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Predicting Rate of Penetration and optimization Weight on bit using Artificial Neural Networks

Tien Hung Nguyen, The Vinh Nguyen, Hong Duong Vu
Faculty of oil and gas, Hanoi university of Mining and Geology, 18 Vien, Duc Thang, Bac Tu Lim, Hanoi, Vietnam, 10000
*Corresponding Author: nguyentienhung.dk@humg.edu.vn

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Abstract

Achieving the greatest Rate of Penetration (ROP) is the aim of each drilling engineer because it could save time, diminish cost and limit drilling problems. Nonetheless, ROP could be affected by many drilling parameters which lead to complication in its prediction. Subsequently, it is essential and critical to propose a new approach to predict ROP with high accuracy and optimize drilling parameters. In this review, another methodology utilizing Artificial Neural Network (ANN) has been proposed to estimate ROP from real – time drilling data of a few wells in Nam Rong - Doi Moi oil field, Vietnam with more than 900 datasets included significant parameters like rotary speed (RPM), the weight on bit (WOB), standpipe pressure (SPP), flow rate (FR), weight of mud (MW), torque (TQ). The number of neurons in the hidden layer were varied then the results of different ANN models were compared in order to obtain the optimal model. The final ANN model shows high exactness when contrasted with actual ROP, in this manner it tends to be suggested as a successful and reasonable approach to predict the ROP of different wells in Nam Rong – Doi Moi field. Also, based on the proposed ANN model, the optimal WOB was determine for the drilling interval from 1800 to 2300 m of oil wells in research region.

INTRODUCTION

Achieving the greatest Rate of Penetration (ROP) is the aim of each drilling engineer because it could save time, diminish cost, and limit drilling problems. Nonetheless, ROP could be affected by many drilling parameters, which lead to complications in its prediction. There have been a lot of studies propose mathematical relationships between various drilling parameters and ROP (AL-Mahasneh, 2017; Bani Mustafa et al., 2021; Bingham, 1965; Bourgoyne Jr & Young Jr, 1974; Eren & Ozbayoglu, 2010; Maurer, 1962). However, these predicted equations are normally proposed from a limited database in a particular research area therefore, when applying them to other case which has different geological properties, the result is normally inaccuracy. Subsequently, it is essential and critical to propose a new approach to predict ROP with high accuracy. Because of the intricacy of the relationship between ROP and drilling parameters, an artificial neural network (ANN) is by all accounts a reasonable choice to demonstrate this complicated interaction. Some ANN models were proposed to predict ROP from drilling data (Adetifa et al., 2021; Al-AbdulJabbar et al., 2018; Chandrasekaran & Kumar, 2020; Elkatatny et al., 2017; Hadi et al., 2019; Irawan et al., 2012; Jahanbakhshi et al., 2012; Kahraman, 2016; Moran et al., 2010). After applying ANN to predict ROP, these studies concluded ANN models are unrivalled and more dependable than conventional models for ROP expectation. However, most of these published just presents ANN models without providing specific equations to predict ROP.

In this study, authors applying ANN method with real time drilling data to generate a specific ANN model and a calculation to predict ROP.

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METHOD

Table 1. Summary of well log data.

	Parameters	Well 406	Well 420	Total
	Number of core	511	472	986
TVD (m)	Top	1800	1800	1800
	Bottom	2300	2300	2300
ROP(m/hr)	Mininum	22.74	10.03	10.03
	Maximum	54.85	38.75	54.85
	Mean	41.73	21.4	31.94
	Stdev	8.67	6.87	12.84
WOB (ton)	Mininum	5.51	0.16	0.16
	Maximum	16.35	5.53	16.35
	Mean	10.41	2.1	6.41
	Stdev	2.52	0.78	4.56
RPM(revs/mn)	Mininum	116	100	100
	Maximum	135	166	166
	Mean	131	134	132.44
	Stdev	5.28	12.04	9.3
TQR(kg.m)	Mininum	1582	189.2	189.2
	Maximum	2478	3215.5	3215.5
	Mean	2068.75	2731.1	2387.5
	Stdev	180.24	255.47	397.29
FR (l/s)	Mininum	42.8	45.3	42.8
	Maximum	57.62	62.11	62.11
	Mean	56.36	57.63	56.97
	Stdev	3.06	2.34	2.8
SPP (atm)	Mininum	98.5	111.52	98.5
	Maximum	134.7	235.81	235.81
	Mean	120.95	181.31	98.5
	Stdev	8.09	21.91	34.28
MW (kg/l)	Mininum	1.11	1.07	1.07
	Maximum	1.2	1.16	1.2
	Mean	1.15	1.11	1.135
	Stdev	0.028	0.027	0.035

