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An Artificial Neural Network for Predicting Rate of Penetration in AL-Khasib Formation – Ahdeb Oil Field

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Abstract

The main objective of this study is to develop a rate of penetration (ROP) model for Khasib formation in Ahdab oil field and determine the drilling parameters controlling the prediction of ROP values by using artificial neural network (ANN).

An Interactive Petrophysical software was used to convert the raw dataset of transit time (LAS Readings) from parts of meter-to-meter reading with depth. The IBM SPSS statistics software version 22 was used to create an interconnection between the drilling variables and the rate of penetration, detection of outliers of input parameters, and regression modeling. While a JMP Version 11 software from SAS Institute Inc. was used for artificial neural modeling.

The proposed artificial neural network method depends on obtaining the input data from drilling mud logging data and wireline logging data. The data then analyzes it to create an interconnection between the drilling variables and the rate of penetration.

The proposed ANN model consists of an input layer, hidden layer and outputs layer, while it applies the tangent function (TanH) as a learning and training algorithm in the hidden layer. Finally, the predicted values of ROP are compared with the measured values. The proposed ANN model is more efficient than the multiple regression analysis in predicting ROP. The obtained coefficient of determination (R^2) values using the ANN technique are 0.93 and 0.91 for training and validation sets, respectively. This study presents a new model for predicting ROP values in comparison with other conventional drilling measurements.

Keywords: Artificial Neural Network, Rate of Penetration, Drilling Average, ROP Models.

موديــل الشبكة العصبيـــة الاصطناعية للتنبـؤ بمعـدل الاختـراق في تكوين الخصيب – حقل الاحدب النفطــي

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الخلاصة

ان الهدف الرئيسي من هذه الدراسة هو تطوير موديل لمعدل الاختراق لتكوين الخصيب في حقل الأحدب النفطي وتحديد متغيرات الحفر التي تتحكم في التنبؤ بمعدل الاختراق باستخدام تحليل الشبكات العصبية الاصطناعية . ولإعداد البحث تم استخـدام العديد من البرامجيات الالكترونيـــة وهــي (Interactive Petrophysics) الاصــدار (4.2,275,2013) لتحويل البيانات الاولية

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(LAS Readings) لقراءات مجس زمن انتقال الموجات الصوتية (Sonic Wave Travel Time) من اجزاء المتر الى المتر مع العمق. وتم استخدام الاصدار (22) من البرنامج الاحصائي (IBM SPSS) لإنشاء ربط بين متغيرات الحفر ومعدل الاختراق ،وتحديد القيم المتطرفة والغير مناسبة من بين البيانات المدخلة وكذلك تحديد المتغيرات ذات التأثير الاكبر اتجاه معدل الاختراق بواسطة اجراء تحليل الانحدار المتعدد وكذلك تم استخدام الاصدار (11) من برنامج ال JMP من (SAS Institute Inc.) لإجراء تحليل الشبكة العصبية الاصطناعية.

تعتمد طريقة الشبكة العصبية الاصطناعية المقترحة على الحصول على بيانات المدخلات من: بيانات تسجيل الطين وبيانات تسجيل المجسات السلكية ثم تحليلها وانشاء ترابط بين متغيرات الحفر ومعدل الاختراق.

يتكون موديل الشبكة العصبية الاصطناعية المقترح من طبقة الإدخال والطبقة المخفية وطبقة المخرجات وتم تطبيق دالة القطع الزائدي(TanH) كخوارزمية التعلم والتدريب في الطبقة المخفية وأخيراً تم مقارنة القيم المتوقعة لمعدل الاختراق مع القيم المقاسة.

ان موديل معدل الاختراق المقترح أكثر كفاءة من تحليل الانحدار المتعدد في التنبؤ بقيم معدل الاختراق. ان قيم معامل التحديد (R2) التي تم الحصول عليها باستخدام تقنية الشبكة العصبية الاصطناعية هي 0.93 و 0.91 لمجموعات التدريب والتحقق ، على التوالي.

تقدم هذه الدراسة موديل جديد للتنبؤ بمعدل الاختراق مقارنة باستخدام قياسات الحفر التقليدية الأخرى.

Introduction

Most of the national state oil companies sign drilling contracts that involve the production of very large amounts of oil and in order to minimize the total cost of well constructions and drilling, it is necessary to increase the drilling rate. Drilling rate is a key parameter in drilling optimization due to its rule in the reduction of drilling operations cost [1]. Prediction of rate of penetration is very important to improve the drilling performance.

There are many conventional mathematical, direct and indirect, models to estimate and calculate the drilling rate and determine the rock mechanical properties.

The drilling optimization is still a very big challenge in oil and gas industry, because of the large number of uncontrolled factors such as type of formation lithology, bottom hole temperature, formation compressive strength, and corrosive gases during the drilling of the formations [2,3].

The main aim of this study is to develop an empirical model for predicting the rate of penetration by using the artificial neural network for Khasib formation in Ahdeb oil field.

