Application of artificial neural network in optimizing the drilling rate of penetration of western desert Egyptian wells

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Abstract

This study presents an intensive artificial neural network ANN model designed using FORTRAN language to predict the drilling rate of penetration ROP with high accuracy. The developed ANN model gives a new correlation to be used in ROP prediction as a function of drilling parameters: bit size, mud circulation rate, drilling interval, weight on bit WOB and rotary speed RPM. The back-propagation algorithm is used as learning procedure to supervise neural nets. In the training process More than 3000 actual data points are collected to be used as inputs for the neural network box. The optimization process of ANN model shows that the optimum number of neurons that gives the lowest average error between the actual and predicted ROP is 20 neurons. The resultant average square error estimated for ANN model was less than 3% with R of 0.958. A comparison between the developed ANN-ROP model and the number of selected published ROP models are performed. The results show that ANN model able to estimate ROP with high accuracy compared with other models. The novel ANN model in this study gives empirical correlation that can be used to estimate the ROP without need for artificial intelligence software.

Keywords Artificial neural network · ROP · Correlation · Drilling parameters

1 Introduction

Drilling operations are considered the core of oil and gas industry and those operations can be very expensive. Therefore, the drilling operations require regular monitoring to minimise the drilling costs. The drilling cost has a direct relationship to the drilling rate of penetration ROP. Hence, by achieving an acceptable rate of penetration (ROP) that led to optimising the drilling process and accordingly minimise the drilling cost, the entire parameters that affect ROP should be optimized during the drilling operation.

In addition, to clarify the significant of optimising ROP, during the drilling process if ROP utilized at a high rate that directs to improper hole cleaning and the drilling cuttings will not be removed properly from the bottom

hole to shale shaker at surface [1–4]. Therefore, it is crucial to enhance a relationship between the ROP and drilling parameters to obtain superior drilling performance with less cost, while preserving safety.

The drilling penetration rate is affected by numerous parameters include bit related parameters, rotary speed, mud properties and rock formation characteristics [5]. Those parameters can be classified into two categories: controllable and uncontrollable parameters. The controllable ones it can be manipulated in order to adjust ROP as weight on bit (WOB), revolution per minutes (RPM) and bit type (IADC). Nevertheless, the uncontrollable parameters include wellbore trajectory, unconfined compressive strength (UCS), and three principal stresses cannot be changed [6, 7]. In the literature review, several models are presented to predict and optimizing penetration

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rate [8–14]. Limitations are associated with these models include the complex relationship between input and output parameters. Therefore, due to the complexity of the relationship and the difficulties in the existing mathematical models that were developed, artificial neural network (ANN) seems to be an attractive alternative to model this complicated physical process. Weight on bit control the efficiency of the drilling performance and the penetration rate is directly proportional to the WOB. On the other hand, the rotary speed can be optimized to improve the efficiency of the drilling process and consequently ROP. The rotation can be provided from the surface or from the downhole motors. The drilling rate of penetration has a direct relationship to the rock strength as well, therefore, several methods have been developed to determine the rock strength from non-mechanical measurements. Those methods based on interpretation of sonic log to estimate the rock compressive strength and mineralogy. To make an accurate estimate of the drilling penetration rate from the rock strength is extremely difficult in view of the large number of parameters that must be matched. The drilling engineer must select and evaluate the performance of the drill bit. There are a wide a range of drill bit types leads to changing the mechanics of rock cutting for each type. The main two types of drill bits are: roller cone and drag bits.

Drilling rate of penetration ROP depends on several factors while the most important are bit type, formation characteristics, weight on bit, rotary speed, and bit hydraulics etc. These factors can be related to penetration rate, R as:

$$R = (f_1) \cdot (f_2) \cdot (f_3) \dots (f_n)$$

where f are the functions and the drilling rate of penetration can be given by:

$$\Delta D = J_1 \cdot J_2 \cdot \tau_H \cdot \left[\frac{1 - e^{-a_7 \cdot hf}}{a_7} + H_2 \left(\frac{1 - e^{-a_7 \cdot hf} - a_7 \cdot hf \cdot e^{-a_7 \cdot hf}}{a_7^2} \right) \right] \quad (1)$$

The above equation shows the footage drilled as a function of formation drillability, abrasiveness and rate of tooth wear.

