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Prediction of Rate of Penetration for wells at Nam Con Son basin using Artificial Neural Networks models

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Abstract

The rate of penetration (ROP) is an important parameter that affects the success of a drilling operation. In this paper, the research approach is based on different artificial neural network (ANN) models to predict ROP for oil and gas wells in Nam Con Son basin. The first is the process of collecting and evaluating drilling parameters as input data of the model. Next is to find the network model capable of predicting ROP most accurately. After that, the study will evaluate the number of input parameters of the network model. The ROP prediction results obtained from different ANN models are also compared with traditional models such as the Bingham model, Bourgoyne & Young model. These results have shown the competitiveness of the ANN model and its high applicability to actual drilling operations.

1 Introduction

To improve drilling efficiency, drilling engineers must consider drilling parameters that can affect the rate of penetration, they need to control them to improve drilling efficiency and the combine of predictive model with the suitable algorithm has great potential.

Efficient prediction of ROP becomes imperative to improve drilling efficiency. There are many traditional direct and indirect methods for the ROP prediction and optimization, but those mainly based on correlations between various parameters affecting ROP (Yilmaz and Kaynar, 2011). However, there is not a specific relationship between the ROP and the mentioned parameters, so it's difficult to predict

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the ROP, the process is mainly based on the experience of the drilling engineer and applies the relationship. Many current ROP models, most of which are performed in the laboratory, have limitations for practical applications (Hegde et al, 2017). These models can be used to show how changes in rock mechanical properties and drilling parameters interact. For example, Bourgoyne & Young considered eight parameters whose coefficients each were found by multiple linear regression. However, there are many factors that directly and indirectly affect ROP, most of which are complex factors to model because of the different correlations between these parameters (Saurabh et al., 2017).

Pre-existing data-driven predictive analytics is of interest because its successful application in other industries. By far, a number of studies have been carried out in ROP prediction and optimization using Artificial Neural Network (ANN) model to predict ROP with positive results. The data collected from geophysicists always have certain deviations due to environmental characteristics, equipment and measurement errors, so it's very important to remove noise values to maximize the results, optimize network time and accuracy.

In this study, the researchers develop many different ANN models and select the model to be applied to predict the ROP of wells more accurately. Then, the study evaluates the number of suitable parameters for the model based on the correlation between the parameters and ROP. From the collection, analysis and processing of input data; build different ANN models through network training to select the optimal network and then apply them to new wells to predict and evaluate ROP. In addition, the survey and comparison of the effectiveness of different ANN models with traditional models such as Bourgoyne & Young's model and Bingham's model in predicting ROP based on the mean square error value (MSE) and correlation coefficient square (R^2).

2 Artificial Neural Network (ANN)

ANNs are similar to neurons that exist inside the human brain. The ANN working structure is like a neural system with a network of connections with a large number of processing neurons. Each neuron consists of n inputs to produce m outputs given by a function called the activation function.

Many neurons combine to develop layers, and these layers combine to develop a network. The layers are divided into three parts as input layer, hidden layer and output layer. The number of neurons and layers depends on the complexity of the problem under investigation. For the network training process, the back-propagation algorithm is suitable (Saurabh et al, 2017). The data is processed through the input layer, then the hidden layer, and finally the output layer.

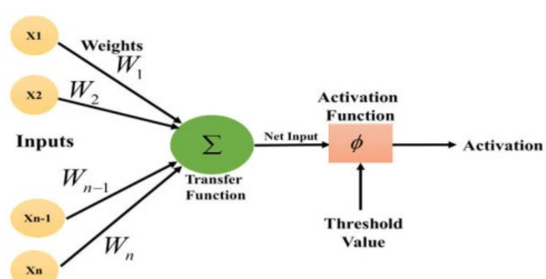

Figure 1. Schematic of a neuron (Saurabh et al, 2017).

2.1 Input data

The proposed Artificial Neural Network model is built and developed on the actual drilling data set in the Nam Con Son basin including 3 wells A, B, C in the same area and well X in the vicinity. The network training dataset consists of 700 data points of well A, 700 data points of well B, prediction data including 340 data points of well C and 44 data points of well X. They are randomly assigned course for network training, evaluation and testing. The dataset is scaled 70% for network training, 15% for evaluation and remaining 15% for testing phase.

In this study, ANN models were developed with ten input parameters to estimate ROP, it's including: measure depth, the difference pressure between surface and bottom hole (Pp), weight on bit (WOB), rotary speed (N), tooth wear (h), pump pressure (P), inclination, equivalent circulating fluid density (ECD), mud weight (MW) and flow rate (Q) and ROP is the only output parameter.

2.2 Evaluation criteria

The optimal number of neurons and the hidden layers required for the network to build on the dataset of the wells are determined by the minimum MSE value.

The learning and generalization ability of the ANN models are evaluated on the basis of two statistical parameters including mean square error (MSE) and correlation coefficient squared (R^2) and at the same time:

$$R^2 = \frac{\sum_{i=1}^{N}(y_i-\overline{y_i})(y_i^*-\overline{y_i^*})}{\sqrt{\sum_{i=1}^{N}(y_i-\overline{y_i})^2 \sum_{i=1}^{N}(y_i^*-\overline{y_i^*})^2}} \tag{1}$$

$$MSE = \frac{\sum_{i=1}^{N}(y_i-y_i^*)^2}{N} \tag{2}$$

Where y_i and y_i* are the actual and predicted values.

