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Drilling Vibration Modes and Penetration Rate Modeling using Artificial Neural Network and Multiple Linear Regression Analysis in Khoman Formation at the Egyptian Western Desert

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Abstract

Drill string vibrations are one of the most serious problems encountered while drilling as the bit and drill string interaction with formations under certain drilling conditions usually induces complex shocks and vibrations into the drill string components resulting in premature failure of the equipment and reduced drilling penetration rate. In severe cases where shocks and vibrations accumulated into drill string till exceeded its maximum yield or torsional strength, fatigue will occur and thereby increase the field development costs associated with replacing damaged components, fishing jobs, lost-in-hole situations, and sidetracks. Thus, real-time monitoring for downhole-generated vibrations and accordingly adjusting drilling parameters, including weight on bit, rotary speed, and circulation rate, play a vital role in reducing the severity of these undesirable conditions. Vibration optimization must be done incorporation with the penetration rate, as a minimum economical penetration rate is required by the operator. In this study, three penetration rate and vibration level models were developed for axial, lateral, and stick-slip drilling modes using both MATLAB™ Software neural network and multiple regression analysis. It is found that the three models' results for vibration level and penetration rate, as compared with those recorded drilling data, showed an excellent match within an acceptable error of average correlation coefficient (R) over 0.95. The prediction of penetration rate and vibration level is thoroughly investigated in different axial, lateral, and stick-slip vibration drilling modes to be able to best select the optimum safe drilling zone. It is found that the axial vibration could be dampened by gradually increasing the weight on the bit and increasing rotary speed, while both the lateral and torsional vibrations are enhanced by increasing the rotary speed and decreasing the weight on the bit.

Keywords: *Drilling optimization; MATLAB; Neural network; Rate of penetration; Regression, Twist-off, and Vibrations.*

1. Introduction

The ability to monitor and accurately interpret dynamic drilling behavior depends on background knowledge of vibration types and how they arise. Thanks to the new advanced technology, measurement while drilling tools can real-time monitor and detect these generated downhole shocks and vibrations. Thus, we can adjust and optimize drilling parameters based on the type of vibration to minimize nonproductive time, save cost, and enhance drilling efficiency. Appropriate real-time corrective action can have a significant impact on the lifetime of the MWD tool, drill string, motor, bit, drill rates, and whole drilling efficiency [1]. As a matter of fact, to avoid these unstable drilling zones with high vibration levels, we are forced to sacrifice the rate of penetration (ROP) which is the principal goal of drilling economically. So, Optimization is to bypass and diminish vibration with a less harmful impact on ROP.

Simulation models; built based on actual recorded data with an acceptable minimal error; will help to dispense with the vibration-monitoring MWD tool as drilling parameters in conjunction with drill string design and area experience can be selected, ROP and vibration level could be predicted.

The objective of this study is to develop axial, lateral, and stick-slip models to predict mainly the vibration level and rate of penetration as outputs by using neural network back-forward-propagation method and multiple linear regression based on previously actual recorded drilling and vibrational data to have the ability to:

- Select and adjust the optimum drilling parameters such as weight on bit, rotational speed, and mudflow rate.
- Enhance the drilling efficiency and avoid drill string twist-off.
- Minimize the cumulative drilling cost by reducing NPT.
- Give minimal error outputs compared to the MWD tool readings.

Downhole vibrations are generally classified into three primary categories, axial, torsional, and lateral/transverse, as shown in Fig. 1.

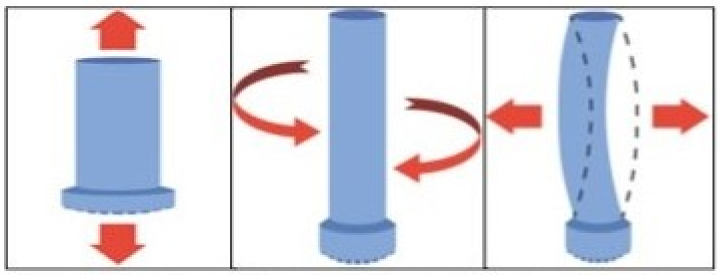

Fig. 1. Vibration modes a) Axial vibration b) Torsional vibration c) Lateral vibration

1.1. Axial vibration

Vibrations that propagate in a parallel direction to the axis of the drill string. Axial vibrations are caused by the movement of the drill string upwards and downwards and may result in a bit of bounce. Bit bounce is observed when the changes in substantial bit weight (WOB) cause the bit to periodically rise off the bottom, along the drill string in a vertical direction, and then drop and affect the formation [2-3].

1.2. Torsional vibration

Torsional vibrations usually occur as a result of excessive twisting motions in the drill string. Stick-slip is the primary mechanism for creating torsional vibrations. Due to the frictional torque of bit and BHA, the vibration is generated by cyclic acceleration and deceleration of bit and drill string [2-3].

