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Neural Network Application to Manage Drill Stem Vibrations and Improve Drilling Performance

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Abstract

Real time drilling optimization is a significant technology, because it mitigates undesirable vibration events, and improves drilling rates without compromising the life span of the drilling equipment. However, the complexity of drill stem vibrations challenges real-time drilling optimization, and continues to adversely impact non-productive time (NPT) primarily due to downhole tool failures.

The objectives of the work in this paper is to improve the management of drill stem vibrations, and increase drilling performance. The aforementioned objectives are achieved by introducing a drilling optimization model that couples Rate of penetration (ROP) with vibrations data. The drilling optimization model presented in this paper has a significant impact on improving the performance of real-time drilling optimization.

To overcome the complexity of drill stem vibrations, Artificial Neural Network (AAN) was used to create a model that couples drilling performance and drill stem vibration. Data was collected from measurement while drilling (MWD)/logging while drilling (LWD) and vibrations measurement of a well in the North Sea. In turn, data analytics was then performed to measure correlations and identify dependencies of drilling parameters along with their impact on drill stem vibrations. Sequentially, data normalization was applied to be used as an input field for the ANN model.

The adopted ANN model was implemented based on multi-layer-feed-forward for back-propagation. The objective of the back-propagation is to develop a training data set that is capable of handling complex drilling conditions. Thus, drilling performance parameter, i.e. ROP, was the ANN output functions.

The application of machine learning in drilling optimization is demonstrated in this paper. ANN was applied to optimize drilling performance and reduce drill stem vibrations. Consequently, artificial intelligence is applied to optimize complex drilling engineering systems.

Introduction

Severe drill stem vibrations lead to premature failure of drilling equipment and leads to inefficient drilling. Drill stem vibrations are mitigated or minimized using post-well analysis and drill stem static and dynamic modeling prior to a field run (Burgess et al. 1987; Aslaksen et al. 2006; Bailey et al. 2008; Al Dushaishi et al. 2015). One major aspect of reducing drill stem vibration for a given bottomhole assembly (BHA), is to control the energy parameters such as the applied rotational speed (RPM) and weight on bit (WOB). However, conservative RPM and WOB results in a lower ROP, which reduces the drilling performance.

Drilling performance is measured based on ROP and/or mechanical specific energy (MSE) (Teale, 1965; Dupriest and Koederitz, 2005). Theoretical modeling of ROP and MSE has been widely used to address and improve drilling performance (Bourgoyne and Young, 1974; Rastegar et al. 2008; Hareland et al. 2010; Soares et al. 2016). To optimize drilling, models such as the ROP and MSE are used to predict the optimum drilling parameters and design configurations that yields the highest efficiency for a giving drilling section.

Data analytics and artificial intelligence have been used to enhance several drilling models such as, the optimization of particle size distribution to seal fractures (Alsaba et al. 2017), optimizing drilling hydraulics (Wang and Salehi, 2015), and casing collapse prediction (Salehi et al. 2009).

Machine learning and data analytics were further applied to ROP prediction using MWD and LWD data to optimize drilling performance. Different ANN methods and input/output parameters have been used by authors to develop drilling optimization models. However, no ANN method in literature considered vibration measurements. For example, Hegde and Gray (2017) used surface RPM, WOB, flow rate and unconfined compressive strength (UCS) as input parameters to predict ROP. Their analysis showed that drilling time can be improved by 12%. Other studies predicting ROP considered more or less input parameters including bit size/type (Moran et al. 2010; Jahanbakhshi et al. 2012; Shi et al. 2016; Abbas et al. 2018), formation drillability and abrasiveness (Moran et al. 2010; Jahanbakhshi et al. 2012; Shi et al. 2016; Abbas et al. 2018), bit wear (Abbas et al. 2018), drilling fluid type (Moran et al. 2010; Jahanbakhshi et al. 2012; Shi et al. 2016; Abbas et al. 2018), pump pressure (Jahanbakhshi et al. 2012; Shi et al. 2016; Abbas et al. 2018), and wellbore trajectory (Abbas et al. 2018). All of these mentioned models achieved model accuracy ranging from $r=0.8$ to $r=0.91$ for either the validation data or the training data. Hegde and Gray (2018) built an ANN model, where the output parameters of their model included torque on bit. However, in their analysis they used surface torque without the use of downhole vibration data.

The significance of this paper is that the developed ROP model takes into account measured downhole drill stem vibrations. The objective of this paper is to improve drilling performance taking into account drill stem vibrations.

