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PENETRATION RATE PREDICTION FOR DRILLING WELLS IN THE OLIGOCENE FORMATION

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ABSTRACT

The main role of drilling optimization is a decrease in the drilling cost and non-productive time (NPT) for drilling operations. The penetration rate directly influences the overall cost and cost per foot of drilling operation. Thus, the penetration rate prediction and optimization for drilling wells is one of the most crucial parameters to enhance drilling efficiency. Normally, physics-based ROP modeling is widely used to predict bit response or investigate ROP by using nearby offset data. Due to the complexity and nonlinear of ROP, and the confidence level of ROP models with low R squares, data-driven modeling such as machine learning (ML) has become a more attractive study. This paper has been developed on ROP models using artificial neural network (ANN) and compares the results of physics-based ROP models such as the Maurer model, Bingham model, Warren model for perfect cleaning model, Warren model for imperfect cleaning model, and multiple regression based on the significant level of correlation coefficients of R square from models. Drilling Oligocene formations on 8-1/2'' hole sections have been collected from six drilled wells in the continental shelf of offshore Vietnam. The ROP prediction results were obtained from the ANN model compared with physics-based models. This comparison has shown that the predictive ROP of the power ANN model with an R square confidence level is higher than that of physics-based models.

Keywords: penetration rate, physics-based ROP model, ANN ROP model, R squared, oligocene formation.

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1. INTRODUCTION

One of the important aims of drilling optimization is a decrease in the drilling time, keeping the drilling issues as low as possible, saving the drilling costs, and increasing drilling performance. Drilling optimization activity is highly incorporated with the maximum rate of penetration (ROP). According to the field experience, there are a variety of methods to decrease the drilling cost of the nearby wells. One method that has been discussed is the optimization of drilling parameters to determine the maximum ROP for each bit run. The rate of penetration (ROP) enhances the penetration rate for rotary drilling but breaks formation rock (Bourgoyne *et al.* 1986). It is developed for investigating the time to drill one foot of well depth. ROP depends on a variety of factors such as mud properties, and mechanical and hydraulic drilling parameters (Bourgoyne and Young 1974). These factors can be divided into two separate parts such as controllable and uncontrollable factors. The controllable drilling parameters consist of the operational drilling parameters that can be changed by drilling activity from the surface, such as revolutions per minute (RPM), weight on bit (WOB), flow rate (Q), and standpipe pressure (SPP). By contrast, the uncontrollable factors can not be changed then because of technological or formation factors such as rock strength pore pressure, mud weight, and wellbore trajectory (Youcefi *et al.* 2020). Among all these factors, RPM, WOB, and Q are known through controllable operational drilling parameters because they can affect significant ROP (Edalatkhah *et al.* 2010). The ROP model has been primarily focused on my studies and companies in industrial petroleum drilling because it is directly affected by the drilling cost. In the previous literature, several researchers studied the influence of operating drilling parameters on the ROP. Initially, they correlated ROP models based on experience results. Graham and Muench (1959) performed the first implementation optimizing of the operating drilling parameters. They have correlated an empirical mathematical expression for the bit life and ROP as a function of WOB, depth, and RPM. Maurer (1962) developed an equation for roller-cone bits for predicting ROR under the constraint of assuming a cleaned bottom hole perfectly. Galle *et al.* (1963) performed a method through a series of charts and diagrams to find the best incorporation of WOB and RPM for roller cone bits. Bingham (1965) proposed a simple and experimental model which is a modification of the Maurer model; it is limited to low WOB and RPM; however, it does not consider the depth of drilling. Teale (1965) developed the mechanical specific energy (MSE) model which investigates the amount of energy required to move a rock volume, and the study demonstrated that the valuable MSE is close to the rock uniaxial compressive strength (UCS) in ps. Eckel (1967) developed several experimental microbits, which showed that decreasing the overbalance pressure can improve the efficiency of the formation drillability by increasing ROP. Bourgoyne and Young (1974) performed one of the most crucial drilling optimization studies and developed an empirical rate of penetration under the constraint of several drilling parameters. This model is widely applied in industrial drilling petroleum and it is considered the best method to optimize drilling parameters in real time (Eren and Ozbayoglu 2011). The ROP model expresses the influence of various drilling parameters on ROP, and they presented the multiple regression analysis to determine eight unknowns from eight functions related to drilling parameters using well drilling datasets. Warren (1987) performed a perfect cleaning ROP model for soft formation, and this model prefers ROP to the WOB, RPM, UCS, and bit size. Al-Betairi *et al.* (1988) developed an ROP model under the constraint of controllable and uncontrollable drilling variables for determining the optimal penetration rate performed by the correlational coefficients determined by multiple regression and analyzed the effect of each drilling parameter on ROP. Maidla and Ohara (1991) introduced optimization software for roller-cone bits to select the best drilling parameters such as WOB, RPM, bit type, and bit wearing with the lowest drilling costs. The study concluded that the drilling model performances are affected by the quality of the data used to determine the model's coefficient. Hareland and Rampersad (1994) presented an ROP model for drag bits that correlate with UCS, WOB, RPM, bit geometry, and W_f. Motahhari et al. (2010) developed a PDC ROP model that builds under the constraint of the wear function and confined compressive strength (CCS) instead of UCS besides RPM, WOB, and bit size. The physics-based ROP models discussed above use empirical coefficients, which are highly dependent on the lithology and continuously varied due to calibration, such that they constrain their functional forms. These ROP models have been performed with low R square confidence level and then applied ROP model for the nearby wells with the results of ROP very far in comparison with actual ROP. Hareland *et al*. (2010) introduced a simple ROP model for applying roller cone bits and used laboratory data to evaluate the UCS. Alum and Egbon (2011) applied the Bourgoyne and Young ROP model in a series of studies, and the results expressed that the equivalent circulation density has a great influence on ROP because of the annular pressure losses; as a result, they proposed an analytical model to estimate ROP. Jahanbakhshi *et al.* (2012) used several drilling parameters to predict ROP, and the study summarized the use of multilayer perceptron in the data-driven model. This work starts by investigating the predictable ROP models such as Maurrer, Bingham, and Warren Regression, and then comparing them with the actual ROP on the graphs through the R square confidence level. Based on the lowest R square confidence levels of these predicted ROP models, the study proposed to develop ROP model for six wells in a large area of the Oligocene formation with a drilling hole section of 8-1/2'' using ANN and then compare ROP prediction with the actual ROP, and compare with ROP prediction of other ROP models. The result of ROP model demonstrated that by applying ANN method to develop ROP model, which performed a good result in ROP prediction with the highest R square confident level.