1.3. Lateral vibration

Lateral vibrations are those vibrations formed in a direction perpendicular to the string. The main source of vibration is a whirl, which is the eccentric rotation of the drill string around a point other than the center of the borehole. Transverse vibrations are approved to be the most damaging process, resulting in significant damage to the BHA components and wellbore [2-3].

2. Literature review

Over the past years, several mathematical models have been proposed to explain the relationship between the rate of penetration and drilling parameters such as weight on bit, rotary speed, circulation rate, and formation rock mechanics neglecting the impact of vibration data. In the following, some of the well-known models are briefly discussed.

Maurer *et al.* [4] present an equation relating the ROP with WOB, RPM, bit size, and rock strength as expressed in Eq. 1:

$$\mathbf{ROP} = \frac{K\,N\,(W-W_0)^2}{{d_b}^2\,S^2} \tag{1}$$

where ROP refers to the rate of penetration ft/hr; K is a constant of proportionality, S denotes the rock compressive strength, psi; W is the WOB, lbf; W_0 is the threshold WOB, lbf; d_b is the bit diameter, in; and N denotes the rotary speed, rpm.

Bingham [5] proposes an experimental model that is applicable for low values of weight on bit (WOB) and rotational speed (RPM). This model neglects the effect of drilling depth. The Bingham model is defined by

$$\mathbf{ROP} = \mathbf{K}\left(\frac{WOB}{d_b}\right)^{a5} N^e \ldots \qquad (2)$$

where K is a proportionality constant, a_5 denotes the weight on bit exponent that should be determined experimentally based on the prevailing conditions.

Bourgoyne and Young [6] develop a model with nine inputs (depth, equivalent mud density, equivalent circulation density, WOB, bit size, rotational speed, Q, mud density, plastic viscosity), but multiple regressions are required to calculate seven different exponents for this model.

Recently, and with the help of progressing neural network modeling method, numerous models were built for ROP prediction using drilling data. Abdolali Esmaeili *et al.* [7] develops an ROP model using neural network and drill string vibration data. As it is realized from previous works of literature, most of the models just illustrate the relationship between penetration rate and drilling parameters such as weight on bit, rotary speed, bit diameter, mud weight, and formation rock mechanics except Abdolali Esmaeili neural network model, which takes into consideration the effect of vibration data on the rate of penetration.

In this approach, we built three models for the rate of penetration and drill string vibration level independently using neural network and multiple linear regression taking into consideration the type of vibration; axial, lateral, or stick-slip; and vibration level, which helps to define the optimum safe drilling zone as a combination between a high rate of penetration and low vibration level for each vibration mode.

3. Data used

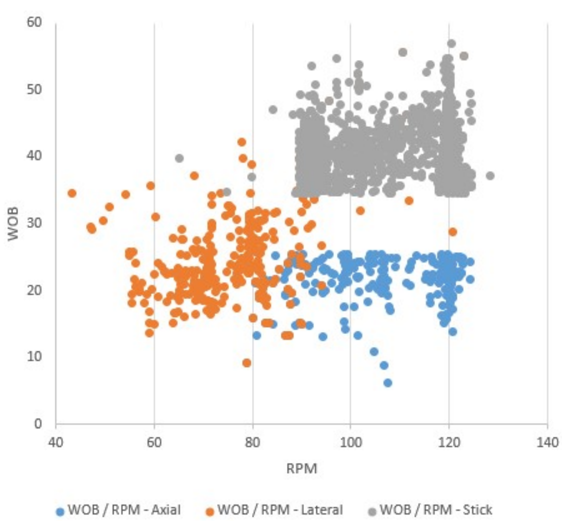

Fig. 2. WOB/RPM relationship

The real data used in this study were collected from different fields in the western desert of Egypt, including 12.25" hole drilling parameters and vibrational data, especially those encountered at Khoman formation with high downhole axial, lateral, and stick-slip vibration levels to be able to understand the drilling behavior and best select the stable drilling zone.

Fig. 2. shows the weight on bit and rotational speed relationship for each vibration mode axial, lateral, and stick-slip. Detecting a stable drilling zone for the whole section would be so difficult, but step-by-step real-time drilling parameters optimization is the best choice for safe drilling practice.

4. Methodology and model description

4.1. ANN model development

To build the artificial neural network model for ROP and vibration level prediction, the model passed through 3 stages as follows [8]: (i) Data preprocessing; (ii) Model learning; (iii) model evaluation.

4.1.1. Data preprocessing

Table 1. illustrates the real field input data ranges for axial, lateral, and stick-slip ANN models. Eight data sets as input parameters across 20 wells, including the depth, WOB, RPM, TQ, standpipe pressure (SPP), the flow in (GPM), DWOB, and MSE. The output data would be the rate of penetration and the vibration level.