Artificial neural networks (ANNs) are information-processing procedures of large numbers of connected nodes and information in an attempt to solve the complicated non-linear relationships with high accuracy [4] . The ANN is an intelligent method which can update itself by an iteration style and depending on the provided database. One of the properties of the ANN is that there is no need for any static functions that requires a complete group of data; it is applying the correlation between the input and output information for the induction of the missing information [5] .

Many experts introduced their studies on using the ANNs to predict and estimate the rate of penetration with different oil fields and cases. Bilgesu et al. [6] introduced a new approach and methodology for the prediction of ROP values at a drill site by using the drilling recorded data and the neural networks. They concluded that if the drilling rate falls below the expected values, a new bit can be selected based on the network predictions. Dashevskiy et al. [7] proposed a model using the neural networks and drilling variables (WOB, RPM) with the aim to obtain the optimum ROP values and down-hole diagnostics. Fonseca et al. [8] used the Auto-Regressive with extra Input Signals (ARX) Neural Networks model and proposed a model for ROP calculation in data from seven oil offshore field wells. With this methodology, they achieved results of high coefficient of determination ranged from 0.888 to 0.988 for the testing sets.

Akin [9] introduced a new approach for diamond bits drilling operations or hard formation through calculating the optimum rate of penetration, weight on bit, and rotary per minute by using the ANNs.

Moran et al. [5] provided a programmed ANN model for sophisticated ROP estimation and total drill-time when the well planning needs to change in wellbore size, formation drilled and total depth. The model had flexibility of the computer software to analyze more information for the estimation and prediction of ROP based on the past experience and drilling information from offset wells.

Elkatany, [10] proposed a neural network model for the prediction of the rate of penetration with high accuracy using Self- Adaptive Differential Evolution Artificial Neural Network (SaDE-ANN). The obtained results showed that the ROP has an intense relation with the other drilling variables (WOB, RPM and Horse Power) and a reasonable relation with the unconfined compressive strength.

Ahmed et al. [11] proposed a method for predicting the rate of penetration in shale formation using fuzzy logic system based on five drilling parameters (WOB, RPM, ROP, Torque and flow rate) and five drilling fluid properties (mud weight, plastic viscosity, marsh funnel viscosity, yield point and solid content %). They proved that the fuzzy logic technique can be used effectively to predict the ROP with high performance, while the results showed a coefficient of correlation of R = 0.97 and an average absolute percentage error of AAPE = 7.3.

Li et al. [12] proposed a new method for the prediction of ROP ahead of the bit through real-time updated machine learning models.

Yuswandari et al. [13] applied an ANN model using data from a geothermal field in Indonesia to predict the rate of penetration. They used a multiple regression for each parameter in the data set by normalizing the importance technique to select the input variables, which have high impact on rate of penetration. They concluded that the final model can provide somewhat a picture of rate of penetration in nearby wells and can be improved by using more data from another well in the training set.

In this study, the proposed ANN predictive ROP model is an empirical model with high accuracy and high performance, which is provided with the weights between the input and hidden layers and hidden and output layers as well as the biases for hidden and output layers.

An artificial neuron is a simple element of a neural network, which consist of major components including, input data, weights, an activation function and output values. Each input parameter is multiplied by adjustable weights as shown in Eq. 1. Then the adjusted inputs are summed in a field called the local receptive field which enters through an activation function that executes a non-linear process on the information output and transmits it into the predicted output. Most of the activation functions are non-linear [14].

$$\boldsymbol{y_i = \sum_{i=1}^{n} W_i\, X_i} \qquad (\mathbf{1})$$

where yi: The summation of multiplying weights by the neuron values in the previous layer, Wi: weight value, Xi: input value.

There is a hidden layer (s) between the input and output layer (s) [15]. In the hidden layer, the signals received from the input neurons are processed and then transformed to the output layer. In addition, there is a bias neuron in the hidden layer which is connected to all neurons in the next layer but none in the previous layer [16] . Biases will be summed with the weighted inputs and the result is the net input, so that Eq. (1) becomes:

$$\boldsymbol{y_i = \sum_{i=1}^{n} W_i\, X_i + b_i} \qquad (\mathbf{2})$$

The net input ($\boldsymbol{y_i}$) will pass through an activation or transfer function to generate the neuron output[17].

1.1 Artificial Neural Network Architecture

Multi-Layer perceptron (MLP) is one of the best ANN structures which is widely used because of its ability of modeling a complex relationship between variables, which gives results with a high accuracy [18]. Multi-layer perceptron has an input layer, one or more hidden layers and an output layer [19]. The input layer only distributes the input elements. The hidden layer is between the input and output layers and the hidden neurons make the weighted sum by using the activation function. The output layer as well as the hidden layer make the weighted sum by applying the activation function.

1.2 Artificial Neural Network Learning Algorithm – Back Propagation

Learning algorithm is used to minimize the total error by updating the weights. Back- propagation algorithm, a supervised neural network, is a type of networks designed to solve the problems of classification through the multi- layer neural networks instead of the perceptron networks which deal with single layer neural networks.