2. PENETRATION RATE MODEL

In the previous literature, there are a wide variety of ROP models that have been developed in the last decade as we mentioned in the previous section. In this paper, we used only: Maurer, Bingham, Warren model, the proposal penetration rate model has been built based on multiple regression analysis and artificial neural network (ANN), and then comparison correlation coefficients among these models.

2.1 Maurer Model

In 1962, Maurer developed ROP, and it can be modeled as a function of WOB, RPM, drillability strength of rock (UCS), bit diameter (D_b), and drillability constant (K), the ROP model is developed for pefect cleaning condition where all cutting has been removed, and Maurer's model is expressed by Eq.1 as follows:

$$\mathrm{ROP} = \mathrm{K}\left(\frac{\mathrm{RPM}\times\mathrm{WOB}^2}{\mathrm{D_b^2}\times\mathrm{UCS}^2}\right) \tag{1}$$

2.2 Bingham Model

In 1965, Bingham proposed a ROP model under the constraint of parameters such as rotary speed, weight of the bit, and bit diameter. However, ROP model is known with the constraint of low WOB and RPM (Niknam, 2008). Bingham's ROP model is expressed by Eq.(2) as follows:

$$\mathrm{ROP} = \alpha \times \mathrm{RPM} \times \left(\frac{\mathrm{WOB}}{\mathrm{D_b}}\right)^{\beta} \tag{2}$$

$$\beta = \frac{\log\left(\frac{\mathrm{ROP}}{60\mathrm{RPM}}\right)}{\log\left(\frac{12\mathrm{WOB}}{1000\times D_b}\right)}$$

2.3 Warren Model for Perfect-Cleaning Model

In 1981, Warren developed ROP model for tricone bits for soft formation bits. The ROP model modeled and related under the constraint of parameters such as rock strength, WOB, rotary speed (RPM), and bit type and bit size. Warren's ROP model expressed by Eq.(3) for the perfect cleaning model as follows :

$$\mathrm{ROP} = \frac{1}{a\times\frac{\mathrm{UCS}^2\times\mathrm{D_b^2}}{\mathrm{RPM}\times\mathrm{WOB}^2}+c\times\frac{1}{\mathrm{RPM}\times\mathrm{D_b}}} \tag{3}$$

Where the constants a and c are the bit constants in the penetration rate model. The first term of the model expresses the maximum rate in which the rock is crushed into cuttings by the bit. The second term of the model adjusts the model to consider the distribution of the applied WOB with more teeth as the WOB is increased and the tooth penetrates into the formation rock (Rastegar *et al*., 2008; Warren, 1987). With low WOB values for a given formation rock, ROP increases at an increasing rate as WOB is increased. ROP overcomes the inflection point and starts to increase at a decreasing rate (Warren, 1987). This is due to the fact that the first term of ROP model is predominant at low ROP values and the second term is predominant at higher ROP values.

2.4 Warren Model for Imperfect-Cleaning Model

Warren developed the initial perfect cleaning model to simplify the complex modelling, that is, a response for developing a good predictable ROP model. The initial perfect cleaning model has been modified in 1987 by Warren with an account for more realistic, imperfect cleaning drilling conditions. The idea of drilling conditions are steady state, the rate of cuttings removed from the bottom hole of the bits is equal to the rate at which new cuttings are formed. The ROP model is therefore related to the cutting generation process, the cutting removal process, or a combination of both (Warren, 1987). Warren, 1987, applied dimensional analysis to prevent variables consisting of the modified impact force (F_{jm}) and mud properties. These were correlated with the perfect cleaning model to account for cutting removal to develop an impact cleaning model for ROP. ROP model with the constraint of impact cleaning is expressed by Eq.(4) as follows:

$$\mathrm{ROP} = \left(a \times \frac{\mathrm{UCS}^2 \times D_b^2}{\mathrm{RPM} \times \mathrm{WOB}^2} + b \times \frac{1}{\mathrm{RPM} \times D_b} + c \times \frac{D_b \times \rho\mu}{F_{jm}}\right)^{-1} \quad (4)$$