The whole input data were collected from the mud logging unit except for the values of downhole weight on bit (DWOB), as measured from the sensor at the MWD tool and mechanical specific energy (MSE); which is an indicator for the amount of energy transfer from the surface to bit [9]; is calculated as per Eq. 3

$$\mathbf{MSE} = \mathbf{E}_{m}\,\mathbf{x}\left(\left(\frac{\mathbf{480\ x\ TQ\ x\ RPM}}{\mathbf{d_{bit}}^{2}\ \boldsymbol{x\ ROP}}\right) + \left(\frac{\mathbf{4\ x\ WOB}}{\boldsymbol{\pi}\ \mathbf{d_{bit}}^{2}}\right)\right)\ldots \qquad (3)$$

where MSE refers to mechanical specific energy (psi), E_m denotes bit mechanical efficiency (assumed to be 0.35).

Table 1. Input data ranges for axial, lateral, stick-slip ANN models

No.	Input parameter	Data Source	Axial		Lateral		Stick-slip		Unit
			Min	Max	Min	Max	Min	Max	
1	Depth	Mud logging unit	2785	6785	3660	5805	2750	6775	Feet
2	Weight on Bit		6	25	13	47	35	61	Klbs
3	Revolution per minute		71	124	55	118	65	128	RPM
4	Torque		2	14	9	14.5	2	11	Klbs.ft
5	Standpipe pressure		543	2096	526	1685	421	2140	Psi
6	Flow in		297	649	242	623	234	658	GPM
7	Downhole Weight on Bit	MWD sensor	3	22	8	41	20	51	Klbs
8	MSE	Calc.	6	77	18	77	2	58	Kpsi

4.2. Model learning

The algorithm of backpropagation in neural networks comprises the following sequence [10]:

- Initialize the number of hidden nodes.
- Initialize the learning rate and the maximum number of iterations (set all weights and thresholds to small random values).
- Select the activation function, which interconnects the input neuron to its output by a mathematical equation.
- Input values for the hidden nodes are determined based on Eq. 4.

$$\mathbf{S_j} = \sum_{\mathbf{i=1}}^{\mathbf{n}} \mathbf{X_i W_{ij}} \ldots \qquad (4)$$

where $\mathbf{X_i}$ is the input variable at node i and $\mathbf{W_{ij}}$ is the weight from input node i to hidden node j.

The output was derived from the hidden nodes, according to Eq. 5:

$$\mathbf{Y_j} = \mathbf{f}(\mathbf{S_j}) = \frac{\mathbf{1}}{\mathbf{1+e^{-S_j}}} \ldots\ldots \qquad (5)$$

where $\mathbf{Y_j}$ is the output variable from hidden node j.

The same algorithm was employed to calculate the inputs to the output nodes.

- The error term for the output node was calculated.
- Iteration ending condition was defined when the network errors were larger than the predefined threshold or the number of iterations was less than the maximum preset iterations, then the calculation process continued till one of these criteria was achieved.

In this study, simple axial, lateral, and stick-slip three-layered ANN networks (one input layer, one hidden layer, and one output layer) were created by programming software MATLAB™. Cross-validation plots were applied to determine the most proper number of neurons in the hidden layer.

Weights and biases of the networks were then appropriately initialized, and therefore the artificial neural networks were subjected to a backpropagation training algorithm [11]. ANN training involves the use of 70% of the original data sets, and the last 30% of the original data sets are allocated for model verification and testing.

4.3. Artificial neural training

The ANN models were trained by the backpropagation method with a learning rate of 0.001. Table 2 show neural network parameters for axial, lateral, and stick-slip models, respectively. Figures (3, 4, and 5) present the network structure of the proposed ANN axial, lateral, and stick-slip models used in this study, respectively.

Table 2. Axial, lateral, and stick-slip neural network parameters

Network structure	Axial neural network parameters	Lateral neural network parameters	Stick-slip neural network parameters
	ANN parameter	ANN parameter	ANN parameter
Input layer neurons	8	8	8
Output layer neurons	2	2	2
Hidden layer	1	1	1
Hidden layer neurons	10	10	15
Activation function	Sigmoid (Log-Sig) & Linear	Sigmoid (Log-Sig) & Linear	Sigmoid (Log-Sig) & Linear
Learning rate	0.001	0.001	0.001

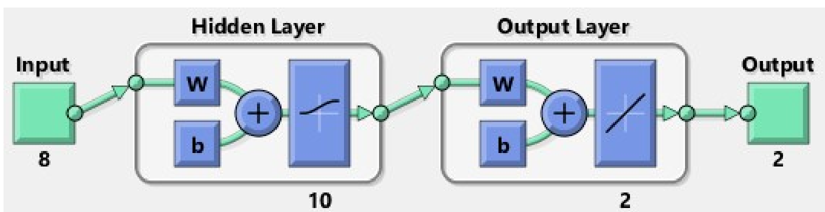

Fig. 3. Axial proposed ANN model architecture (Generated by MATLAB ™)