The values of a_7 through a_8 are determined through drilling tests. Furthermore, the exponent for weight on bit a_5 and rotary speed of a_6 are generally determined from a series of experiments of penetration rate of different rotational speeds. However, frequent changes in lithology and with depth make it hard to determine the WOB and rotary speed exponent. To overcome this problem, usually a drill off test is performed or to generate a mathematical correlation to predict the ROP.

Several methods propose relationships between various drilling parameters and ROP. Maurer [15] proposed a theoretical model for roller cone bits based on several

parameters: weight on bit (WOB), bit size, drill ability strength of the rock (UCS) and rotary speed. The Maurer's developed model is shown in Eq. (2).

$$ROP = K \frac{RPM * WOB^2}{d^2 * UCS^2} \quad (2)$$

where k is the drillability constant, RPM is rotary speed, WOB is weight on bit (Klbf), d_b is diameter of bit (in), and UCS is rock compressive strength (kPa).

Bingham [16] modified Maurer's model by neglecting the drilling depth and introduced two new constants a and b based on laboratory experiments as follows:

$$ROP = k * \left(\frac{WOB}{d} \right)^a RP \quad (3)$$

The two fitting parameters (a and b) represent a measure of the drill ability of each lithology.

Burgoyne and Young's [17] introduced one of the most substantial models to predict ROP using the following Eq. (4).

$$R = (f_1) \cdot (f_2) \cdot (f_3) \dots (f_8) \quad (4)$$

where f are the functions, for example: f_1 , Formation drill ability; f_2 , Decrease in penetration rate with depth; f_3 , Increase in penetration due to under-compaction; f_4 , Change in penetration due to mud weight; f_5 , Change in penetration rate due to mud weight; f_6 , Change in penetration rate due to N (rpm); f_7 , Change in penetration rate due to tooth wear; f_8 = Change in penetration rate due to jet impact force.

These functional relations can be expressed as follows:

$$f_1 = e^{2.303a_1} \quad (5)$$

f_1 , accounts for formation durability.

$$f_2 = e^{2.303a_2 \cdot (10,000 - D)} \quad (6)$$

f_2 , accounts for the normal decrease in penetration rate with depth from the reference depth of 10,000 ft.

$$f_3 = e^{2.303a_3 D^{0.69} (\rho_f - 9)} \quad (7)$$

where ρ_f = pore pressure gradient, lb/gallon and f_3 accounts for increase in penetration rate due to under compaction.

$$f_4 = e^{2.303a_4 \cdot D (\rho_f - \rho_m)} \quad (8)$$

where ρ_m = mud weight, lb/gallon and f_4 accounts for the change in penetration rate with overbalance assuming a reference overbalance of zero.

$$f_5 = \left[\frac{\left(\frac{W}{d_b} \right) - \left(\frac{W}{d_b} \right)_t}{4 - \left(\frac{W}{d_b} \right)_t} \right]^{a_5} \quad (9)$$

where $(W/d_b)_t$ = threshold bit weight per inch of bit diameter at which the bit begins to drill, in 1000 lb/in. and f_5 accounts for the change in penetration rate with bit weight assuming a reference bit weight of 4000 lb/in. of bit diameter.

$$f_6 = \left(\frac{N}{60} \right)^{a_6} \quad (10)$$

where f_6 accounts for the change in penetration rate with rotary speed assuming a reference speed of 60 rpm.

$$f_7 = e^{-a_7 \cdot h} \quad (11)$$

where f_7 accounts for the change in penetration rate with tooth dullness using zero tooth wear as reference.

$$f_8 = \left(\frac{F_j}{1000} \right)^{a_8} \quad (12)$$

where F_j = hydraulic impact force in lb and f_8 accounts for the change in penetration rate with jet impact force using an impact force of 1000 lb as reference.

a_1 to a_8 = constants that must be chosen based on local drilling conditions.

