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Modeling of Drilling Rate of Penetration Using Adaptive Neuro-Fuzzy Inference System

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Abstract

Drilling rate of penetration (ROP) is a crucial factor in optimizing drilling cost. This is mainly due to the excessive cost of the drilling equipment and rig rental, where the longer the drilling activity would reflect a higher expenditure. If the drilling rate of penetration can be predicted accurately, we would be able to avoid unnecessary spending. Hence, this can lead to minimizing the drilling cost significantly. In this paper, an Adaptive Neuro-Fuzzy Inference System (ANFIS) model is generated using MATLAB environment. A total number of 504 data sets from a Sudanese oilfield is used to develop a well-trained and tested ANFIS model for ROP prediction. The parameters included in the model generation are: depth, bit size, mud weight, rotary speed and weight on bit. Training options were set to give the best predicted ROP against the real data. This model is proven to give a high performance with an error as low as 1.47% and correlation coefficient of 98%. With this model, the estimation of the duration of drilling activities in the nearby wells can be done accurately if relevant data from the same reservoir is available. Caution must be taken to avoid using the results from this model beyond the range of training data.

Keywords: rate of penetration; neuro-fuzzy; bit size; mud weight; rotary speed; weight on bit.

INTRODUCTION

Drilling optimization is the key aspect to achieve minimum cost and making the drilling operation economically feasible. By understanding the drilling parameters that affect drilling rate of penetration (ROP), a model can be constructed to predict the drilling rate of penetration through a formation. The ability to predict ROP accurately will result in avoiding unnecessary spending and hence cut the drilling budget considerably. For this reason, several authors and researchers attempted to develop a model for ROP prediction. Generally, the drilling rate of penetration is a dependent parameter that can be predicted as a function of independent drilling parameters [1]. The drilling parameters are divided into three categories: formation related, drilling bit related and hydraulics down hole. There are some models proposed in the past in the effort of predicting ROP including Bingham model, Bourgoyne and Young model, Warren model etc. although these models are less accurate in predicting ROP, they are always used as a guideline for modification of mathematical models in these days. In This paper, a Neuro-Fuzzy model is generated using ANFIS architecture in MATLAB. A set of data consists of 504 Data samples from Sudanese oil field was used to train and test the model. Then, trend analysis is curried out for the Neuro-Fuzzy, Bingham mode and Bourgoyne and Young model (BYM). From the results, the Neuro-Fuzzy model shows a high performance in predicting ROP against the real data. The model can be used to predict the ROP of the nearby well in the same reservoir. However, one limitation of Neuro-Fuzzy technique is that it doesn't generate a universal model that can be used to predict ROP for all the fields all over the world. Instead, the model must be retrained if it is to be used in another reservoir. It's also recommended to train the model using a wide range of data to enhance the model reliability.

FACTORS AFFECTING THE DRILLING RATE OF PENETRATION (ROP)

Prediction of ROP is a complicated task because it involves many factors [2, 3]. Researchers realized that ROP is a function of rock properties such as: the uniaxial compressive and tensile strength of the rock [4, 5], as well as the dry and the saturated rock density [6]. In addition , ROP is a function of operational parameters such as: bit type [7], rotation speed [8] and weight of bit (WOB) [9]. Moreover, ROP is a function of the mud weight and wellbore cleaning.

Increasing the speed of rotation will normally increase ROP in soft formation. However, in hard formation this is not the relation, where ROP is not directly proportional to the rotation speed [10]. For this reason, a high rotary speed is used in a soft formation while low rotary speed is normally used to penetrate hard formation [11].

ROP is also affected with the hydraulics at the bottom of the bit during drilling operation. Lack of hydraulic energy will reduce the efficiency of removing the drilled cuttings from the bottom hole. As a result, part of the bit's energy will be spent on re-grinding drilled cuttings and this reduces the penetration rate [12]. In addition, different bit types and different nozzle arrangement will also affect the performance of borehole cleaning [13].

The effect of drilling fluid (mud) properties on ROP was studied in the past. Especially, drilling fluid density. It is proven that ROP increases with decreasing equivalent circulating density (ECD) [14]. Therefore, to achieve a higher ROP, a lower fluid density would be preferred. However, a minimum density must be determined to avoid putting drilling operation in jeopardy. In the worst scenario, insufficient mud density will put the wellbore in excessive underbalanced condition and lead to borehole collapse.

Simulation was conducted and the influence of bottom hole pressure on ROP was proven. From the results, it was observed that ROP decreases as logarithm of bottom hole pressure increases [15].

Weight on bit (WOB) is one of the drivers that let the bit tooth penetrate throw the rock until the force by bit tooth is equalized by the resistant force. Throughout the rock fracturing process, every bit tooth will continue penetrating the formation until shear stress generated due to WOB is balanced by the rock (formation) shear strength [12]. Judging on this, formation drillability can also be related to rock strength, which is considered as a part of the formation properties. The prediction of the rock strength or more specifically, the minimum principal in-situ stress of rock is also part of interest to provide information on the fracturability of the reservoir rock [16].

