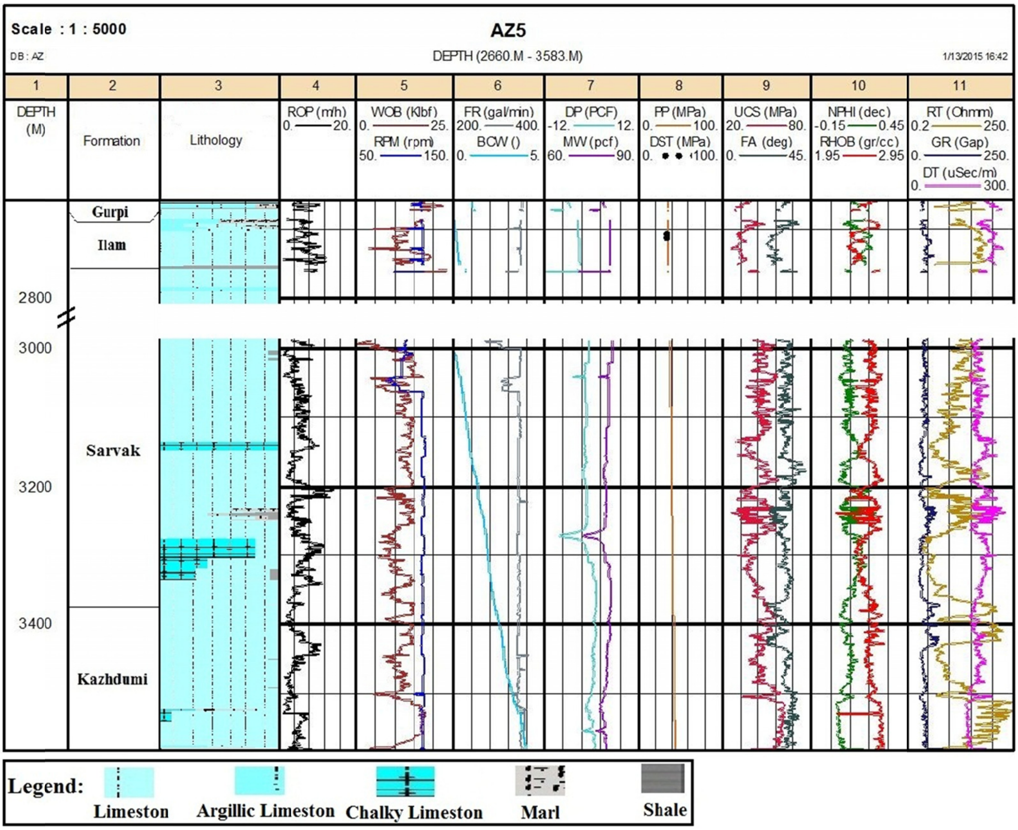

Fig. 2. Lithostratigraphic column, rock properties, operational parameters and rate of penetration

4. Methodology

4.1. Regression analysis method

Available data and mathematical models revealed that statistical analysis have crucial role in predicting behavior of processing in future (Bates & Watts, 2007). Statistical method of regression analysis investigates the relationship between variables. The multiple nonlinear regression is one of the methods that estimates Y dependent values based on the given independent values (X_1, X_2,..., X_n)(Tiryaki, 2008). In this study, twin-logarithmic method is used in the multivariate nonlinear regression analysis to estimate ROP (Choi, 1978). The equation is as follows:

$$Y = aX_1^{b_1} X_2^{b_2} \ldots X_n^{b_n} \tag{5}$$

Where Y is the dependent variable, a is the intercept, X_1, X_2 and the X_n are independent variables and b_1, b_2 and b_n are the regression equation constants. Based on this method, 80% of data for creating the regression equation are considered. Then, the variance inflation factor (VIF) for the polylinearity of the parameters was studied. Hence the parameters with lower *VIF* (*VIF* < 10) remain in the equation (Famini et al., 1992). Also the *P*-value was calculated at significant level of 5%. Finally the regression equation was tested with the remaining 20% of the data.