Warren [18] proposed ROP model for soft formation where the cutting removal has no effect on ROP. The model presents a relationship between rock and bit on one side and the effects of chips hold down, bit wear cutting removal on the other. Warren's model for ROP as follows:

$$ROP = \left(\frac{aS^2d_b^3}{N^bWOB^2} + \frac{c}{Nd_b} \right)^{-1} \quad (13)$$

where a , b and c are constants of the bit. N rotary speed rpm, d_b bit diameter (in), and WOB weight on bit (klb_f).

The aim of this paper is to present a reliable artificial neural network (ANN) model developed using FORTRAN language based on back propagation algorithm to forecast the ROP rate as a function of drilling data and other drilling fluid parameters. The outcome attained from the ANN is compared with ROP models to illustrate the model accuracy based on the highest R^2 value and the minimum root mean square error (RMSE).

1.1 Artificial neural networks (ANN)

Artificial neural networks are very sophisticated techniques used to model enormously complex functions. The

idea behind artificial neural network technique is same as the biological nervous system composed of interrelated processing elements called (neurons) to solve definite problems. The first artificial neural network model was created by [19]. In petroleum engineering, numerous successful applications are performed using the neural network technique that include drill bit diagnosis [20], identification of well test interpretation model [21], pump card diagnosis [22], well productivity identification [23] and wire line log analysis [24].

The neural network system receives several inputs and each input comes via connection that has a weight. The inputs weighted sum is designed to compose the transfer function of the neuron and then it provides an output. Next, the output compared with the target that is needed. Then, if the difference between the network output and target is not in an acceptable range, the weights of the neuron are adjusted. Figure 1 shows how artificial neural network system works in this study. The process of adjusting weights called Training (learning) the model. The network training proceeds by performing weights changes based on the entire set of input vectors. The transfer function is a mathematical function used to give spatial output. The most common functions are: (1) linear function and (2) tan sigmoid function. The tan sigmoid is a nonlinear relationship function between the input and output neurons.

The neural network system composed of multilayer neural, the first layer is the input one and last layer is the output. The layer between input and output layers called hidden layers and the number of neurons in those layers define the performance of the neural network system. Each layer consists of processing elements called neurons. In addition, the number of neurons presented in the hidden layer is hard to define a priori and it usually determined by trial and error [25–28]. The input layer neurons are connected to every neuron in the hidden layer/s by a simple weighted link. Each link has a weight either positive or negative value. Each of the output layer neuron receives

Fig. 1 Flow chart of how artificial neural network perform

signal from hidden layer neurons and provides a similar weight response.

1.2 Application of ANN models in ROP prediction

Jahanbakhshi et al. [29] built ANN model with R^2 correlation coefficient of 0.916 and mean square error of 0.015 for the testing data. In this model, he divided the data as follows: 70% of the data for training, 15% for testing and 15% for model validation. Jahanbakhshi used numerous input parameters in ANN model to predict ROP that include mud type, yield point, 10 s gel strength, bit wear, bit type, bit hydraulic power, density of rock, porosity, permeability, formation drillability, differential pressure, hole depth and hole size, plastic viscosity, mud pH, solid percent, and 10 min gel strength.

Moran et al. [30] used six input drilling parameters include WOB, RPM, abrasion, type of rock and rock strength in ANN model to improve the prediction of ROP. In this model, the R^2 coefficient achieved is 0.8 between ANN predicted and actual ROP data.

Elkatatny et al. [31] developed an ANN model to predict the ROP by using drilling fluid and mechanical parameters. The model achieved accuracy of $R^2=0.997$ for training and $R^2=0.993$ for the testing data. The model results show that the drilling fluids parameters have a significant effect on ROP prediction.

Bodagh et al. [32] developed a relationship between drilling parameters and ROP using support vector regression (SVR) that is optimized by genetic algorithm. He used 193 datasets collected from 13 wells and he divided the data into 154 point for training and the rest (39 points) are for testing operation. The ANN developed model achieved R^2 of 0.95 with absolute average error of 0.22.