This type is widely used in the pattern recognition and consists of a multi-layer neural network, which can be a training in a prompt and repetitive form until reaching the optimum level of the network performance according to the variables of weights and biases; this type was developed by Paul Werbos in 1974 and discovered by Rumelhart and Parker. To test whether an improvement is achieved through the performance of the network, two error-based metrics including the coefficient of determination (R^2) and the root mean square error (RMSE) are founded for the proposed model. This algorithm works by propagating the input values forward across the network, then propagating them from the last layer to the first layer and adjusting the connection weights and biases so that the overall error between the predicted and target outputs is minimized, ideally reaching zero [20].

Data Analysis and Methodology

Drilling Mud Logging and Selection of Wire Line Logging Data Variable

Khasib formation is one of the main pay zones in Ahdeb oil field that is located between Nomania town and Kut town of Wassit Province, 140 km southeast of Baghdad, in the fluvial plain between the Euphrates and Tigris rivers. The upper part is mainly consisted of light grey to grey limestone and the lower part consists mainly of light brown limestone [21]. It is important to determine the most significant variables that will affect the output function. Accordingly, different input parameters were selected for optimizing the rate of penetration.

Using multi-layer perceptron (input, hidden and output) layers and ANN analyses for ROP prediction, the network was trained by the back propagation method. The tangent function (Tanh) was used as an activation function and the data were randomly divided as 70% for training the network and 30% for the validation (Hold back Validation).

After analyzing the neural network, the best determination coefficient (R^2) value was 0.93 for the training set and 0.91 for the validation set. The results for each group of input parameters are shown in Table-1, which were obtained by establishing more than ninety attempts of training the neural networks with different selections of input parameters.

Neural Network Analysis of Raw Data

A neural network analysis was applied for the Khasib formation dataset. The raw dataset was obtained from one well in Ahdeb oil field (AD1-5-1H) for Khasib formation (raw dataset). The raw dataset consisted of independent variables (depth, WOB, RPM, TORQUE, pump pressure, wave travel time) and one dependent variable (ROP)[22].

The neural network consists of multilayer perceptron (input layer, hidden layer, and output layer). The input layer contained independent variables (depth, WOB, RPM, Torque, flow rate, pump pressure, and wave travel time), whereas the output layer contained the dependent variable ROP. The hidden layer consisted of one layer that contained seven neurons and applied TanH as an activation function. The training set is the section that rates the ROP model parameters, while the validation set is the section that validates the predictive strength of the ROP model .The validation method is the Hold Back method, which randomly divided the raw data into the training and validation sets, where the used validation proportion was 0.3333 of the original data.

Table 1- Prediction of the Rate of Penetration with Different Selections of input Variables.

Final Input Variable Selection (Optimization)		
Input Variable Selection	Determination Coefficient, (R^2)	
	Training	Validation
DEPTH, WOB, RPM, Q, TRQ, SPM, WTT	0.9337634	0.9055535
DEPTH, WOB, RPM, Q, TRQ, SPM,	0.8757587	0.8288593
DEPTH, WOB, RPM, Q, TRQ, WTT	0.917128	0.832934
DEPTH, WOB, RPM, Q, , SPM, WTT	0.8251977	0.6983541
DEPTH, WOB, RPM, TRQ, SPM, WTT	0.9230936	0.895346
DEPTH, WOB, Q, TRQ, SPM, WTT	0.9110697	0.9032697
WOB, RPM, Q, TRQ, SPM, WTT	0.8935787	0.8609942
WOB,RPM	0.6001305	0.5062489
WOB,TRQ	0.7332279	0.6978608
WOB,Q	0.3962398	0.2500142
WOB,SPM	0.3443269	0.3285626

WOB,WTT	0.6058865	0.59355
Q	0.0397367	0.0390452
RPM	0.597532	0.4070751
TRQ	0.7051982	0.6949183
WOB	0.3425569	0.2948616
SPM	0.0211111	0.0052643
WTT	0.5165625	0.2989639

Actual versus Predicted Plot of Raw Data

Figures-(1, 2) demonstrate the cross plots of actual versus predicted ROP that were obtained from the neural network analysis for the training and validation sets, respectively.