4.2. Neural Network

In the recent decades, the Artificial Neural Networks are known as suitable methods for modelizing existing complicated maps among various variable. In the studies related to oil and gas industry, using the neural network is considered as a helpful option in predicting *ROP* (Rahimzadeh et al., 2010). The feed-forward multilayer networks and the back propagation methods are used in this research. In order to network training, the Levenberg-Marquardt algorithm was used as the fastest training method. The use of these networks with sigmoid transfer function in the hidden layer and linear transfer function in output layer can predict any complicated function based on number of the neurons (Bontempi et al., 2001; Haykin, 1999). In the present study, various architectures were tested along with various numbers of neurons. Before entering data into the network, normalization is done in order to increase the network performance (Sivanandam and Deepa, 2006). Finally 80% of data are entered into the network for training and 20% of them are used for testing.

4.3. Model assessments

Model architecture was based on trial and error in regression analysis. To analysis the neural network, the number of hidden layers, neurons in layers, optimal repetitions and adjustment of related coefficients was performed based on the comparison of *RMSE* and *R* indices in various topologies. Thus the estimated values were compared with the recorded values of *ROP*. To evaluate the model's performance, the *RMSE* performance Indices (Mean Square Error) and *R* were used (Basarir et al., 2014; Rodgers & Nicewander, 1988).

5. Results

Considering the multiplicity of parameters, affecting *ROP* and the close relationship between these parameters, the correlation analysis was used to identify the relevant parameters. This correlation coefficient is between –1 and 1. Among the parameters, (*UCS*, *RHOB*, *DT*, *NPHI*), (*BWC*, *D*), (*FA*, *GR*) and (*DP*, *MW*), that the absolute correlation coefficients were upper than 0.7 or lower than –0.7, must not be used simultaneously in equation (Table 1) (Pallant, 2010). Thus, parameters which had the highest absolute significant correlation coefficients with target parameter, was used in regression and neural network models.

TABLE 1

Correlation between dependent and independent parameters

	DP	WOB	D	RPM	FR	MW	MCW	NPHI	RHOB	FA	RT	GR	DT	UCS	ROP
DP	1														
WOB	0.04	1													
D	0.12	–0.08	1												
RPM	–0.16	–0.09	0.25	1											
FR	0.02	0.46	–0.1	0.04	1										
MW	0.95	0.05	–0.2	–0.2	0.03	1									
MCW	–0.18	0.02	0.9	0.37	0.01	–0.2	1								
NPHI	–0.11	–0.39	–0.51	0.15	–0.05	–0.16	–0.44	1							
RHOB	0.14	0.39	0.42	–0.14	0.08	0.18	0.36	–0.87	1						
FA	0.2	0.05	0.3	–0.03	0.02	0.23	0.22	–0.41	0.38	1					
RT	0.02	0.45	0.17	0.04	0.3	0.01	0.32	–0.32	0.27	–0.09	1				
GR	0.12	0.22	0.01	–0.04	0.01	0.14	0.06	–0.2	0.15	–0.78	0.34	1			
DT	–0.09	–0.26	–0.5	0.13	–0.04	–0.16	–0.49	0.91	–0.81	–0.4	–0.2	–0.1	1		
UCS	0.11	0.28	0.58	–0.1	0.06	0.17	0.5	–0.92	0.81	0.44	0.3	0.11	–0.9	1	
ROP	–0.08	–0.07	–0.2	0.22	0.09	–0.02	–0.16	0.48	–0.44	–0.1	–0.1	–0.2	0.41	–0.4	1

5.1. Estimating the penetration rate using the multiple regression method

In order to present *ROP* models, the best linear and non-linear combinations were evaluated. In this assessments, the effect of first and second class of parameters and also interaction of parameters together, were investigated. The most relevant model was obtained between *ROP* and operational parameters, presented in equation 6 in Table 2. In this method, mud weight parameter was removed at low significance level. The rotational speed as the most effective parameter, coupling with fluid flow rate through its positive impact (while there is an excessive weight on bit), can improve performance of detached fragments transmission.