Shi et al. [33] used more than 5000 points of drilling variables include rotary speed, weight on bit, pump pressure, mud density, mud viscosity, formation abrasiveness, formation drillability, unconfined compressive strength, bit wear, bit type, and bit size to compare the ROP prediction using two techniques; ANN and extreme learning machine (ELM). The study results show that R^2 value for training and testing operations are improved by using ELM technique ($R^2=0.95$ and 0.92 for training and testing respectively).

Hegde and Gray [34] used statistical learning technique to predict the ROP. Moraveji and Naderi [21] study was on the effect of drilling variables on ROP using surface methodology response. Kahraman [35] study concluded that ANN models are superior and more reliable than regression model for ROP prediction.

Ahmed et al. [36] assessed three different techniques to estimate the ROP. The techniques are extreme learning machine (ELM), support vector regression (SVR) and artificial neural network (ANN). Ahmed collected data for two

wells that includes weight on bit, flow rate, rotary speed, mud weight, and bit size. 70% of the collected data is used for training and 30% for testing. The results show SVR and ELM techniques give the lowest R^2 and RMSE of 0.94 and 0.82, respectively. Moreover, the results of ROP prediction in well#B were closed to that in Well#A.

The main drawback of the previous published work is the convergence scheme. Convergence here means the global minimum of the error function is obtained in a reasonable number of iterations or epochs. The network may get stuck in a local minimum during training. This means that the network will fail to predict targets efficiently and give large errors.

Therefore, in this study, two parameters are used to speed up the convergence: step size and momentum [37]. The speed of convergence in this study improved by using an acceleration method in the gradient algorithm to modify the velocity of the point in weight space of its position. This will assist in getting fast weight changes and more even path by adding fraction to previous weight changes.

In addition, most of previous ANN models are black box means that those models do not provide an equation to predict ROP. Therefore, one of the main aims of this study is to provide a reliable ANN model and an equation for ROP prediction.

2 Methodology

2.1 Data description

Tested data are collected from daily drilling reports for 2-wells drilled in western desert-Egypt to be used in ANN model and to generate the approximate weight for each parameter affect the ROP value. The data set of 3000 points for upper part of Bahariya formation. The data used to train the model consists of 5 inputs and one target (bit ROP, ft/h). The inputs data are: Bit size (in), mud circulation rate (gal/min), drilling interval length (ft), and weight on bit (1000 lbs), rotary speed (h). The input data are normalized by using the methodology presented in Sect. 2.2.

The input data are analyzed and filtered before starting the neural network process. The selected data are cleaned by eliminating the unrepresentative values like negative ones. Table 1 shows the statistical analysis of the input data. Different scenarios are conducted to optimize the ANN parameters to get the highest accuracy and lower root mean square error. The optimized parameters are as follows:

- Input layer: It contains input features which are Bit size (in), mud circulation rate (gal/min), drilling interval length (ft), weight on bit (1000 lbs), rotary speed RPM.

Table 1 Statistical analysis of the input data

Drilling parameter	Bit size (in)	Mud circulation rate (gal/min)	Drilling interval length (ft)	Weight on bit (1000 lbs)	Rotary speed (rev/min)
Min	6	6	9.8	1	20
Max	36	1130	12,000	55	311
Mode	17.5	1000	2060	25	100
Skewness	1.29	0.419	1.2003	2.14	1.109

- One Hidden layer: It contains the optimized number of neurons which was found to be 20 neurons.
- Output layer: It contains the output parameter (ROP).

The input data are sub divided into two parts: the training data 70% and testing data 30% of the total collected data from Well#A. The dataset collected from well #B is kept to validate the ANN model. After normalizing the input data, the data fall within a range of (0, 1), then the de-normalizing technique is used to get the actual output.

