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# Rate of Penetration (ROP) Prediction Using Artificial Neural Network to Predict ROP for Nearby Well in a Geothermal Field

Astrini Yuswandari[1], Advarel Prayoga[1], Dorman Purba[2]
[1]Petroleum Engineering Department, Institut Teknologi Bandung, Bandung, Jawa Barat, Indonesia
[2]Rigsis Energi Indonesia, Jakarta, Indonesia
astriniyuswandari@gmail.com

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## ABSTRACT

With heterogeneous formation, it is necessary to find the correlation between varied and complex parameters with the rate of penetration (ROP). More data sets need to be taken in order to predict accurately and properly. On the other hand, procuring newer data sets is economically and technically arduous. Hence, a method called as Data Driven Modelling has been developed in order to utilize previous obtained data for predicting ROP.

Lately, the industry has been shifting to the development toward easier way of analyzing data by setting up a machine learning algorithm, a computational system for identifying and classifying data. In this case, supported by assortments of drilling surface measured input data parameters, Artificial Neural Network (ANN) is promoted to predict the ROP. Setting up the input-output mapping with interconnected neural, industry is capable of accurately forecasting the output data. ANN conduct training cycle until error for data validation has been derived. This cycle will generate the relation between parameters. The output of ANN will be more accurate and has been theoretically proven by contemplating more than one parameter to obtain one set of goal. All the surface measured input data parameters including mud rheology and bit data will be expected to predict the ROP. This paper discusses the first stage of the present study conducted by the authors in applying ANN for predicting drilling ROP in a geothermal field in Indonesia, which includes literature review on previous models and correlation analysis between ROP and surface measured input data, such as weight-on-bit (WOB), mud density, lithology, rotation-per minute (RPM), etc.

## 1. INTRODUCTION

Drilling in geothermal has been the most crucial part since it takes 35% up to 50% of the total cost. Several methods have been experimented to be applied in reducing the drilling time by optimizing the rate of penetration. Rate of penetration (ROP) is assumed influenced by several factor i.e.: weight on bit, mud weight, torque, stand pipe pressure, rotation per minutes, lithology hardness, and rotation-per minute (RPM).

These parameters were then predicted using the physics-based correlation such as Bourgoyne and Young (1974), Bingham (1964), and so on in order to predict the ROP. This correlation is then believed to produce the most optimum ROP in geothermal drilling meanwhile it was originally adopted from oil and gas drilling. The issue started to appear when geothermal is found with a more heterogenous formation. The conventional correlation could not overcome an accurate estimation. Hence, people start to drill 2-10 exploratory wells in order to find the best data fitted for targeted well which is costly for the development of the field.

Lately, the industry starts to develop an advancement toward data processing since sampling newer data is technically difficult to be obtained. Aside from that, real time data sampling will require more time and cost. As a result, data driven modelling is established in order to process previous data set for doing matching, predicting and so on. Artificial Neural Network (ANN) is then used to analyze the pattern for developing an algorithmic for predictive model by processing the drilling surface response data. The interconnected hidden layer is then conducted in series of trial and error in order to find the data validation for the pattern. This study proposes method for predicting the optimum ROP in nearby well in a geothermal field by using the ANN.

## 2. METHODOLOGY

This study will be conducted with the input data sets of ROP, WOB, RPM, SPP, and all drilling data provided. To maximize the accuracy and reliability of the model, the variables are being selected based on the importance toward the ROP. The selection will be based on the R-Square for each parameter. The variables with high R-square will then selected. In order too minimize the randomness and increase the relevancy of the model, the data is then being simplified before being evaluated in *Artificial Neural Network*.

Artificial Neural Network will be trained for the input of the selected variable with simplified data and the output of the target data, in this study, ROP. With trainings and validations, the simulation for sample data will then be evaluated in order to find the matching between predicted and actual. An error analysis is then being observed in order to find the relevancy of the matching.

