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AN OPTIMUM DRILL BIT SELECTION TECHNIQUE USING ARTIFICIAL NEURAL NETWORKS AND GENETIC ALGORITHMS TO INCREASE THE RATE OF PENETRATION

MOHAMMADSADEGH MOMENI[1,2,] *, SEYED JAVAD HOSSEINI[1], SYAHRIR RIDHA[1], MOACYR BARTHOLOMEU LARUCCIA[1], XIANHUA LIU[1]

[1]Department of Petroleum Engineering, Universiti Teknologi PETRONAS, 32610 Bandar Seri Iskandar, Perak Darul Ridzuan, Malaysia
[2]Department of Petroleum Engineering, Curtin University, Sarawak, Malaysia
*Corresponding Author: ms.momeni65@yahoo.com

Abstract

Drill bit is the most essential tool in drilling and drill bit selection plays a significant role in drilling process planning. This paper discusses bit selection by employing a method of combining Artificial Neural Network (ANN) and the computation of Genetic Algorithm (GA). In this method, offset well drilling records are used for training the ANN model and International Association Drilling Contractors (IADC) bit codes are used to name each bit. However, some researchers have used bit codes as input or output variables. This paper illustrates that the bit codes are better used in referring to the name of each bit instead of using them as values for calculation in the ANN model. The ANN black box was converted to white box to obtain a visible mathematical model for predicting the Rate of Penetration (ROP). This mathematical model, which was the objective function in the GAs, was used to find the optimum drilling values and to maximize the ROP. When drilling a new well, bit selection process requires the maximum ROP of a bit that corresponds to the optimum drilling parameters being obtained by combining the trained ANN model with GA. A bit selection example is provided by using the Shadegan oil field drilling data. The mean square error (MSE) obtained a value of 0.0037 whereas the coefficient of determination obtained a value of 0.9473. In other words, the predicted ROP model based on the field drilling data indicated a good correlation with the real ROP.

Keywords: Artificial Neural Network, Bit Selection, Genetic Algorithm, Mean Squared Error, Drilling Data Optimization

Nomenclatures

D	Depth
N	Number of data
R^2	Coefficient of determination
w	A vector of connection weights
x	A vector of input data
x_i	Input data
x_{max}	Maximum value of x_i
x_{min}	Minimum value of x_i
y_{exp}	Experimental value
y_i	standardized value of x_i
y_{prd}	Foreseen value by ANN

Greek Symbols

з	Normally distributed random noise term

Abbreviations

ANN	Artificial Neural Network
GA	Genetic Algorithm
IADC	International Association of Drilling Contractors
MATLAB	Matrix Laboratory
MSE	Mean Squared Error
MW	Mud Weight
RNNs	Replicator Neural Networks
ROP	Rate of Penetration
RPM	Revolution per Minutes
WOB	Weight on Bit

1. Introduction

There are various challenges faced by drilling researchers prior to and after the drilling process for a new well. The constraints associated with hardware and regular routine operations are designed and altered with the drilling process development [1].

Bit selection is, among others, a critical measure to drill an oil well. Therefore, selecting proper bits is a challenging duty as there are several factors, such as ROP, revolution per minutes (RPM), mud weight (MW), and Depth (D), on the bit performance [2-4]. Over the years, many researchers have carried out studies for estimating the bit conduct which relied upon operational parameters and data gathered in offset wells [5, 6].

