

DETECTION OF DRILLING VIBRATIONS IN CURVE & HORIZONTAL SECTIONS

BY

RAMY MAHMOUD SAADELDIN

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DEANSHIP OF GRADUATE STUDIES

This thesis, written by **RAMY MAHMOUD SAADELDIN** under the direction of his thesis advisor and approved by his thesis committee, has been presented and accepted by the Dean of Graduate Studies, in partial fulfillment of the requirements for the degree of **MASTER OF SCIENCE IN PETROLEUM ENGINEERING**.



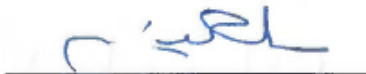
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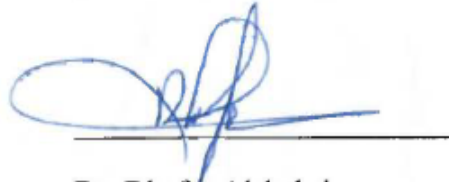
Dr. Dhafer A. Al Shehri
Department Chairman



Dr. Abdulazeez Abdulraheem
(Member)



Prof. Suliman Saleh Al-Homidan
Dean of Graduate Studies



Dr. Dhafer Alshehri
(Member)

26/12/2023

Date



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I dedicate my thesis work to my parents, family, and all my friends.

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LIST OF ABBREVIATIONS

AAPE	Average absolute percentage error
ANN	Artificial neural networks
BHA	Bottom hole assembly
DSR	Drillstring rotation in revolutions per minute
Fitnet	Function fitting neural network
hardlims	Hard-limit transfer function
logsig	Log-sigmoid transfer function
ML	Machine learning
netinv	Inverse transfer function
newcf	Cascade-forward backpropagation network
newcf	Create cascade-forward backpropagation network
Newtdnn	Create distributed time delay neural network
newelm	Create Elman backpropagation network
newff	Create feedforward backpropagation network
newfftd	Create feedforward input-delay backpropagation network
newfit	Create fitting network
newlrn	Layer-Recurrent Network
newpr	Create pattern recognition network
PCA	Principal component analysis
Purelin	linear-type
purelin	Linear transfer function
Q	Flow rate
R	Coefficient of correlation

radbas	Radial basis transfer function
ROP	Rate of penetration
satlin	Saturating linear transfer function
softmax	Softmax transfer function
SPP	Standpipe pressure
SVM	Support vector machines
T	Torque
Tansig	Hyperbolic tangent sigmoid
tansig	Hyperbolic tangent sigmoid transfer function
trainbfg	BFGS quasi-Newton backpropagation
trainbr	Bayesian regularization back-propagation algorithm
trainbr	Bayesian regularization
traingdx	Gradient descent with momentum and adaptive learning rule backpropagation
trainlm	Levenberg-Marquardt backpropagation
trainoss	One step secant backpropagation
tribas	Triangular basis transfer function

ABSTRACT

Full Name : RAMY MAHMOUD SAADELDIN MOHAMED

Thesis Title : DETECTION OF DRILLING VIBRATIONS IN CURVE & HORIZONTAL SECTION

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During the drilling operations and because of the harsh downhole drilling environment, the drill string suffered from downhole vibrations that affect the drilling operation and equipment. This problem is greatly affecting the downhole tools (wear and tear), hole problems (wash-out), mechanical energy loss, and ineffective drilling performance. Extra non-productive time to address these complications during the operation, and hence, extra cost.

Detecting the drillstring vibrations during drilling through the downhole sensors is costly due to the extra service and downhole sensors. Currently, the new-technology-based solutions are providing huge capabilities to deal intelligently with the data, and machine learning applications provide high computational competencies to learn and correlate the parameters for technical complex problems. This study provides a successful application for utilizing the surface drilling data to auto-detect the downhole vibrations during drilling curve and horizontal sections by means of machine learning (ML) techniques.

The three types of downhole vibrations (axial, torsional, and lateral) are detected through testing five ML techniques named, Artificial Neural Network (ANN), radial basis function (RBF), support vector machines (SVMs), adaptive neuro-fuzzy inference system (ANFIS), and functional networks (FN) with real field data. The models' development was achieved by comprehensive study starting from data collection, preprocessing, analytics, training and optimizing the models' parameters, and evaluating the performance till reported the best prediction results. Evaluating the models' performance showed that obtained predictions have a great match with actual measurements for the different stages of training, testing, and even through validation with unseen well data. Generally, the developed models showed a high correlation coefficient (higher than 0.9) and technically accepted average absolute percentage error (below 7.5%) between actual readings and predictions.