Nam Rong Doi Moi oil field is located in Cuu Long basin along Vietnam shelf. In this field, there is an Oil and Gas Contract between PetroVietnam and three partners -Zarubezneft, PVEP, and Idemitsu. Wells here often face many complications and problems related to borehole instability when constructing in Miocene and Oligocene stratigraphy. It is because of rock has a high content of montmonrinolite mineral (~60%) (Соловьев & Нгуен, 2015) and wells in open hole conditions for a long time. Based on drilling data of interval from 1800 to 2300 m lies in Miocene stratigraphy from 2 wells in Nam Rong Doi Moi field (table 1), figure 1 and figure 2 were generated to present the changing of WOB and ROP in 2 wells.

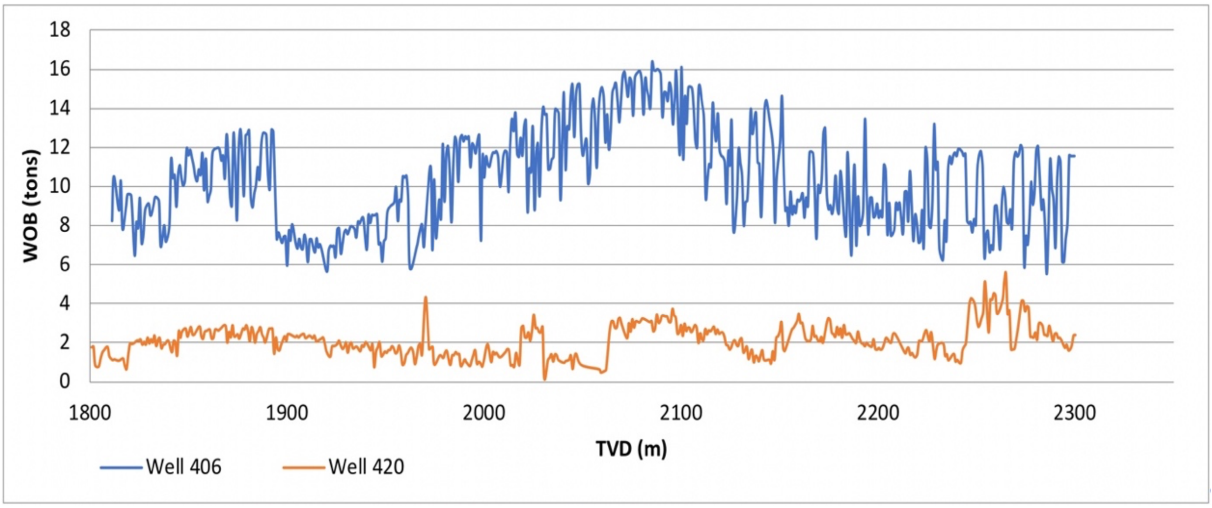

Figure 1. WOB versus TVD of 2 wells.

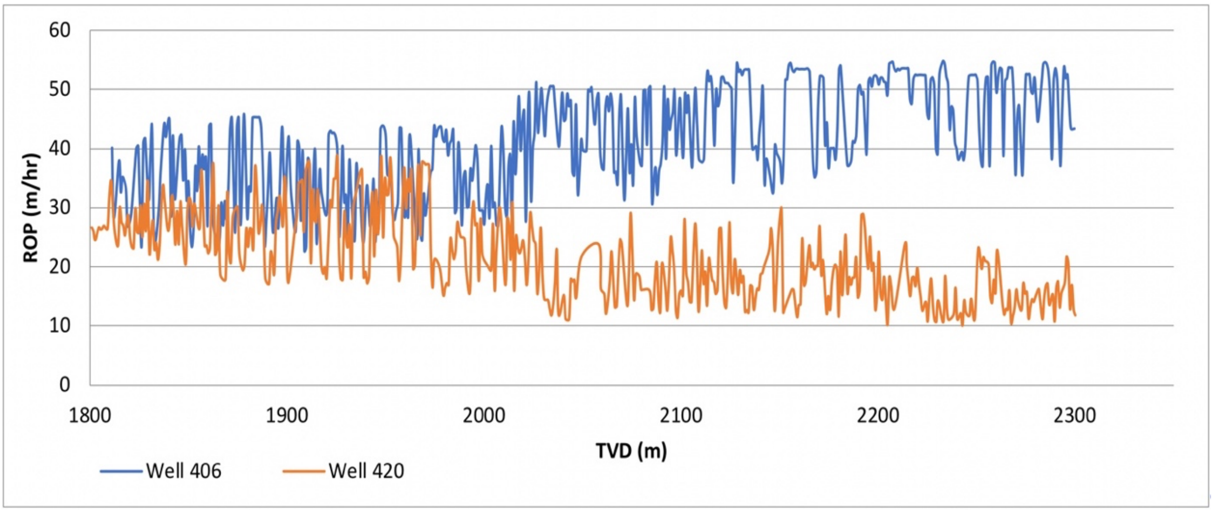

Figure 2. ROP versus TVD of 2 wells.