Also, bit wear affects ROP. Bit wear can be defined as the reduction in height of bit tooth because of being worn after contacting with rock during drilling operation. Worn bit will result in reduced depth of penetration due to the shortened bit tooth height, thus reduces the bit efficiency in cutting the rocks which ultimately reduces ROP.

Different ROP models take in to account different parameters. However, WOB, rotation speed and bit size are the most important parameters as they appear in most of the models [17].

RATE OF PENETRATION MODELS

Bingham model

One of the earliest models is Bingham model. The following mathematical equation was proposed based on laboratory studies [1]. This simple model assumes the threshold bit weight to be negligible and neglects the depth of the formation. Therefore, usually the ROP predicted are less reliable. According to Bingham model, ROP is function of applied WOB, bit size and rotary speed. Mathematically:

$$ROP = K\left[\frac{WOB}{D_b}\right]^a N \quad \text{.....} (1)$$

Where, 'k' is the proportionality constant that accounts for formation strength. 'a' is the bit weight exponent. 'WOB' is the applied weight on bit. 'D_b' is the bit diameter and 'N' is the rotary speed. Notice that the value of both 'k' and 'a' varies from one field to another. Hence, they must be determined empirically using multiple regression and curve fitting. In this study, the values of 'K' and 'a' are listed in table 1:

Table 1: The value of 'k' and 'a' constants in Bingham model

k	**a**
0.18	0.38

Bourgoyne and Young model (BYM)

Bourgoyne and Young model is widely practiced by researchers to predict ROP for future wells in the same field. This is one of the complete mathematical models and it has a great acceptance in the industry [1]. It accounts for a total of 8 drilling parameters, including formation strength, depth of formation, effect of formation compaction, bit diameter, weight on bit, pressure differential across hole bottom, rotating speed, bit wear and bit hydraulics. Mathematically:

$$ROP = f_1 \times f_2 \times f_3 \times f_4 \times f_5 \times f_6 \times f_7 \times f_8 \qquad (2)$$

In which:

$$f_1 = e^{2.303 a_1} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3)$$

$$f_2 = e^{2.303 a_2 (10000 - D)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$$f_3 = e^{2.303 a_3 D^{0.69} (gp - 9)} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

$$f_4 = e^{2.303 a_4 D (gp - ECD)} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

$$f_5 = \left[\frac{\left[\frac{w}{d_b}\right] - \left[\frac{w}{d_b}\right]_t}{4 - \left[\frac{w}{d_b}\right]_t} \right]^{a_5} \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (7)$$

$$f_6 = \left[\frac{N}{60}\right]^{a_6} \qquad (8)$$

$$f_7 = e^{-a_7 h} \qquad (9)$$

$$f_8 = \left[\frac{F_j}{1000}\right]^{a_8} \quad \ldots\ldots (10)$$

where:

'D' is the true vertical depth of the formation being drilled.

'gp' is the pore pressure gradient.

'ECD' is equivalent circulating density of the drilling fluid.

$\left[\frac{w}{d_b}\right]$ is the ratio of the applied weight on bit to the bit diameter.

$\left[\frac{w}{d_b}\right]_t$ is the ratio of bit threshold to the bit diameter.

'N' is rotation speed.

'h' is the fractional tooth dullness. An average value of 0.4 is used in this study.

'F_j' is the jet impact factor.

The constants a1-a8 are not universal constant as they change from one field to another. Hence, they must be identified for each field using multiple regression and curve fitting. The value of the constants a1-a8 in this study is listed in table 2:

Table 2: The values of the constant a1-a8 in Bourgoyne and Young model.

a1	**a2**	**a3**	**a4**	**a5**	**a6**	**a7**	**a8**
1.4	0.000075	1.00E-06	1.00E-06	0.65	0.65	0.3	0.3

NEURO-FUZZY SYSTEM

Fuzzy logic technique has been used in petroleum industry in different sectors. This technique was used to estimate permeability from wireline logs [18], to curry out EOR risk assessment [19] and in hydraulic fracturing [20]. Artificial neural network (ANN) is also used extensively in Petrophysics

[21], determination of reservoir permeability [22], water saturation prediction [23], ROP prediction [3], cutting transportation modeling [24] and to predict the bottom hole flowing pressure [25]. However, the application of neuro-fuzzy system is comparatively new thus less in petroleum industry compared to both fuzzy logic and artificial neural network (ANN). Neuro-Fuzzy is a combination of Neural Networks and Fuzzy logic to learn the non-linear relationship between many input parameters which will generate a certain output [26]. The idea of combining fuzzy logic and artificial neural network to tune the membership functions to minimize the error margin is developed to overcome the tiring process of numerous trial and errors in finding appropriate membership functions and rules, especially if it involves many input parameters [27].