In the analysis of the effect of rock properties, relation between *ROP* and all parameters was studied separately. The results showed that the porosity and compressional wave velocity

TABLE 2

The regression model between the operational and environmental parameters with the penetration rate

Equation number	Regression equation	Train		Test		Overall	
		R	RMSE	R	RMSE	R	RMSE
(6)	$ROP = 4.9\times10^{-9}\left(\dfrac{FR^{3.8}RPM^{2.64}e^{0.001WOB^2}}{WOB^{0.4}D^{1.6}}\right)$	0.38	0.42	0.35	0.43	0.36	0.43
(7)	$ROP = 1.4\times10^{-21}\left(\dfrac{FR^{7.25}RPM^{2.2}e^{0.004WOB^2}}{WOB^{0.7}BWC^{0.06}}\right)\left(\dfrac{NPHI^{0.2}}{RT^{0.1}FA^{0.3}}\right)$	0.63	0.36	0.61	0.36	0.62	0.61

are directly related to *ROP*. On the other hand, other rock properties had significant reverse relationship with ROP. Because of the omission of the highly correlated parameters, the VIF index of all parameters was obtained below 10. Therefore they could entered into the model. Finally the model achieved a general solidarity and added to the operational parameters. The final result of regression analysis between *ROP* dependent variable and independent variables (operational parameters and rock properties), are presented in Table 2.

Both operational and rock parameters are affected ROP in equation 7. The first part of the equation includes the operational parameters, in which the depth parameter was omitted with insignificance level (below 0.05). Then, the bit wear coefficient is entered into the equation. Rock properties at the second part of the equation can be considered as drillability index as follow:

$$K = \frac{NPHI^{0.2}}{RT^{0.1} FA^{0.3}} \tag{8}$$

In this equation the porosity factor was obtained from the neutron log that had the most impact on ROP. This factor is among rock properties that is closely related to the physical and mechanical properties. The presence of resistivity log in the equation indicated the importance of mentioned log in the porous formation of the reservoir. The resistivity was increased because of porosity reduction and tightness increase. Friction angle was used due to the lack of gamma significance in the equation.

The best obtained results of regression analysis of equations 6 and 7 are shown in Figure 3 as an estimated and observed values diagram. Due to the addition of rock properties, data dispersion from the $y = x$ line was reduced in Figure 3.

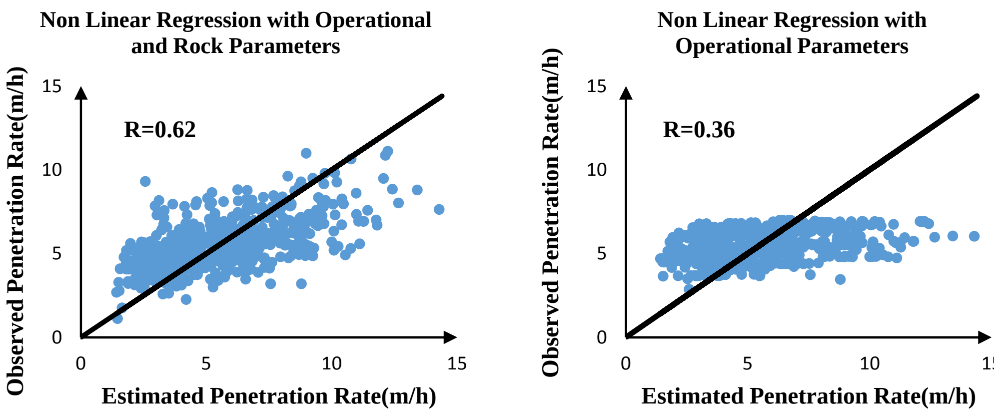

Fig. 3. The correlation between observed and estimated ROP by non-linear regression before and after adding rock properties

5.2. Estimating *ROP* using artificial neural network

In this part, in order to create a model to estimate *ROP*, the independent parameters which had the highest correlation with the target parameter, had entered network training. Hence, at first (*D*, *WOB*, *RPM*, *FR*, *MW*) were entered network training and then (*NPHI*, *RT*, *GR*, *DP*) were added to them. *DP* is replaced, since *MW* has less correlation with target parameter. The network reached its lowest error level with the sigmoid transfer function in the hidden layer and linear transfer function in the output layer with 16 neurons. Results summary of the neural network is presented in Table 3.