It can be seen from Figure 1 and 2 that:

- ROP changes rapidly and does not follow any rules.
- There is a significant difference between ROP from 2 wells due to the different WOB applied, it means WOB is one of the most sensitive parameters which effect to ROP.
- Although obtained ROP in well 406 is much higher than in well 420, the adjustment range of WOB is very wide (5.51 to 16.35 Tons) and does not follow any rules.
- When applying higher WOB, although high achieved ROP was maintained, it would increase the cost of destruction energy and reduce bit life.

Therefore, it is necessary to determine the optimal rate ROP to save time and minimize drilling problems for wells in Nam Rong Doi Moi field. In this study, authors present an ANN model to predict ROP from real data of two wells in research oil field with more than 900 datasets including significant parameters like rotary speed (RPM), the weight on bit (WOB), standpipe pressure (SPP), flow rate (FR), weight of mud (MW), torque (TQ) (table 1).

DATA PREPROCESSING

Outlier detection and removal

Abnormal data can consider as noise because they can affect the ANN model negatively and reduce the model generalization. The dataset of 3 wells is investigated for abnormal values by the Z-score outlier detection algorithm (Tripathy, 2013). Outlier data points were removed out of the input data. The Z-score is the score given to the participant as per their performance:

$$z = \frac{|X_i - X_{mean}|}{SD} \tag{1}$$

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where,

X_{mean} is the mean value of the data;

SD is the standard deviation of the data.

To simplify the interpretation of the z-scores, the following agreements were made as z < 2 implies the result is satisfactory 2 < z < 3 implies the result is questionable z > 3 implies the result is unsatisfactory.

To reduce volatility and eliminate statistical noise, the input data was further analyzed and smoothened by Butterworth filter (Selesnick and Burrus 1998).

Data Selection

The selection of input parameters for the training process is an important step, which determines the accuracy of the ANN model. In order to decide which parameter to be used as input data, the inter-relationships between parameters were investigated (figure 3). A regression coefficient closer to 1 stands for a positive correlation, and closer to -1 stands for a negative correlation between parameters. From figure 3, we can see that all drilling parameters are suitable and can be retained in the ANN model development.