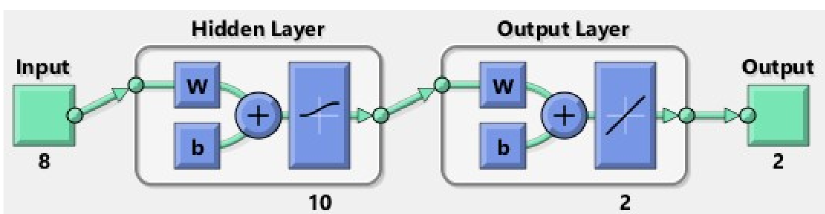

Fig. 4. Lateral proposed ANN model architecture (Generated by MATLAB™)

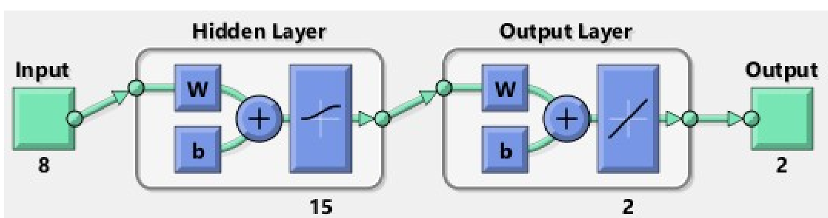

Fig. 5. Stick-slip proposed ANN model architecture (Generated by MATLAB™)

4.4. Model evaluation

The accuracy of the neural network model is evaluated by using validation and testing sample data through several statistical error analyses, including average absolute percent relative error (AAPRE), Mean squared error (MSE), Root mean squared error (RMSE), and Standard deviation (SD) [12-13].

4.4.1. Garson algorithm

Garson *et al.* [14-15] used the connection weights in the ANN architecture to assess the desired relative importance of each variable. The relative importance for each variable is given by the following formula:

$$\mathbf{IM}(\mathbf{X_p}) = \frac{\sum_{j=1}^{n_h}\left[\left(|\mathbf{I}|_{p_j} \Big/ \sum_{K=1}^{n_p}|\mathbf{I}|_{p_{j,K}}\right)|\mathbf{O}|_j\right]}{\sum_{i=1}^{n_p}\left(\sum_{j=1}^{n_h}\left[\left(|\mathbf{I}|_{p_{i,j}} \Big/ \sum_{K=1}^{n_p}|\mathbf{I}|_{p_{i,j,K}}\right)|\mathbf{O}|_j\right]\right)} \ldots\ldots \qquad (6)$$

where $\mathbf{IM}(\mathbf{X_p})$ represents the relative importance measure of the input variable *P*th on the output. $\mathbf{n_p}$ is the number of input parameters and $\mathbf{n_h}$ is the number of neurons in the hidden layer. The term $|\mathbf{I}|_{\mathbf{p_j}}$ is the absolute value of the weight in the neural network for the *P*th input variables and Jth hidden layer. The term $|\mathbf{O}|_\mathbf{j}$ is the absolute value of the output layer weight in the neural network for the *J*th hidden layer.

4.5. Multiple linear regression analysis

Multiple linear regression is a statistical method of data analysis to estimate the relationship between two or more independent variables and one dependent variable. Eq. 7 shows the basic model relationship:

$$\boldsymbol{Y_i = \beta_0 + \beta_{1i} X_1 + \beta_{2i} X_2 + \beta_{2i} X_2 + \cdots + \beta_k X_{ki} + \epsilon_i} \ldots \qquad (7)$$

where $\boldsymbol{Y_i}$ is the dependent variable, and there are k of independent variables (x_1, x_2, …..x_k). $\boldsymbol{\beta_0}$ and $\boldsymbol{\beta_k}$ are the intercept and slope parameters. $\boldsymbol{\epsilon_i}$ is the error term, and i = 1…*n* refers to the total number of observations [16].

In this study, two regression models for each vibration mode; axial, lateral, and stick-slip; were developed in which the rate of penetration (ROP), vibration level represent the dependent variables and the depth, WOB, RPM, TQ, SPP, GPM, DWOB, MSE represent (x_1….x_8) the independent variables. The estimated coefficients and intercept were selected to minimize the sum of squared errors.

Once a multiple linear regression model was formed, A regression report is typically outlined. With the help of estimated coefficients and statistical data, the strength of the model can be verified. A parametric sensitivity analysis is performed later on each model by increasing and decreasing some variables by 10% to find out which parameters have a greater impact on the ROP and vibration level. Table 3 displays the regression statistics results and the estimated coefficients for both ROP and vibration level models in the axial, lateral, and stick-slip drilling modes.

