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Prediction of penetration rate and optimization of weight on a bit using artificial neural networks

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Abstract. ***Relevance.*** Achieving the greatest rate of penetration is the aim of every drilling engineer because it is one of the most significant factors influencing drilling costs. However, a variety of drilling conditions could have an impact on rate of penetration, complicating its forecast. ***Aim.*** To suggest a novel strategy to accurately predict rate of penetration and optimize drilling parameters. ***Objects.*** Real-time drilling data of a few wells in the Ca Tam oil field, Vietnam, with more than 900 datasets including significant parameters like rotary speed, weight on bit, standpipe pressure, flow rate, weight of mud, torque. ***Methods.*** Various methods using Artificial Neural Network was proposed to estimate rate of penetration. ***Results.*** The number of neurons in a hidden layer was varied then the results of different Artificial Neural Network models were compared in order to obtain the optimal model. The final Artificial Neural Network model shows high exactness when contrasted with actual rate of penetration, in this manner, it tends to be suggested as a successful and reasonable approach to predict the rate of penetration of different wells in the Ca Tam oil field. Based on the proposed Artificial Neural Network model, the optimal weight on bit was determined for the drilling interval from 1800 to 2300 m of oil wells in the research region.

Keywords: optimization of drilling parameters, rate of penetration, artificial neural network, Ca Tam field

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Прогнозирование механической скорости бурения и оптимизация нагрузки на долото с использованием искусственных нейронных сетей

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Аннотация. ***Актуальность.*** Достижение максимальной механической скорости бурения является целью каждого инженера-буровика, поскольку механическая скорость бурения является одним из наиболее важных факторов, влияющих на затраты на бурение. Однако различные условия бурения могут оказать влияние на скорость бурения, усложняя ее прогноз. ***Целью*** исследования является предложение новой стратегии для точного прогнозирования механической скорости бурения и оптимизации параметров бурения. ***Объектом*** исследования являются данные бурения в реальном времени нескольких скважин на нефтяном месторождении Белуга в Кыулонгском бассейне шельфа Южного Вьетнама с более чем 900 наборами данных, включая важные параметры, такие как скорость вращения, нагрузка на долото, давление на стояке, дебит, вес бурового раствора, крутящий момент. ***Методы.*** Для оценки механической скорости бурения была предложена различная методология, использующая искусственную нейронную сеть. ***Результаты.*** Количество нейронов в скрытом слое варьировалось, после чего сравнивались результаты разных моделей искусственной нейронной сети с целью получения оптимальной модели. Окончательная модель искусственной нейронной сети показывает высокую точность по сравнению с фактической механической скоростью бурения, поэтому ее можно рассматривать как успешный и разумный подход к прогнозированию механической скорости бурения различных скважин на нефтяном месторождении Белуга. Также на основе предложенной модели искусственной нейронной сети был определен оптимальный режим нагрузки на долото для интервала бурения от 1800 до 2300 м в районе исследования.

Ключевые слова: оптимизация параметров бурения, механическая скорость бурения, искусственная нейронная сеть, месторождение Белуга

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Introduction

Achieving the greatest Rate of Penetration (ROP) is the aim of every drilling engineer because it could save time, diminish cost and limit drilling problems [1]. Nonetheless, ROP could be affected by many drilling parameters which lead to complication in its prediction. There have been many studies propose mathematical relationships between various drilling parameters and ROP. In 1962, W.C. Maurer proposed an equation for roller-cone bits that predicts ROP assuming that the bottom hole is perfectly cleaned [2]. Galle et al. [3] developed a method using graphs and diagrams to determine the optimal combination of weight on bit (WOB) and rotation per minute (RPM) for roller cone bits, while Bingham modified Maurer's model with a simple experimental model that only considers low WOB and RPM, but doesn't account for drilling depth [4]. Bourgoyne and Young created an empirical model to predict ROP based on multiple drilling parameters, which has become a widely used approach for real-time optimization of drilling parameters [5]. Warren presented a perfect cleaning ROP model for soft formations that relates ROP to WOB, RPM, and bit size. Later, he added a wear function to reflect the bit wear impact [6]. Al-Betairi et al. proposed a new ROP model that uses controllable and uncontrollable drilling variables to predict the optimum penetration rate, evaluated the sensitivity of each parameter on ROP, and determined correlational coefficients through multiple regression analysis [7]. However, these predict equations normally proposed from limited database in particular research area. Therefore, when applying them to other case, which has different geological properties, the result is normally inaccurate. 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, 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 [8–16]. These authors discuss the application of various artificial intelligence (AI) techniques such as ANNs, support vector regression (SVR), decision trees (DT), and machine learning (ML) in predicting the rate of penetration during drilling operations. They compare the performance of these models against traditional empirical models and evaluate their accuracy using statistical measures such as mean absolute error (MAE), root mean square error (RMSE), and determination coefficient (R^2). These articles demonstrate the potential of AI techniques to improve drilling efficiency and reduce costs in the petroleum industry. However, most of these published articles just present ANN models without providing specific equations to predict ROP.

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

Input data

The Ca Tam field is located at block 09-3/12 of the Cuu Long basin, Vietnam, about 160 km to the southeast of Vung Tau city (Fig. 1). The block covers an area of approximately 6,000 km^2, with water depths ranging from 15 to 60 m. The field is being developed by a consortium comprising Vietsovpetro (55%), a joint venture between Vietnam Oil & Gas Group (PetroVietnam) and Zarubezhneft, PetroVietnam Exploration Production (PVEP, 30%) and Bitexco Group (15%).