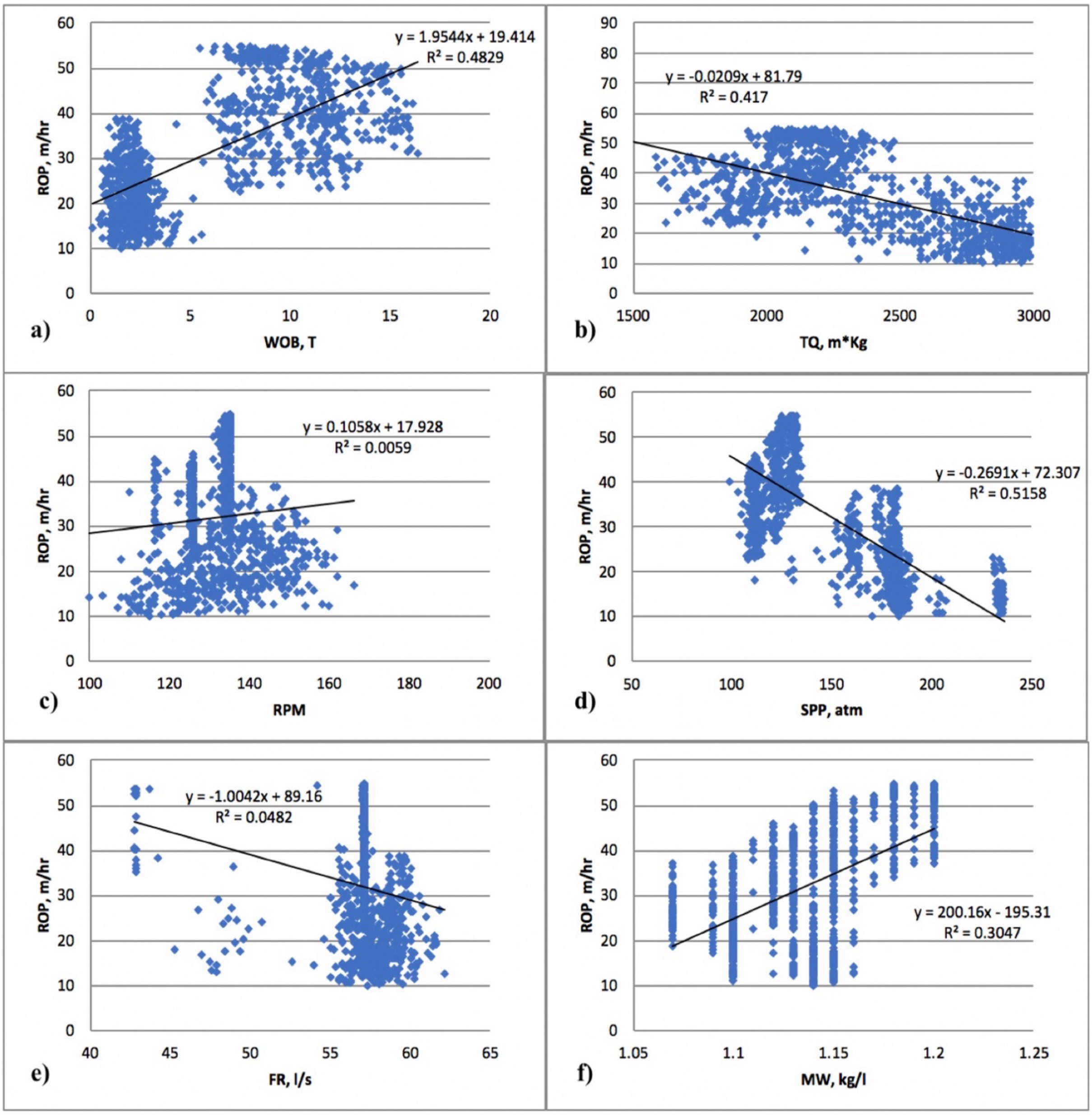

Figure 3. Crossplot between drilling parameters from database.

Data Normalization

The scales for different drilling parameters are wildly different, this can have a huge effect on the accuracy of model. Normalization is needed because it removes geometrical biases towards some of the dimensions of the data vectors. In this way every bit of data gets treated in a fair manner. Therefore, authors using the following equation to normalize input data:

$$X_{normalize} = \frac{(X - X_{min})}{X_{max} - X_{min}} \tag{2}$$

where,

$X_{normalize}$ – the normalized value;

X – input data;

X_{min} – the minimum value of raw variable;

X_{max} – the maximum value of raw variable.

Model Development

In this paper, authors propose an ANN with back-propagation training algorithm (BPNN) and logsig activation function to predict ROP from drilling parameters (Mohaghegh, 2000). A training data set of 986 samples of 2 well in Nam Rong Doi Moi oil field is divided into 3 sets: 70% of the sample is used to train the network, 15% is used for testing, and 15% for the validation. Six parameters: WOB, RPM, TQ, FR, SPP, MW are considered as input data, and the output value of the ANN model is ROP value (Fig.4). Besides, the learning rate was set as 0.1, and the number of epoch to train the model is 10000.

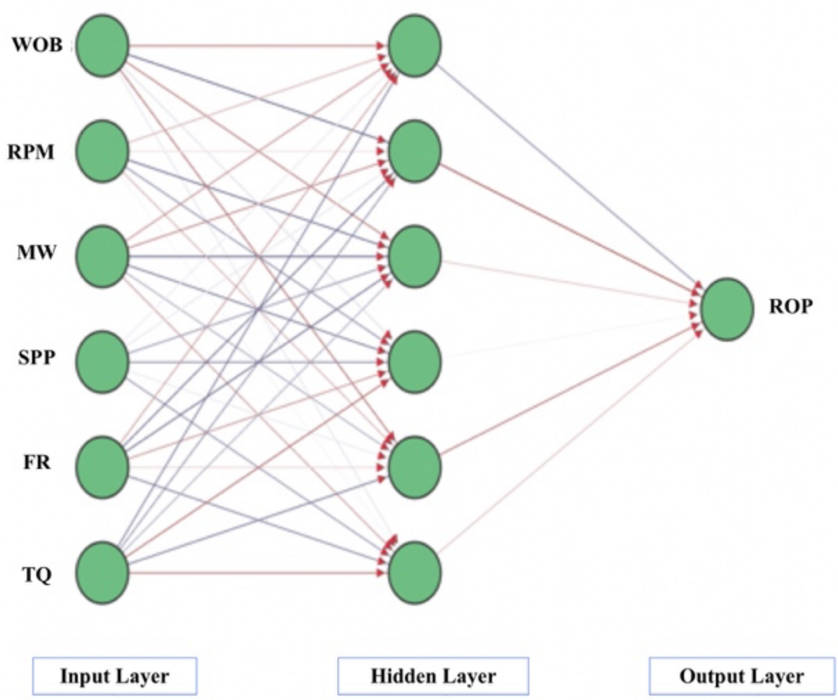

Figure 4. Model of ANN to predict ROP.