TABLE 3

Evaluation of Neural Network Model

Step	Train		Test		Overall	
	R	RMSE	R	RMSE	R	RMSE
Operational parameters	0.76	0.041	0.75	0.013	0.75	0.013
Operational and Rock Parameters	0.88	0.008	0.86	0.0104	0.87	0.009

The results obtained from the networks presented the distribution between observed and estimated data in Figure 4. So the network had a correlation coefficient of 0.75 at the level of the effect of the operational parameters. After adding the rock properties to the model, this coefficient became 0.87.

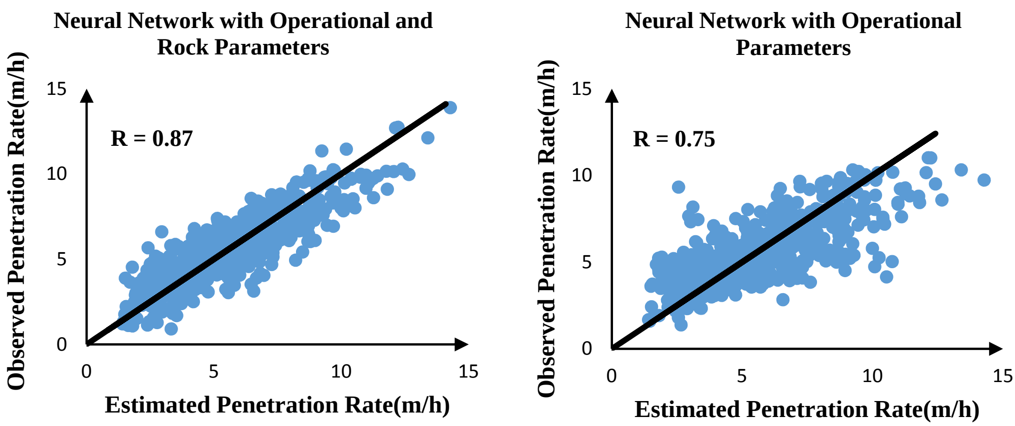

Fig. 4. Correlation between observed and estimated *ROP* by neural network before and after adding rock properties

Figure 5 compared the estimated and observed ROP by the operational and rock parameters. This diagram paralleled the estimation of ROP through multivariate nonlinear regression analysis and the neural network with real values. The estimated regression and neural network showed the correlation of 0.62 and 0.87 with observed values, respectively. So the neural network had an important role in the improvement of the estimating ROP. It made a relationship between all input parameters and the target parameter, regarding its complicated algorithm in solving nonlinear problems.

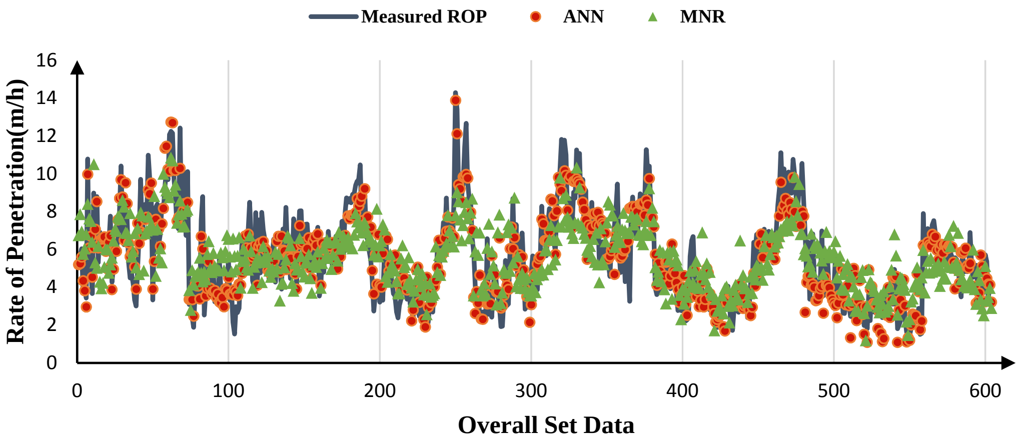

Fig. 5. A comparison between estimated ROP and the observed ROP in the regression analysis and neural network

7. Conclusion

In this study, the factors affected rate of penetration were evaluated through focusing on environmental parameters. The database of operational and environmental parameters (physical and mechanical rock properties) was formed. The high correlation between rock properties and penetration rate indicate the importance of these factors in modelizing. By adding the physical and mechanical parameters of the rock to the operational parameters in regression model, porosity, resistivity and internal friction angle were introduced as drillability index. This index had important role in the improvement of the provided model of *ROP*. Then, regarding to the complicacy of the neural network maps in solving problems, this method was used to estimate *ROP*. The results indicated that accuracy of the neural network was enhanced by adding the rock properties to the operational parameters. Accordingly, two different methods results showed that neural network can better predict *ROP* values. Although this study conducted based on the restriction of access to information in one of the wells in oil fields located southwestern Iran, it can be a step forward in the effectiveness of rock properties in optimizing the well drilling planning in other areas through verification.