Where the constants of a, b, c are the bit constants in the penetration rate model. The modified impact force (F_{jm}) is expressed as follows:

$$F_{jm} = (1 - A_v^{-0.122}) F_j \quad (5)$$

Where the ratio of jet velocity to determine (A_v) and (F_j) are given in field units as follows:

$$F_j = 0.000516 \rho q v_n \quad (6)$$

$$A_v = \frac{v_n}{v_f} = \frac{0.15 D_b^2}{3 d_n^2} \quad (7)$$

Where, A_v is the annular velocity fraction, ρ is the mud weight, ppg, F_j is the impact force, lbf, D_b is the bit diameter, inch, and d_n is the nozzle diameter, inch, inch, and μ is the viscosity of drilling mud, cp.

Rock strength has been firstly calculated. In order to do this, the following assumption is made. Accoring to Teale's compressive strength at perfect efficiency. Dupriest and Koederitz, 2005 thought the peak bit efficiencies are ranged between 30-40%, therefore thought the mechanical efficiencies were 35%, and the rock compressive strength (UCS) is therefore assumed to equal 35% of the mechanic specific energy (MSE) value. Cherif, 2012, developed, the mechanical efficiency ranged between 26-64% instead of 35%. For the directional drilling, the MSE values may become several times the confined compressive strength (CCS) formation due to the torsional friction of the drilling string. Amadi and Iyalla, 2012 thought the MSE were 12.5%. Thus, the mechanical efficiency is not only bit specific but also formation specific. Warren's ROP model in Eq.(3) can be expressed by Eq.(8) as follows

$$\left(\frac{\mathrm{UCS}^2 \times D_b^2}{\mathrm{RPM} \times \mathrm{WOB}^2}\mathrm{ROP}\right) a + \left(\frac{1}{\mathrm{RPM} \times D_b}\mathrm{ROP}\right) b + \left(\frac{D_b \rho\mu}{F_{jm}}\mathrm{ROP}\right) c = 1 \quad (8)$$

Eq. (8) can be expressed in matrix form as follows : Ax=B

$$\begin{pmatrix} x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ \dots & \dots & \dots \\ x_n & y_n & z_n \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} \quad (9)$$

Where x, y, z are the first, the second, and the third term, respectively. Warren ROP model can then be calculated using the following equaiton:

$$\text{Warren ROP} = \frac{\mathrm{ROP}}{\left(\frac{\mathrm{UCS}^2 \times D_b^2}{\mathrm{RPM} \times \mathrm{WOB}^2}\mathrm{ROP}\right) a + \left(\frac{1}{\mathrm{RPM} \times D_b}\mathrm{ROP}\right) b + \left(\frac{D_b \rho\mu}{F_{jm}}\mathrm{ROP}\right) c} \quad (10)$$

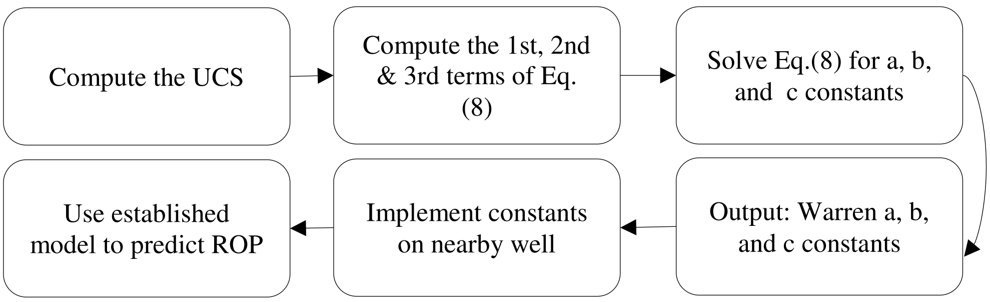

Figure-1. Warren model process flowchart.

2.5 Multiple Regression

Regression analysis is a method for investigating the relationships between one dependent variable and two or more independent variables. This data analysis technique is useful while comparing a quantitative variable to other variables. The multivariate analysis describes an observation factor by having several variables and taking into consideration all changes in properties that may happen simultaneously. The model assumes that the relationship between the dependent variable Y_i and the vector of regressor x_{ki} is linear. The following represents a multiple linear regression equation (Pedhazur, 1982):

$$Y = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \beta_3 x_{3i} + \dots + \beta_k x_{ki} \quad (11)$$