Various models were designed and implemented by investigators, however, the assumptions during design limited their applications [7]. In this study, a mathematical model was proposed for the drill bit selection using the south west oil field of Iran (700 data sets) as a productive oil field in the Middle East based on the offset bit records together with the factory recommendation. Drill Bit Classifier of World Oil provides a comprehensive list of dominant manufacturers' drilling bits in aiding drilling supervisors and engineers regarding field drill bit selection. Drill Bit Classifier also supplies the most current classification charts including the information of bits with the recommended Weight on Bit (WOB), rotary speed, suitable formations, and available bit size to be used [8]. Nevertheless, due to some limitation on offset bit records such as lack of data for all the bits and unavailable data in other fields, the prediction cannot be applied in a variety of oil fields. Furthermore, the bit codes named by IADC should not be used as a mathematical value in the algorithms and equations because those codes represent a given name to the bit, therefore, they are not valid variables to be inserted as the input or output data in mathematical models. In the current study, ANN method is employed to foresee the ROP while the GA is appropriated to optimize the drilling parameters in the specific oil field. The utilization of neural networks has been proposed in recent years to categorize complex relationships when large data are present [9]. For modeling of the ROP, Bilgesu et al. [10] used ANN and achieved the proper results but they did not optimize the drilling parameters which involved inaccurate variables. In order to optimize controllable parameters (i.e. RPM, WOB and so on), an optimization tool has been used. The GA is an optimization algorithm to solve both constrained and unconstrained problems based on a natural selection process by imitating genetic evolution. The algorithm iteratively alters a population of individual solutions. However, it should be noted that bit selection procedure is a trial process due to a large number of variables involved. In this paper, ROP and the drilling data were optimized by using the combination of ANN and GA. The best bit was selected based on the optimum ROP.

Overview of bit selection methods

Clegg and Barton [11] described results from a specific region as a case study and showed a scientifically balanced method toward bit selection. Four main points, which were ROP, stability, steer ability, and durability, were explained when describing the bit performance. Using a tool which is capable of calculating these four parameters allows the development of optimal bits. Thus, the bit selection based on indices can provide a better performance than those of traditional methods which are mostly based on driller experience and bit records of similar bits from offset wells.

Rastegar et al. [12] have optimized drilling performance according to an ROP model. The ROP model developed in their report defined the relations between penetration rate and operational conditions as well as the bit parameters and the rock strength. This model is used for future wells located in one of the carbonate fields in a Mediterranean Sea of Western Asia namely, the Persian Gulf. The new well survey was matched by using a rock strength log which was created based on the previously drilled wells. Thus, a robust simulator was developed based on the proposed ROP model. This methodology has indeed been used for pre-planning and post analysis purposes. Besides that, this study has also shown how ROP is affected by applying higher WOB and lower RPM compared to the one being used in the well. It has also proved how smaller nozzle sizes can enhance ROP in another field.

Bataee et al. [13] used ANN to create two models. First, a proper bit was chosen according to the ROP that the inputs were bit size, total flow area, depth in and depth out, WOB, RPM, mud circulation flow rate, pressure, and unconsolidated compressive strength. The second model, IADC code (3-digitnumber) was set as the output and GA was utilized to find maximum ROP. This model was built to optimize the modeled ROP function that was derived from the ANN. Although they presented an optimum ROP for their study, the method of calculation needs to be reconsidered as the 3-digit number is not a mathematical value. It was inevitably led to inaccurate results which caused the bit failure during the drilling process.

Bataee et al. [14] also employed ANN systems in ROP optimization. The modeling process was used for making an appropriate selection of parameters based on the desired ROP. The ANN model was fed with the hole size, D, WOB, RPM, and MW as the input data and the ROP was set as output. An optimum ROP can be attained using modeled function and applying necessary drilling bit parameters. The results of this study showed that ANN is capable of predicting the ROP considering drilling parameters affected in the drilling procedure.

Bataee et al. [15] compared different methods of ROP prediction and found that the incorporation of ANN was the most reliable method. The results validated the effectiveness of ANN model especially for reducing cost. Hence, the ANN can be used for bit selection.

Wang and Salehi [16] presented an ANN model that was applied in a toolbox of MATLAB®(Math works, MA, USA) to forecast hydraulics. In order to determine the optimum model, forward regression method was used for the sensitivity analysis of input parameters on the created model. Furthermore, a part of data which was never added to the model was used to verify the quality of the developed model.

Moraveji and Naderi [17] used Response Surface Methodology to develop a mathematical relation between penetration rate and six factors (i.e. well depth, WOB, bit rotational speed, bit jet impact force, yield point to plastic viscosity ratio (Yp/PV), 10 min to 10 s gel strength ratios (10MGS/10SGS)). Through the usage of this mathematical correlation and bat algorithm, drilling ROP and the other six factors were optimized. However, they did not apply any limitation for their optimization, for instance, they did not follow the factory recommendation which may put drilling safety at risk.

