Artificial Neural Network Model to Predict Formation Penetration Rate in "T" Field

(Model Jaringan Syaraf Tiruan Untuk Memperkirakan Laju Penembusan Formasi Pada Lapangan "T")

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Abstract

Drilling is a costly activity with high risk. Time is a key variable to minimize costs and risks and increase the overall efficiency of drilling activities. An important factor related to the drilling time is the rate of penetration (ROP). The rate of penetration varies widely and is influenced by many factors. In this research, the correlation is derived using Artificial Neural Network (ANN) Model to predict the penetration rate by considering 11 parameters including formation conditions, drilling bit, drilling fluid, and drilling operations to validate the penetration rate data that are obtained from the surrounding wells. Determination of the neural network structure is carried out to obtain the best ANN model. This model produces an equation that can predict the penetration rate of the 'T' field with an error percentage of $\pm 20\%$. The existing model is used to optimize the next well drilling activity. Data processing using the ANN method which is relatively fast and precise shows that the application of this method is interesting to discuss and develop.

Keywords: Artificial Neural Network, Prediction, Rate of Penetration, Weight on Bit, Drilling

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Pemboran merupakan kegiatan yang menghabiskan biaya besar dengan resiko yang tinggi. Waktu menjadi variabel kunci untuk meminimalisir biaya dan resiko serta meningkatkan efisiensi keseluruhan kegiatan pemboran. Faktor penting yang berhubungan dengan waktu pemboran adalah rate of penetration (ROP) atau yang dikenal sebagai laju penembusan. Laju penembusan sangat beragam dan dipengaruhi oleh banyak faktor. Dalam penelitian ini akan diturunkan korelasi menggunakan Jaringan Syaraf Tiruan (JST) untuk memprediksi laju penembusan dengan mempertimbangkan 11 parameter meliputi kondisi formasi, pahat bor, fluida pemboran, dan operasional pemboran untuk memvalidasi data laju penembusan yang didapat dari sumur sekitar. Penentuan struktur jaringan syaraf dilakukan untuk mendapatkan model JST terbaik. Model ini menghasilkan persamaan yang dapat memprediksi laju penembusan pada Lapangan 'T' dengan persentase kesalahan \pm 20%. Model yang ada akan digunakan untuk optimasi kegiatan pemboran sumur berikutnya. Pengolahan data secara cepat dan presisi menunjukkan bahwa penerapan metode ini menarik untuk dibahas dan dikembangkan.

Kata-kata kunci: Jaringan Syaraf Buatan, Prediksi, Laju Penembusan, Berat Pada Pahat, Pemboran

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I. INTRODUCTION

"T" is a field that has been developed since 1990 with more than 300 wells drilled. With a large amount of hydrocarbon reserves, this area still needs further development to maximize the cumulative production of hydrocarbon economically. Therefore, several development wells will be created in the near future.

In drilling activities, costs are always directly proportional to time. The additional time will have an impact on excessive drilling costs, so that time becomes a key variable to reduce existing costs and risks. The main factor associated with the drilling time is the Rate of Penetration (ROP).

ROP is influenced by many and varied

parameters including formation and drilling equipment characteristics. Derivation of the correlation among ROP and the parameters did not yield promising results, since there are unknown parameters and heterogeneity factor. In the end, the drilling engineer uses the ROP data from the surrounding wells to make further drilling plans. This assumption does not have a correct justification with a high probability of being wrong. This inaccuracy of predictions can cause losses due to miscalculating the cost of making a well, poor time management, and the occurrence of non-productive time. Hence, the ANN approach to predicting the rate of penetration becomes inevitable.

Artificial Neural Network (ANN) is an application of artificial intelligence and is an approach method that adapts the workings of the human brain as a biological process in thinking. The first work on neural networks was done by Warren McCulloch and Walter Pitts in 1943. They consider that neural networks are conceptually capable of calculating arithmetic or any logical function. This triggers the development of neural networks to the next stage in the form of application in specific industries [1].