When drilling through the Miocene strata, wells frequently encounter numerous difficulties and issues connected to borehole instability. It is as a result of the long-term open-hole conditions of wells and the high clay content of the rock (Table 1 summarizes the stratigraphic description of three study wells).

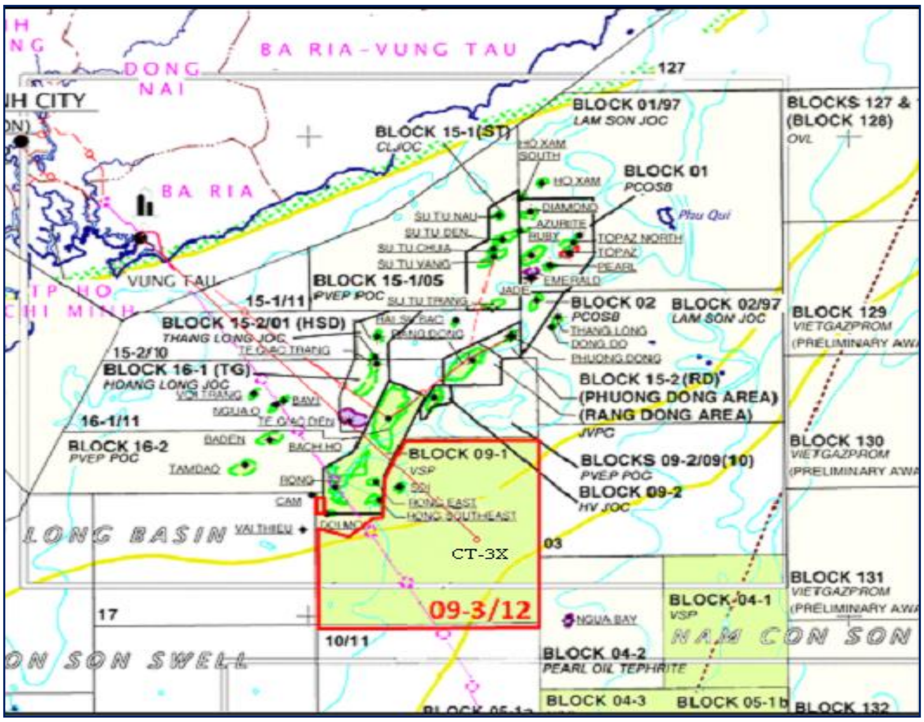
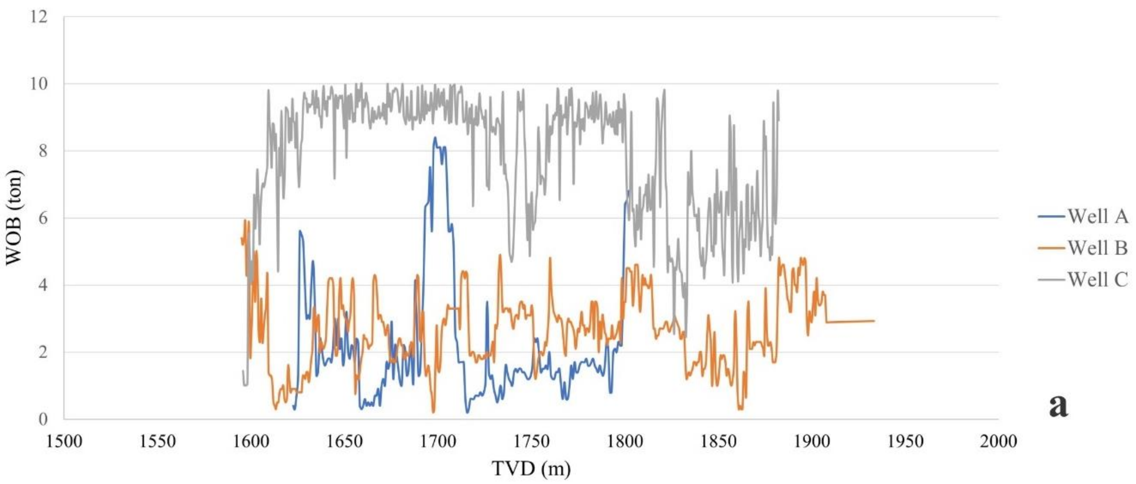


Fig. 1. *Red rectangle shows the study area*
Рис. 1. *Красный прямоугольник показывает района исследования*

Table 1. *Stratigraphic description of three study wells*
Таблица 1. *Стратиграфическое описание трех изучаемых скважин*