Acknowledgments

The authors would like to appreciate Petroleum Engineering and Development Company (PEDEC) for sponsorship, data preparation and permission to publish current study.

References

Afsari M., Ghafoori M.R., Roostaeian M., Haghshenas A., Iranian N., Company O., 2009. *Mechanical Earth Model (MEM): An Effective Tool for Borehole Stability Analysis and Managed Pressure Drilling (Case Study).* In SPE Middle East Oil and Gas Show and Conference, p. 1-12.

Akbari B., Miska S., Yu M., Ozbayoglu M., 2014. *Experimental Investigations of the Effect of the Pore Pressure on the MSE and Drilling Strength of a PDC Bit.* In SPE Western North American and Rocky Mountain Joint Meeting, p. 1-9.

Al-muhailan M., Hussain I., Maliekkal H., Ghoneim O., Nair P., 2013. *New HTHP Cutter Technology Coupled with FEA-Based Bit Selection System Improves ROP by 60% in Abrasive Zubair Formation.* In International Petroleum Technology Conference, p. 1-11.

Ameen M.S., Smart B.G.D., Somerville J.M., Hammilton S., Naji N., 2009. *Predicting rock mechanical properties of carbonates from wireline logs (A case study: Arab-D reservoir, Ghawar field, Saudi Arabia).* Marine and Petroleum Geology, 26(4), 430-444. doi:10.1016/j.marpetgeo.2009.01.017

Andrews R., Hareland G., Nygaard R., Engler T., 2007. *Methods of Using Logs to Quantify Drillability.* In Rocky Mountain Oil & Gas Technology Symposium. doi:http://dx.doi.org/10.2118/106571-MS

Babatunde Y., Butt S., Molgaard J., Arvani F., 2011. *Investigation of the Effects of Vibration Frequency on Rotary Drilling Penetration Rate Using Diamond Drag Bit.* In 45th U.S. Rock Mechanics / Geomechanics Symposium.

Basarir H., Tutluoglu L., Karpuz C., 2014. *Penetration rate prediction for diamond bit drilling by adaptive neuro-fuzzy inference system and multiple regressions.* Engineering Geology, 173, 1-9. doi:10.1016/j.enggeo.2014.02.006

Bataee M., Kamyab M., Ashena R., 2010. *Investigation of Various ROP Models and Optimization of Drilling Parameters for PDC and Roller-cone Bits in Shadegan Oil Field.* In International Oil and Gas Conference and Exhibition, p. 1-10.

Bataee M., Mohseni S., 2011. *Application of Artificial Intelligent System in ROP Optimization a Case Study in Shadegan Oil Field.* In SPE middle east unconventional gas conference and exhibition, p. 1-10.

Bates D.M., Watts D.G., 2007. *Nonlinear Regression Analysis and Its Applications*. p. 392. Wiley-Interscience; 1 edition.

Bielstein J.,, 1950. *Factors Affecting the Rate of Penetration of Rock Bits.* In Drilling and Production Practice, p. 61-78.

Bontempi G., Bersini H., Birattari M., 2001. *The local paradigm for modeling and control: from neuro-fuzzy to lazy learning.* Fuzzy Sets and Systems, 121(1), 59-72.

Bourgoyne A.T., Young F.S., 1974. *A Multiple Regression Approach to Optimal Drilling and Abnormal Pressure Detection*, 4, 371-384.

Bourgoyne A.T., Millheim K.K., Chenevert M.E., Jr., F.S.Y., 1986. *Applied Drilling Engineering*. p. 502.