2.2 Neural network data normalization

The computation process in neural network use nonlinear squashing function, most commonly the sigmoid curve. This function is used to constrain the output values from the hidden and output neurons to a range of 0 and 1. Therefore, it is mandatory to normalize the target and input signals values to the same range before starting the training process. The normalization method uses maximum and minimum values as follows:

$$y = \frac{y^* - y_{\min}^*}{y_{\max}^* - y_{\min}^*} \quad (14)$$

where y is the normalized value, y^* is the raw data, $y_{\min}^*$ and $y_{\max}^*$ are the minimum and maximum values of the raw variable, respectively.

2.3 Neural network learning algorithm

The back-propagation algorithm is used as learning procedure in this study to supervise neural nets. In the training process, small random numbers are used to initiate the weighting of each connection. The forward propagation pattern is required in this algorithm to send input signals through the neurons of each layer until actual output values are calculated. Then the back-propagation step calculates the resultant error by comparing actual and target

outputs. Then weights are updated for each layer backwards from the output, by modifying the existing weights [24]. The root mean square always used to measure the global error and defined as:

$$er = \sqrt{\frac{\sum_1^{n_1} \sum_1^{n_2} (x_p - y_p)}{n_1 \cdot n_2}} \quad (15)$$

where n_1 is the number of training patterns, n_2 is the number of output neurons in the output layer. Values of x_p and y_p are the target and calculated output values, respectively.

2.4 Weight updating

Updating weights during network training can be achieved in two ways: stochastic and epoch updating. Epoch updating add weights changes for input patterns before the updating process is completed in contrast with stochastic updating in which the weights changes are added after presenting of each pattern. Figure 2 shows a simple flow chart for back propagation algorithm and the weight updating process. The stochastic updating in previous studies shows failure in improving convergence between the target and outputs data. Thus, the epoch updating method is preferred, and will be used in this study.

2.5 Convergence scheme updating

The convergence scheme updates in this study is used the following equation during the computation process:

$$w(t+1) = w(t) + \beta[\Delta w(t)] + \alpha[w(t-1)]$$

where α is the momentum constant, w is the weight value, Δw is the weight change, t incremented by 1 for each epoch, and β is the learning constant. This constant is used to effectively increase the step size to reduce abrupt gradient changes. The learning and momentum constants are set in a range of 0 and 1.

Fig. 2 Flow chart of back propagation algorithm used in this study **Table 2** Results of various data distribution for training and testing data

Trial	Distribution		R training	Absolute error	R testing	Absolute error
	Training	Testing				
1	10	90	0.589	3.41	0.61	3.25
2	20	80	0.685	2.78	0.648	2.58
3	30	70	0.795	2.45	0.764	2.37
4	40	60	0.725	2.89	0.718	2.85
5	50	50	0.805	1.85	0.794	1.83
6	60	40	0.825	1.65	0.786	1.89
7	70	30	0.921	0.062	0.889	0.095
8	80	20	0.892	0.095	0.878	0.097
9	90	10	0.88	1.03	0.865	1.102

Italic indicates the optimum data distribution for training process

Fig. 3 The results of R^2 for BP, SCG, and OSS functions

Fig. 4 The results of RMSE for BP, SCG, and OSS functions

2.6 Statistical analysis

2.6.1 Selection of the best distribution of input data

Several trials are performed using ANN model to select the best distribution of the collected data for training and testing operations. The results show that distribution of 70% for training and 30% for testing gives the highest R^2 value and lowest mean square error, as shown in Table 2. The input parameters used in the analysis are Bit size (in), mud circulation rate (gal/min), drilling interval length (ft), and weight on bit (1000 lbs), rotary speed (h).

In this study, three types of learning functions are used for training the network; Back propagation (BP), scaled conjugate gradient (SCG), and one-step secant (OSS). The results show that back propagation function yield the best performance in terms of values of R^2 for training = 0.96

Fig. 5 MSE versus number of hidden layers

Fig. 6 MSE versus number of neurons in the hidden layer

and testing = 0.91 and RMSE for training = 0.068 and testing = 0.082 comparing to other functions that are used (see Figs. 3, 4). Thus, this function was selected for designing an ANN for the prediction and optimization of ROP.