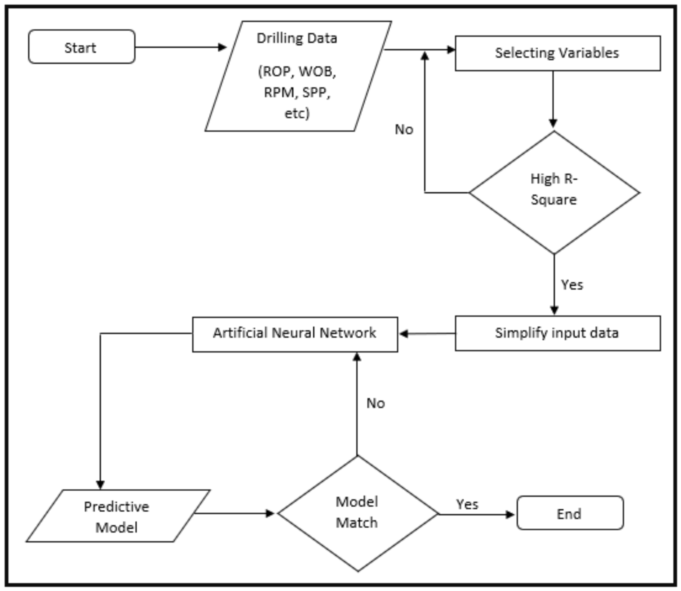


**Figure 1: Method Flowchart**

### 2.1 Variables Selection

This study will propose a method of obtaining 22,109 data from four well in an Indonesia geothermal field. The drilling data is obtained from Drilling Daily Report (DDR) and End of Well Report (EOWR). The data set is then consisted of: TVD, ROP, WOB, RPM, torque, SPP, and mud rheology. To increase the accuracy and a deepen analysis, only the most significant parameters for drilling rate is being selected.

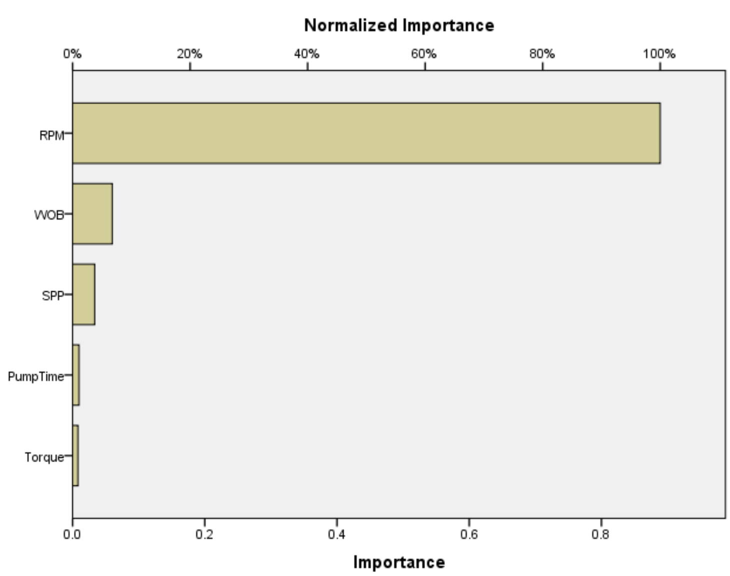


**Figure 2: Parameter Importance Normalization**

A variable selection is evaluated for all parameters. With finding the correlation to ROP, a regression has been done for each parameter by normalizing to find the importance toward the ROP. As a result, RPM and WOB are the two highest importance factors for ROP. Shown in **Figure 2**, RPM has an importance of 100% which represents its significant contribution toward the result of the ROP meanwhile the WOB is approximately 10%. There is no significant difference between WOB and *Stand Pipe Pressure* (SPP). Since the SPP is a pressure response toward the change in ROP (Kummen, 2015), thus WOB is preferably used in the prediction of ROP using the *Artificial Neural Network (ANN)*.