Field Data and Methodology

Drilling and vibration data of an offshore well, previously published in Al Dushaishi et al. 2016, was used in this paper. The data consist of vibration data and the conventional measured drilling parameters of a 12 ¼” section as shown in **Figure 1**. Measured vibration data consist of lateral and centripetal acceleration. The centripetal acceleration provides information regarding the tangential velocity, i.e. torsional vibrations. UCS was calculated using the sonic travel time velocity, following Al Dushaishi et al. 2018, to reflect the formation strength contribution to the measured ROP. **Figure 1** shows the measured drilling and vibration data including the calculated UCS.

Artificial Neural Network Modeling

A basic ANN model consists of three main elements (**Figure 2**). The first element is a set of connecting links from the input parameters x_i, where each input is characterized by a weight w_{ki}. In which i is an index of the input number n, and k is the target neuron. The second element is the summation, which is used for summing the input signal x_i weighted by its respective weight w_{ki}. And lastly, an activation function f used for limiting the amplitude of the output neuron y_k. Some ANN models also include an external applied bias b_k, which either increases or decreases the net input of the activation function (Kantardzic, 2011).

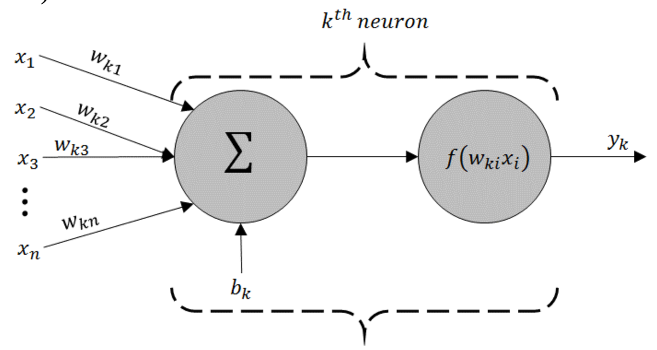

Figure 2. Basic ANN Model

The feed forward ANN consist of neurons that include input layers, hidden layers and output layers. The input layer consists of n input parameters having values of $x_{i=1..n} \in R$, where random initial weight w_{ki}, ranging from *[-1,1]*, is assigned to each input (Kantardzic, 2011). Each neuron in the hidden layers receives the weighted sum of all input parameters x_i. The value of the output layer is computed as:

$$y_k = f\left(\sum_{i=1}^{n} w_{ki}x_i\right) \tag{1}$$

where f is an activation function. The activation function, i.e. transfer function, used in this paper is the hyperbolic tangent (TanH) function. The TanH function transforms values of the input parameters to be between *[-1, 1]*. The TanH transfer