2.6.2 Choosing the optimum number of hidden layers and number of neurons

The iterative process used to optimize the choosing of number of neurons in hidden layers by utilizing various number of hidden layers and the optimum one is selected based on the least mean squared error between the network estimate outputs (f) and the real output (o). MSE can be calculated using:

$$MSE = \frac{1}{N} \sum_{i=1}^n (O_i - f_i)^2 \quad (16)$$

where N is the number of data points.

Fig. 7 **a** Actual ROP versus predicted values using ANN model for training data and **b** actual ROP versus predicted values using ANN model for testing data

Fig. 8 ROP prediction using ANN model for testing data

The decision is taken to use 20 neurons in one hidden layer. Figure 5 shows that the one hidden layer given the minimum $MSE = 2.00E-05$ while Fig. 6 shows that 20 neurons gives the minimum $MSE = 2.2E-05$. It is important to state that the number of hidden layers and the number of neurons in the hidden layer should be chosen carefully since having multiple numbers of hidden layers cause overfitting which makes the network lose its generalization.

3 Results and discussion

70% of the input data used for training. The data are highly fluctuated and is too hard to predict the ROP values with low percentage of error using the existing numerical models. Figure 7a, b and Fig. 7a shows a good match between the actual and predicted ROP from the developed ANN model in terms of scatter diagram for training with R^2 value of 0.948 and $RMSE = 0.0258$.

Similarly, 30% of the data are used for the testing process. The developed ANN model can predict ROP with $R^2 = 0.953$ and $RMSE = 0.0224$ as shown in Fig. 7b. Figure 8 show the match between actual ROP and predicted ROP from ANN model.

3.1 Development of new model equation

Based on the results of training and testing processes, a new model equation is generated. The generated equation includes all normalized inputs and the output (ROP).

Table 3 ANN weights and layers bias for normalized ROP mathematical correlation Eq. (18)

Hidden layer neuron	Weight connecting the input neuron and the hidden neuron (W1)						Weight connecting the hidden neuron and the output neuron (W2)	Hidden layer bias (B1)	Output layer bias (B2)
1	-0.11008	0.2436	0.130853	-0.11704	0.251512	-1.33288		0.384944	-0.0027
2	0.125757	0.262222	-0.03659	-0.23023	0.316195	1.076148		-0.25708	
3	-0.91292	0.801875	0.377567	0.572026	0.090235	0.505765		0.097705	
4	-1.08125	0.546197	0.65122	-0.14819	0.660581	0.702604		0.848815	
5	0.149762	-0.23245	0.34694	0.242685	-0.28096	0.182629		-0.27184	
6	-0.23437	0.18993	-0.11586	0.112136	0.222786	-0.79872		-0.30039	
7	-0.0685	0.079676	0.070381	0.006963	-0.22677	-2.29595		0.121123	
8	-0.27172	-0.27172	-0.23937	-0.03174	0.108537	-1.23632		-0.02307	
9	0.313295	-0.03731	-0.03059	0.15942	-0.32522	1.152529		-0.2106	
10	-0.24708	0.062463	0.208933	-0.16213	0.137767	-0.39974		0.269394	
11	0.110669	-0.29979	0.123984	0.088784	-0.00194	-1.2695		-0.26237	
12	0.613452	-0.304	-0.25813	-0.20752	-0.46304	0.587836		0.233911	
13	0.066182	-0.00528	0.267303	0.128966	0.326376	0.512088		0.150063	
14	-0.77571	-0.97205	-0.46546	0.460742	-1.08403	-1.31966		-0.3372	
15	-0.25512	0.158981	-0.33123	0.09695	0.541568	-0.94515		-0.28398	
16	-0.30053	0.099893	-0.2033	-0.3026	0.043484	-1.40185		-0.11335	
17	-0.13846	-0.30816	-0.10352	-0.29138	-0.04697	0.699882		-0.16224	
18	0.235273	0.352454	-0.24	-0.01715	-0.24782	0.746925		-0.02437	
19	0.01744	-0.22058	-0.19227	-0.00357	0.07866	-0.13965		-0.12509	
20	-1.32909	0.902179	-0.87511	0.43652	-0.78674	0.870128		-0.15479	