In short, the objective of this present study is to find an optimum method for bit selection and evaluation with factory recommendation being considered for every different bit. Furthermore, it is also aimed at converting a black box of the neural network to a visible mathematical equation that can be used to predict the ROP.

2. Methodology

2.1. Outlier detection using replicator neural networks

Outlier detection was used to cleanse data by removing noise effects and detecting any problems from the data obtained. RNNs are used to measure the outlyingness of the data [18]. Multi-layer perceptron neural networks, with three hidden layers, and an equal number of output and input neurons were used to model the data in this paper. The input and output parameters were similar in order to ensure that a compressed implicit model of the data was formed. The outlyingness of individuals was measured and developed by reconstructing the error of individual data points. Outliers are data poorly generated by the trained neural network. The size of the reconstruction error was used to rank the data and measure its outlyingness. Only 12.36% of data set was considered as outliers.

2.2. ANN model for drill bit performance

The Neural Network was applied in MATLAB® software to predict the ROP by applying a mathematical model. The 3-layer model, which incorporated a tangent sigmoid transfer function at the hidden layer, a linear transfer function at output layer and Levenberg-Marquardt backward propagation of errors with 1000 iterations, was utilized. As it is shown in Fig. 1 for all models, the data were randomly distributed into three sets – 70% of training, 15% of cross validation and another 15% of the testing set. In this work, 17 offset wells (700 data set) from the south west oil field of Iran were used as the case study. In the prediction process, 1 to 23 neurons in the hidden layer were applied to achieve the optimum number in the hidden layer and one neuron in the output layer was utilized. The input and output data were standardized between 0 and 1 for the ANN model to escape numerical overflow generated because of high or low weights [19]. The standardization equation is given by [20]:

$$y_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{1}$$

The ANN models' performance was validated by utilizing the MSE and the coefficient of determination (R^2). These parameters are expressed as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_{prd,i} - y_{exp,i})^2 \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_{prd,i} - y_{exp,i})^2}{\sum_{i=1}^{N}(y_{prd,i} - y_m)^2} \tag{3}$$

A good source of offset drilling data is the bit record. It covers data relative to the actual on-bottom drilling operation. Drilling data contain bit size, depth, WOB, RPM, MW, flow rate, bit meter, rotation hour, pump pressure and dull bit grading. The process parameters were taken as design parameters based on literature [13-15, 21].

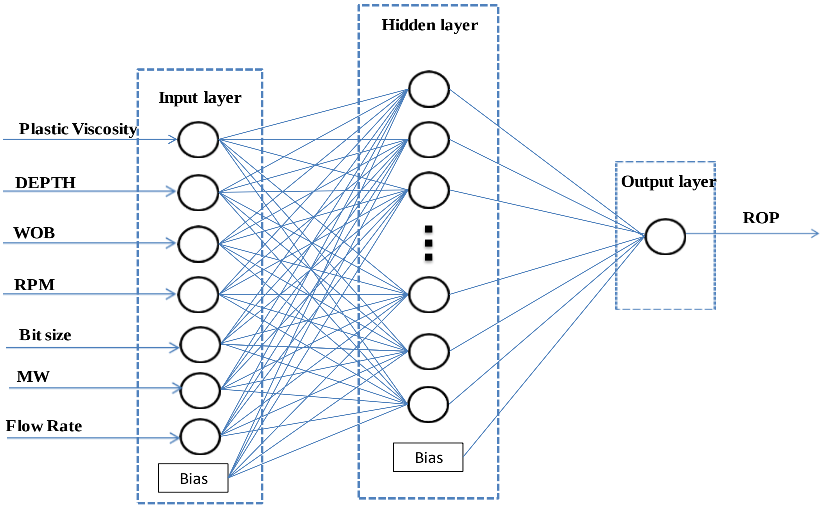

Fig. 1. A backward propagation of errors ANN model for drill bit performance.