Learning algorithms, something ANN is good at, is introduced to the fuzzy system. System will be told to learn and mimic the pattern of the data sets input for prediction modeling by neural networks. Yet, fuzzy system is able to give easy interpretation of results and provide capacity to represent inherent uncertainties of human knowledge regarding linguistic variable [27]. Thus, combination of technique from neural network and fuzzy logic gives idealistic prediction and is called neuro-fuzzy system.

Adaptive Neural Fuzzy Inference Systems (ANFIS) is a type of artificial neural network that is based on the fuzzy inference system by Takagi-Sugeno. It is an architecture that falls under hybrid neuro-fuzzy system. A typical ANFIS structure consists of 5 layers. In the first layer, input variables will be mapped relatively to each membership functions. In second layer, operator T-norm will be applied to calculate the antecedents, where each node in this layer represents the fire strength of the rule. The rule strength is normalized in the third layer and the consequent parameters from the rules will be presented in the fourth layer. In the last layer, overall output is computed as the summation of all incoming signals. Figure 1 below, shows the work flow of MATLAB ANFIS structure.

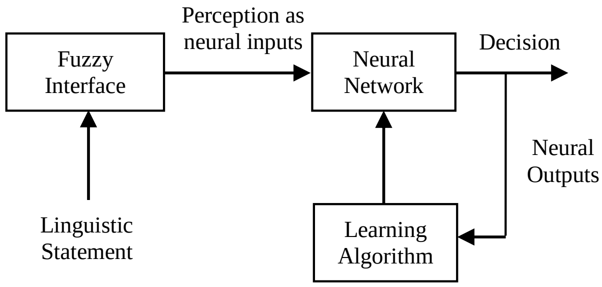

Figure 1: MATLAB ANFIS structure workflow.

In Monika and Amrit's work, there is a solid proof concluding the simulation from neuro-fuzzy model is better in providing loading capacity than fuzzy logic model as neuro-fuzzy inherits adaptability and learning [28]. Neuro-fuzzy algorithm was implemented in some past research works such as in prediction of Poisson's ratio [29] and Young modulus of shale and sandstone [30]. It is proven to work well and best compared to other linear multivariate regression analysis due to the complicated and non-linear relationship among input parameters.

METHODOLOGY

Data gathering

The data required for ROP modeling and calculation was extracted from the Daily Drilling Report (DDR) from a Sudanese oil field. Five parameters were extracted from the daily drilling reports, including:

- Bit size.
- Rotary speed(N).
- Weight on bit(WOB).
- Mud weight(MW).
- Depth.
- The actual rate of penetration(ROP).

Data optimization

DrillSIM500 model was created by setting the formation properties and geological information to simulate the real field. This included the formation depth, strength, fluid type, permeability, pressure gradient and normal pressure at each formation. To make sure the simulation model was correct, weight on bit and rotary speed were adjusted as recorded in DDR, and the measured ROP by DrillSIM500 was compared to the actual ROP in the DDR. After confirming DrillSIM500 gave the exact value of ROP as recorded in DDR, two parameters, the weight on bit and rotary speed were adjusted to obtain the optimized maximum ROP without fracturing the formation. Optimization step was carried to all the data sets. This optimization step is necessary and important upon the fact that the pace and progress of drilling can be made faster and complete in shorter time if optimized ROP is achieved. Thus, it will lead to lower cost incurred.

Construction of Neuro-Fuzzy model

504 sets of optimized data from the previous optimization stage was divided into two pools for training the neuro-fuzzy model and testing the model, with a partitioning ratio around 2:1. The drilling parameters used for neuro-fuzzy model are shown in table 3. The code has been written and executed under MATLAB environment for flexible editing.

With input parameters determined, training options of ANFIS neuro-fuzzy system in MATLAB are to be identified to produce the best model. These training options are: the clustering radius, learning step size, increasing rate and decreasing rate.

Table 3: Drilling input parameters for neuro-fuzzy model.

Drilling Parameters	Minimum	Maximum	Average
Depth (m)	0.00	1660.00	827.62
Bit size (inch)	8.50	24.00	11.21
Mud weight (ppg)	8.60	11.30	10.32
Weight on bit (ton)	3.00	15.00	9.96
Rotary speed (rpm)	100.00	150.00	141.33

Comparing the Nero-Fuzzy model with Bingham Model and

Figure 2, shows a schematic diagram of the Neuro-Fuzzy model.

Bourgoyne and Young model

The constructed neuro-fuzzy model has been used to predict the value of ROP. Then, the results are compared with two models that currently used in the industry, Bingham model and Bourgoyne and Young model(BYM). Lastly, statistical analysis will be curried on for all the three models.