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Where β_0 is the intercept, β_i are slopes or coefficients, and (i) is the number of observations. The simple linear regression model is used to find the straight line that best fits the data, while the multiple linear regression is used to find the best plan that fits the data. The penetration rate is related to the constraint of different variables. Based on Eq. (11), the ROP would be referred to as the factor of observation Y in this study. The Y value is based in its turn on several properties simultaneously, in addition to the drilling operational factors. Relevant drilling parameters make up the regression variables. By processing the regression data analysis, the work will end up with the values of the coefficients. By having the values of the coefficients, the work will be able to estimate the Y value as predicted ROP model. This analysis is achieved for six wells to drill in the Oligocene formation in the White Tiger field offshore Viet Nam, with the hole section of 8.5", and the other well will examine to validate the ROP model. The data supported in the multiple regression analysis includes WOB, torque, RPM, jet impact force of bit nozzles, and the interaction between these variables, together with the observation factor ROP. The regression data analysis is first performed. As described above, the Y range represents the ROP, while the (x) range is the remaining data. The depth on the other hand, is only included as a reference and is not included in the analysis. The coefficients, which is the area of interest, are then provided by the analysis. The intercept value is represented by the initial value of coefficients (β_0). The other coefficients such as β_1, β_2, β_3, β_5,.., β_7, are then multiplied according to their order with the regression variables such as x_1, x_2, x_3, x_4, and these interaction variables. Eq. (12) is used to predict ROP model and is given by:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_1 x_2 + \beta_6 x_1 x_3 + \beta_7 x_2 x_3 \qquad (12)$$

Thí equation can be applied for multiple regression on eight wells in terms of ROP and other drilling parameters as follows:

$$\mathrm{ROP} = \beta_0 + \beta_1 \mathrm{F_j} + \beta_2 \mathrm{WOB} + \beta_3 \mathrm{RPM} + \beta_4 \mathrm{T} + \beta_5 \mathrm{F_j} \times \mathrm{WOB} + \beta_6 \mathrm{F_j} \times \mathrm{RPM} + \beta_7 \mathrm{WOB} \times \mathrm{RPM} \qquad (13)$$

The multiple regression procedure shown in Figure-1 is applied to both the first phase and the second phase. In the first phase, the multiple regression procedure is applied to the Oligocene formation of the reference wells such as W1, W2, W3, W4, W5. W6, providing six coefficients such as β_0, β1, β_2, β_3, β_4, β_5, β_6, β_7. By using Eq. (13), the coefficients are then implemented to the wells such as W1, W2, W3, W4, W5. W6 in order to predict ROP model, and W7 is nearby these wells, which is tested with these models. The coefficients are then tested with other nearby wells. By using field data of six wells with hole section 8-1/2'' in the Oligocene formation for each drilled meter indicated penetration rate (ROP), weight of the bit (WOB), rotary per minute (RPM), jet impact force (F_j), and torque (T) of the drilling string, the correlation between predicted penetration rate with independent variables, and the interaction variables with Correlation coefficient of R square of 59.44% has been shown in the model as follows:

$$\mathrm{ROP} = -146.050 + 0.238\mathrm{F_j} - 0.25\mathrm{WOB} + 1.09\mathrm{RPM} + 0.00474\mathrm{T} - 0.0125\mathrm{F_j} \times \mathrm{WOB} - 0.00166\beta_6 \mathrm{F_j} \times \mathrm{RPM} + 0.066\mathrm{WOB} \times \mathrm{RPM} \qquad (14)$$

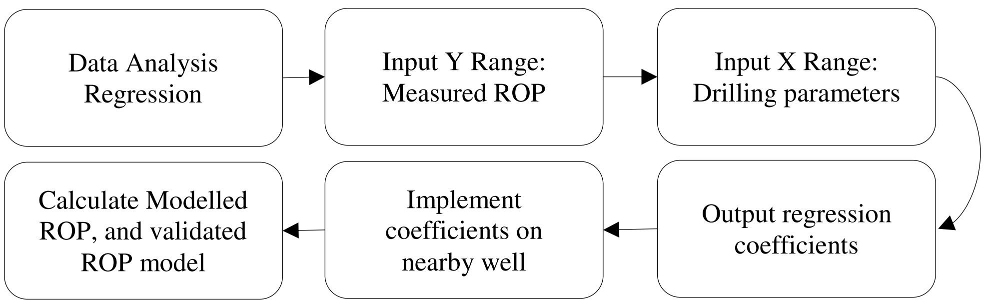

Figure-2. Multiple regression process for drilling wells.

3. ARTIFICIAL NEURAL NETWORKS

ANNs are based on neurons that exist inside the human brain. ANN workflow structure, like a neural system, has a network of connections with many processing neurons. Each neuron consists of n inputs to produce m outputs given by a function called functional activation.

$$\mathrm{m} = \mathrm{f}\left(\sum_{i=1}^{n} \mathrm{W_i x_i} + \mathrm{b}\right) \qquad (15)$$

$$\mathrm{Tansig(x)} = \frac{1}{1+e^{-2x}} - 1 \qquad (16)$$

$$\mathrm{Logsig(x)} = \frac{1}{1+e^{-x}} \qquad (17)$$

$$\mathrm{Purelin(x)} = \mathrm{x} \qquad (18)$$

Where x_i is the i-th input, w_i is the weight associated with each input variable, b is the bias, and f is the activation function.