2.3. Model calibration (training)

Predictive errors are one of the most important factors that prevent ANN from being considered as reasonable hydrological models. As a result, ANN is calibrated on predictive errors alone. ANNs are functions within a system that relate sets of independent predictor parameters to one or more dependent parameters of interest. ANN calibration (training) is performed in order to calibrate (train) the data and create an acceptable approximation of the relationships formed, after which the model can be used with new data to produce accurate forecasts. The following formula was used during the calibration:

$$y = f(xIw) + \mathcal{E} \qquad (4)$$

where y is the target variable, x is a vector of input data, w is a vector of connection weights, and Ɛ is a normally distributed random noise term. As such, w should be a vector that characterizes the data generating the relationship, whereas Ɛ has a mean of zero and a constant variance (i.e. white noise). In order to obtain the best fit between model predictions and field data during the calibration, weights were adjusted so that predetermined errors or objective functions were minimized.

2.4. Optimized bit selection

An ANN was employed to model the ROP. Field data were collected with varying operating conditions and were utilized for preparing and testing the neural network model [22]. The optimum architecture of the ANN model was attained by using the highest value of R^2 and the least possible value of the MSE for the testing set. In network optimization, 1 to 23 of neurons were applied in the hidden layer. Figure 2 illustrates the dependence between neuron number at the hidden layer and MSE in the Levenberg-Marquardt algorithm. As Fig. 2 shows, with the increase in neurons for hidden layer, the MSE reduces abruptly. It is observed that by using 18 hidden neurons in modeling the ROP, the R^2 and MSE reached values of 0.94 and 0.0037 respectively. As such, the results indicate that there is a decent assent between experimental information and predicted data using the present model. The ANN black box was converted to white box to obtain a visible mathematical model that can be used to predict the ROP using the field drilling data. This mathematical model, which was considered as the objective function in the genetic algorithms, was used to find the optimum drilling values and maximize the ROP. Based on the ANN model, the objective function which gave a connection between inputs and output is given below:

$$\mathrm{ROP} = \mathrm{Purelin}\left(\sum_{i=1}^{N} w_{2i}\, tansig\left(\sum_{j=1}^{j} w_{1\mathrm{i,j}} x_j + b_{1\mathrm{i}}\right) + b_2\right) \qquad (5)$$

in which, x_j represents the inputs, W_{1i} is weight and b_{1i} is a bias of hidden layer and W_{2i} and b_2 are the weight and bias of output layers.

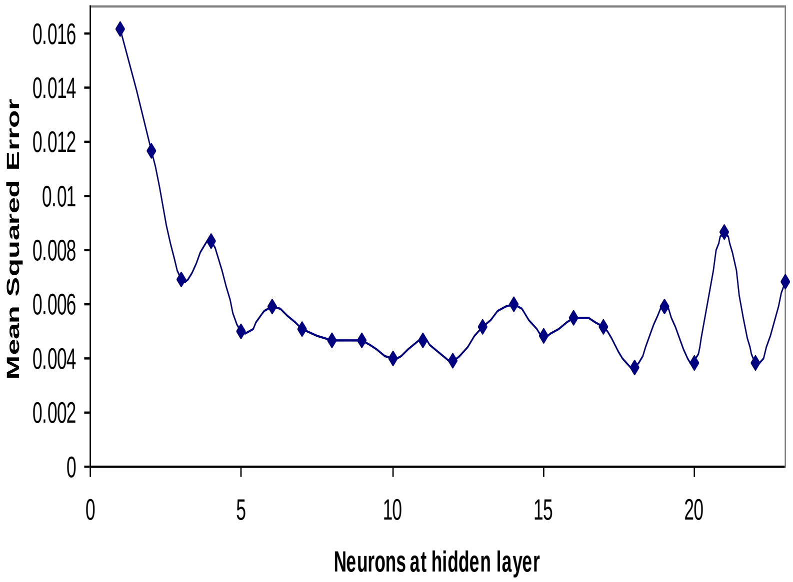

Fig. 2. Dependence between MSE and number of neurons at hidden layer.

The proper bit selection is carried out for the modeling process which is based on the targeted ROP. This model takes into consideration of bit size, D, WOB, RPM, plastic viscosity, penetration rate and mud circulation flow rate as inputs for ANN [23, 24]. Therefore, a drilling bit can be selected which leads to yielding the targeted ROP by the application of definite drilling operation parameters. This approach focuses on all important parameters in bit performance for bit IADC function modeling to make proper bit selection. In the following section, the optimization of bit selection is examined based on getting the highest value of ROP.