Table 3. ROP & Vibration regression statistics and coefficients

Parameter		ROP Regression Model			Vibration Regression Model		
		Axial	Lateral	Stick-slip	Axial	Lateral	Stick-slip
Multiple R		0.926728	0.9084	0.88471127	0.908693	0.720211	0.8927944
R Square		0.858826	0.825191	0.78271403	0.825724	0.518704	0.7970818
Adjusted R Square		0.852551	0.819364	0.78061971	0.817978	0.370612	0.795126
Standard Error		6.127561	2.630403	8.63204927	0.377199	0.303361	0.2828931
Observations		189	249	839	189	35	839
Coefficients							
Intercept	(X0)	16.93501	0.648517	22.9482996	-1.87064	3.482601	4.4615572
Depth	(X1)	-0.00207	0.00045	0.00534881	0.000204	-0.0001	9.315E-05
WOB	(X2)	-1.58102	0.493951	-2.3755313	-0.00634	0.049479	-0.005993
RPM	(X3)	0.268227	0.215426	0.34981771	0.019703	-0.03226	-0.000143
TORQ.	(X4)	0.003179	0.001963	0.00235017	0.000413	0.000156	3.039E-05
SPP	(X5)	-0.00117	0.004695	-0.0103191	-8.5E-05	0.001257	-0.000366
FLOW IN	(X6)	0.014828	-0.00862	-0.0006879	0.000375	-0.00467	-0.00463
DH WOB	(X7)	1.891414	-0.46128	2.44481598	-0.0125	-0.03314	0.0095891
MSE	(X8)	-0.75143	-0.49127	-0.8780216	-0.00299	0.005036	-0.006303

5. Result and discussion

5.1. ANN model structure

The ANN total data set was divided into three data sets: training set, validation set, and testing set. More specifically, 30% of the whole dataset was randomly selected as the testing and validation sets and then utilized for comparison between the proposed ANN model results and actual recorded data.

Figs. (6, 7, and 8) shows the prediction results of regression analysis for training, validation, testing, and total data set related to axial, lateral, and stick-slip models, respectively. It is observed that the difference in the correlation coefficient (R) between training and testing data sets for all models is relatively small, which indicates that these ANN models' training process is reliable.

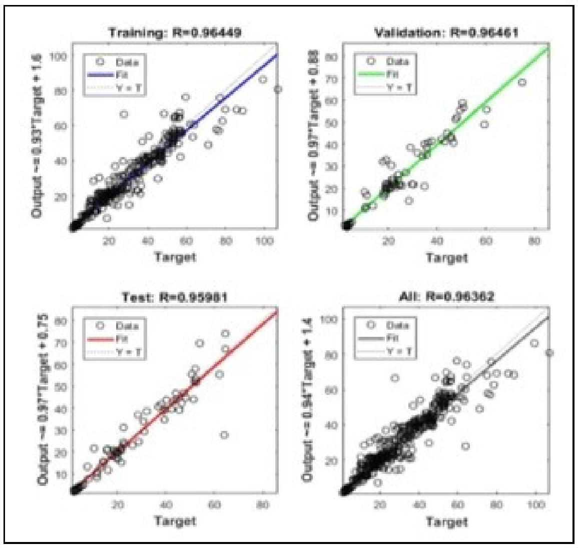

Fig. 6. Regression for Axial proposed ANN model (Generated by MATLABTM)

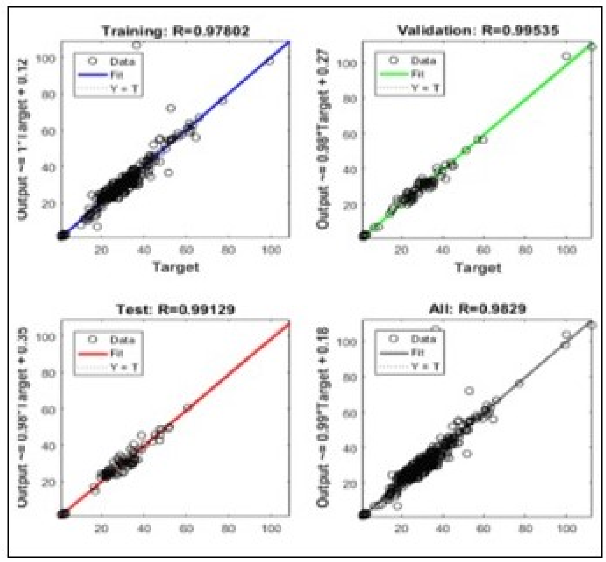

Fig. 7. Regression for Lateral proposed ANN model (Generated by MATLAB™)