Every input is associated with its weight and the output is calculated as the weighted sum of its input parameters. The commonly used activation functions are tag-sigmoid, log-sigmoid, and pure linear, etc., many neurons combine to form layers, and these layers combine to form a network. The layers are divided into three types: input layer, hidden layer, and output layer. The number of neurons and layers depends on the complexity of the problem under investigation. For the training of the network, the back-propagation algorithm is the most suitable (Tewari and Dwivedi, 2017). The data is processed through the input layer, then the hidden layer, and finally the output layer.

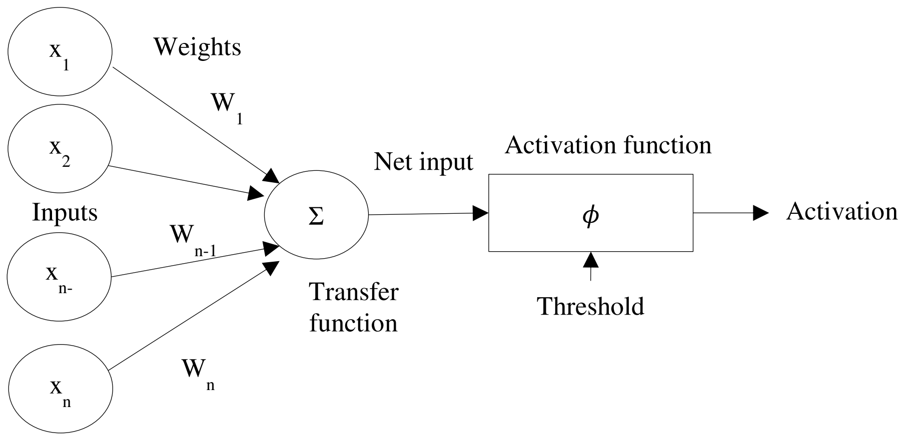

Figure-3. Schematic of a neuron (Tewari and Dwivedi, 2017).

4. DATA DESCRIPTION

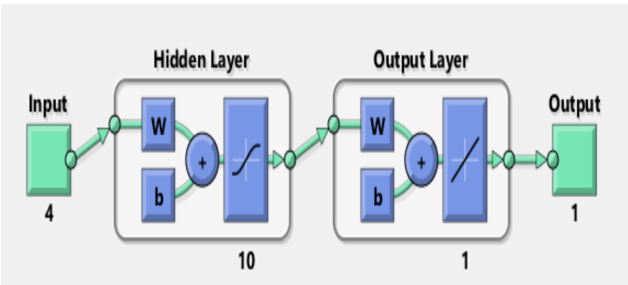

Figure-4. Hidden layer artificial neural network model is ten neurons.

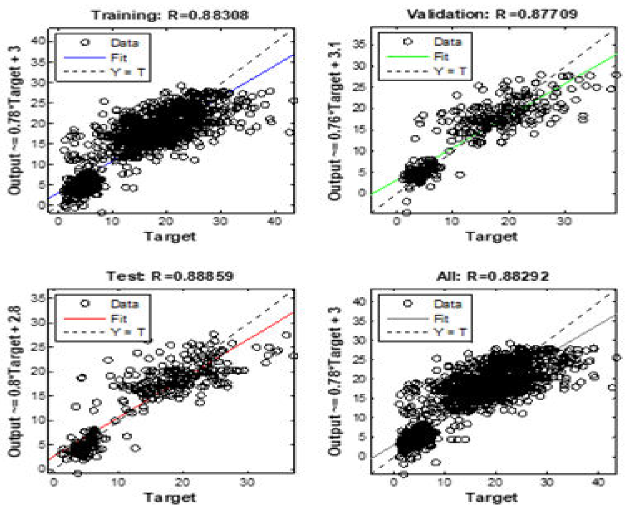

Figure-5. Regression of neuron network.

The artificial neural network's model is built and developed on the actual drilling data set for a hole section of 8-1/2'' in the Oligocene formation of the White Tiger field offshore Viet Nam including six drilling wells such as W1, W2, W3, W4, W5. W6. All sample wells have been covered to drills with the objective Oligocene formation. The network training dataset consists of 1733 data points from six wells, and 372 data points for validation and 372 data points for testing. They are randomly assigned for network training, validation, and testing. The dataset is scaled 70% for network training, 15% for validation, and the remaining 15% for the testing phase. There are four drilling parameters such as weight on bit (WOB), rotary per speed (RPM), jet impact force (F_j), and torque of drilling string, on the response of the penetration rate (ROP).

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Table-1. The operating parameters for drilling section 8-1/2'' in the Oligocene formation.