Equation (5) has been applied as an objective function in GA. The number of variables is equal to the number of inputs in ANN-GA which follows the steps as outlined below: Step 1 – Setting of initial parameters for GA: mutation percentage, crossover percentage, and population size. Step 2 – Setting the boundaries based on factory recommendation and drilling data limitation. Step 3 – Generating the initial population randomly. Step 4 – Finding ROP and comparing the optimum ROP with the real ROP. Step 5 – Running GA as far as finding the maximum ROP because in each run, the ROP will be different. Step 6- After finding the best ROP and drilling data, changing the bit and repeating steps 3 to 5 to find the best bit based on the optimum ROP.

3. Results and Discussion

The optimization, which was carried out in the use of 5 separate drill bits, provided the well-profile bit selection. The process allows the variations in flexible parameters like WOB, RPM, and mud circulation flow rate while the bit size was kept constant. Hence, applying the maximum ROP values as produced by GA in optimization process will give us the best bit condition in each hole section [25]. The neural networks, which were used in this research work, selected successfully the proper bits for new sections and thus, can be applied to improve the planning process for a new well. The obtained results were validated since 15% of the field data, which were never inserted into the ANN model for any training purposes and were selected absolutely randomly, showed a good correlation between the real ROP and the predicted ROP. The minimum MSE of 0.0037 and coefficient of determination (R^2) 0.9473 were identified for the model of ROP. R^2 for training and validation were 0.9709 and 0.9134 respectively. Figure 3 illustrates the normalized predicted ROP versus the real ROP. The low error indicates high performance of the designed algorithm. Table 1 provides drilling data before optimization.

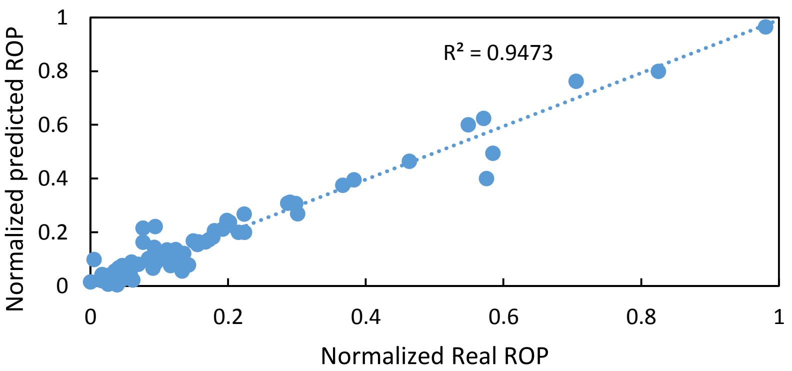

Fig. 3. Predicted ROP versus real ROP.

In Figs. 4 and 5, the generalization of neural network is shown using a 3D diagram by plotting the predicted ROP against two input variables. Figure 4 is showing an interaction effect between RPM, WOB and ROP while Fig. 5 is showing an interaction effect between RPM, MW and ROP.

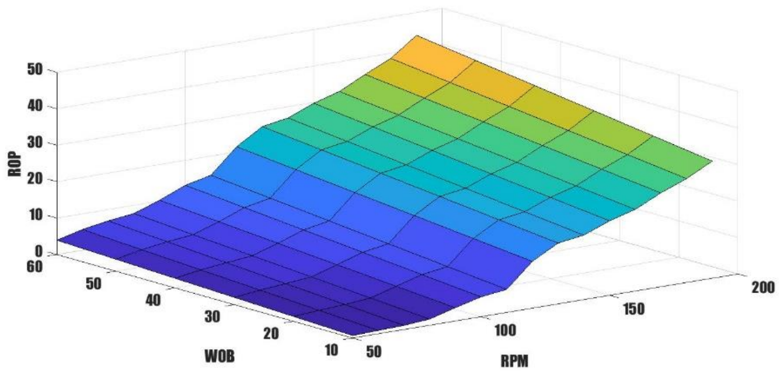

Fig. 4. Interaction effect between RPM, WOB and ROP.