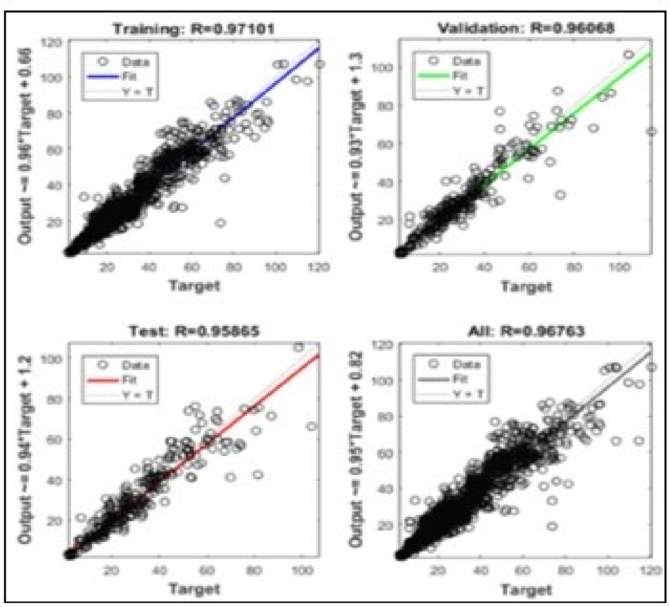

Fig. 8. Regression for Stick-slip proposed ANN model (Generated by MATLAB ™)

Moreover, it can be observed that the predicted rate of penetration and vibration level have a good match with the target values with an acceptable range of accuracy. The R of the testing data set for all models is estimated to be around 0.95, indicating that these ANN models have relatively strong predictive behavior.

5.2. Modeling analysis

Table 4 presents the relative importance of various input parameters, as per garthon formula calculations, on the rate of penetration and vibration level outputs from axial, lateral, and stick-slip ANN models. These results indicate that each input plays a great role according to each input weight, therefore optimizing the drilling process through controlling vibration level severity with little harmful impact on the rate of penetration.

Table 4. Relative importance of various input parameter in ANN models

#	Parameters	Relative Importance %		
		Axial	Lateral	Stick-slip
1	Depth	9.3%	10.1%	5.9%
2	WOB	3.3%	7.1%	7.2%
3	RPM	14.6%	27.2%	10.9%
4	TORQ.	22.2%	7.8%	21.9%
5	SPP	4.5%	7.2%	4.1%
6	Flow in	10.6%	11.6%	13.6%
7	DH WOB	6.3%	7.9%	8.0%
8	MSE	29.1%	21.0%	28.3%

Tables 5 and 6 demonstrate a more comprehensive set of error calculations for the modeled regression-neural ROP, and vibration level results in axial, lateral, and stick-slip drilling modes. As can be seen that all error statistical values are small which confirms the reliability of both neural and regression model results.

Table 5. Regression and neural ROP models error calculation

Parameter	Regression ROP			Neural ROP		
	Axial	Lateral	Stick-slip	Axial	Lateral	Stick-slip
MSE	32.2719	4.95589	79.2959249	17.1506	0.0785	0.046767
RMSE	5.68084	2.22618	8.90482593	4.14133	0.28018	0.2162568
AAPRE %	10.9171	7.26036	19.0695773	7.0563	0.72482	0.4327411
SD	0.15789	0.09657	0.25026054	0.10842	0.01175	0.0091985

Table 6. Regression and neural vibration models error calculation

Parameter	Regression vibration			Neural vibration		
	Axial	Lateral	Stick-slip	Axial	Lateral	Stick-slip
MSE	0.17403	0.19722	0.07712291	1.30369	0.29578	0.0401002
RMSE	0.41717	0.44409	0.27771012	1.14179	0.54386	0.2002505
AAPRE %	10.0791	17.523	8.96420062	27.7601	14.1371	3.766567
SD	0.1359	0.3204	0.10827111	0.42918	0.27279	0.069284

5.3. ROP vs. depth

Fig. 9 illustrates the relationship between regression, neural modeled, and actual ROP results with depth for all axial, lateral, and stick-slip vibration drilling modes. Moreover, the predicted values for both neural and regression ROP models showed a very good match with actual values with an acceptable minimal error. The neural network model has more consistent results than the regression model with the actual recorded values.