The neural network model has been successfully applied to several fields of petroleum engineering such as reservoir engineering such as permeability estimation [2], reservoir heterogeneity characterization [3] and designing improved oil recovery methods [4]; production engineering such as multiphase flow measurements in pipes [5,6], pump identification [7], and production prediction [8, 14]; and drilling engineering such as drill bit diagnostics [9], rate of penetration [10, 15, 16], and bit selection [11,12, 13].

A neural network designed for a region or a field to predict unknown parameters depends on the availability of data sets. In this study, the neural network was designed to predict rate of penetration using 11 parameters. In addition, the optimum rotation per minute (RPM) will be predicted to result in a maximum ROP.

II. METHOD

The approach is made using artificial intelligence with the concept of machine learning to obtain solutions in the form of equations. The equation presented is a non-linear equation which is used to predict the penetration rate. The ANN model made in this study is for roller cone drill bits. This model considers the design parameters of the drill bit, the formation, the drilling fluid, and the operational parameters of the drilling. There are 11 parameters used in this research. The parameters are IADC I, IADC II, IADC III, drill tool size, TFA, depth of tool pulled, length of drilled holes, density of mud, GPM, RPM, and WOB.

IADC (International Association of Drilling Contractors) Code describes the characteristics of bits. IADC Code for Tricone Bits defines its bearing design and other design features such as Shirt Tail, Leg, Section, and Cutter. The first digit of the IADC Code (IADC I) describes general formation characteristics and types of tooth namely milled tooth or tungsten carbide. The second digit of the IADC Code (IADC II) describes a further breakdown of the formation into 4 degrees of hardness. Third digit of IADC Code (IADC III) classifies the bit according to bearing design and gage protection [17].

The accuracy of the model created will be determined based on mean absolute percentage

error (MAPE) and regression analysis. Mean absolute percentage error is the most commonly used method of expressing the accuracy of a prediction. The smaller the value, the smaller the deviation that occurs between the actual and predicted values.

III. RESULTS AND DISCUSSION

Although all variables used theoretically have an influence on the penetration rate, the analysis of the parameters used as input must still be carried out because not all variables can play a significant role in the model created. Selection of input parameters will be made based on the model that produces the smallest error percentage. The input parameter selection graph is carried out by plotting the number of variables against the error percentage as shown in Figure 1.

The selection of input parameters is based on the model that gives the lowest error percentage. Figure 1 shows that the more variables used, the more accurate the resulting model will be. This indicates that each parameter has an effect on ROP. The use of 11 variables produces an equation with an error percentage of 23.9%.

This MAPE value becomes the basis for selecting data for regression analysis. Predictions that have a MAPE greater than 100% will be considered as outliers. The chosen ANN model has a MAPE of 20.84%.

The made model is validated, which means that the predicted results will be compared with the actual values to improve the solutions that have been made. Determination of the accuracy of the created equations can be determined quantitatively by making regression analysis. After determining the outliers data, a regression analysis plot was made. The regression analysis showed that the R2 value was 0.7213. The regression analysis graph can be seen in Figure 2.

Sensitivity analysis is performed to determine the effect of certain variables on the desired results. In this research, RPM is a drilling operation parameter which is considered to be a controllable variable. The RPM variable is the independent variable to see the response of ROP. The wells with the smallest percentage of error are taken to be simulated in this sensitivity analysis.

In actual conditions, the drilling operational conditions use a drill string rotation of 75 RPM and a weight on bit of 10 klbs to produce an ROP of 174.85 feet per hour. The different RPM values are entered into the model which is ready to calculate the ROP that can be generated.

In Figure 3, it can be seen that the ROP experiences a maximum point on the drill string rotation of 240 RPM. The resulting ROP increases to 240 feet per hour with the addition of ROP of 65 feet per hour. ROP will decrease if it is less or

more than that point.

The application of the ANN model to predict the penetration rate has the potential to be used in planning the future drilling. Although the percentage of errors obtained is still quite high, there is a significant trend to be used as justification.