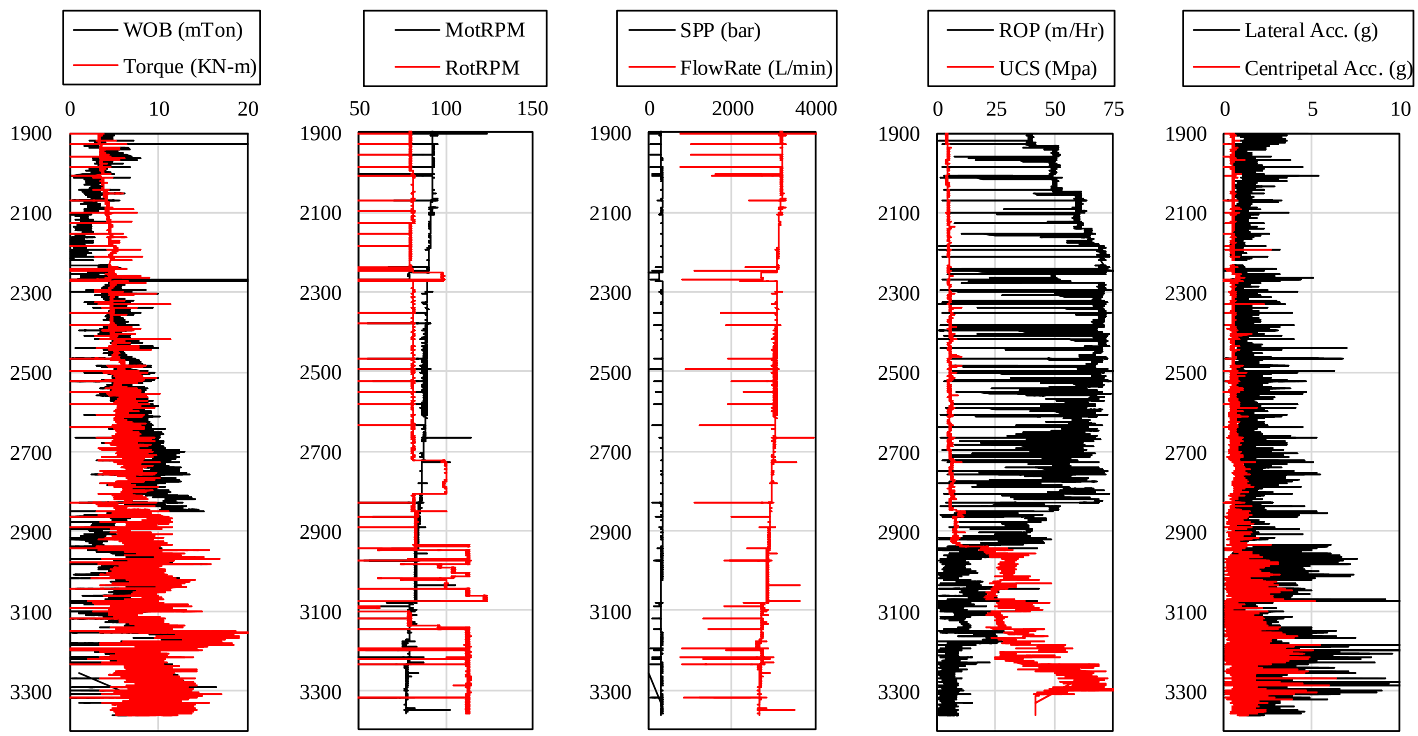

Figure 1. Measured Drilling and Vibration Data and Calculated UCS

function is described as (SAS Inst. 2018):

$$f = \frac{e^{2\, w_{ki} x_i} - 1}{e^{2\, w_{ki} x_i} + 1} \qquad (2)$$

The goal of running different combination number of neurons is to find the number of neurons that will yield the highest R^2 between the predicted and the actual ROP data. The input and output variables are normalized to generate the R^2 value using the standard nonlinear least-squares regression method of both the training and validation data set (SAS Inst. 2018).

Analysis and Discussion

In this work, the ANN modeling was constructed using the Neural platform in SAS JMP®. The platform uses multilayer perceptron, which is a class of feedforward ANN. One hidden layer with a range of neurons were performed using different input parameters with the output parameter being the ROP. Data training was performed using random holdback cross validation method, which divides the original data into training and validation set randomly. Due to the large data set (*N>6,000*), 30% of the original data was used for validation.

First and before initiating ANN modeling, data preprocessing, i.e. normalization, was performed. Data normalization decreases training time and produce less errors (Abbas et al. 2018). Several input parameters were considered as input parameters. The parameters that showed the highest contribution to ROP are shown in **Figure 3** using only two hidden neurons, i.e. nodes.

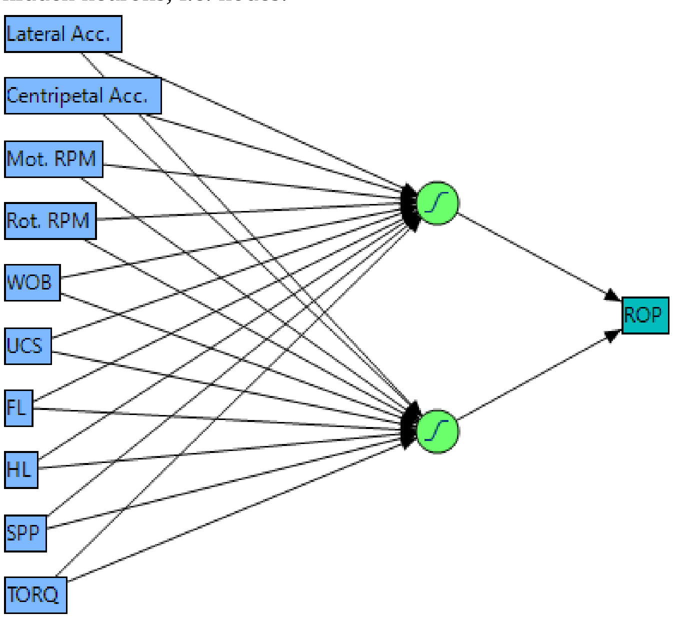

Figure 3. Input Parameters Used for ANN Modeling

A second model was considered using less input parameters to compare the ANN performance. Model 2 consist of only 6 input parameters, which includes lateral and centripetal accelerations, rotary and motor RPM's, WOB, and UCS.