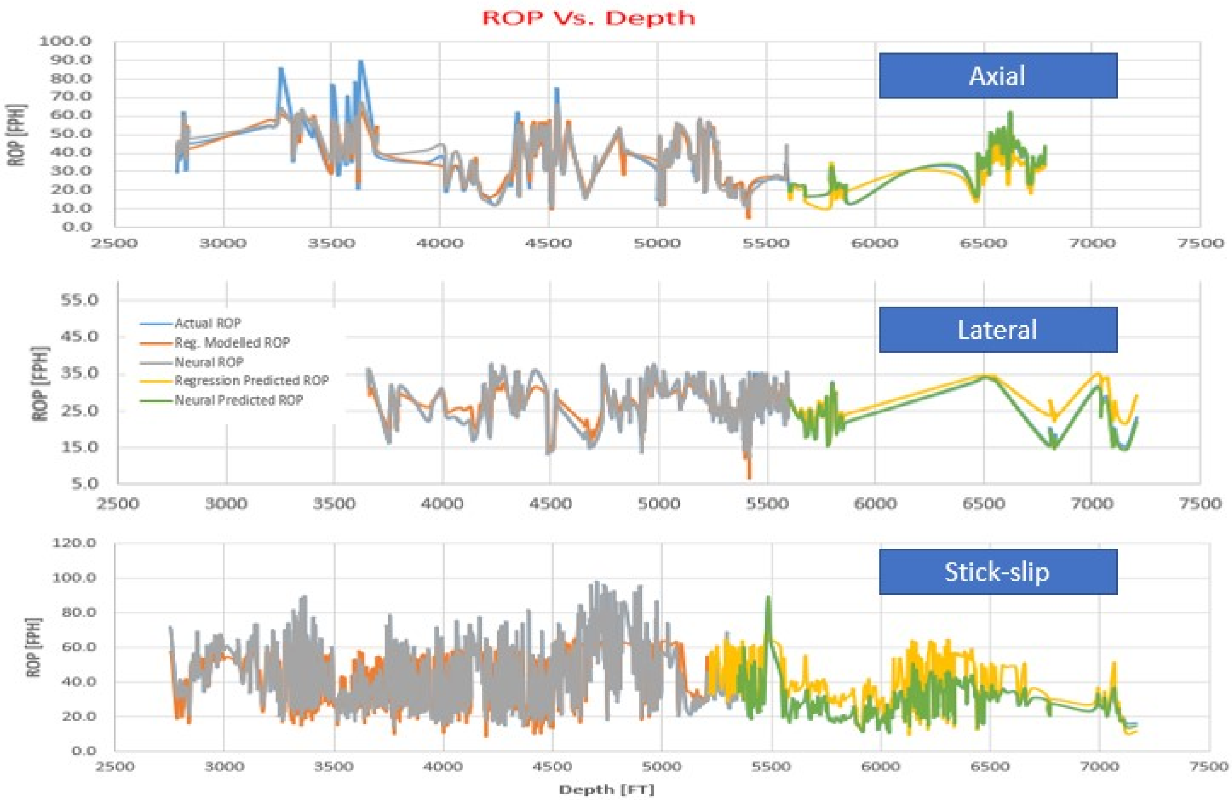

Fig. 9. ROP neural, regression and actual vs. depth

5.4. Vibration vs. depth

Fig. 10 illustrates the relationship between regression, neural modeled, and actual vibration level results with depth for all axial, lateral, and stick-slip vibration drilling modes. The integrity and combination of penetration rate and vibration level results can help to best select the suitable safe drilling behavior.

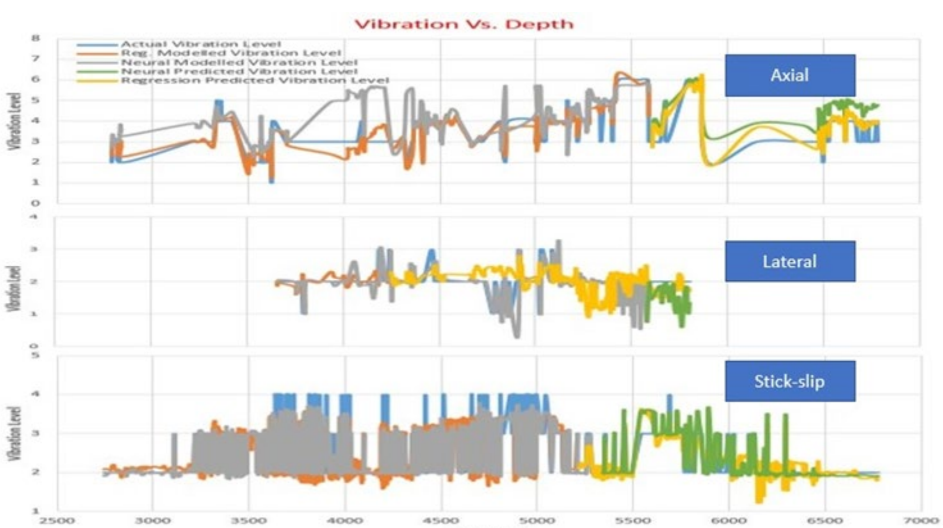

Fig. 10. Vibration neural, regression and actual vs. depth

5.5. Parametric sensitivity analysis

A parametric sensitivity analysis is applied to determine the most influential operational drilling parameters on the regression developed ROP and vibration models. The analysis is performed on the models which were developed using the multiple regression analysis for axial, lateral, and stick-slip drilling modes. The weight on bit, revolutions per minute, and torque are increased and reduced by 10% separately. A combination set of 10% increasing and decreasing is applied on standpipe pressure and circulation rate commingle. Finally, a combination set of 10% weight on bit increase in conjunction with 10% revolutions per minute decrease, then compared with 10% weight on bit decrease in conjunction with 10% revolutions per minute increase.