	Well/Скважина		
	A	B	C
Formation Формация	Middle Miocene: 1707.0–1985.0 mMD (1584.3–1833.5 mTVD) Средний Миоцен: 1707.0–1985.0 м (глубина по стволу) 1584.3–1833.5 м (Истинная глубина по вертикали)	Middle Miocene (N_1^2): (1992.0–2511.0 mMD) (1595.2–1933.15 mTVD) Средний Миоцен: 1992.0–2511.0 м (глубина по стволу) 1595.2–1933.15 м (Истинная глубина по вертикали)	Middle Miocene: 2156– 2654 mMD (1595–1882.33 mTVD) Средний Миоцен: 2156– 2654 м (глубина по стволу) 1595–1882.33 м (Истинная глубина по вертикали)
Description Описание	1722–1800 m: Predominantly sand and clay. Clay: brownish gray, brown, reddish brown, soft. Sand: greenish gray, transparent to translucent, fine to coarse, commonly medium grains, poorly sorted, sub-angular to sub-rounded. 1800–1985 m: Predominantly sandstone and claystone. Claystone: gray, brownish gray, light gray, light brownish gray brown, reddish brown, soft, soft to firm. Sandstone: greenish gray, light gray, transparent to translucent, fine to coarse, commonly very coarse grains, poorly sorted, sub-angular to sub-rounded.	1992–2100 m: Predominantly clay and sand. Clay: brownish gray, brown, reddish brown, soft, washable. Sand: light gray, light greenish gray, transparent to translucent, fine to coarse grains, common medium grains, subangular to subrounded, poorly sorted. 2100–2410 m: Predominantly clay and sand. Clay: brown, light brown, brownish gray, light gray, soft, and washable. Sand: light gray, greenish gray, occasionally light reddish brown, transparent to translucent, fine to coarse grains, common medium grains, subangular to subrounded, poorly sorted. 2410–2480 m: Predominantly clay and sand. Clay: greenish gray, light gray, soft, washable. Sand: light gray, greenish gray, occasionally light reddish brown, transparent to translucent, fine to coarse grains, common medium grains, subangular to subrounded, poorly sorted. 2480–2511 m: Predominantly clay, sand, claystone and sandstone. Clay: greenish gray, light gray, soft, soluble in part. Sand: light gray, greenish gray, occasionally light reddish brown, transparent to translucent, fine to coarse grains, common medium grains, subangular to subrounded, poorly sorted.	2156–2200 m: Predominantly clay, sand. Clay: grayish green, light brown, soft, subblocky. Sand: transparent to translucent, light gray to gray, greenish gray, medium to coarse, commonly coarse grained, subangular to subrounded, poorly sorted. 2200–2300 m: Predominantly clay, sand. Clay: moderate brown, light gray to gray, greenish gray, soft, subblocky. Sand: transparent to translucent, light gray to gray, greenish gray, fine to medium grained, subangular to subrounded, moderately sorted. 2300– 2400 m: Predominantly clay, sand. Clay: light gray, moderate brown, gray, greenish gray, soft, subblocky. Sand: transparent to translucent, light gray to gray, greenish gray, fine to medium grained, subangular to subrounded, moderately sorted. Trace of coal. 2400– 2650 m: Predominantly clay, sand. Clay: moderate brown, light gray to gray, greenish gray, soft, subblocky. Sand: transparent to translucent, light gray, greenish gray, fine to medium grained, subangular to subrounded, moderately sorted.



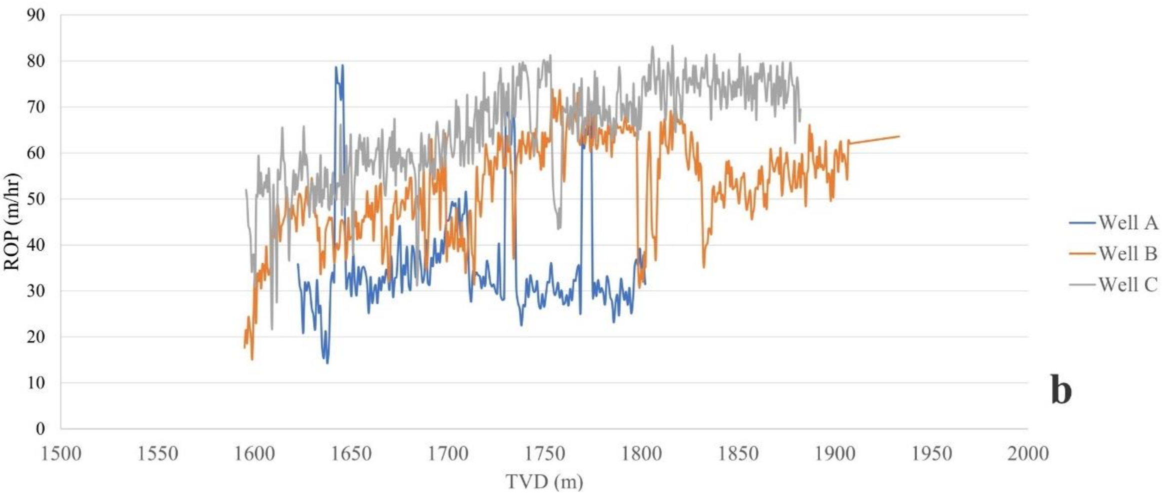


Fig. 2. *WOB and ROP changing trend of three wells: a) WOB data; b) ROP data*
Рис. 2. *Тенденция изменения нагрузки на долото (a) и механической скорости бурения (b) по трем скважинам*

It can be seen from Fig. 2 that:

- ROP is unpredictable and changes quickly;
- due to the different WOB used, there is a considerable variance in ROP between three wells, indicating that WOB is one of the most sensitive parameters that affect ROP;
- despite the fact that the obtained ROP in well C is significantly higher than that of other wells, the adjustment range of WOB is quite broad and defies all laws;
- although high achieved ROP was maintained when applying increased WOB, it would raise the cost of destruction energy and shorten bit life.

The best rate ROP must be established in order to avoid drilling issues and save time for wells in the Ca Tam area. The authors present an ANN model to predict ROP from real data of three wells in a research oil field with more than 1220 datasets that include significant parameters like RPM, WOB, standpipe pressure (SPP), flow rate (FR), and torque (TQ) (Table 2).