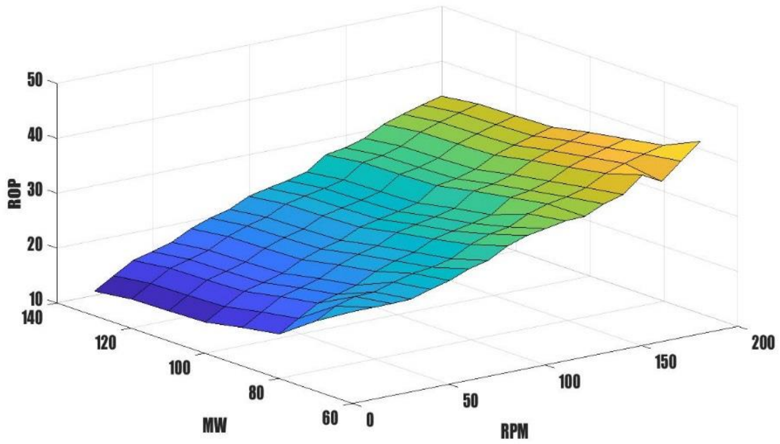

Fig. 5. Interaction effect between RPM, MW and ROP.

As can be seen in Fig. 4, a strong interaction effect occurs between the variables. As the values of RPM and WOB increase, ROP will increase as well. Figure 5 illustrates the ROP is directly proportional to RPM and inversely proportional to MW.

Table 1. Operation condition before optimization.

IADC	Bit meter (m)	Rot hours (hrs)	Flow area (in^2)	RPM (rev/min)	WOB(lb)	ROP(m/hr)
115M	61	24	0.994	60	40	2.54
115M	39	64.5	0.994	45	10	0.6
115M	203	54.41	1.298	72.5	80	3.73
115M	170	50.96	1.052	80	110	3.34
415	179	38.8	1.335	95	110	4.61
115M	176	29.54	0.838	110	125	5.96
415	588	92.72	0.838	175	195	6.34
M323	21	5.48	1.167	195	13	3.83
M323	9	3.86	1.167	197.5	150	2.33
M323	317	85.83	1.167	148.5	11	3.69
415	596	61.04	0.307	157.5	70	9.76

The chosen bit with the maximum rate of penetration and other optimum-related factors like WOB, RPM, and flow area are offered in Table 2. Hence, the optimal ROP and associated factors, which are WOB, RPM and flow area when drilling various hole sections, were evaluated. At the end, the bit with maximum predicted ROP was suggested for selection. A GA was applied to find the optimum value for each parameter while considering the limitation from bit manufacturers.

Table 2. Operation condition after optimization.

IADC	Bit meter (m)	Rot hours (hrs)	Flow area (in^2)	RPM	WOB	ROP
115M	341.07	43.98	1.43	62.63	98.85	7.75
214	477.77	35.31	1.04	49.31	248.38	13.53
M333	315.16	40.69	1.22	45.64	264.32	7.74
M442	343.91	35.49	1.12	63.62	239.42	9.69
M442	222.15	30.13	1.73	45	318.76	7.37
M442	317	46.89	1.15	45	303.62	6.76
437	342	34.25	1.74	45	320	9.98

In optimization procedure, under each formation, the same bit has been used. The total bit meter was the same before and after optimization, however, the bit plan as in number of the trip in and trip out was changed, and consequently the drilling time had been decreased. For instance, bit 115M is suitable for soft and soft sticky formations with low compressive strength such as clay, this bit was used to drill 341 meters of a soft formation applying bit factory limitation to ensure drilling safety. The Total Rotation Hour after optimization for 244 hours had decreased.

4. Conclusions

Accurate drilling optimization is highly demanded for drilling cost reduction. Based on the literature review, the criteria for bit selection are usually based on the IADC codes which could not represent an accurate value for the calculations. Outlier detection by RNNs was performed to cleanse data by removing noise effects and detecting any problems from the data obtained. The ANN black box was converted to white box to obtain a visible mathematical model that can later be used as an objective function in GA. The combination of ANN and GA showed a good result for drilling optimization. The mean square error obtained a value of 0.0037 whereas the coefficient of determination obtained a value of 0.9473. Based on the type of formations and factory recommendations, in each interval, potential bits were tested and then the best bit with maximum applicable ROP was selected. The best bit runs are presented as evaluated by observing the ROP thus able to reduce drilling time by 47%. In short, such drilling simulation is able to improve the drilling program.

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