RESULTS AND DISCUSSION

Neuro-Fuzzy Model

351 sets of data are used to train the neuro-fuzzy model. The trained neuro-fuzzy model will then be tested with 153 sets of data. To develop a good neuro-fuzzy model, the following training options need to be optimized:

I. Clustering radii

This clustering radius specifies the cluster center’s range of influence. It is used to arrange data into clusters with different degrees of membership having a spherical neighborhood of influence with the given radius. In this study, clustering radii is chosen to be 0.4551.

II. Learning step size

The step size is kept optimum at a value of 0.01 to keep the learning process stable.

III. Increasing rate

If the error measure of training experiences four consecutive decreases, the step size will be scaled up by this factor. This training is to make the learning faster once the model is detected to be learning correctly. Increasing rate of neuro-fuzzy model in this study is 9.

IV. Decreasing rate

If error measure of training experiences any increase, the step size will be scaled down by this factor. It is to slow down and make the learning more precise once the model faces increasing error. A decreasing rate of 0.7 is applied in this model.

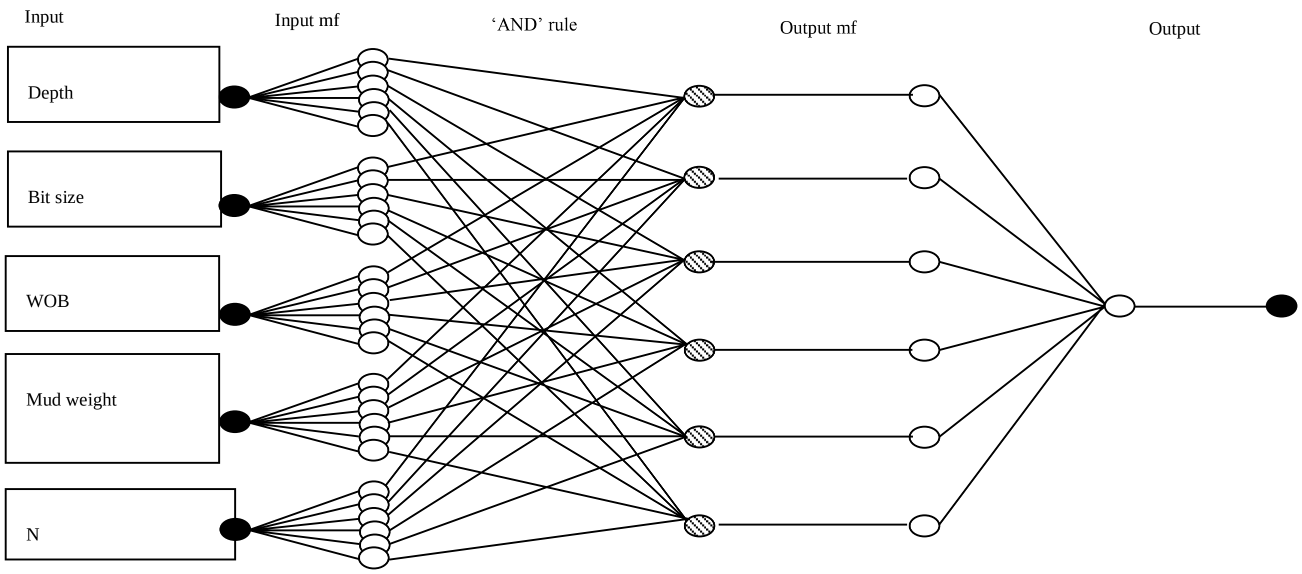

Figure 2: Schematic diagram of MATLAB ANFIS neuro-fuzzy model.

Trend Analysis of Neuro-Fuzzy model, Bingham Model and BYM Model

In figure 3, trend analysis is curried out to study the effect of changing WOB while keeping the other parameters (depth, bit size, rotation speed, mud weight) constant.