Chang C., Zoback M.D., Khaksar A., 2006. *Empirical relations between rock strength and physical properties in sedimentary rocks.* Journal of Petroleum Science and Engineering, 51(3-4), 223-237. doi:10.1016/j.petrol.2006.01.003

Choi S., 1978. *Introductory Statistics in Science*. New Jersey: Prentice-Hall Inc.

Collins P.M., 2002. *Geomechanics and wellbore stability design of an offshore horizontal well, North Sea.* In SPE International Thermal Operations and Heavy Oil Symposium and International Horizontal Well Technology Conference, p. 1-14.

Cunningham R.A., Eenink J.G., 1959. *Laboratory Study of Effect of Overburden, Formation and Mud Column Pressures on Drilling Rate of Permeable Formations*. Society of Petroleum Engineers, 217, 9-17.

Duklet C.P., Bates T.R., 1980. *An Empirical Correlation To Predict Diamond Bit Drilling Rates.* In SPE Annual Technical Conference and Exhibition, p. 1-7.

Eaton B.A., 1975. *he Equation for Geopressure Prediction from Well Logs.* In Fall Meeting of the Society of Petroleum Engineers of AIME, p. 1-11.

Esmaeili A., Elahifar B., Fruhwirth R.K., Thonhauser T.D.E., Engineering D., 2012. *ROP Modeling Using Neural Network and Drill String Vibration Data.* In SPE Kuwait International Petroleum Conference and Exhibition, p. 1-13.

Famini G.R., Penski C.A., Wilson L., 1992. *Using theoretical descriptors in quantitative structure activity relationships: Some physicochemical properties.* Journal of Physical Organic Chemistry, 395-408.

Fernandez-Ibanez F., Felipe Cardona M.H., Araujo E.M.P., Brudy M., Alvarellos J., Ordonez L.Y., Mateus D.C., 2010. *3D Geomechanical Modeling for the Apiay and Suria Oil Fields (Llanos Orientales Basin, Colombia): Insights on the Stability of Reservoir-Bounding Faults.* In SPE Latin American and Caribbean Petroleum Engineering Conference. p. 1-14.

Fjaer E., Holt R.M., Horsrud P., Raaen A.M., Risnes R., 2008. *Petroleum Related Rock Mechanics*. 2nd Editio., p. 1-490.

Gholami R., Moradzadeh A., Rasouli V., Hanachi J., 2014. *Practical application of failure criteria in determining safe mud weight windows in drilling operations.* Journal of Rock Mechanics and Geotechnical Engineering, 6(1), 13-25. doi:10.1016/j.jrmge.2013.11.002

Gstalder S., Raynal J., 1966. *Measurement of Some Mechanical Properties of Rocks and Their Relationship to Rock Drillability.* Journal of Petroleum Technology, 991-996.

Hareland G., Wu A., Rashidi B., 2010. *A Drilling Rate Model for Roller Cone Bits and Its Application.* In International Oil and Gas Conference and Exhibition in China, p. 8-10.

Haykin S.S., 1999. *Neural Networks: A Comprehensive Foundation*. p. 842. Prentice Hall.

Hoover E.R., Middleton J.N., 1981. *Laboratory Evaluation of PDC Drill Bits Under High-Speed and High-Wear Conditions.* Journal of Petroleum Technology, 2316-2321.

Howarth D.F., 1987. *The Effect of Pre-existing Microcavities on Mechanical Rock Performance in Sedimentary and Crystalline Rocks.* International Journal of Rock Mechanics and Mining Sciences & Geomechanics, 20(4), 223-233.

Jadbavi H., 2012. *Mudlogging Data Check and Accept Sheet.* p. 187.

Kahraman S., Balcõ C., Yazõcõ S., Bilgin N., 2000. *Prediction of the penetration rate of rotary blast hole drills using a new drillability index.* International Journal of Rock Mechanics and Mining Sciences, 37, 729-743.

Li R., Chengjin Y., Yunzhang Z., Zhiping L., 2012. *An Integrated Approach to Improve Drilling Performance and Save Cost in North Azadegan Field.* In IADC/SPE Asia Pacific Drilling Technology Conference and Exhibition. p. 1-8.

Ma H., 2011. *Formation drillability prediction based on multi-source information fusion.* Journal of Petroleum Science and Engineering, 78(2), 438-446. doi:10.1016/j.petrol.2011.06.017

Nauroy J.-F., 2011. *Geomechanics Applied to the Petroleum Industry*. p. 198.