In addition to prediction, the ANN model can be used as an optimization medium for drilling parameters. The increase in penetration rate can be seen in the sensitivity analysis so that it can be inputted for the next well drilling activity.

It should be noted that the model created has its own limitations in application. The limitation in this model is the use of data that does not exceed the range of training data, requires a lot of valid data to increase the validity of the model, and is only suitable for application in the area where the data sample is taken.

IV. CONCLUSIONS

Based on the analysis and discussion presented above, several conclusions are made as follows:

- 1. Increasing the number of variables and data as input can increase the accuracy of the prediction of the formation penetration rate.
- 2. Model A is able to predict the penetration rate with an error percentage of 20.84% and an R2 value of 0.7213.
- 3. The maximum rotation per minute of a series of drilling pipes is obtained at a value of 240 RPM with a penetration rate of 240 feet per hour. The increase in the penetration rate that can be achieved with a change in RPM is 65 feet per hour.
- 4. The ANN model is unable to predict values that exceed its training range. The results given will diverge so that they deviate from the actual conditions.

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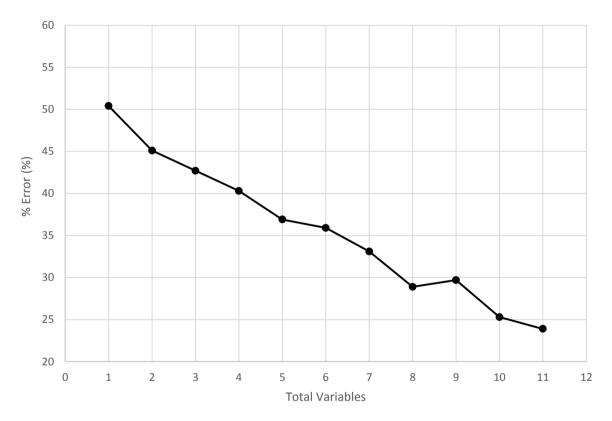
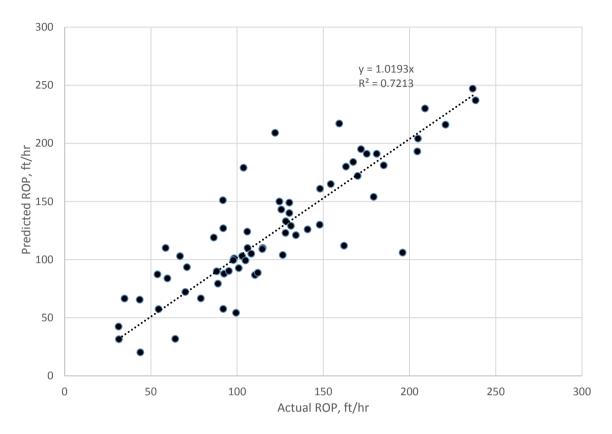
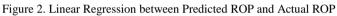


Figure 1. The effect of 11 Variables on %Error





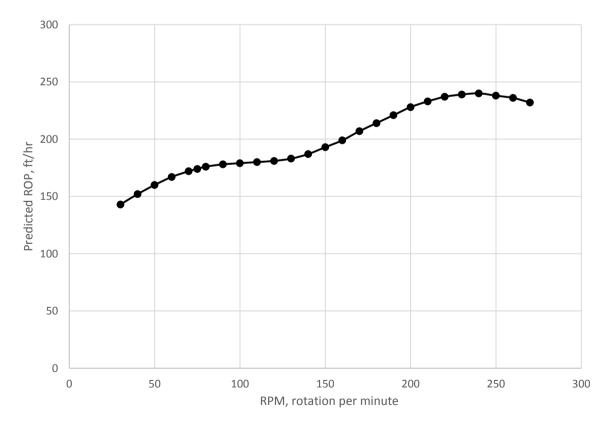


Figure 3. Sensitivity of RPM on ROP