Data preprocessing

Outlier detection and removal

Abnormal data might be regarded as noise as they can harm the ANN model and limit model generalization. The *Z*-score outlier identification technique examines the dataset of three wells for aberrant results [17]. The supplied data was stripped of any outlier data points. The participant is awarded a score based on their performance, which is known as the *Z*-score:

$$z = \frac{X_i - X_{mean}}{SD},$$

where X_{mean} is the mean value of the data; *SD* is the standard deviation of the data.

The following agreements were made as z<2 imply the outcome is satisfactory in order to make the interpretation of the *z*-scores simpler. 2<*z*<3 implies that the outcome is uncertain. *z*>3 denotes an undesirable outcome.

The input data was further examined and smoothed using the Butterworth filter in order to decrease volatility and eliminate statistical noise [18].

Table 2. *Well-log data*
Таблица 2. *Данные по скважинам*

Parameters/Параметры		Well/Скважина		
		A	B	C
Number of core/Количество проб		201	520	499
TVD (m) Вертикальная глубина забоя (м)	Top/Кровля	1594.1	1595.04	1595.77
	Bottom/Подошва	1833.5	1933.23	1882.33
ROP (m/hr) Механическая скорость бурения (м/ч)	Min/Минимум	78.47	73.84	83.26
	Max/Максимум	14.29	15.12	22.41
	Mean/Среднее	35.52	53.25	65.15
	Stdev/Стандартное отклонение	11.91	10.57	10.65
WOB (ton) Нагрузка на долото (т)	Min/Минимум	8.4	5.9	9.99
	Max/Максимум	0.2	0.2	1.01
	Mean/Среднее	2.2	2.66	7.85
	Stdev/Стандартное отклонение	1.9	1.05	1.86
RPM (revs/mn) Обороты в минуту (об/мин.)	Min/Минимум	130	130	193
	Max/Максимум	60	79	49
	Mean/Среднее	115.25	116.02	139.89
	Stdev/Стандартное отклонение	17.57	11.45	16.94
TQ (kg/m) Крутящий момент (кг/м)	Min/Минимум	2782.56	3474.12	4074.78
	Max/Максимум	2014.5	2554.08	3057.02
	Mean/Среднее	2329.67	2969.34	3635.3
	Stdev/Стандартное отклонение	118.87	230.02	252.43
FR (l/s) Дебит (1/с)	Min/Минимум	57.07	58.83	60.31
	Max/Максимум	46.79	44.33	23.12
	Mean/Среднее	56.3	58.32	57.86
	Stdev/Стандартное отклонение	2.26	1.29	4.11
SPP (atm) Давление в стояке (атм)	Min/Минимум	110.1	112.92	180.1
	Max/Максимум	72.31	75.04	61.2
	Mean/Среднее	98.69	102.42	158.6
	Stdev/Стандартное отклонение	7.04	6.71	18.48

Data selection

The accuracy of the ANN model is largely dependent on the input parameters chosen for the training phase. The inter-relationships between parameters were looked into in order to choose, which parameter should be used as input data (Fig. 3). A regression coefficient that is closer to 1 indicates a positive correlation between parameters, whereas one that is closer to –1 indicates a negative correlation. Fig. 3 demonstrates that all drilling parameters are appropriate and can be kept when creating an ANN model.

Data normalization

The scales used for various drilling parameters vary greatly, which can have a significant impact on the model accuracy. It is necessary as normalization eliminates geometrical biases against specific data vector dimensions. Every piece of data is handled fairly in this way. As a result, writers normalize the input data using the following equation:

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

where $X_{normalize}$ is the normalized value; X is the input data; $X_{\min}$ is the minimum value of raw variable; $X_{\max}$ is the maximum value of raw variable.

Model development

In this paper, to forecast ROP from drilling parameters, the authors suggest an ANN using a back-propagation training approach (BPNN) and a log-sigmoid activation function [19]. In the Ca Tam oil field, a training data set of 1220 samples from three wells is divided into three sets: 70% of the samples are used to train the network, 15% are used for testing, and 15% are used for validation. The ANN model output value is the ROP value, and its five parameters –WOB, RPM, TQ, FR and SPP – are taken into consideration as input data (Fig. 4).

To identify the mistake, the calculated output from the ANN after a cycle (or iteration) is contrasted with the real output provided in the sample dataset (actual ROP). In order for output neurons and hidden neurons to modify their weights, this error is communicated back to them. The mistake is propagated in both directions repeatedly, either until it falls below a predefined minimum or until the number of loops hits a predetermined threshold (Fig. 5). The RMS difference between the ANN model projected ROP and the actual ROP is a measure of the model accuracy:

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

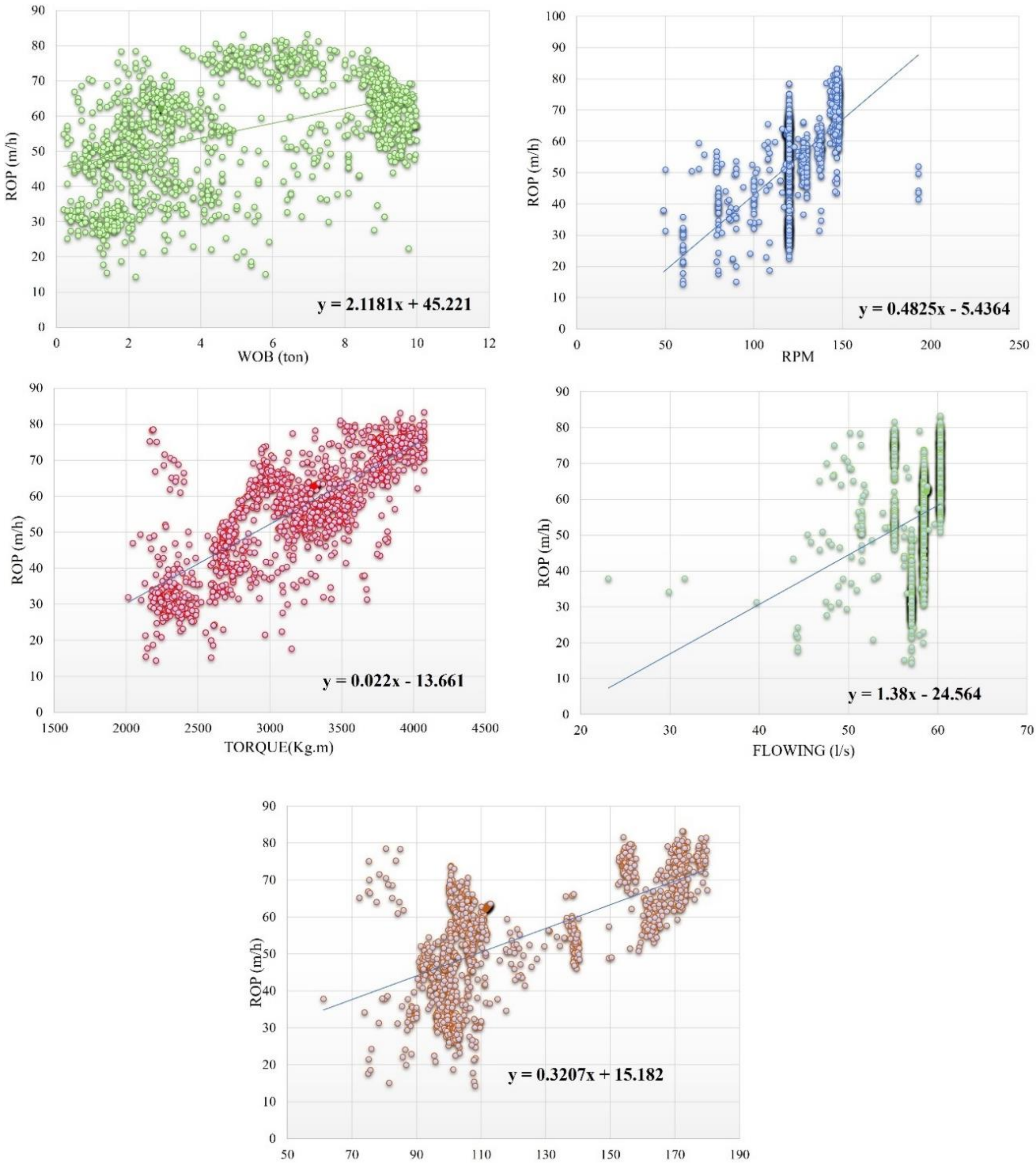


Fig. 3. *Cross-plot between drilling parameters from database*
Рис. 3. *Кросс-плот между параметрами бурения из базы данных*