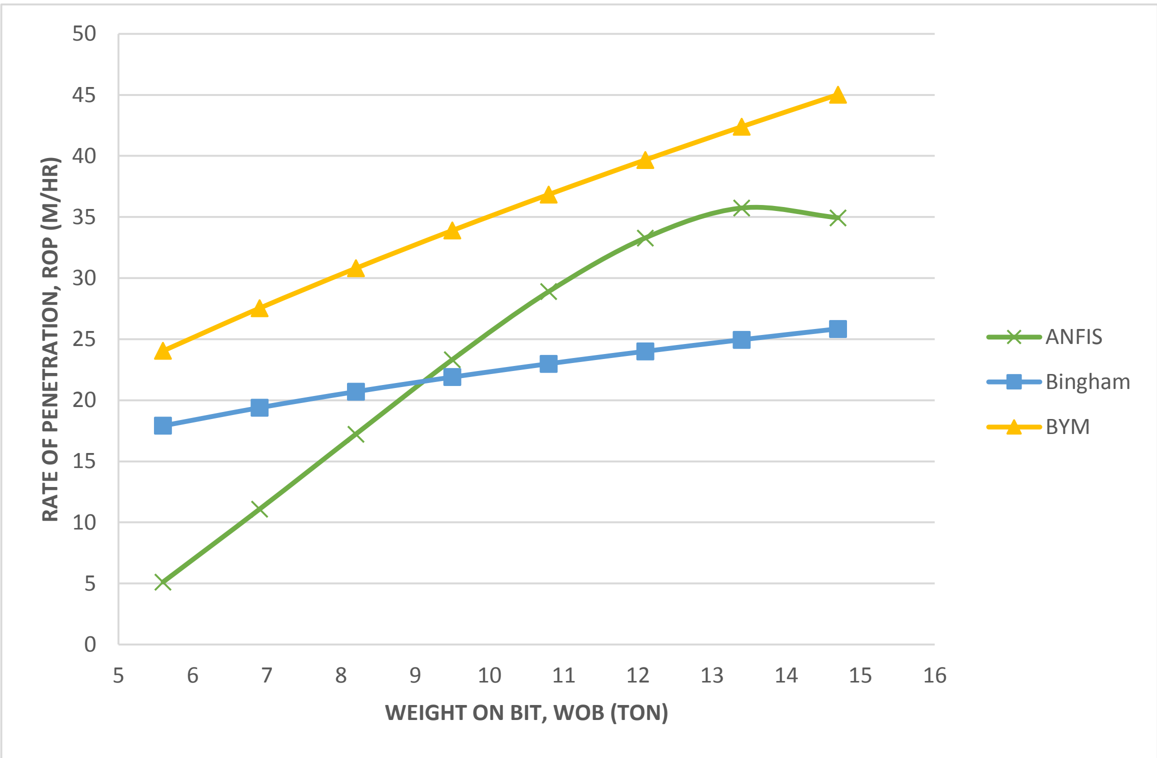

Figure 3: Effect of weight on bit on rate of penetration in Neuro-Fuzzy model, BYM model and Bingham model.

From figure 3, increasing the weight on bit will increase the rate of penetration until the bit floundering point is reached (at around 13 ton). Bingham model and BYM model also shows this direct proportionality relationship between the weight on bit and the rate of penetration. However, both Bingham model and BYM model failed to account for the floundering effect. The trend of the Neuro-Fuzzy model perfectly matches the trend proposed by Bourgoyne et. al in Applied Drilling Engineering which is shown in figure 4:

Next, trend analysis is carried out to study the effect of changing the rotation speed while keeping the other parameters (depth, bit size, WOB, mud weight) constant. The result is shown in figure 5:

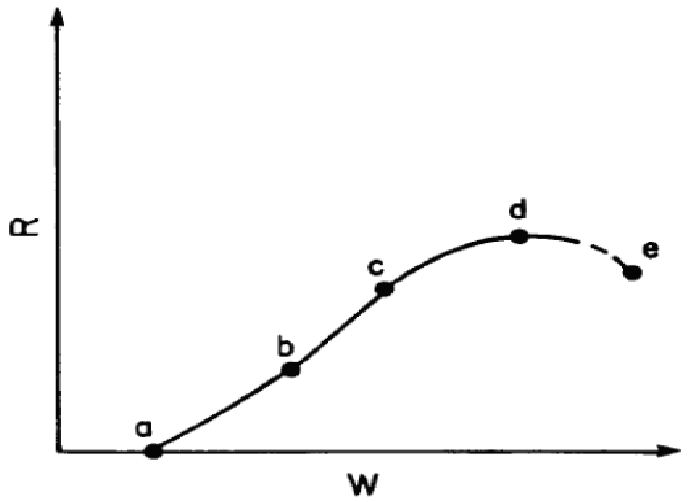

Figure 4. Effect of weight on bit on rate of penetration proposed by Bourgoyne et. al in Applied Drilling Engineering [31].

