Bit selection using field drilling data and mathematical investigation

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Abstract. A drilling process will not be complete without the usage of a drill bit. Therefore, bit selection is considered to be an important task in drilling optimization process. To select a bit is considered as an important issue in planning and designing a well. This is simply because the cost of drilling bit in total cost is quite high. Thus, to perform this task, a back propagation ANN Model is developed. This is done by training the model using several wells and it is done by the usage of drilling bit records from offset wells. In this project, two models are developed by the usage of the ANN. One is to find predicted IADC bit code and one is to find Predicted ROP. Stage 1 was to find the IADC bit code by using all the given filed data. The output is the Targeted IADC bit code. Stage 2 was to find the Predicted ROP values using the gained IADC bit code in Stage 1. Next is Stage 3 where the Predicted ROP value is used back again in the data set to gain Predicted IADC bit code value. The output is the Predicted IADC bit code. Thus, at the end, there are two models that give the Predicted ROP values and Predicted IADC bit code values.

Keywords--Artificial Neural Network (ANN), International Association of Drilling Contractors (IADC), Rate of Penetration (ROP).

1. Introduction

1.1. Background

The basic form of bit selection is normally done based on cost per foot. This method is simply choosing the bit that will provide the lowest cost per foot over the upcoming interval. In addition to that, other factors are taken into consideration as well such as offset, journal angle, and other design aspects. This differentiates one bit to another according to the specific environments. Therefore, understanding bit types is a vital step before moving on to bit design as well as bit selection.
1.2. Bit Types

Rotary drilling bits can be generally classified as either drag bit or rolling cutter bits according to the design features. Drag bits have fixed cutter blades in common. These blades are integrated within the body of the bit. The rotation takes place with the drill string as one unit. On the other hand, the rolling cutter bits normally have 2 or more cones which have basic cutting elements. These cutters rotate about the axis of the cone during the bottomhole rotation [1]. There are two main types of bits which are Drag Bit (PDC Bit) and Rolling Cutter Bit (Tricone Bit).

1.3 Bit Design

1.3.1 Bit Design for Rolling Cutter Rock Bits

Basically, there are 3 basic types of bearings:
- The Non-Sealed Roller Bearings (NSRB)
- The Sealed and Lubricated Roller Bearings (SLRB)
- The Sealed and Lubricated Journal Bearings (SLJB)

1.3.2 Bit Design for PDC Bits

The PDC bit is known to be a solid one piece tool holding polycrystalline diamond cutters. The synthetic diamonds are molded into a thin layer to be attached to a tungsten carbide disc. This is done via a HPHT process. The shock load propagates through entire cutting via the random orientation of the cleavage planes that indirectly allows reduction in breakage. PDC bits are known to shear the rock which helps save energy. Thus, optimized drilling can be gained with the usage of less WOB. Given a favorable formation, PDC bits are acknowledged to perform longer and harder. The effectiveness is about 3 times than conventional rolling cutter bit [2]. Having all these plus points, PDC bits are quite expansive and can be destroyed by gumbo type formations. Therefore, a proper geologic analysis together with PDC bit compatibility must be done before drilling. The detailed field analysis for PDC bit has not been completed and this report is based on the data limitations [3].

1.4 Bit Selection Methods

A bit cost might be relatively small in a well’s budget which is approximately 5% of the total expense of a well, but the impact of bit performance on overall well cost might end up being considerably large [4-6]. Bit selection is basically classified into three categories namely:

- Cost Analysis
- Offset Well Log Analysis
- Bit Performance Modeling Using ANN and Genetic Algorithm