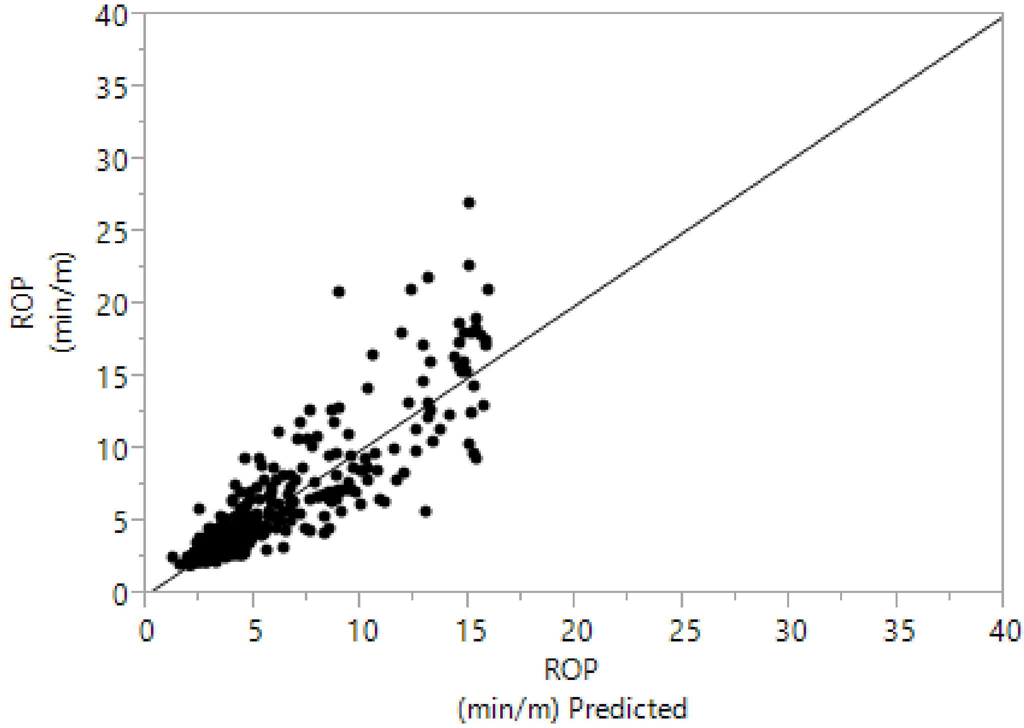

Figure 1- ROP measured Vs. ROP Predicted (Training Set).

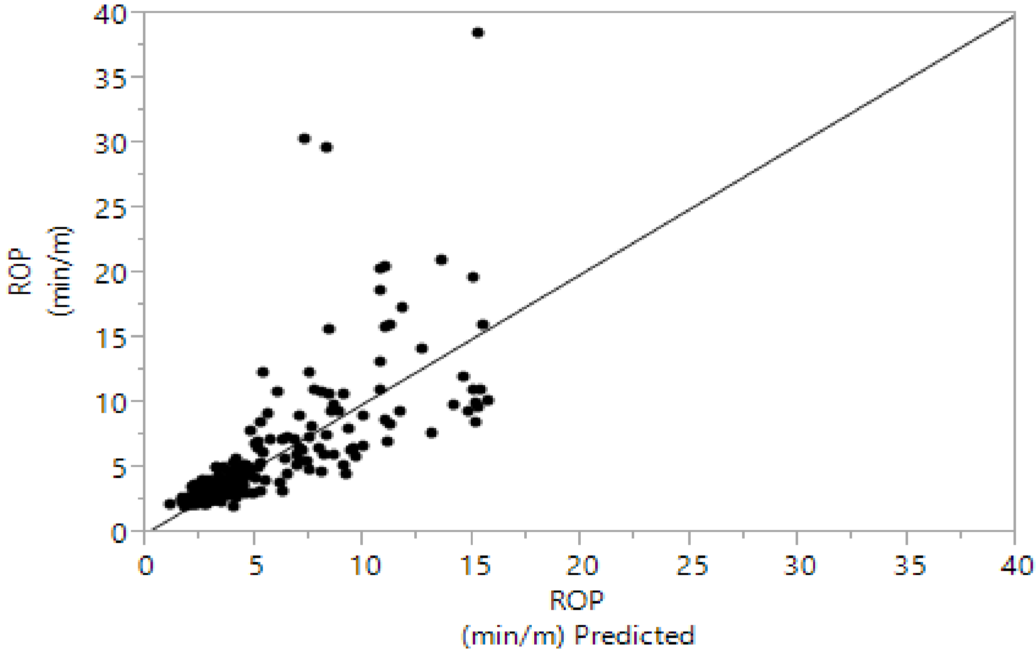

Figure 2- ROP measured Vs. ROP Predicted (Validation Set).

ROP Model Performance Analysis of Raw Data

The results of ANN analysis of the data showed R^2 values of 0.8013983 and 0.5578696 for the training and the validation sets, respectively. In addition the values of RMSE were 1.5842187 and 2.8684367 for the training and validation sets, respectively.

The results from training and validation sets showed that the values of R^2 are low and need to be improved by excluding the outliers. We used the box plot method to determine the outliers and noise in the data set and raw data of Khasib formation.

Table-2 shows the number of outliers for each variable according to the box plot method.

Table 2- Drilling Parameters Outliers for Khasib Formation

Variable	Outliers Number
Depth	0
ROP	27
WOB	26
RPM	15
TORQUE	4
Pump Pressure	16
Flow Rate	20
Travel Time	19

Multiple Regression Analysis for Data without Outliers

Figure-5 shows the actual ROP vs. predicted ROP by using the multiple regression analysis of Khasib Formation data after excluding the outliers of the input variables.

The analysis resulted in an R^2 value of 0.85 and an RMSE value of 0.6037.