### 2.2 Input Data Simplification

With sampling random data sets, to reduce the amount of inaccuracy, the data is simplified for a 100 m interval of TVD. As a result, 34 data are selected from 3,000 data as shown in **Table 1**. A deep screening toward the data by reducing random data is also applied in order to reduce the inaccuracy.

| TVD Depth (m) | ROP (m/hr) | WOB (klbs) | RPM (rpm) |
|---|---|---|---|
| **1900** | 69.53 | 26.9 | 60 |
| **2000** | 46.67 | 16.1 | 60 |
| **2100** | 50.48 | 25.8 | 135 |
| **2200** | 39.27 | 33.3 | 135 |
| **2300** | 62.02 | 30.8 | 135 |
| **2400** | 91.31 | 36.3 | 204 |
| **2500** | 30.96 | 15.8 | 205 |
| **2600** | 40.27 | 49.2 | 128 |
| **2700** | 92.38 | 23.7 | 204 |
| **2800** | 37.7 | 32.9 | 205 |
| **2900** | 60.79 | 31.8 | 204 |
| **3000** | 71.56 | 34.2 | 205 |
| **3100** | 11.28 | 42.4 | 133 |
| **3200** | 33.44 | 31.4 | 81 |
| **3300** | 36.43 | 33.1 | 90 |
| **3400** | 27.25 | 31.9 | 89 |
| **3500** | 35.66 | 33.2 | 86 |
| **3600** | 43.5 | 29.2 | 80 |
| **3700** | 41.15 | 37.7 | 84 |
| **3800** | 77.58 | 13.3 | 81 |
| **3900** | 43.09 | 20.6 | 81 |
| **4000** | 40.31 | 35.6 | 81 |
| **4100** | 73.41 | 33.1 | 81 |
| **4200** | 65.57 | 31.9 | 80 |
| **4300** | 66.4 | 28.3 | 80 |

**Table 1: Sorted Data in Well-1 Field X**

## 3. RESULT AND DISCUSSION

### 3.1 Artificial Neural Network

Basically the main concept of ANN is to set an algorithmic pattern for determining the output of values of input data set. ANN will set interconnected hidden layers to set weights of its data sets. In this study, the ANN will be trained with input data sets of WOB and RPM to predict the target data of ROP. The ANN was trained with one well data sets to produce a pattern. With assumption that each of the geothermal well in one field has similar characteristic, thus the pattern that produced in one well can be used to evaluate the ROP in nearby well.

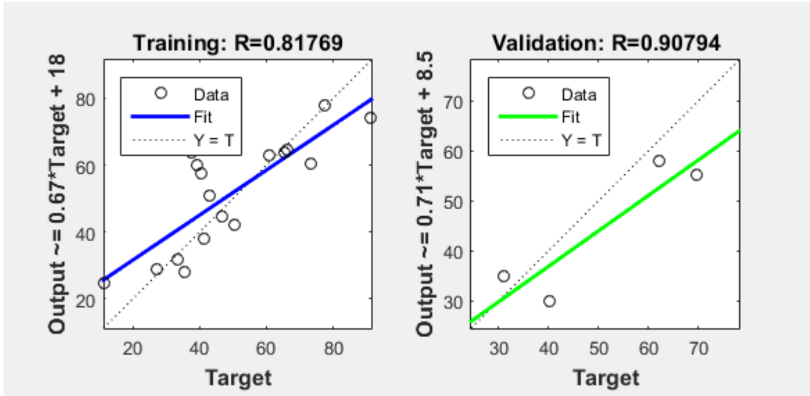


**Figure 3: Training and Validation Input and Output in Well 1**

The process starts by doing the training for each of the data set and producing pattern with hidden layers. Once the training are done, several data sets are randomly picked to do validation. **Figure 3** shows approximtely 0.8 and 0.9 R-square for training and validation respectively. Combined with good and sufficient training data and independent measurement for validation, the neural network can be utilized to develop a good performance program (Priyangga, 2018). Simulation is then developed to predict the validity of the algorithm for the nearby well. The result and the data of the simulation is shown in table below.