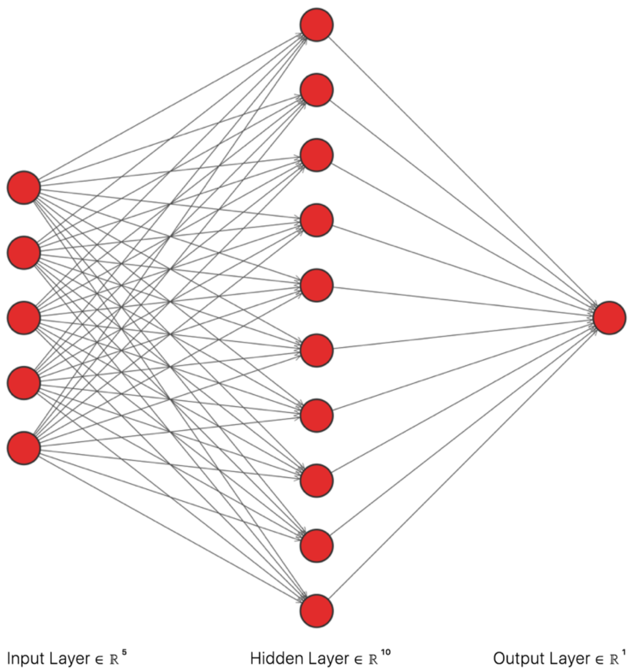


Fig. 4. *ANN model to predict ROP*

Рис. 4. *Модель ИНС для прогнозирования механической скорости бурения*

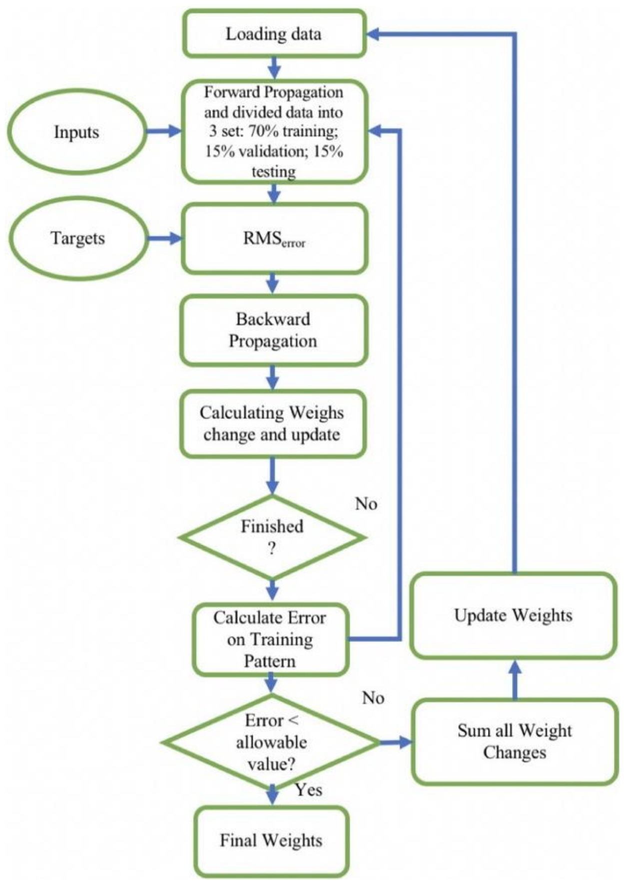


Fig. 5. *ANN model flow chart*

Рис. 5. *Блок-схема модели ИНС*

There is no set formula for calculating the number of neurons in the hidden layer, making it a difficult stage in model construction. In this work, various scenarios with varying numbers of neurons in the hidden layer were run along with tests for their impact on the final prediction in order to establish the ideal number of hidden neurons (Table 3). It is crucial to remember that the hidden layer neuron count should be carefully set because too many neurons there can cause overfitting, which reduces the network generalization.

Table 3. *Result of using different number of neurons in hidden layer*

Таблица 3. *Результат использования разного количества нейронов в скрытом слое*

Number of neural in hidden layer Количество нейронов в скрытом слое	Data training Обучение данных		Data validation Проверки данных		Data test Тестирование	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
5	0.965	0.0026	0.969	0.0024	0.928	0.0041
6	0.957	0.0034	0.949	0.0032	0.922	0.0039
7	0.961	0.0029	0.959	0.0028	0.963	0.0029
8	0.972	0.003	0.962	0.0025	0.961	0.0031
9	0.923	0.0042	0.89	0.0042	0.898	0.0045
10	0.983	0.0017	0.975	0.0021	0.972	0.0026
11	0.981	0.0018	0.9715	0.0023	0.967	0.0027
12	0.98	0.0018	0.962	0.0026	0.972	0.0025
13	0.979	0.0016	0.962	0.0027	0.958	0.0031
14	0.981	0.0018	0.973	0.0021	0.969	0.0028
15	0.976	0.0016	0.966	0.0026	0.944	0.0036

The authors found that a model with 10 neurons in the hidden layer is best for predicting ROP of the investigated wells by comparing the correlation coefficient (R^2) and RMSE between these models (Table 3).

Results and discussions

In order to prove the efficacy of the proposed ANN model, the authors used Multivariate regression method to generate equations to predict ROP from drilling parameters then compare the results of two models (Fig. 6).

$$ROP=a_1\mathrm{WOB}+a_2\mathrm{RPM}+a_3\mathrm{TQ}+a_4\mathrm{FR}+a_5\mathrm{SPP}+b,$$

where a_1, a_2, a_3, a_4, a_5 and b are the empirical parameters, which values are respectively: a_1= –1.15743; a_2=0.178066; a_3=0.019056; a_4=0.351704; a_5=0.064732; b= –50.1241.

When comparing accuracy of two models – ANN and Multivariate Regression, it is observed from Fig. 6 that ROP prediction from the ANN model has better match and follows the changing trend of actual ROP in three wells. Therefore, the authors generated a new equation to determine ROP from the proposed ANN model with biases and weights of each neural (Table 4).