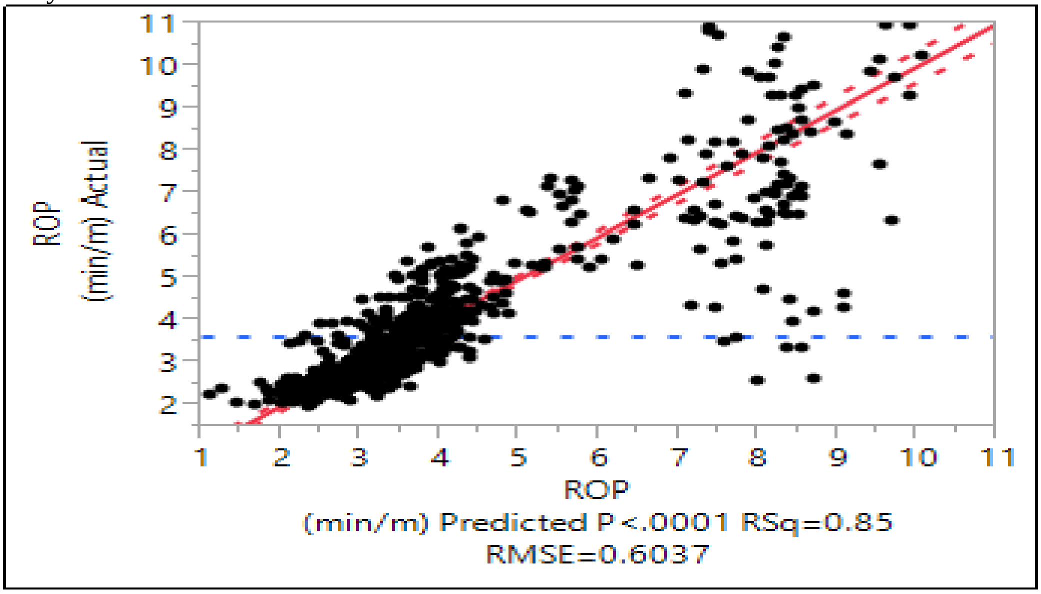

Figure 3- ROP Actual vs. ROP Predicted by Multiple Regression Analysis.

Eq. (3) shows the ROP model for Khasib Formation data without outliers by using the Multiple Regression Analysis:

$$\begin{aligned}ROP = {} & 11.3856720311665 + 0.0032497969915059 * Depth + \\ & - 0.0151962837563356 * WOB + \\ & 0.00853766181451426 * RPM + \\ & - 0.767212724589397 * Torqu + \\ & 0.0424244667317726 * SPM + \\ & - 0.00397946264878767 * Flow\ rate + \\ & - 0.109527264225027 * Wave\ Travel\ Time \end{aligned} \tag{3}$$

Neural Network Analyzing for Data without Outliers

From the results of box plots and the outliers, both independent and dependent showed many outliers values, which resulted in a negative effect on the results of R^2 R square and RMSE and thus on the prediction capacity of the developed ROP model of Khasib formation. Because of the exclusion of all the outlier values from the raw dataset, the ANN technique was applied again on the same data to obtain the best predictive model of the rate of penetration.

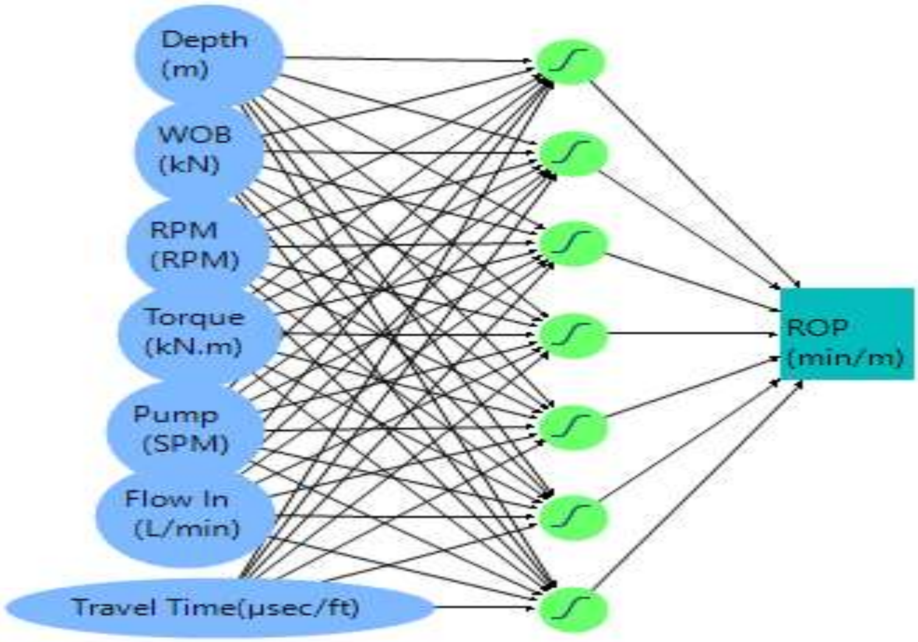

Figure 4- The architecture of ANN Constructed for ROP prediction without outliers.