Several number of neurons were simulated for both models, **Figure 4** and **Figure** 5 show the correlation coefficient of both models for the training and validation data sets with increasing number of neurons, respectively.

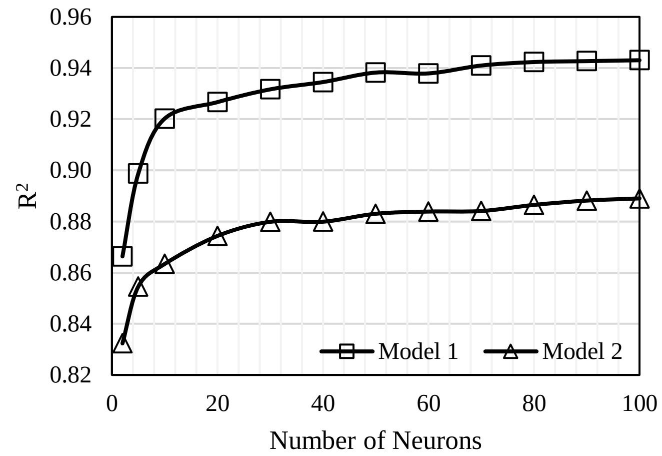

Figure 4. Training Data Correlation Coefficient

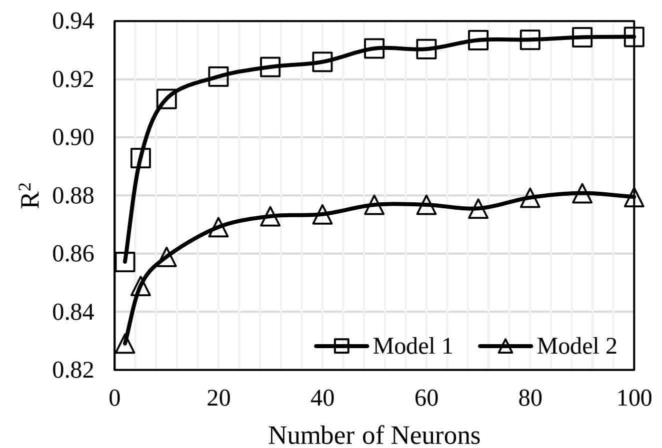

Figure 5. Validation Data Correlation Coefficient

It can be seen in **Figure 4** and **Figure** 5 that correlation coefficient of Model 1, using 10 input parameters, is higher than Model 2, using 6 input parameters, for both the training and validation data sets. Higher correlation coefficient can be obtained with a smaller number of neurons using Model 1. Thus, Model 1 was used for further analysis. It is worthwhile mentioning that there is no direct set method to select the number of neurons. In this paper, the number of neurons was selected when the slope of the correlation coefficient decreases. The increase of the correlation coefficient of Model 1 is insignificant with more than 20 neurons. Thus, to avoid overfitting the ANN model, 20 neurons were used, which gives correlation of coefficient of 0.93 and 0.92 for the training and the validation data sets, respectively. **Figure 6** shows both the measured ROP and the ROP predicted by the ANN model. It can be seen that the ANN model details with accuracy the input parameters variations to describe the measured ROP.