The calculated output from ANN after a cycle (or iteration) is compared with the actual output given in the sample dataset (actual ROP) to trace the error. This error is propagated back to output neurons and hidden neurons so that these neurons adjust their weights. This bidirectional propagation is carried out repeatedly until the error reaches a minimum value less than a certain allowable value, or until the number of loops reaches a predetermined value (Fig.5). The accuracy of ANN model is estimated by the root mean square between predicted ROP from the ANN model and actual ROP:

$$RMS_{error} = \sqrt{\sum \frac{\left(ROP_{predict} - ROP_{actual}\right)^2}{n}} \tag{3}$$

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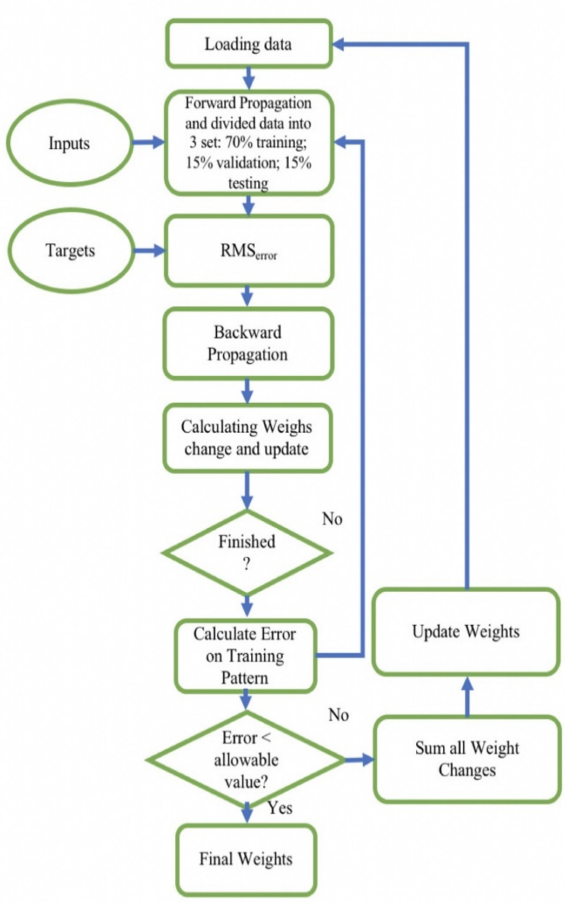

Figure 5. Flow chart of ANN model.

Determining the number of neurons in the hidden layer is a challenging step in model design, and there is no rigid rule to do it. It is important to note that the number of neurons in the hidden layer should be chosen carefully since having too many neurons in hidden layer can lead to overfitting, which makes the network lose its generalization. In this study, to determine the optimal number of hidden neurons, different scenarios were carried out with variable numbers of neurons in the hidden layer and tests for their effect on the final prediction (table 2). Besides the root mean square error, Pearson correlation coefficient R was also used as an evaluation metric to assess the model performance because it could measure the statistical relationship and indicate how well the prediction fit to actual ROP.

Table 2. Result when using different number of neurons in hidden layer

Number of neural in hidden layer	Train data		Validation data		Test data	
	R	RMSE	R	RMSE	R	RMSE
3	0.91	5.21	0.87	6.15	0.89	5.46
4	0.916	5.05	0.915	4.99	0.87	5.85
5	0.924	4.82	0.912	5.19	0.926	4.85
6	0.93	4.48	0.88	5.87	0.91	5.37
7	0.923	4.62	0.89	5.80	0.898	5.65
8	0.92	4.81	0.908	5.35	0.899	5.44
9	0.93	4.64	0.906	5.18	0.91	5.39
10	0.935	4.45	0.903	5.24	0.898	6.21

It can be seen from table 2 that the ANN model with one hidden layer including 5 neurons is the best model (figure 6).