2. Methodology

ANN is a computational technique used to solve complex problems. MLP network is one of the most popular neural network architectures for modeling process [7]. It consists of input layer of source nodes, hidden layer of computation nodes (neurons), and output layer. The number of nodes that is being used in the input as well as the output layer is completely dependent on the number of input and output variables being used respectively [8]. The figure shown is a schematic of MLP network. Further theoretical details about MLP networks is presented by [9]. In this project, the MLP network is trained by the usage of LM technique. One of the advantages of using the LM technique is that it produces efficient and faster second order convergence rate and is capable to maintain the stability at the same
time [10, 11]. Based on the research papers, it is clearly stated that the single layer is good enough to approximate a complex function [12]. Therefore, in this study, a three layered Feed-Forward Network is developed namely input, hidden, and output layers. Among the available data sets which are gathered from different offset wells, 70% is used for training, 15% is applied for validation process and the remaining 15% is used to test gained results from the bit being modeled as well as the ROP functions. Stage 1 was to find the IADC bit code by using all the given field data. This data include Size (in), Flow area (in2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), ROP (m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Targeted IADC bit code.

| Table 1. Method in Obtaining ANN Results |
|-----------------------------------------|
| Model | Data Being Used | Description |
|-------|------------------|-------------|
| ANN   | Drilling Data    | 10=512X     |
|       |                  | 20=434X     |
|       |                  | 30=532M     |
| Output| Example          | Ex: ANN predicts |
| IADC Bit Code | 10, 20, 30 | the numbers as perhaps 11.5 (10), 23.4 (20), and 38.7 (30) |

The results of the three methods discussed above are considered for ROP prediction and improve predicted IADC bit code value.

3. Results and Discussion

For the ANN simulation process, the Matlab software was used. The Neural Network tool which was prebuild in this Matlab software was used to gain all the results and generate all the graphs needed. The type of data used for this project comprises of drilling data. The table below shows an example of data set that was used. The following table represents the range of the data which was used.

| Table 2. Data Type Example |
|---------------------------|
| Type | MITO | Rotation min(rpm) | 60 |
|------|------|-------------------|----|
| Size (in) | 17, 50 | Rotation max (rpm) | 60 |
| IADC Code | 115M | Total bit revolution | 86400 |
| Input For ANN | 1 | Weight min (kN) | 20 |
| Flow area (in2) | 0.994 | Weight max (kN) | 60 |
| Depth out (m MD) | 68 | Flow min (l/min) | 2500 |
| Bit meter (m) | 55 | Flow max (l/min) | 2500 |
| Rot hours (hrs) | 24, 00 | Pump min/max (bar) | 20 |
| ROP(m/hr) | 2, 3 | Pump max (bar) | 22 |

| Table 3. Data Type Range |
|--------------------------|
| Type | -------- | Rotation min (rpm) | 0-271 |
|      | -------- |-------------------|-------|
The following was done to gain the results that will be discussed below. The Azar Well data was used in the ANN modeling process. The modeling process was done in three stages. Stage 1 was to find the IADC bit code by using all the given filed data. This data includes Size(in), Flow area (in2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), ROP(m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Targeted IADC bit code. Stage 2 was to find the Predicted ROP values using the gained IADC bit code in Stage 1. This time, the data used as input in the ANN modeling process include Targeted IADC bit code, Size(in), Flow area (in2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), Predicted ROP(m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Optimized ROP. Next is Stage 3 where the Predicted ROP value is used back again in the data set to gain Predicted IADC bit code value. The input parameters were Size(in), Flow area (in2), Depth out (m MD), Bit meter (m), Rotation hours (hrs), Predicted ROP(m/hr), Minimum Rotation (rpm), Maximum Rotation (rpm), Total bit revolution, Minimum Weight (kN), Maximum Weight (kN), Minimum Flow (l/min), Maximum Flow (l/min), Minimum Pump Pressure (bar), and Maximum Pump Pressure (bar). The output is the Predicted IADC bit code. The results were gained and they were used to plot regression graphs. The graphs are shown below. In all the simulations done under the ANN modeling, the data was used with 70% for training data, 15% for validation data, and 15% for test data.