No	Depth, m, in	Depth, m, out	WOB, tons	RPM	Q, l/sec	SPP, atm	MW, sg
W1	3608	4043	1-3	110-130	35-36	164-194	1.35-1.43
W2	3856	4219	5-8	100-130	29-33	203-220	1.42-1.48
W3	3538	3986	5-8	110-130	30-34	201-220	1.46-1.49
W4	3639	3712	3-4	119	34	183	1.46-1.47
W5	3426	3927	2-8	130	30	209	1.55
W6	3573	3905	8-10	140	38	194-200	1.35

Firstly, the data is normalized between -1 and +1 with the average value set up to 0 to improve the accuracy of the model according to the following conversion formula (Ashrafi *et al.,* 2019).

$$x_i^n = 2 \times \frac{x_i - x_{min}}{x_{max} - x_{min}} - 1 \quad (15)$$

Where x_i is the actual value of the parameter, x_{min} and x_{max} are the minimum and maximum values of the parameter. Then, the analysis of bias values is also performed to determine and remove unwanted noise data points. In this study, in order to evaluate ROP, ANN model was applied with four input drilling parameters such as weight of the bit (WOB), rotary per minute (PRM), momen (T), and jet impact force (F_j), and the predicted ROP are the only output parameters for different well samples. The learning and generalization ability of the ANN model is investigated based on the correlation coefficient R squared (R^2). For regression analysis, the R-squared metric are a preferable option to compare the models. It is nearly close to 1, the ROP model is considered accurate:

$$R^2 = 1 - \frac{\sum_i^n (y_i - \hat{y_i})^2}{\sum_i^n (y_i - \bar{y_i})^2} \quad (16)$$

Where n is the number of data samples, y_i is the actual ouput, and $\hat{y_i}$ is the predicted output

5. RESULTS AND DISCUSSIONS

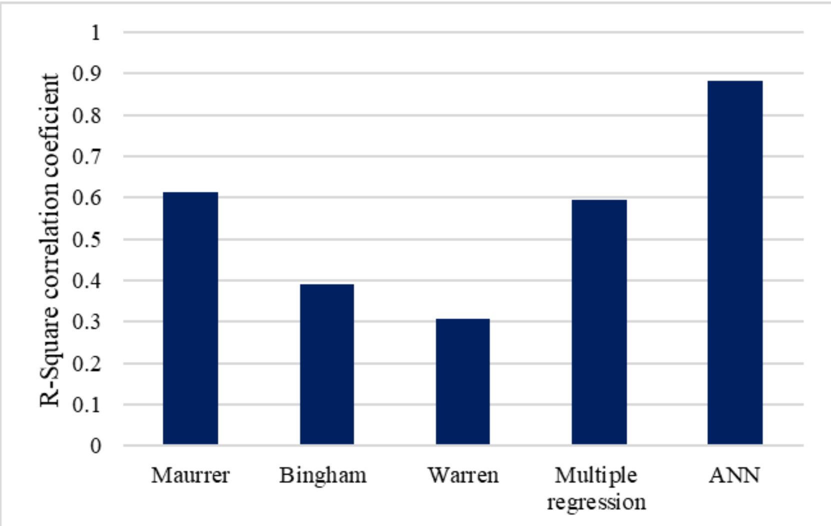

Figure-6. Comparison of correlation coefficients among different ROP models.

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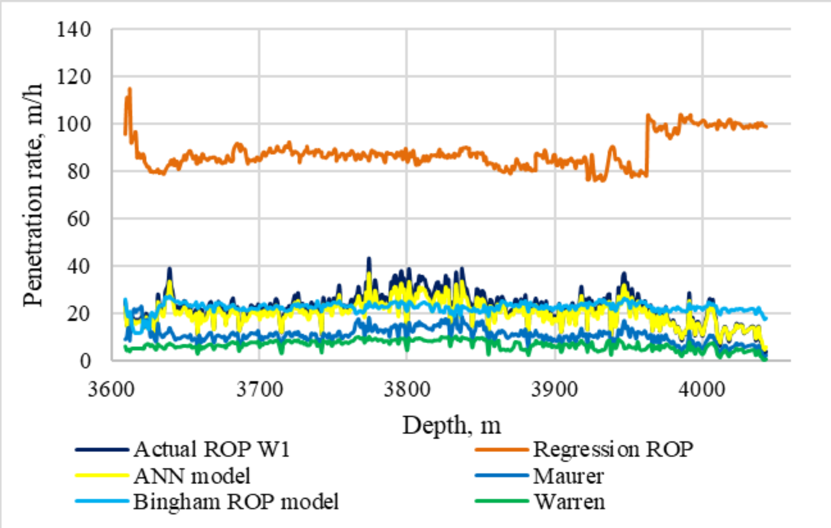

Figure-7. Comparison between predicted ROP models and actual ROP according to W1.

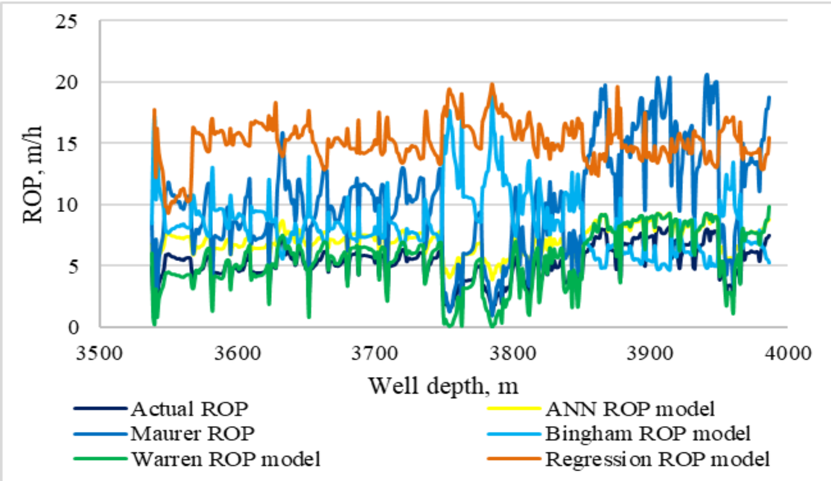

Figure-8. Comparison between predicted ROP models and actual ROP according to W2.