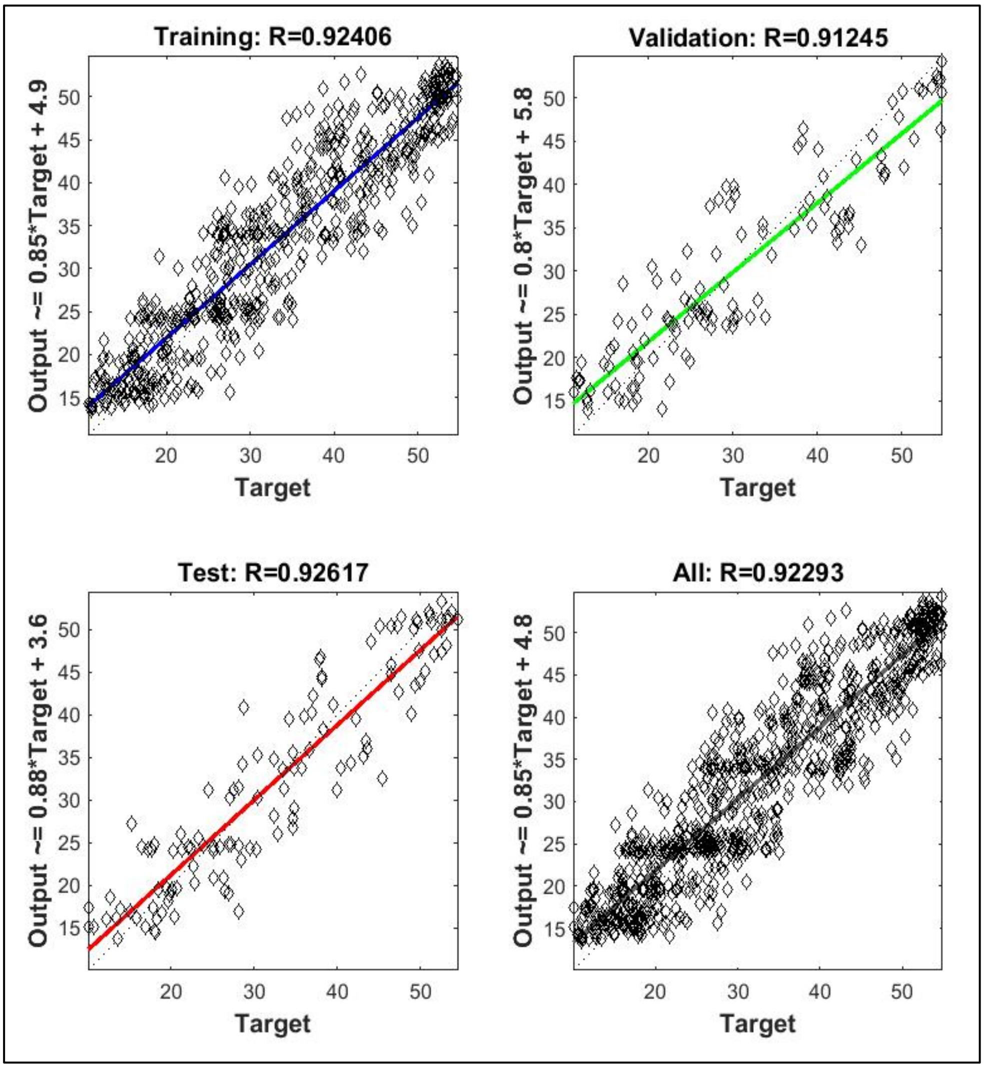

Figure 6. Result of the ANN model with 5 neural in hidden layer.

RESULTS AND DISCUSSIONS

In order to prove the efficacy of the proposed ANN model, authors used Multivariate regression method to generate equations to predict ROP from drilling parameters of each well then compare the results of 2 models (figure 7, 8 and table 4).

$$ROP = a_1\,WOB + a_2\,RPM + a_3\,TQ + a_4\,FR + a_5\,SPP + a_6\,MW + b \qquad (4)$$

Table 3. Coefficients of equations to predict ROP (Multivariate regression method)

Coefficients	Well 406	Well 420
Intercept (b)	-32.61193	98.09547
WOB (a1)	-1.13360	-0.59646
RPM (a2)	0.30291	0.01264
TQ (a3)	0.01976	0.00276
FR (a4)	-1.93851	1.04423
SPP (a5)	-0.03135	-0.20186
MW (a6)	103.62633	-98.65324