Actual versus Predicted ROP Plot

Figures-(5, 6) show the actual vs. predicted ROP in the training and validation sets for the results obtained from the ANN analysis of Khasib formation dataset after excluding the outliers.

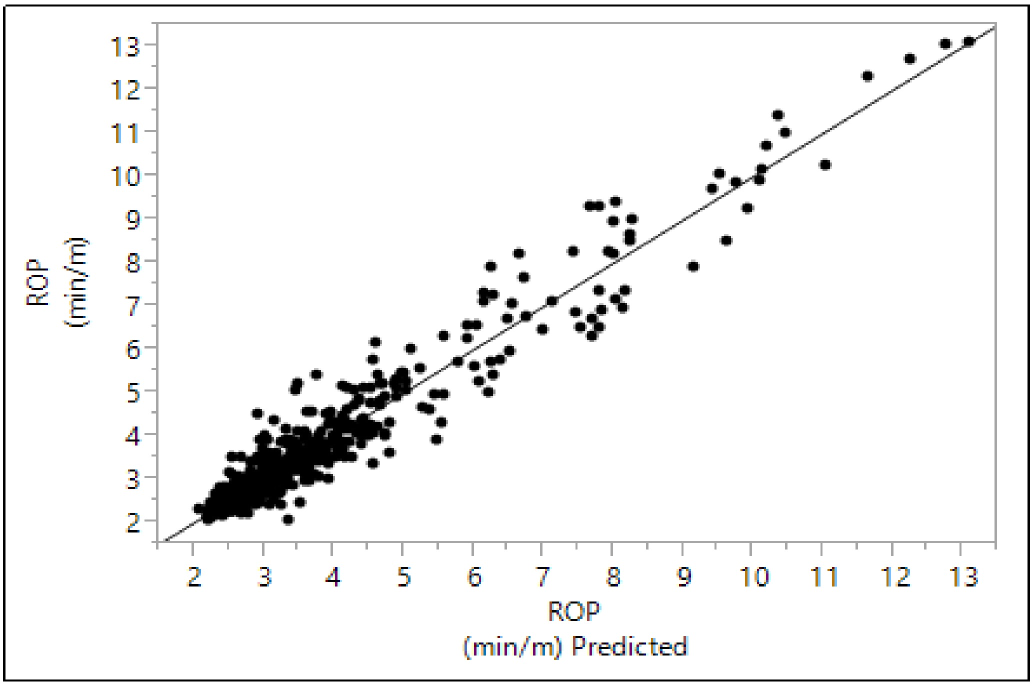

Figure 5- ROP Measured vs. ROP Predicted (Training Set)

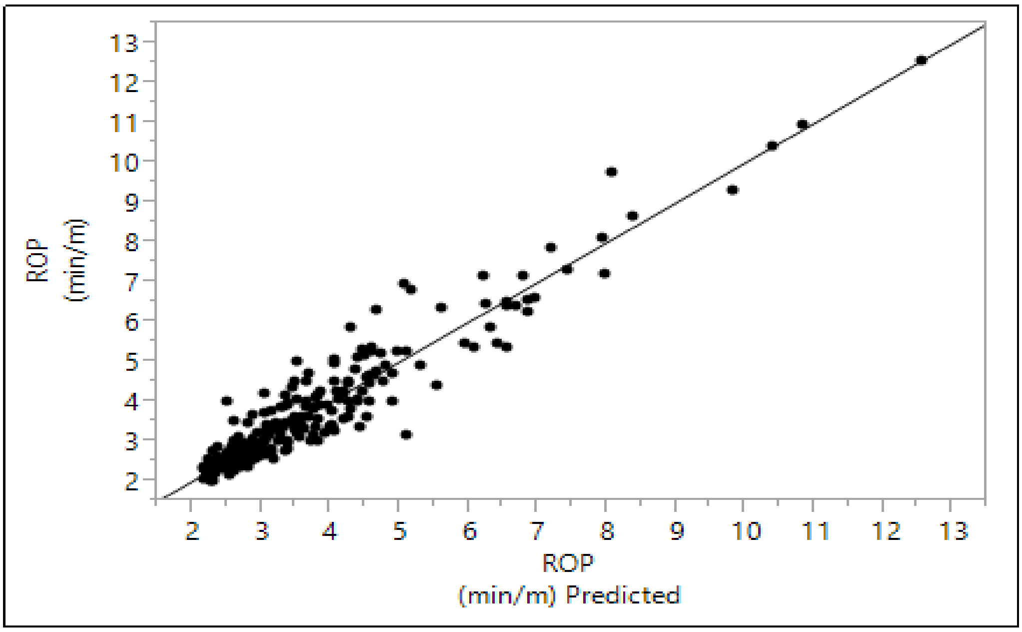

Figure 6- ROP measured vs. ROP Predicted (Validation Set)

2.4.2 ROP Model Performance Analysis

The results of ANN analysis of the data after excluding the outliers demonstrated R^2 values of 0.93 and 0.91 for the training and validation sets, respectively. The results also showed RMSE values of 0.4872786 and 0.469345 for the training and validation sets, respectively.