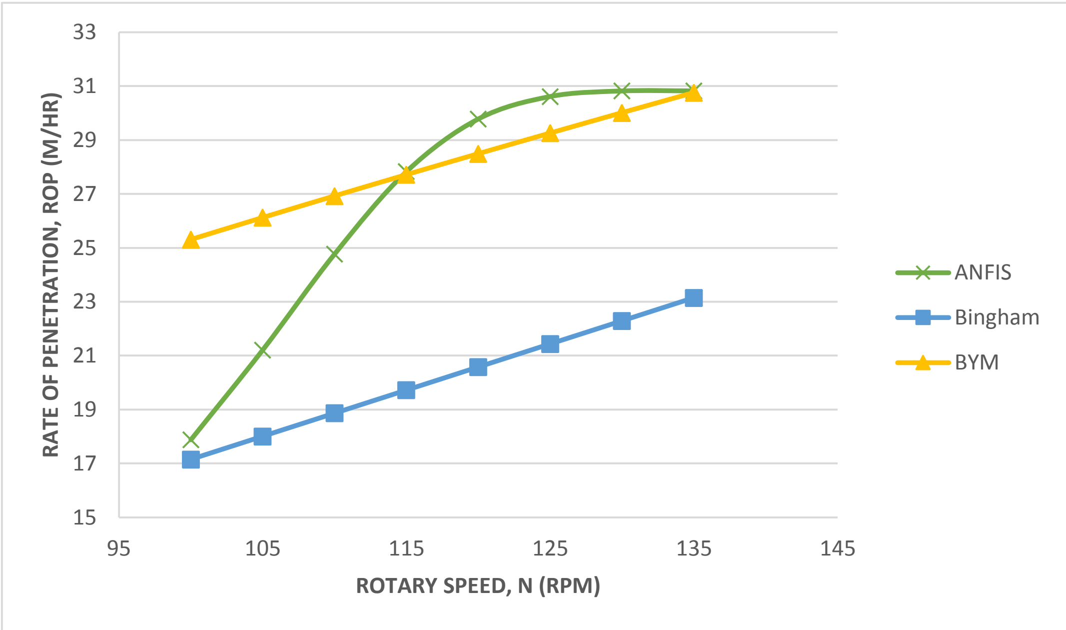

Figure 5: Effect of rotary speed on rate of penetration in neuro-fuzzy model, BYM model and Bingham model.

Again, there is a direct proportionality relationship between the rotary speed and the rate of penetration. From figure 5, the Neuro-Fuzzy model shows that increasing the RPM above 130 will hardly increase the rate of penetration as the high rotation speed will be wasted in re-grinding the cutting that was already drilled. Bingham model and BYM model failed to model this phenomena since both models shows straight line in figure (5). The trend of the Neuro-Fuzzy model in Figure (5) matches the trend that was proposed by Bourgoyne et. al in Applied Drilling Engineering which is shown in figure 6.

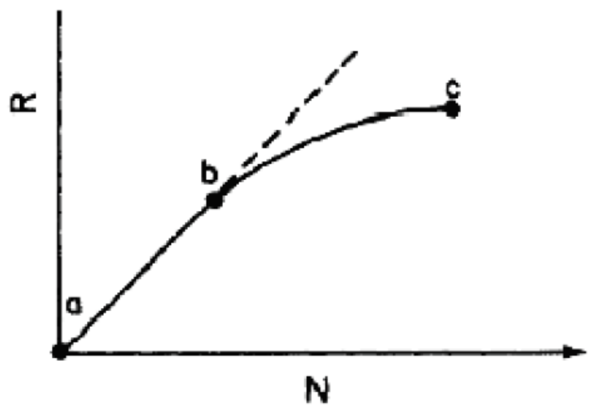

Figure 6: Effect of rotary speed on rate of penetration proposed by Bourgoyne et. al in Applied Drilling Engineering [31].

The Purpose of conducting trend analysis is to check whether the developed model is predicting the right pattern or not. Even the model might be able to mimic the relationship of parameters in training model and give good prediction in testing model, yet there is a possibility of the model not predicting in a manner like previous established model that is well accepted by the industry. Hence for this checking purpose, the effects of variation in weight on bit and rotary speed on rate of penetration were assessed by keeping all other parameters constant.

The result of investigation shows that an increase in weight on bit will lead to increment in rate of penetration up to an optimum value, passing the peak further, increasing weight on bit will only result in lower rate of penetration due to well bore cleaning issues [32]. This trend matches well with the weight on bit trend established and proposed by Bourgoyne et. al [31], where an increase in weight on bit surpassing point d (shown in Figure 3), the optimum value, decrease the rate of penetration. This effect is also known as bit floundering.

While for rotary speed, it can be observed in **Error! Reference source not found.** that rate of penetration increases as rotary speed increases. After an optimum value of rotary speed is reached, further increment of rotary speed results in lesser increment of rate of penetration. This point is also referred as bit floundering point. It shows similar pattern as compared to model proposed by Bourgoyne et.al. in the textbook, Applied Drilling Engineering [31]. It can be concluded that this neuro-fuzzy model is predicting the right behavior. Thus, the following result obtained by this model is reliable.