The ANN model uses the biases and weights of neurons-connections among input, hidden and output layers. The normalized value of ROP (RN) is calculated using Eqs. (17, 18) with its optimized coefficients listed in Table 3:

$$RN = A \times \left(\frac{2}{1 + \exp(-2 \times (B \times X + b_1))} - 1 \right) + b_2 \quad (17)$$

$$RN = \left[\sum_{i=1}^N w_{2,i} \left(\frac{2}{1 + \exp(-2(B_5 \times w_{1,i,1} + Q \times w_{1,i,2} + I \times w_{1,i,3} + WOB \times w_{1,i,4} + RS \times w_{1,i,5}))} - 1 \right) \right] + b_2 \quad (18)$$

where X is the input values, $A (w_{2,i})$ is the weight vector linking the hidden and output layer, $B (w_{1,i})$ is the weight vector linking the input and the hidden layer, i is the index of the neuron in the hidden layer, b_1 is the biases vector for the input layer, and b_2 for the output layer, bit size (BS), mud circulation rate (Q), weight on bit (WOB), rotary speed (RS), and drilling interval (I).

Finally, the required ROP value can be obtained by deformalizing RN as follows:

$$ROP = 294.7 \times RN + 2.2. \quad (19)$$

3.2 Comparison between artificial neural network and other ROP empirical models

To validate the new developed ROP correlation using ANN model, a comparison is done against published ROP models [15 and 16]. By applying ANN model results of whole used data ($R^2 = 0.953$ and $RMSE = 0.0258$ where were achieved in Figs. 7 and 8.

In this study, a regression analysis is used to calculate the k constant for Maurer model ($k = 294.34783$). As shown

Fig. 9 Comparison between actual ROP prediction and ROP from Bingham and Maurer models

from Fig. 9 that the Maurer's model could not match the actual ROP properly. The model $R^2 = 0.0193$ with $RMSE = 23$. These results can be explained as Maurer's model neglects the drilling fluid properties.

The Bingham's model is too simple as it neglects the bit weight threshold and the depth of the drilled formation.

Therefore, usually the ROP predicted is less reliable. Figure 9 shows that the Bingham's model gives worst ROP values comparing to Maurer's model. Same here, the regression analysis is used to compute Bingham's model constants, drillability (k) = 0.032 and bit weight = 0.002. The predicted ROP using Bingham's model resulted in R^2 of 0.0093 and $RMSE = 28$ (Fig. 10).

3.3 Prediction of new ROP data using ANN model

A new dataset is collected from well#B drilled in the lower part of studied formation. This dataset was never used during the building of ANN model. The ROP ranges from 3.2 to 125 ft/h. The results show (see Fig. 11) that ANN model can predict ROP with a high accuracy with $R^2 = 0.956$ and $RMSE = 0.0189$.

4 Conclusion

A new approach is proposed in this study to predict and estimate the value of ROP at a drill site for the next drilling interval by using artificial neural network. ANN model shows the ability to predict ROP with high accuracy ($R^2 = 0.953$ and $RMSE = 0.0258$) with using an iterative process to the number of inputs by adjusting the weights of the network.

The developed ANN ROP model shows its robustness over other ROP published models (Maurer and Bingham models). The results of this study indicate that combining of drilling fluid properties and proposed updating the convergence technique in this study led to improving the results of ROP prediction accuracy.

The proposed ROP ANN model applied on data range of (5–160 ft/h) and any data has a close range can be used in this study ANN model to predict ROP with reasonable accuracy.

Recommendations for future work is to integrate the formation and geomechanical properties in the developed ROP ANN model to increase the model accuracy and test the effect of other properties on ROP prediction performance.

Fig. 10 Scatter diagram comparing predicted ROP values and actual values for the new ANN model and **a** Maurer's model and **b** Bingham's model

Fig. 11 New data set from well#B for model validation

Compliance with ethical standards

Conflict of interest The author declares that he has no conflict of interest.

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