As shown in Fig. 11: In the axial mode, the best optimization parametric set which generates less vibration level with little harmful impact on ROP is increasing WOB and decreasing RPM. In the lateral and stick-slip modes, the best optimization parametric set which generates less vibration level with little harmful impact on ROP is increasing RPM and decreasing WOB.

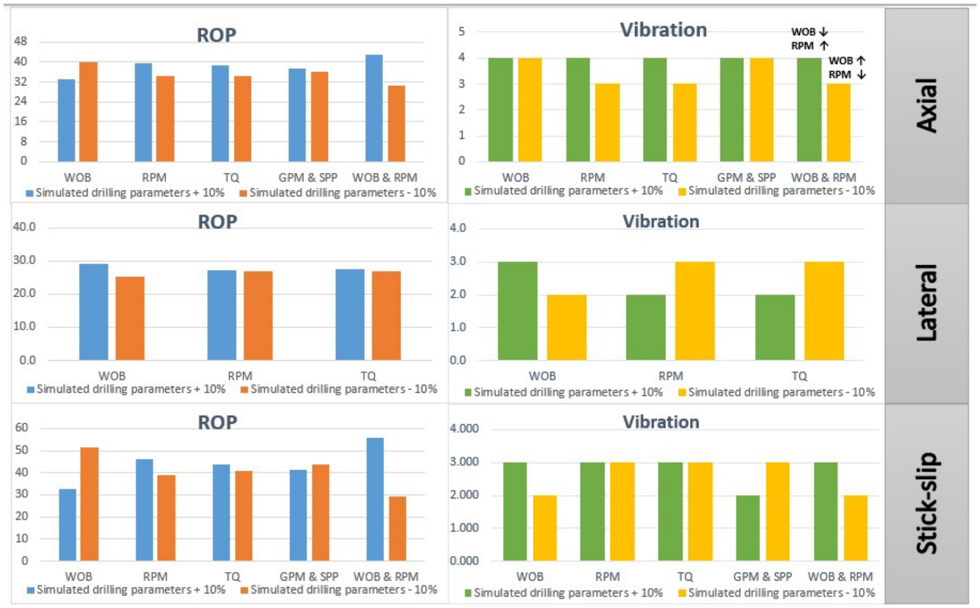

Fig. 11. ROP and vibration parametric sensitivity analysis

6. Conclusion

Utilization of the ANN approach through MATLAB™ software and multiple regression analysis for predicting the vibration level and the rate of penetration in axial, lateral, and stick-slip drilling modes have been investigated in the present study.

For any planned combination set of drilling parameters (i.e. WOB, RPM, GPM, TQ), Real-time checking the expected type and severity of vibration accompanying with resulting penetration rate could be achieved, and hence based upon models results, we can readjust the drilling parameters to be in the optimum safe drilling zone.

Real-time monitoring of vibration type and penetration rate will reduce the risk of exceeding the drill string manufacture yield or torsional limit and so avoid drill string twist-off. Routine inspection and very good tracking for the drill string components working conditions and environment history will help to diminish the cases of abrupt fatigue.

Modeling usually provides an effective solution to give reliable simulated results compared with those obtained from measurement while drilling (MWD) data which saves cost and enhances drilling efficiency.

Drilling parameters play the primary role in determining the vibration type and level in addition to affecting the rate of penetration as follows:

- Axial vibration mode is dampened by gradually increasing WOB and decreasing RPM.
- Lateral vibration mode is associated with a whirl, bending of the drill string, decrease in ROP, and requires immediate action through decreasing RPM and monitor the effect on torque and ROP.
- Stick-slip usually occurred while drilling with a tri-cone bit is due to drill string and wellbore contact. So, an excellent drill string design and placement of stabilizers will have a good impact on the vibration, therefore the drilling efficiency.

In future work, applying different types of bits other than rock bit in addition to mud properties in order to spread out the applications of developed models in different areas.

Nomenclature

ANN	*Artificial neural network*	*ROP*	*Rate of penetration, [feet per hour]*
DWOB	*Downhole weight on bit, [klbs]*	*RPM*	*Revolutions per minute*
GPM	*Gallons per minute*	*SPP*	*Standpipe pressure, [psi]*
MSE	*Mechanical specific energy, [psi]*	*TQ*	*Torque, [klbs.ft]*
MWD	*Measurement while drilling*	*WOB*	*Weight on bit, [klbs]*

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