From the results of the training and validation sets which were obtained after excluding the outliers and noise from the raw data, we achieved a good improvement for the R square and RMSE values and, thus, a good ROP predictive values for Khasib formation.

3. Khasib Formation Predictive ANN Model

The TanH(x) function is:

$$\boldsymbol{f}\,(\mathbf{x}) = \mathbf{TanH}(\mathbf{x}) = \frac{\mathbf{2}}{\mathbf{1}+\,\boldsymbol{e}^{-\mathbf{2}\boldsymbol{x}}} - \mathbf{1} \tag{4}$$

All the input variables will be normalized in the range of - 1, 1 before substituting in the Eq. (6), since we use TanH as an activation function.

The normalization equation is as follows:

$$\boldsymbol{X_n} = \mathbf{2} * \left(\frac{\boldsymbol{X}-\boldsymbol{X_{min}}}{\boldsymbol{X_{max}}-\boldsymbol{X_{min}}}\right) - 1 \tag{5}$$

where: $\boldsymbol{X_n}$**:** normalized input parameter, X: actual input parameter, $\boldsymbol{X_{max}}, \boldsymbol{X_{min}}$: maximum, minimum limits of the input parameters.

(ROP)n=

$$\left[\sum_{i=1}^{n} \boldsymbol{W_{2i}} * \left(\frac{\mathbf{2}}{\mathbf{1}+\boldsymbol{e}^{-2(W_{1i,1}*Depth+W_{1i,2}*WOB+W_{1i,3}*RPM+W_{1i,4}*TRQ+W_{1i,5}*Q+W_{1i,6}*SPM+W_{1i,7}*WTT+b1_{i})}} - \mathbf{1}\right)\right] + \boldsymbol{b_2} \tag{6}$$

where **(ROP) n**: normalized rate of penetration, $\boldsymbol{W_{1i}}$: input hidden weights, $\boldsymbol{W2_i}$: hidden -output weights, $\boldsymbol{b1_i}$: bias-hidden, $\boldsymbol{b_2}$: bias- output,

Now we make the de-normalization by using Eq. (5) for the values of $(\mathrm{ROP})_{\boldsymbol{normalized}}$ obtained from Eq. (6) to get the real values of ROP.

Eq. (6) shows the ROP model for Khasib Formation by using the artificial neural network.

Table-3 shows the weights and biases for Khasib formation ANN-ROP predictive model, which was estimated following the artificial neural analysis of the data after excluding the outliers. The weights are between the input and hidden layers and between the hidden and the output layers. The biases are for the hidden and output layers.

Table 3- Weights and Biases of Khasib Formation ANN Model

Hidden Node (i)	Input-Hidden Weight ($W\mathbf{1}_i$)							Hidden-Outputs Weight	Bias	
	Depth	WOB	RPM	TRQ	SPM	Q	WTT	$\boldsymbol{W2_i}$	Hidden (□□□)	Output □□
1	-0.00928309	0.017861895	-0.03401906	1.622583311	0.188827295	-0.01660859	0.0208548285	-1.73418035	37.013667831	8.510084573
2	-0.00170755	0.040488184	-0.16587834	0.040817501	0.958782525	-0.02799647	-0.02724516	5.227166618	3.8792421079	
3	-0.00076188	-0.01135332	-0.02253042	0.130465558	-0.60967664	0.039113552	0.1984152221	-2.63800279	-30.64647407	
4	-0.00124255	0.011936537	0.131888801	0.166263041	0.800555442	-0.11545785	0.0240815012	4.063256434	132.80245773	
5	0.003097655	-0.04369832	0.148919447	-0.08006962	-1.59417833	0.071155066	0.0982883188	4.563577602	-37.78632199	
6	0.007439321	0.025550338	-0.00999551	0.048242769	-1.25210953	0.056690997	0.0634289805	-5.64829569	-22.69718596	
7	0.011392401	0.030842133	0.043318395	0.519942269	0.724565089	0.070455912	0.0806720624	-0.31573271	-246.4887632	

4. Mathematical Validation of the ANN - ROP Predictive Model Equation for Khasib Formation

To validate the developed ANN – ROP predictive model, the values of ROP were calculated based on the artificial neural network predictive model for Khasib formation datasets by using Eq. (6).

Figure -7 shows the actual and predicted ROP values obtained from the ANN model along a depth of 2626 - 3585 meter. The proposed predictive model achieved a high accuracy between the actual ROP and the calculated ROP.

The predicted ROP showed a symmetric distribution with depth and followed the trend of the actual ROP, except for the data point at the depth of 2644 m because of using a high WOB while drilling. We can confirm that the drilling and wireline parameters used in the model were physically appropriate and that the ANN predictive ROP model can represent the relationships between the parameters involved in ROP modelling.