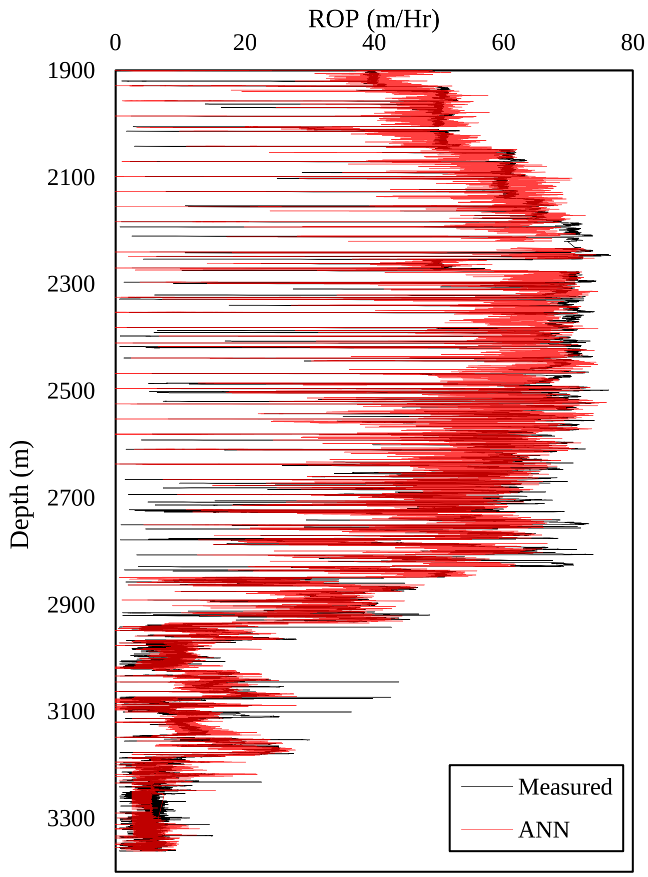

Figure 6. Measured ROP and Predicted ROP Using ANN Model

Figure 7 shows the factor prediction of the ANN model to visualize each parameters effect on ROP. The ROP factor prediction profiles shows the prediction of each parameters in black line, where the ROP value in the *y*-axis corresponds to the vertical dotted redline location (i.e. current value) of each parameter. In other words, the factor prediction profiles can be used to optimize ROP and control drill stem vibrations for given drilling parameters.

It can be seen in the model profile that ROP tends to increase with the increase of WOB, rotary RPM, flow rate and torque. While ROP decreases with the increase of UCS. These behaviors are expected as it follows the behavior of the previously published analytical models (Rastegar et al. 2008). The vibration profilers show that ROP tends to decrease with the increase of lateral acceleration, and increases with the increase of centripetal acceleration. Drill stem vibration may increase ROP, as some studies showed (Bavadiya et al. 2017; Xiao et al. 2018). Certain vibrations levels are acceptable. However, high magnitude of drill stem vibrations increases the dynamic stress on drilling equipment and may lead to equipment failure and interfere with measurement while drilling.

Conclusions

An ANN model was developed to predict ROP, which includes the effect of drill stem vibrations. The model was constructed using 10 input parameters including two vibrations input parameters. The study showed that:

- The ANN model was capable of predicting ROP with model accuracy of $r=0.93$ for the training data and $r=0.92$ for the validation data.
- The behavior of the energy drilling parameters such as WOB, applied RPM, and torque of the ANN model follow the same behavior as the analytical models.
- High correlation between centripetal acceleration and ROP was obtained. The increase in centripetal acceleration increases ROP.
- ROP tends to decrease with the increase of lateral vibrations.

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Nomenclature

ANN= Artificial neural network
BHA = Bottomhole assembly
FL = Flow rate (L/min)
HL = Hookload (mTon)
LWD = Logging while drilling
MSE = Mechanical specific energy
MWD = Measurement while drilling
NPT = Non-productive time
ROP = Rate of penetration (m/Hr)
SPP = Standpipe pressure (bar)
TanH = Hyperbolic tangent
TORQ = Torque (KN-m)
UCS = Unconfined compressive strength (Mpa)
WOB = Weight on bit (mTon)

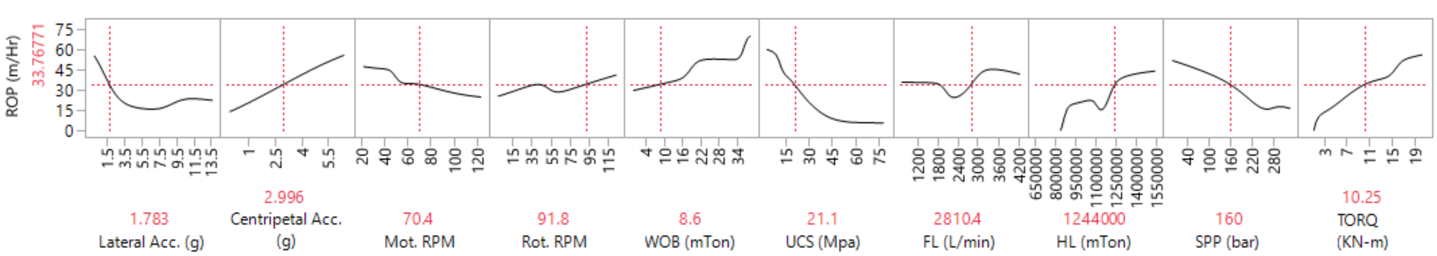

Figure 7. Factors Profiles with Respect to ROP

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