| TVD Depth (m) | WOB (klbs) | RPM (rpm) | $ROP_{actual}$ (m/hr) | $ROP_{predicted}$ (m/hr) |
|---|---|---|---|---|
| **1900** | 27.6 | 200 | 114.23 | 47.4341 |
| **2000** | 31.4 | 200 | 78.86 | 60.081 |
| **2100** | 9.8 | 202 | 74.48 | 31.652 |
| **2200** | 15.6 | 201 | 51.33 | 34.976 |
| **2300** | 4.1 | 202 | 58.76 | 40.946 |
| **2400** | 14.7 | 132 | 90.31 | 45.0637 |
| **2500** | 17.6 | 200 | 64.01 | 59.9196 |
| **2600** | 21.7 | 132 | 80.04 | 54.5811 |
| **2700** | 21.4 | 130 | 48.08 | 61.2525 |
| **2800** | 29.1 | 105 | 114.06 | 56.5168 |
| **2900** | 16.2 | 173 | 49.7 | 82.2671 |
| **3000** | 44.2 | 129 | 39.86 | 33.5495 |
| **3100** | 42.9 | 118 | 24.5 | 31.0276 |
| **3200** | 27.6 | 203 | 44.27 | 80.3987 |
| **3300** | 25.8 | 203 | 90.53 | 80.1648 |
| **3400** | 36 | 199 | 30.18 | 40.6363 |
| **3500** | 9.3 | 199 | 43.42 | 88.1866 |
| **3600** | 21.9 | 211 | 63.54 | 72.9037 |
| **3700** | 14.7 | 205 | 51.1 | 82.6524 |
| **3800** | 26.1 | 194 | 85.86 | 44.2739 |
| **3900** | 24.8 | 210 | 57.99 | 42.9902 |
| **4000** | 34.9 | 213 | 86.53 | 57.4452 |
| **4100** | 25.6 | 190 | 44.15 | 44.5429 |
| **4200** | 47.7 | 132 | 42.24 | 65.8345 |
| **4300** | 38.2 | 212 | 63.37 | 71.3003 |

**Table 2: Predicted Data in Well-2 Field X**

### 3.2 Error Analysis

In forecasting activity, it is necessary to define an objective parameter to evaluate the accuracy of predicted value with actual value. A good accuracy measure should provide an informative and clear summary of the error distribution. The evolution of accuracy measures can be seen through the measures used in the major comparative studies of forecasting methods (Chen, 2017). Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) can be considered as the very early and most popular accuracy measures. In this paper, MAPE will be used to evaluate the error between the predicted ROP and the actual ROP.

MAPE will measure the size of the error by calculating the average of the unsigned percentage error as shown in eq. (1).

$$MAPE = \left(\frac{1}{n}\sum\frac{|Actual-Forecast|}{|Actual|}\right)\text{............}(1)$$

Where n is the amount of data, *Actual* is the actual data and *Forecast* is the predicted data.

Nevertheless, the study still shows some relative error between predicted and actual value, the calculated MAPE for predicted data in well-2 field X is 0.38 .

## 3. CONCLUSION AND RECOMMENDATION

The investigation on the neural network model to predict the ROP has been done. As prediction ROP for nearby well, the model training will be train by the affected parameter of ROP based on the first well. Neural network as an information processing paradigm, its performance depends on the input of the training model, hence it's important to determine the most affected parameter using the importance normalization for each parameter. As the result, the most contributing parameter for ROP that will be used on the neural network is TVD, WOB and RPM. Not only selecting the significant parameter, the quality of the input needed to be control by filtering the noise data which contribute on the randomness of the data and increase the inaccuracy, therefore the drilling data sense is important to control the reliable data as the input model.

Prediction from artificial neural network model based on first well can be applied to change surface parameters on the rig when drilling the second well. Although the result of the MAPE is not quite enough, the model can at least give a picture about the ROP in nearby well and also the model can be improved by increasing the training data from another well. With the advancement of this study, several deep analysis toward the lithology or the drilling prognosis is strongly suggested in order to match the subsurface condition between two wells. Therefore, the prediction from the neural network will also be supported by the subsurface matching.

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