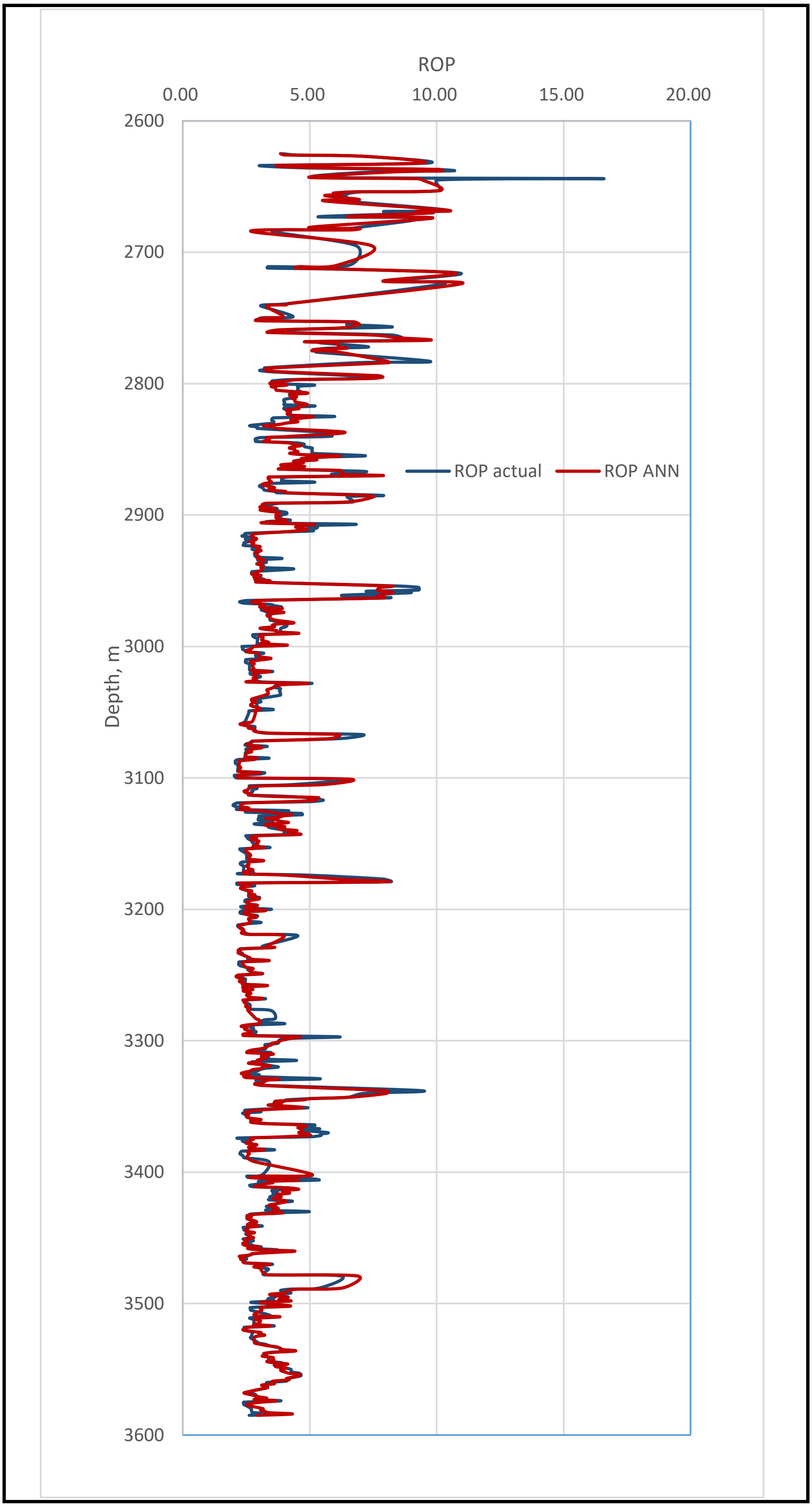

Figure-7 Actual ROP and ANN- ROP Values along Depth

Conclusions

The proposed ANN model for Khasib formation-Ahdeb oil field, based on the high performance of the coefficient of determination (R^2), gives a good prediction capacity of ROP values in comparison with the actual values.

The multiple regression analysis gives good results for predicting ROP when it is compared with the measured ROP, but with lower efficiency than the predicted values of the ANN model.

1. Acquisition and analysis of inputs data is one of the most important steps in ANN analysis method for predicting the ROP.

2. The selected number of neurons or nodes in the hidden layer is an important step in developing ROP-predictive models by using ANN.

If the number of neurons in the hidden layer is high, the ANN network tends to memorize the data and if the number of hidden neurons is small, the ANN predictive ROP is poor.

The increasing of the neurons in the hidden layer does not necessarily improve the predicting of ROP and the best method to determine the number of neurons in the hidden layer for Khasib formation is by trial and error.

3. The validation of the proposed ANN model equation by using the Microsoft Excel program gives a good matching between the actual and predicted ROP values.

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