Statistical Analysis of Neuro-Fuzzy Model

To visualize the accuracy of the Neuro-Fuzzy model, cross plots are shown in figure (7) and figure (8) for the training and testing respectively.

sets of data were used to train the model to learn the relationship among the five parameters input given the observed output data. The result of the training produced a model that gives a prediction with an absolute average percent error of 1.49%. The trained model was then used to test another 153 sets of data for prediction of rate of penetration. The testing set yields a result of 1.47% average absolute percent errors. Table 4, shows the result for Neuro-Fuzzy training and testing:

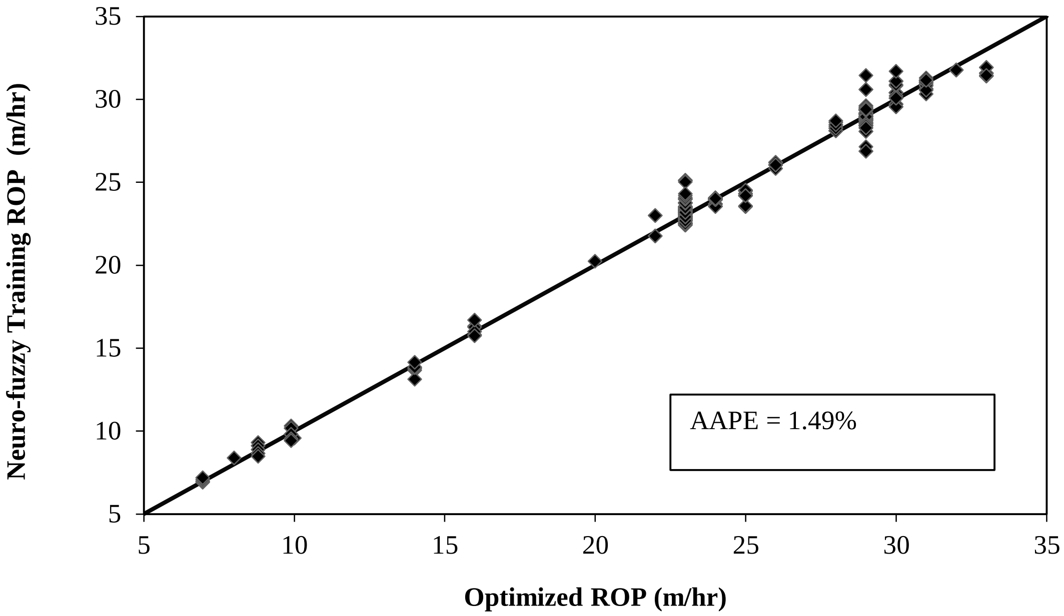

Figure 7: Cross plot of the value of optimized rate of penetration against the value of rate of penetration in Neuro-Fuzzy training model.

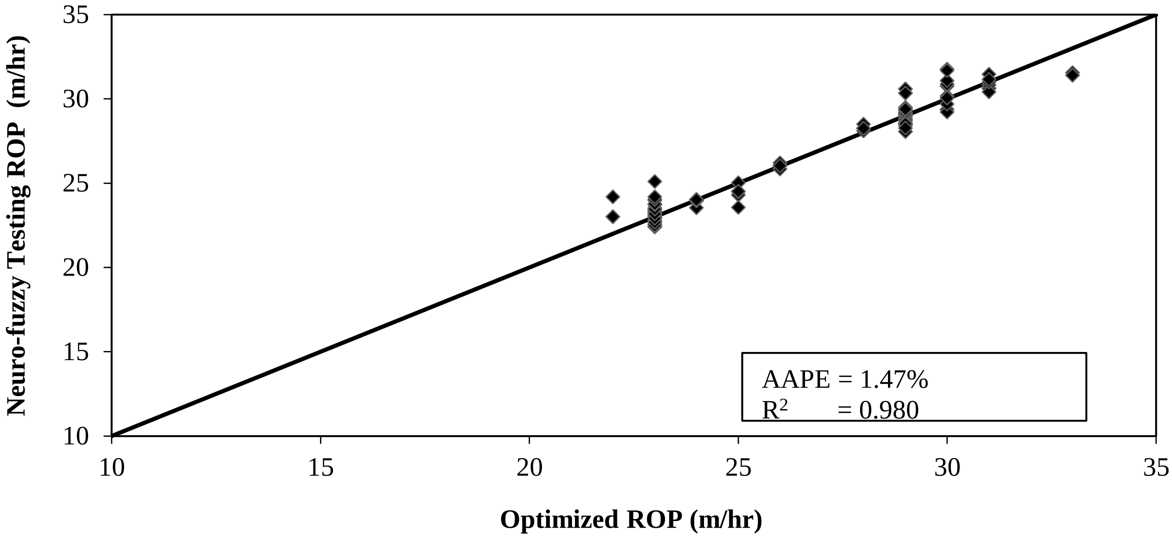

Figure 8: Cross plot of the value of optimized rate of penetration against the value of rate of penetration in Neuro-Fuzzy testing model.