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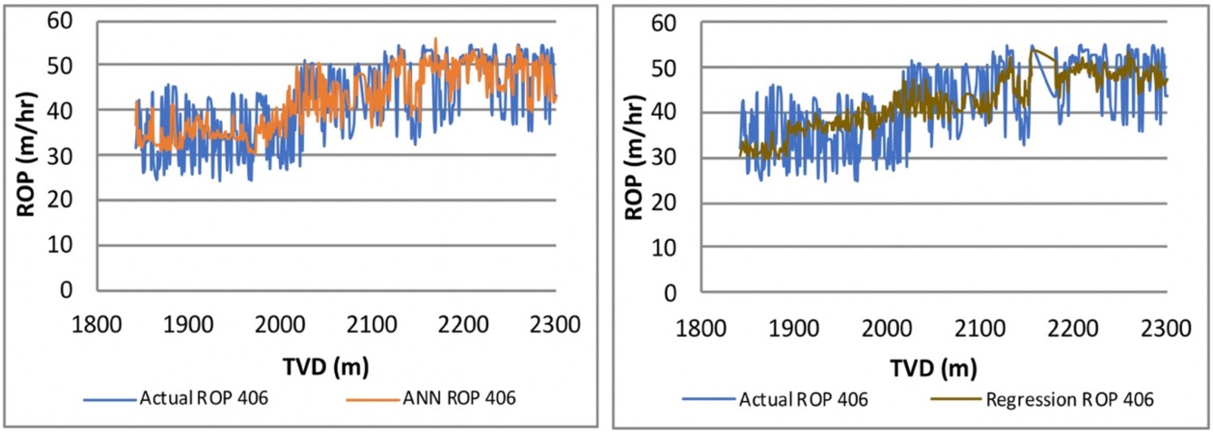

Figure 7. Comparing ROP prediction by ANN, multivariate regression and ROP actual in Well 406.

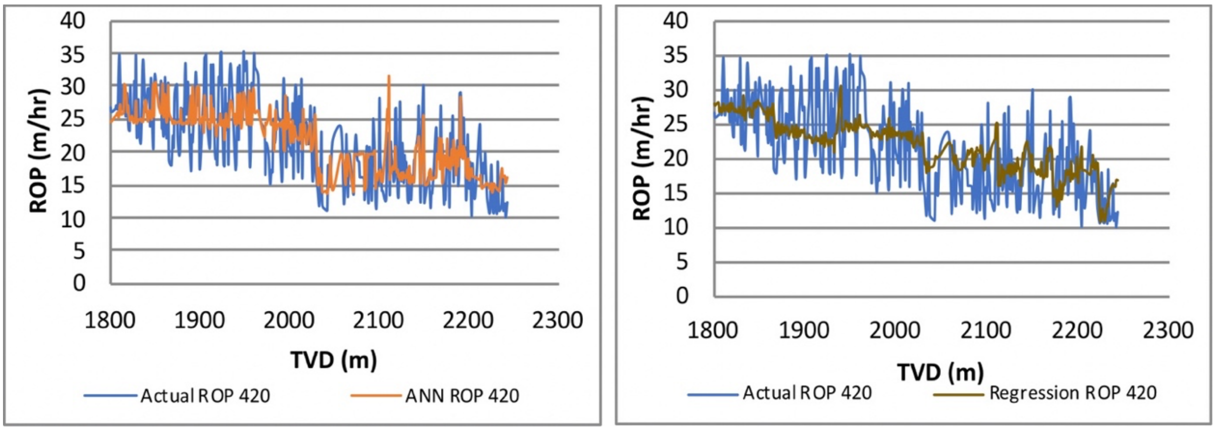

Figure 8. Comparing ROP prediction by ANN, multivariate regression and ROP actual in Well 420.

Table 4. Model performance comparison.

Model	Well 406		Well 420	
	RMSE	R	RMSE	R
ANN	3.94	0.93	3.56	0.89
Multivariate Regression	6.05	0.71	5.28	0.62

When comparing accuracy of 2 model ANN and Multivariate Regression, it is observed from figure 7, 8 and table 4 that ROP prediction from the ANN model has better match and follows the changing trend of actual ROP in both 2 well. Therefore, authors generated a new equation to determine ROP from the proposed ANN model with biases and weights of each neural (table 5).

$$ROP = A2\left(\frac{2}{1 + exp^{(-2(A1X + b_1))}} - 1\right) + b2$$

$$ROP = \left[\sum_{i=1}^{5} W_{2,i}\left(\frac{2}{1 + exp^{\left(-2\left(WOB.W_{1i,1}+RPM.W_{1i,2}+TQR.W_{1i,3}+FR.W_{1i,4}+SPP.W_{1i,5}+MW.W_{1i,6}\right)\right)}} - 1\right)\right] + b2 \tag{5}$$

where,

A1(w_1, i) is vector of weight link the input neurons and the hidden neurons;

A2(w_2, i) is vector of weight link the hidden neurons to the output neurons;

b1 is the bias vector for input layer;

b2 is the bias vector for output layer;

X is the input data.

Table 5. ANN weights and layers bias.

