Predicting Drilling Rate of Penetration Using Artificial Neural Networks

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Abstract. Oil well drilling processes are generally high-cost operations; however, these costs can be reduced by optimising drilling operations. In particular, it is vital to optimise the drilling rate of penetration during oil well drilling operations. Many parameters affect drilling penetration rate, and these have complex relationships with each other. The accurate prediction of the drilling rate of penetration has particular importance in the optimisation of all drilling parameters and the reduction of drilling costs. In this paper, a neural network model is developed to predict the rate of penetration for an Iraqi oil field as a function of well depth, drilling fluid inflow, bit rotation speed (RPM), weight on bit (WOB), standpipe pressure, and bit size. The data on which the network was trained was collected from one drilled oil well, and 3,939 data points were used to develop the new model. These were randomly divided into two parts, with 70% used for training and 30% used for testing. The results showed that the resulting neural network model offers high accuracy for predicting the drilling rate of penetration. The statistical analysis showed that the developed neural network model predicted the rate of penetration very high accuracy (correlation coefficient of 0.983 and average absolute error of just 7.78%). The new model can also be used to determine the optimum drilling parameters to obtain a desired rate of penetration.

1. Introduction

Optimising the drilling rate of penetration by amending drilling parameters represents one of the most important tasks of drilling engineers [1]. Due to the high cost of oil well drilling, it is very important to select optimum drilling parameters [2], and various studies have been performed to study the possibility of increasing rig capability based on drilling formation [1, 3]. The optimum selection of bit and drilling parameters to give the maximum rate of penetration is important, as this reduces drilling costs; however, while it is important to achieve the highest possible drilling rate, this should be associated with an accurate bit selection programme in order to reduce bit damage, as bit damage will increase the cost of well drilling not only due to the high cost of bits but also due to the time required to pull the drill string out of the well in order to replace a damaged bit. The drilling rate of penetration is affected by various parameters, including the type of bit, drilling string rotary speed (rotary table speed), bit nozzle numbers and sizes, weight on bit (WOB), and rock properties [4, 5]. Clearly, it is not possible to alter rock properties; thus, optimising the other drilling parameters is the focus of drilling engineers seeking to obtain the maximum possible drilling penetration rate. In the related literature, no direct method for choosing the optimum drilling parameters for each formation has emerged. Drilling parameters such as drill string rotation speed, bit nozzle number and size, and the weight exerted on bit are thus often based on practical experience. Drilling engineers use their field experience to select different values of drilling parameters for the different drilled formations in the knowledge that the optimum selection of such
drilling parameters improves the drilling rate of penetration [6]. However, more studies and investigations are required to find procedures that can improve the process of selecting optimum drilling parameters. As drilling rate of penetration is affected by many factors, the process of selecting the optimum drilling parameters using conventional mathematical methods is prohibitively difficult [7, 8]. To simplify the evaluation of the effect of drilling parameters on the drilling rate of penetration, artificial neural networks have been recently adopted as an alternative method [8, 1, 3] to reduce the uncertainties in selecting optimum drilling parameters. The difference between traditional mathematical models and artificial neural networks is that the former requires prior accurate information about all parameters involved and their relationships [9, 10], while the latter can predict relationships between large numbers of variables without prior accurate knowledge about these relationships [4, 5]. Artificial neural networks solve this problem by creating structures of neurons.

In this work, a new artificial neural network model was established for an Iraqi oil field based on 3,939 field measurements. This new model thus correlates most drilling parameters (well depth, drilling fluid flow in, Bit Rotation Speed (RPM), Weight on Bit (WOB), stand pipe pressure, and bit size) with the drilling rate of penetration.

2. Methodology

In this work, an Artificial Neural Network (ANN) was used to establish new model to predict the drilling rate of penetration as a function of six different drilling parameters. ANN is now a well-known technology for dealing with complex problems involving relationships between input and output parameters [7]. ANNs have been used to solve problems in various branches of science and engineering, including health science, chemical science, astronautical engineering, electronic engineering, and petroleum engineering [11, 12]. Network architecture, transfer function, and learning algorithm are the main three components of an ANN [6], and ANN structure is organised in three layers (input layer, hidden layer and output layer) [13]. In some cases, the ANN model may include more than one hidden layer. Data can be transferred from the input layer to the hidden layer based on a parameter called weight. The performance of the ANN model is thus mainly influenced by its weights and the number of neurons in the hidden layer. The development of an ANN model consists of two main processes, training and testing [1]. During the training step, the hidden layer transfers the data from the input layer to the output layer. Then, the data estimated by the ANN is compared with the measured (real) data in the output layer. ANN training is stopped when the required accuracy is reached, and after the training process, the testing process is applied, with the model used to predict the output layer based on input data only [14-16].