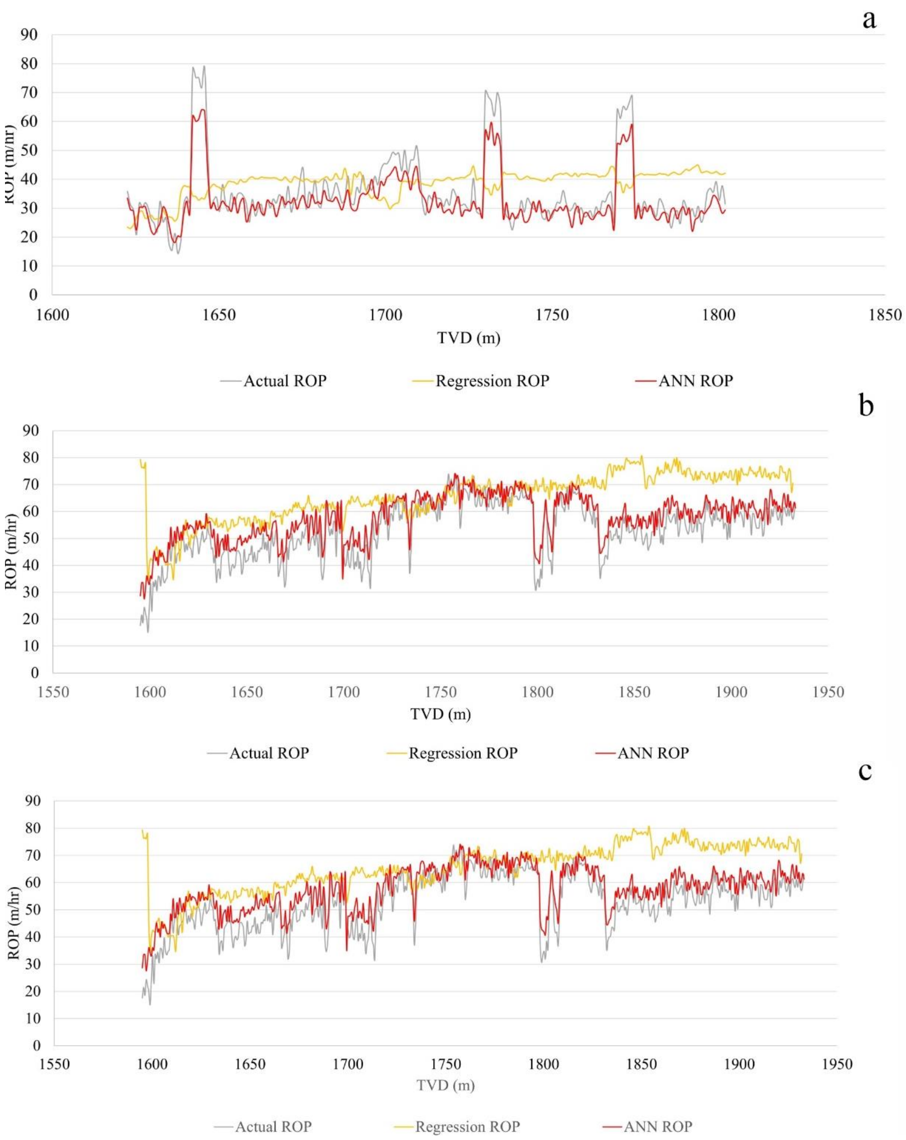


Fig. 6. *Comparing ROP prediction by ANN, multivariate regression and actual ROP in well: a) A; b) B; c) C*

Рис. 6. *Сравнение прогноза механической скорости бурения с помощью ИНС, многомерной регрессии и фактической механической скорости бурения в скважине: a) A; b) B; c) C*

$$ROP = A_2\left(\frac{2}{1+\exp^{\left(-2\left(A_1 X + b_1\right)\right)}} - 1\right) + b_2;$$

$$ROP = \left[\sum_{i=1}^{5} W_{2,i}\left(\frac{2}{1+\exp^{\left(-2\left(\begin{array}{l}WOB.W_{1i,1}+RPM.W_{1i,2}+\\ +TQ.W_{1i,3}+FR.W_{1i,4}+SPP.W_{1i,5}\end{array}\right)\right)}} - 1\right)\right] + b_2,$$

where $A_1(w_1, i)$ is the vector of weight link the input neurons and the hidden neurons; $A_2(w_2, i)$ is the vector of weight link the hidden neurons to the output neurons; b_1 is the bias vector for input layer; b_2 is the bias vector for output layer; X is the input data.

Determination of WOB optimal value

In this section, the WOB is optimized to achieve the best ROP for a particular formation with the aid of neural network model and brute force algorithm. As an example, the optimization is achieved by splitting formation in database, which spans from 1595 to 1933 m into 7 sections of each 50 m. The minimum and the maximum of WOB for every division is determined and used as reference limits. The brute force algorithm evaluates all the possible value of WOB between the limits (from 1 to 10 tons) and the ROP in each scenario is then projected using the suggested ANN model. The optimal WOB is determined based on two criteria: the mean value and standard deviation of the predicted ROP because the objective of this study is not only to find the optimal value of WOB to achieve ROP max, but also to maintain a stable ROP value throughout the drilling interval (Fig. 7).

Table 4. *ANN weights and layers bias*

Таблица 4. *Веса ИНС и смещение слоев*

Hidden layer neuron Нейрон скрытого слоя	Weight from the input neurons to the hidden neuron (W_1) Вес от входных нейронов к скрытому нейрону (W_1)					Bias of hidden layer (b_1) Смещение скрытого слоя (b_1)	Bias of outputlayer (b_2) Смещение выходного слоя (b_2)
1	0.716160	–0.086680	1.011533	–0.137673	–2.989703	–0.805459	0.638699
2	1.391110	0.549202	0.869311	–0.857077	–1.981862	–0.212758	
3	0.757028	0.081891	0.549014	2.223974	–0.353078	–0.970811	
4	–0.107131	0.549205	–2.865236	–0.081505	2.628079	–1.009392	
5	0.440916	–1.213588	–0.707841	0.839954	–2.058846	–0.734020	
6	–0.962696	0.885008	1.359589	–0.459556	0.102182	–0.614032	
7	3.071694	–1.486080	0.018324	1.449299	–1.835713	2.467094	
8	1.336814	1.212675	–6.615816	–2.594175	0.389015	1.523646	
9	0.528138	–1.219627	1.560386	1.797248	–0.443743	1.319486	
10	0.476239	–1.711590	–3.138083	1.854319	–3.359954	2.284501	