3 Results and discussion

The trial and error method is used to determine the number of neurons in the hidden layer for each input dataset to find the most suitable structure. The results show that the model built on well dataset A has the optimal structure of 10-8-4-1 and the suitable structure for data set B is 8-14-4-1.

Choosing the right number of input parameters for the model is also very important because it affects the predictability as well as the time to complete the network. The process of collecting parameters from geophysical work requires high cost of equipment because it is essential to optimize drilling costs while still providing efficiency for ROP prediction. Based on the method of expressing correlation coefficient, the influence of the parameters on ROP has been ranked. Based on the MSE and R^2 criteria, this study has assessed the number of parameters increasing according to the level of influence for the model from one to ten input parameters as shown in **Table 1**.

No Input	Selected inputs	MSE	R^2
1	WOB	0.174383	0.45127
2	WOB, ECD	0.181471	0.42207
3	WOB, ECD, MW	0.07531	0.81048
4	WOB, ECD, MW, Incline	0.065405	0.83777
5	WOB, ECD, MW, Incline, P,	**0.04471**	**0.89213**
6	WOB, ECD, MW, Incline, P, N	0.045375	0.8904
7	WOB, ECD, MW, Incline, P, N, MD	0.037636	0.91018
8	WOB, ECD, MW, Incline, P, N, MD, Q	0.030039	0.92895

9	WOB, ECD, MW, Incline, P, N, MD, Q, P_p	0.026258	0.9383
10	WOB, ECD, MW, Incline, P, N, MD, Q, P_p, h	0.015721	0.96368

Table 1: Results of input parameters based on ANN model.

However, in order to have a different comparison with Bourgoyne and Young's model, the research will proceed to use eight parameters of Bourgoyne and Young's model listed above as input for the ANN models.

Based on the comparison results in **Figure 2**, **Figure 3** and **Table 2**, when the prediction results of the most efficient ANN model (model B->A) are compared with two Bourgoyne & Young model and Bingham's model. The results show that the ANN model had a closer match with the actual results in both C and X than the other two models. Bourgoyne & Young's model and Bingham's model were not effective in predicting the rate of penetration for well X in the vicinity.

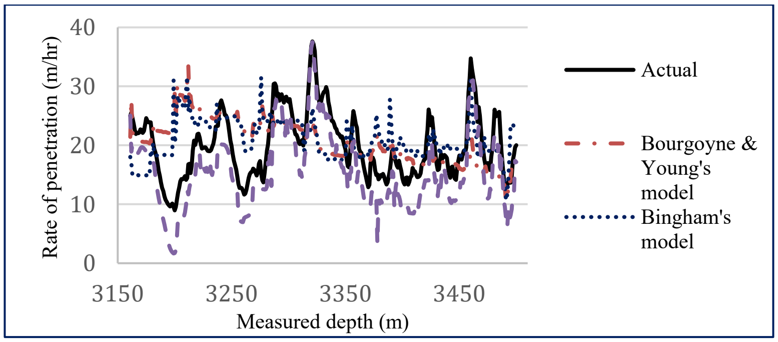

Figure 2. ROP prediction results of the models compared to the actual ROP of well C.

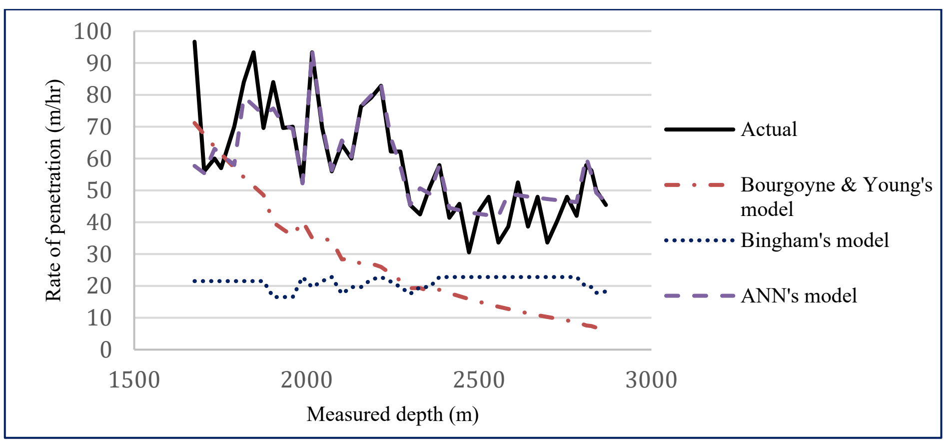

Figure 3. ROP prediction results of the models compared to the actual ROP of well X.

	Well C		**Well X**	
	MSE	**R^2**	**MSE**	**R^2**
Bourgoyne & Young's model	44,226	0,2578	1178,1	0,419
Bingham's model	39,664	0,164	1689,1	0,1007
ANN's model (model B->A)	22.34289	0.930276	50.92847	0.83366

Table 2: ROP prediction results for wells C and X of the models.

4 Conclusion

Artificial Neural Network models have been successfully built, developed and tested in predicting ROP for well in the area and well in the vicinity. The study also evaluated the appropriate selection of the number of parameters for the models to save costs as well as training time.

The results obtained from applying ANN models according to different methods in predicting ROP provide higher accuracy than traditional models such as the Bourgoyne & Young’s model and Bingham’s model. In which the results from the global ANN model (well by well) get high efficiency in prediction compared to other models. This further shows the competitiveness of different ANN models and their high applicability to actual rate of penetration.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgment

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