3. Results and discussion

The 3939 well measurements used in this work were collected from three sections of an Iraqi oil well. A real time sensor was used to measure the well depth, drilling fluid flow in, Bit Rotation Speed (RPM), Weight on Bit (WOB), stand pipe pressure, bit size, and drilling rate of penetration for every metre of the drilled formation.

The ANN model development process was begun with a training step. Figure 1 shows the drilling parameters used as input data during the training process for the developed model. The minimum and maximum values of the drilling parameters and drilling penetration rate used in this study are summarised in Table 1. During the network training, 2,757 measurements (70% of all data) were used as input parameters (well depth, drilling fluid flow in, Bit Rotation Speed (RPM), Weight on Bit (WOB), stand pipe pressure, and bit size) and their output parameters (drilling rate of penetration) were also provided to the network. The remaining 1,181 measurements were used during the testing process.
Figure 1. Drilling parameters used to develop the new model.

Table 1. Range of data used during the training and testing processes

| Property                                      | Minimum Value | Maximum value |
|-----------------------------------------------|---------------|---------------|
| Depth (m)                                     | 4064          | 124           |
| Drilling Fluid Flow In (Gal/Min)              | 1150          | 287           |
| Drilling Rate of Penetration (m/hr)           | 0.97          | 143           |
| Weight on Bit (Klb)                           | 67            | 3             |
| Bit Rotation Speed (Rotation/Min; RPM)        | 228           | 16            |
| Bit Size (In)                                 | 17.5          | 8.25          |
In the model, a feed-forward backprop network was applied with three layers (Figure 2). Table 2 summarises the developed model. A trial and error process was used to assign the best number of neurons for the hidden layer. The structure of the developed model, the algorithms used, and the training progress are shown in Figure 2. As shown in Figure 3, the mean square error of the best validation performance was 0.69285 at epoch 64 from a total of 1,000 epochs.

**Table 2.** Description of the rate of penetration model

| Property | Rate of Penetration Model |
|----------|----------------------------|
| Number of layers | 3 (Input, hidden, output) |
| Number of input variables (Nodes) | 6 (Depth, Fluid Flow in, Weight on Bit, Bit Rotation Speed, Bit Size, Standpipe Pressure) |
| Number of output variables | 1 (Rate of Penetration) |
| Number of hidden layers | 1 |
| Number of neurons in the hidden layer | 11 |
| Performance goal (MSE) | 0 |
| Max. number of epochs to train | 1000 |
| Network type | Fed-forward backprop |
| Number of the training sample | 2757 |
| Number of testing sample | 1181 |
| Learning function | Learngdm |
| Train function | Trainlgdx |
| Transfer functions | tansig, purelin |
Figure 2. Topology of the neural network model, the algorithms used, and the training progress

Figure 3. Model training and validation progress

Figure 4 presents a comparison between the measured and predicted rates of penetration from the new artificial neural network model during the training process (2,757 data points). The neural network model is thus shown to predict the drilling rate of penetration with excellent accuracy. At the end of the training process, the model could predict the rate of penetration with average absolute error (AAER) of 5.37% and a correlation coefficient of 0.993, as shown in Figure 4.

New data points (1,181) that were not imported to the model during training, were then used to test the established rate of penetration model. Figure 5 shows that the new model predicted the drilling rate of penetration for the testing data with a very low average absolute error (7.78%) and a good correlation coefficient (0.983).
Generally, the drilling rate of penetration can thus be accurately predicted by the new artificial neural network model as a function of drilling parameters.

![Figure 4. Drilling rate of penetration predictions during training process (2,757 data points)](image)

![Figure 5. Drilling rate of penetration predictions during testing process (1,181 data points)](image)

**4. Conclusions**

Drilling parameter optimisation is a major challenge in oil well drilling operations as it significantly affects drilling costs [3, 8]. Drilling rate of penetration is highly influenced by various factors, including bit type, bit characteristics, rotation speed, Weight on Bit (WOB), and type of formation [4, 5]. This complexity makes it difficult to use conventional mathematical methods to develop the relationships between drilling parameters and the drilling rate of penetration. In this paper, a new model was
developed using an artificial neural network to correlate the rate of penetration with well depth, drilling fluid flow in, Bit Rotation Speed (RPM), Weight on Bit (WOB), stand pipe pressure, and bit size. To achieve this, 3,939 data points were used (2,527 samples in the training process and 1,181 samples in the testing processes). The results indicated that the new model can accurately predict the drilling rate of penetration with average absolute error (AAER) rates of just 5.37% and 7.78%, and correlation coefficients of 0.993 and 0.983 for training and testing data, respectively. The ANN technique should thus be carried out on other Iraqi oil wells to validate the application of this method to confirm this as a reliable approach.

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