Onyia E.C., 1988. *Relationships Between Formation Strength, Drilling Strength, and Electric Log Properties.* In SPE Annual Technical Conference and Exhibition, p. 1-14.

Paiaman A.M., Al-askari M.K.G., Salmani B., Masihi M., 2009. *Effect of Drilling Fluid Properties on Rate of Penetration.* Nafta Scientific Journal, 60, 129-134.

Pallant J., 2010. *A Step by Step Guide to Data Analysis Using SPSS*. p. 330. Open University Press.

Prasad U., 2009. *Drillability of a Rock in Terms of its Physico-Mechanical and Micro-Structural Properties.* In 43rd U.S. Rock Mechanics Symposium & 4th U.S. – Canada Rock Mechanics Symposium.

Qiu K., Cheng N., Ke X., Liu Y., Wang L., Chen Y., Xiong P., 2013. *3D Reservoir Geomechanics Workflow and Its Application to a Tight Gas Reservoir in Western China.* In International Petroleum Technology Conference, p. 1-11.

Rahimzadeh H., Mostofi M., Hashemi A., Salahshoor K., 2010. *Comparison of the Penetration Rate Models Using Field Data for One of the Gas Fields in Persian Gulf Area.* In CPS/SPE Internatioanl Oil& Gas Conference and Exhbition. p. 1-11.

Rodgers J.L., Nicewander W.A., 1988. *Thirteen Ways to Look at the Correlation Coefficient.* The American Statistician, 42, 59-66.

Shirkavand F., Hareland G., 2009. *Rock Mechanical Modelling for a Underbalanced Drilling Rate of Penetration Prediction.* In 43rd U.S. Rock Mechanics Symposium & 4th U.S. – Canada Rock Mechanics Symposium.

Sivanandam S.N., Deepa S.N., 2006. *Introduction to Neural Networks Using Matlab 6.0*. p. 656. Tata McGraw-Hill Education.

Somerton W.H., 1969. *Further Studies of the to Relation of Physical Properties of Rock to Rock Drillability.* In Drilling and Rock Mechanics Symposium, p. 87-96.

Spaar J.R., Ledgerwood L.W., Christensen H., Goodman H., Graff R.L., Moo T.J., 1995. *Formation Compressive Strength Estimates for Predicting Drillability and PDC Bit Selection.* SPE/IADC Drilling Conference, 569-578.

Tiab D., Donaldson E.C., 2011. *Petrophysics-Theory and Practice of Measuring Reservoir Rock and Fluid Transport Properties*, p. 1-976.

Tiryaki B., 2008. *Application of artificial neural networks for predicting the cuttability of rocks by drag tools*. Tunnelling and Underground Space Technology, 23(3), 273-280. doi:10.1016/j.tust.2007.04.008

Villalobos M.E.T., Frydman M., Casalis D.J., Ramirez A., C., M.F.L., Villalba E., 2005. *3D Analysis for Wellbore Stability: Reducing Drilling Risks in Oriente Basin, Ecuador.* In SPE Latin American and Caribbean Petroleum Engineering Conference, p. 1-13.

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.* In SPE Annual Technical Conference and Exhibition, p. 1-12.

Warren T.M., Smith M., 1985. *Bottomhole Stress Factors Affecting Drilling Rate at Depth.* Journal of Petroleum Technology, 1523-1533.

Winters W.J., Warren T.M., Onyia E.C., 1987. *Roller Bit Model With Rock Ductility and Cone Offset.* In SPE Annual Technical Conference and Exhibition, p. 1-12.

Yasar E., Erdogan Y., 2004. *Correlating sound velocity with the density, compressive strength and Young's modulus of carbonate rocks.* International Journal of Rock Mechanics and Mining Sciences, 41(5), 871-875. doi:10.1016/j.ijrmms.2004.01.012

Zhang J., 2011. *Pore pressure prediction from well logs: Methods, modifications, and new approaches.* Earth-Science Reviews, 108(1-2), 50-63. doi:10.1016/j.earscirev.2011.06.001

Zoback M.D., 2007. *Reservoir Geomechanics*, p. 1-443.