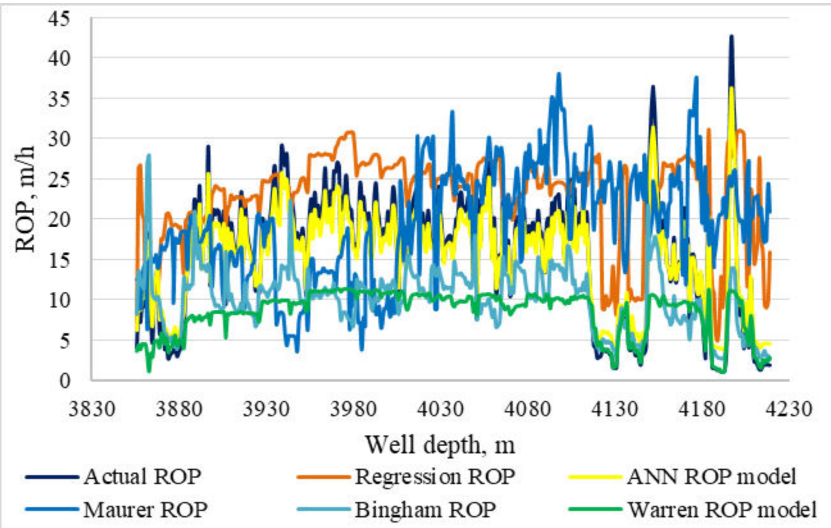

Figure-9. Comparison between predicted ROP models and actual ROP according to W3.

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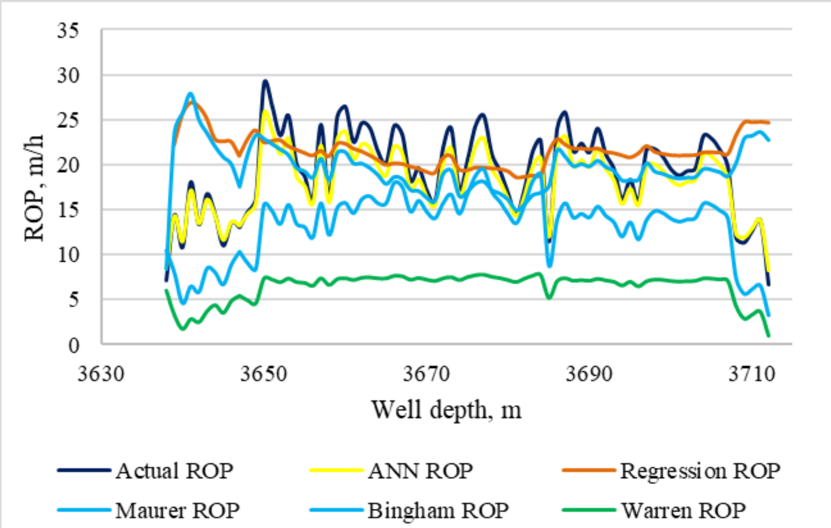

Figure-10. Comparison between predicted ROP models and actual ROP according to W4.

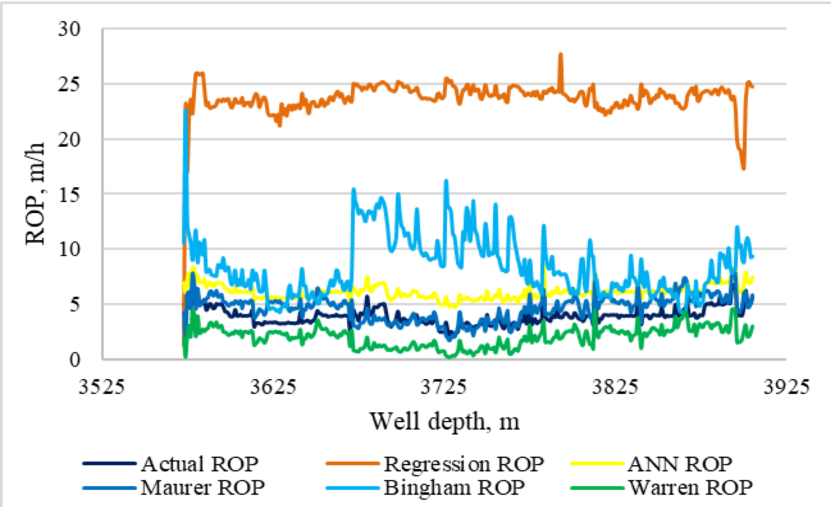

Figure-11. Comparison between predicted ROP models and actual ROP according to W5.