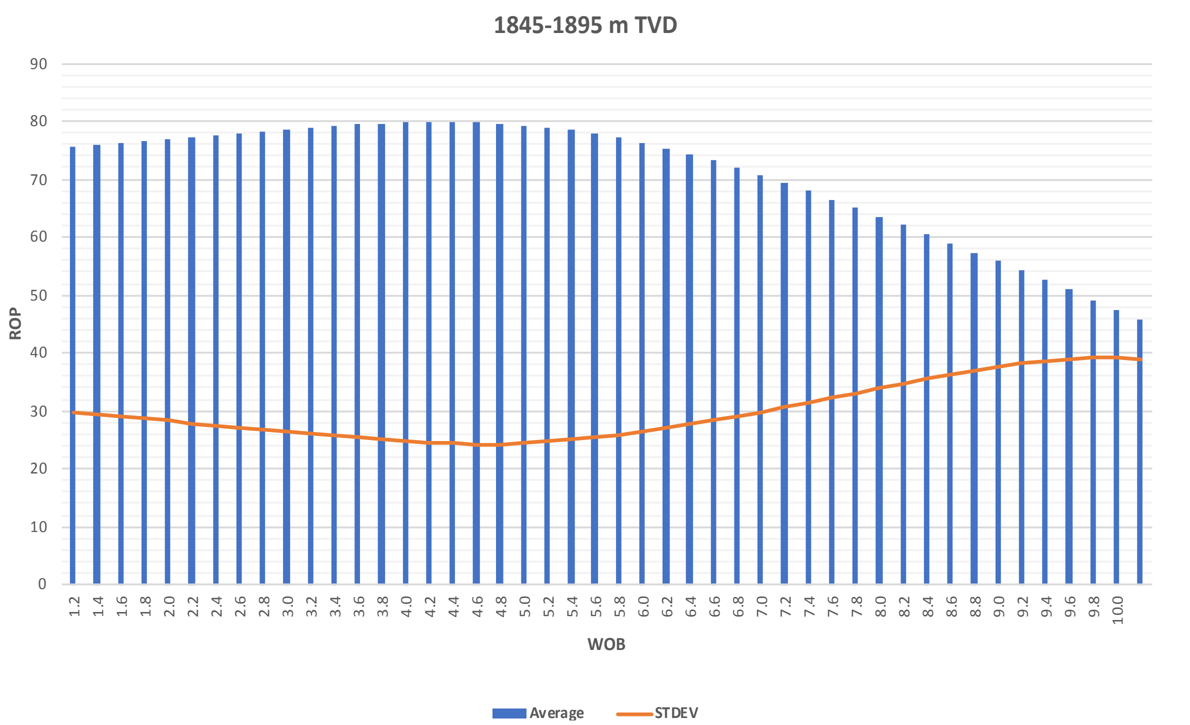


Fig. 7. *Example of ROP prediction by ANN when changing WOB value for the interval depth from 1845 to 1895 m*

Рис. 7. *Пример прогнозирования механической скорости бурения по ИНС при изменении значения нагрузки на долото для интервала глубины с 1845 до 1895 м*

It can be seen from Fig. 7 that:

- When WOB increases from 1.2 to 4.4 tons, ROP has an upward trend. Keep increasing WOB, ROP is not only enhanced but also has a decreased trend. It is consistent with the result of previous studies when indentation depth increases, but hole cleaning is not good enough [20–22]. Furthermore, it leads to increasing cost of destruction energy and bit life reduction.
- Furthermore, when applying WOB value of 4.4 tons, the standard deviation was just 24.25 m/hr, which means the predicted ROP, in this case, was relatively stable through interval depth. Comparing to the real data, it is seen that there is also an increase in the mean value of ROP (24.48%). Therefore, 4.4 tons can be considered as the optimal value of WOB.

Following the same process for other sections, we obtain the following optimal WOB values as it is shown in Table 5.

Table 5 shows that ROP improves significantly (from 14 to 26%) when the optimal WOB is applied to the prediction model. Especially at the two-section depth S6 and S7, the recommended optimal WOB is even smaller than the actual WOB, although predicted ROP rises by 24.48 and 14.54%, respectively. This demonstrates that boosting WOB is not always a good method to increase drilling efficiency.

Table 5. *Optimal WOB for drilling intervals*

Таблица 5. *Оптимальная нагрузка на долото для интервалов бурения*

Drilling interval (TVD) m Интервал бурения (м)	Optimal WOB (tons) Оптимизация нагрузки на долото (т)	Actual WOB (average) (tons) Фактическая нагрузка на долото (сред.) (т)	Predicted ROP when applying optimal WOB (m/hr) Прогнозируемая скорость бурения при оптимизации нагрузки на долото (м/ч)	Actual ROP (m/hr) Фактическая механическая скорость бурения (м/ч)	ROP change Изменение скорости бурения (%)
S1: 1595–1645	4	4.9	52.11	44.55	16.97
S2: 1645–1695	3.8	5.1	60.63	47.98	26.37
S3: 1695–1745	3.6	5.1	66.36	55.1	20.44
S4: 1745–1795	3.6	4.72	71.19	58.29	22.13
S5: 1795–1845	3.4	4.73	75.12	63.82	17.71
S6: 1845–1895	4.4	4.22	79.78	64.09	24.48
S7: 1895–1933	4	3.69	66.47	58.03	14.54

Conclusions

This paper demonstrates the practical use of ANN to predict ROP from drilling parameters of wells in Ca Tam oil field, Vietnam. The ANN model using back-propagation training algorithm with 10 neurons in hidden layer shows the ability to predict ROP accurately.

The optimal value of WOB, when drilling through Miocene stratigraphy for three study wells in Ca Tam oil field, is from 3.6 to 4.4 tons (Table 5). This result could be applied to other wells in the research region.

Furthermore, this method can be applied similarly for the optimization of other drilling parameters such as RPM, FR, MW, etc.

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

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