Table 4: Statistical analysis of neuro-fuzzy training and testing model

Sets	No. of Data	Average Absolute Percent Error, AAPE (%)	Correlation Coefficient, R2(%)
Training	351	1.49	99.4
Testing	153	1.47	98.0

Statistical Analysis of Bingham Model and Bourgoyne and Young Model(BYM)

In this study, Bingham model and Bourgoyne and Young model were applied to get an idea of how well do the models currently used in industry predict ROP given the same set of data. Figure 9 and Figure 10 shows the cross plots of optimized value of rate of penetration from field data against the prediction value by both Bingham model and Bourgoyne and Young model:

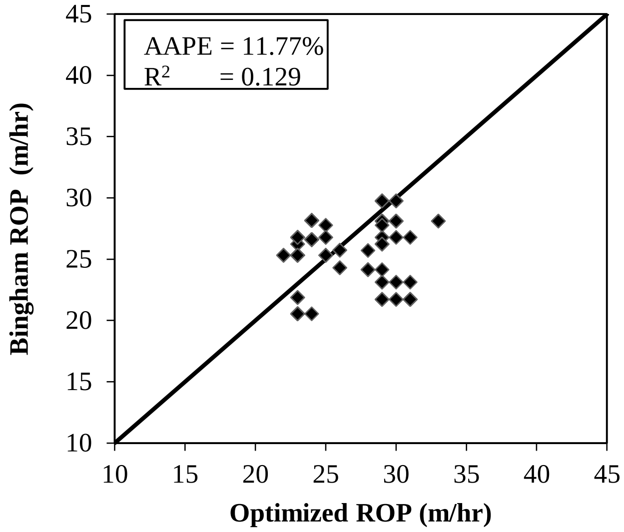

Figure 9: Cross plot of the value of optimized rate of penetration against the value of penetration rate predicted by Bingham model**.**

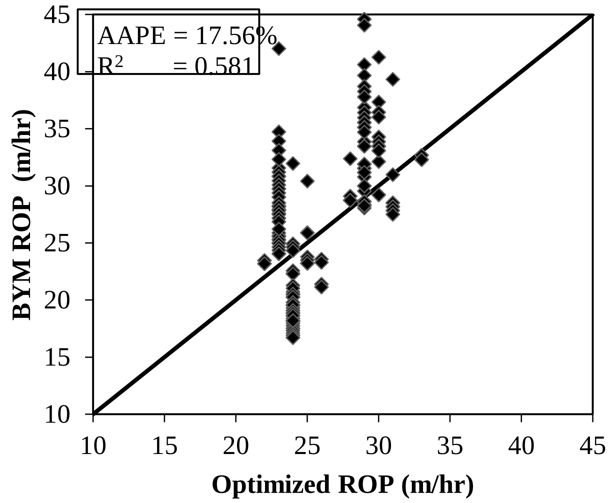

Figure 10. Cross plot of the value of optimized rate of penetration against the value of penetration rate predicted by Bourgoyne and Young model.

The summary of the statistical analysis for both models is shown in table 5:

Table 5: Statistical analysis of Bingham model and Bourgoyne-Young model.

Model	No. of Data	Average Absolute Percent Error, AAPE (%)	Correlation Coefficient, R^2 (%)
Bingham	153	11.77	12.94
Bourgoyne and Young	153	17.56	58.1

From overall results, it is proven that neuro-fuzzy gives a high performance in predicting ROP, a low percent error and high correlation coefficient. Despite the high performance, there are some limitations in this neuro-fuzzy model. A good neuro-fuzzy model can be generated when there is available data from a specific field, and the model will take the inputs and outputs from the field to learn the relationship among the inputs to give the mentioned outputs. This indicates that applying neuro-fuzzy model in green field to predict the rate of penetration in wildcat might not yield performance as good as the results discussed in this paper. A developed neuro-fuzzy model is suitable to be implemented within same field it is modeled for, where same formation types will be encountered.

On the other hand, looking at both Bingham and Bourgoyne and Young model, the two models give lower performance compared to neuro-fuzzy model. The errors are much larger compared to neuro-fuzzy model, and often both Bingham model and Bourgoyne and Young model are reported to give errors in a range of 20% to 40%, and in some cases the errors are as high as 80% [33]. The inconsistent performance of these two models can be explained by their characteristics being a general model, which can be used in any field globally. They are not designed for a specific field unlike neuro-fuzzy technique.

CONCLUSION AND RECOMMENDATION

In conclusion, through this work, neuro-fuzzy model is proven to accurately predict the rate of penetration (ROP). The model which has an average absolute percent error as low as 1.47%, and the correlation coefficient of 98% has confirmed that the Neuro-Fuzzy can find a good relationship between the drilling input parameters and ROP. Trend analysis has proven that the developed model is physically sound where the patterns of weight on bit and rotary speed are found to match well with patterns proposed by Bourgoyne et. al. However, this neuro-fuzzy method is recommended only to be implemented within the same range of data input for model development and same reservoir formation or rock fabric. Neuro-fuzzy model is strongly recommended for ROP prediction of nearby wells after first well is drilled, whereby there is enough information for neuro-fuzzy model development.

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