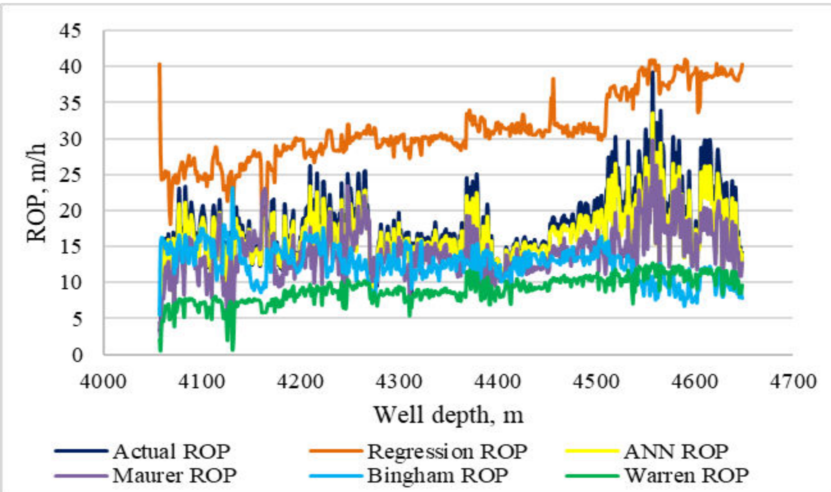

Figure-12. Comparison between predicted ROP models and actual ROP according to W6.

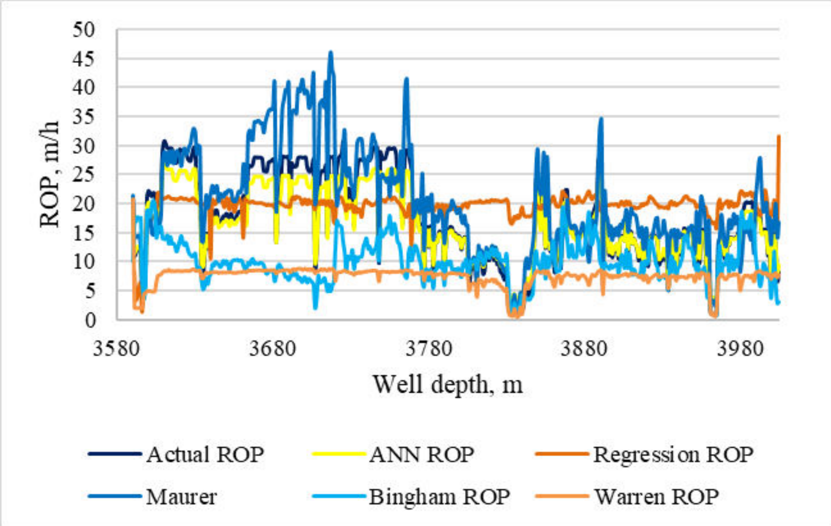

Figure-13. Comparison between predicted ROP models and actual ROP according to the nearby well.

Figure-6 shows that the correlation coefficient of the ROP regression model reaches R^2 = 59.44%, which proves that the drilling parameters of the predicted ROP model have been explained by approximately 60%, and nearly 40% of the drilling parameters are not explained. Thus, the ROP prediction model by the regression method has not been significant. The predicted ROP model by Maurrer has a correlation coefficient of R^2=61.2%, which means that about 61.2% of the drilling parameters in the ROP model are explained, and about 38.9% of the drilling parameters in the model are not yet explained. Thus, the ROP prediction model according to Maurrer is not satisfied. The predicted ROP, models by Bingham and Warren have the lowest correlation coefficient at 39% and 30.7%, respectively. ANN model has the highest correlation coefficient, nearly 90%, and all parameters in the model are explained. Based on these graphs from Figure-7 to Figure-12, these figures have been demonstrated that the ANN model was predicted ROP nearest to the actual ROP in the field in comparison with others predicting ROP models such as Maurrer, Bingham, Warren, and Regression. This is because the correlation coefficient of R squared (R^2) of 0.8882 by ANN is higher than that of the correlation coefficient from the other ROP models such as Maurer, Bingham predicted, Warren, and ROP by regression.

CONCLUSIONS

A new ROP model for predicting ROP while drilling these wells in the Oligocene formation of the White Tiger field had been developed based on the highest correlation coefficient of artificial neural networks. The following were observed out of this study:

- The ROP was obtained from ANN model for predicting ROP, which provides the highest correlation coefficient at R squared (R^2) in comparison with these correlation coefficients obtained from these physic-based ROP models such as Maurer, Bingham, Warren, Regression.
- The developed ROP model is based on the surface measurable of operating drilling parameters such as torque of drilling string (T), weigh on the bit (WOB), rotary per minute (RPM), impact force of bit nozzles (F_j); which allows to correlate the ROP in real-time is possible.
- The ANN model was the predicted using the ROP for the training dataset of 1733 data points from six wells to drill the Oligocene formation with a hole section of 8-1/2''with R squared of 0.88308.
- The ANN model was the predicted using the ROP for the testing dataset of 372 data points with R-squared 0.88859.
- In comparison with the actual ROP of the nearby well in the Oligocene formation on hole section 8-1/2'', the ANN model is nearly to the actual ROP. Thus, the ANN model is more accurate than other physic-based other ROP models.

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