Hidden layer neuron	Weight from the input neurons to the hidden neurons (W_1)						Weight from the hidden neurons to the output neuron (W_2)	Bias of hidden layer (b_1)	Bias of output layer (b_2)
1	1.1819	7.9487	-32.758	-2.323	-18.4813	-4.4536	-0.1200	25.377	0.3753
2	-17.049	37.7191	25.1685	7.1090	-30.9046	-0.6084	0.1124	2.1487	
3	4.3699	-1.3774	4.3397	-3.151	9.6375	4.7937	-0.2236	-0.262	
4	-0.1775	0.9205	1.1825	0.3012	1.2996	-0.2673	-10.2108	1.8162	
5	0.2333	-0.9895	-1.4471	-0.2991	-1.5920	0.2689	-9.2303	-2.165	

Determine optimal value of WOB

In order to determine the optimal WOB to enhance ROP, authors changed WOB value in database from 1 to 15.5 tons. Then, using the proposed ANN model to predict ROP in every scenario and evaluate which is the best WOB base on two criteria: the mean value and standard deviation of predicted ROP (figure 9).

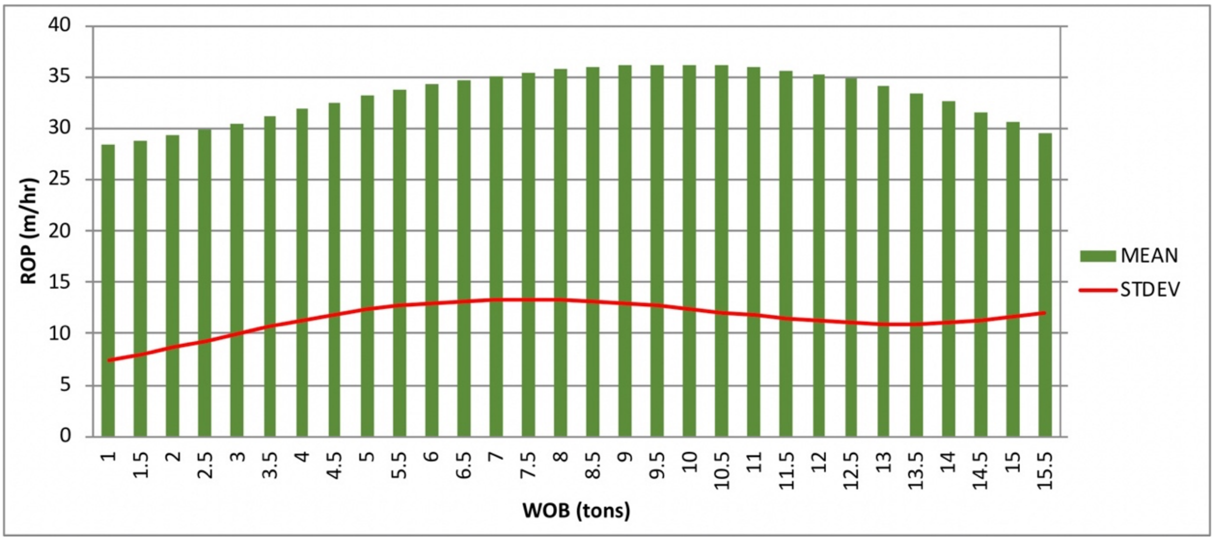

Figure 9. Comparing ROP prediction by ANN when changing WOB value.

It can be seen from Figure 9 that:

• When WOB increases from 2 to 9 tons, ROP has an upward trend. After that, although WOB rises from 9 to 10.5 tons, ROP is almost unchanged (around 36 m/hr);

• Keep increasing WOB, ROP is not only enhanced but also has a decrease trend. It is consistent with the result of previous studies when indentation depth increases but hole cleaning is not good enough (Нескромных 2015, Нескромных 2017, Барон et al. 1966). Furthermore, it leads to increasing cost of destruction energy and bit life reduction.

Furthermore, when applying WOB value of 10.5 tons, the standard deviation was just 12.07 m/hr, it means predicted ROP in this case was relatively stable through interval depth. Compared to the real data, it can be seen that there is a rise in the mean value of ROP (from 31.94 to 36 m/hr) therefore 10.5 tons can be considered as the optimal value of WOB.

CONCLUSION

This paper demonstrates the practical use of ANN to predict ROP from drilling parameters of wells in Nam Rong Doi Moi oil field, Vietnam. The ANN model using back-propagation training algorithm (BPNN) with 5 neurals in hidden layer shows the ability to predict ROP accurately. The optimal value of WOB when drilling through Miocene stratigraphy for 2 wells in Nam Rong Doi Moi oil field is from 8 to 10 tons. This result could be applied for other wells in the research region. Furthermore, this method can be applied similarly for optimization other drilling parameters such as: RPM, FR, MW. Recommendation for future

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work is to update data from new wells, collect data of other drilling parameters and integrate the geomechanical properties into ANN model to increase the accuracy.

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