For the simulation process, the number of hidden neurons can be varied from a range of 1 until 23. The best simulation results were gained when the number of hidden neurons was set to 10. The following table shows the Mean Square Error values and R values for Training Data, Validation Data, and Test Data.

| Table 4. MSE And R Value For 10 Number Of Hidden Neurons (Stage 1) |
|------------------|------------------|------------------|
| SAMPLES | MSE | R |
| TRAINING | 71 | 498.46659 | 0.82799 |
| VALIDATION | 16 | 1287.67076 | 0.68085 |
| TESTING | 16 | 2095.87942 | 0.83949 |
For the stage 3 simulation process, it is seen that the number of hidden neuron layers of 17 showed a better response compared to number of hidden neuron layers of 10.

Table 5. Predicted IADC Bit Code Value And Predicted ROP Value Examples

| IADC Bit Code | ANN Output | Predicted IADC Bit Code Value | Predicted ROP (ft/hr) | Predicted ROP Value (ft/hr) |
|---------------|------------|--------------------------------|-----------------------|-----------------------------|
| 1,1,1         | 10         | 8.540809                       | 19.263360             | 20.03738                    |
| 1,1,1         | 10         | 10.49332                       | 16.2142857            | 18.74017                    |
| 1,3,4         | 70         | 74.78044                       | 7.77586207            | 3.43065                     |
| 2,1,4         | 90         | 93.24648                       | 3.37209302            | 2.866403                    |
| 2,1,4         | 90         | 85.00292                       | 3.09090909            | 2.379206                    |
| 1,3,4         | 70         | 65.81053                       | 2.80991736            | 1.642444                    |
| 1,3,5         | 80         | 83.09457                       | 2.80991736            | 2.324059                    |
| 2,1,4         | 90         | 90.54357                       | 1.39534884            | 1.711341                    |
| 2,1,4         | 90         | 71.90172                       | 2.00000000            | 1.35653                     |
| 2,1,4         | 90         | 72.16207                       | 1.60655738            | 1.455876                    |
| 2,1,4         | 90         | 70.22408                       | 1.5106383             | 1.02429                     |
| 2,1,4         | 90         | 88.04242                       | 1.41176471            | 1.29425                     |
| 2,1,4         | 90         | 83.33124                       | 2.63157895            | 1.329831                    |
| 1,1,1         | 10         | 6.796307                       | 13.5396825            | 12.9523                     |
| 1,1,1         | 10         | 8.319983                       | 6.40000000            | 5.959551                    |
| 1,1,1         | 10         | 6.990621                       | 4.30769231            | 3.70865                     |
| 1,1,1         | 10         | 9.344001                       | 3.38000000            | 3.596977                    |

These values can be concluded as a good approximation as the predicted values are almost near to target values provided. The graph below shows the comparison of predicted IADC Bit Code versus the targeted IADC Bit Code.
Based on the second set of data set used to recheck the accuracy of ANN simulation, it can be said that the ANN simulation process is quite accurate to be used as a prediction tool. Thus, a third set of data was taken into consideration to confirm the accuracy of the ANN simulation process whereby the results were predicted to be at least 95% accurate.

4. Conclusion

In conclusion, the objective of the project has been achieved. The ANN simulation modeling process has been used to Predict ROP value and the Predicted IADC Bit Code has been found. Generally, the training is done for about 10 to 15 times for each Number Of Hidden Neurons Layers to gain the best output of Mean Square Error, MSE and Regression value, R. It has been seen during the simulation process that the most suitable hidden neuron number is 10 and 17. For the Azar Well 1 and 2 data sets, the final accuracy levels of the Predicted IADC Bit Code Values were 0.99 and the final accuracy level of the Predicted ROP Values were 0.95. This clearly shows that the usage of ANN simulation as a prediction tool can provide and accuracy level of more than 95 percent which is fairly accurate. In order to reconfirm that these values were accurate enough, a new set of data was also used to see if it gives a proper prediction. Once again, the final accuracy levels of the Predicted IADC Bit Code Values were 0.96 and the final accuracy level of the Predicted ROP Values were 0.95 for the second set of data set. Therefore, it is clearly seen that this project has managed to utilize the ANN simulation to predict the IADC Bit Code and ROP values quite effectively. However there are still some errors in the prediction. This is simply due to certain reasons which are insufficient data, limited time frame to complete the project, and also the absence of Log Data.

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