The study outcomes will add to the automation process of drilling operations to avoid many tools failure by comparing predicted vibrations versus downhole tools

limits such as red zone and continuing drilling without interruption to the well total depth especially while drilling curve and horizontal sections.

ملخص الرسالة

الاسم الكامل: رامي محمود سعدالدين محمد

عنوان الرسالة: اكتشاف الاهتزازات اثناء الحفر في القطاع المائل والافقي

التخصص: هندسة البترول

تاريخ الدرجة العلمية: يونيو 2023

أثناء عمليات الحفر وبسبب بيئة الحفر القاسية في قاع البئر ، عاني عمود الحفر من اهتزازات قاع البئر التي تؤثر على عملية الحفر ومعداته. تؤثر هذه المشكلة بشكل كبير على أدوات قاع البئر (التمزيق والاهتراء) ، ومشاكل الابار (الثقب) ، وفقدان الطاقة الميكانيكية ، وأداء الحفر غير الفعال. وقت إضافي غير منتج لمعالجة هذه المضاعفات أثناء عمليات الحفر ، وبالتالي ، تكلفة إضافية.

يعد اكتشاف اهتزازات عمود الحفر أثناء الحفر عبر مستشعرات قاع البئر مكلفًا بسبب التكلفة الإضافية نتيجة استخدام أجهزة إضافية لا إستشعار قاع البئر. في الوقت الحالي ، توفر الحلول القائمة على التكنولوجيا الجديدة إمكانيات هائلة للتعامل بذكاء مع البيانات ، وتوفر تطبيقات التعلم الآلي كفاءات حسابية عالية للتعلم والربط بين دلالات المشكلات التقنية المعقدة. توفر هذه الدراسة تطبيقًا ناجحًا لاستخدام بيانات حفر السطح للكشف التلقائي عن اهتزازات قاع البئر أثناء منحني الحفر والأقسام الأفقية عن طريق تقنيات التعلم الآلي (ML).

تم اكتشاف الأنواع الثلاثة من اهتزازات قاع البئر (المحورية ، الالتوائية ، الجانبية) من خلال اختبار خمس تقنيات ML المسماة ، الشبكة العصبية الاصطناعية (ANN) ، وظيفة الأساس الشعاعي (RBF) ، آلات ناقلات الدعم (SVMs) ، نظام الاستدلال العصبي الغامض التكيفي (ANFIS) ، والشبكات الوظيفية (FN) مع بيانات ميدانية حقيقية. تم تطوير النماذج من خلال دراسة شاملة تبدأ من جمع البيانات والمعالجة المسبقة والتحليلات والتدريب وتحسين معايير النماذج وتقييم الأداء حتى الإبلاغ عن أفضل نتائج التنبؤ. أظهر تقييم أداء النماذج أن التنبؤات التي تم الحصول عليها تتطابق بشكل كبير مع القياسات الفعلية للمراحل المختلفة من التدريب والاختبار وحتى من خلال التحقق من صحة البيانات غير المرئية. بشكل عام ، أظهرت النماذج المطورة معامل ارتباط مرتفع (أعلى من 0.9) ومتوسط نسبة الخطأ المطلق المقبول تقنيًا (أقل من 7.5٪) بين القراءات الفعلية والتنبؤات.

ستضيف نتائج الدراسة إلى عملية رقمنة عمليات الحفر لتجنب فشل العديد من الأدوات من خلال مقارنة الاهتزازات المتوقعة مقابل حدود أدوات قاع البئر مثل المنطقة الحمراء والحفر المستمر المتصل دون انقطاع إلى العمق الكلي للبئر خاصة أثناء الاجزاء المنحنية والافقية من البئر.

CHAPTER 1

INTRODUCTION

The drilling performance monitoring is a critical role for the drilling team to be aware of the operation situation and be ready to take the correct actions for safe operations and saving extra cost for the nonproductive time due to any drilling problems. The downhole vibration of the drillstring is one of the most critical issues during the drilling operation and many drilling problems can be associated with the extraordinary level of vibrations as the wear and tear for the drill bit and drillstring, equipment failure, inefficient performance for the drilling operation, power and cost losses, and drilled hole instability issues (Bailey et al., 2008; Okoli et al., 2019). Consequently, close monitoring for the downhole drillstring vibration will help to make the right decision for the drilling operation to mitigate all of the consequent problems (Millan et al., 2019).

During the drilling operation, the power is transmitted to the rotating action through the rotation system of the drilling rig that caused the drill bit rotation to make the hole and penetrate the drilled formation. The interaction between the drilled hole wall and drillstring, bottom hole assembly (BHA), and drill bit might cause some disturbance in the rotation mechanism and finally leads to the unplanned drillstring downhole vibrations. The downhole vibrations for the drillstring can be classified into three types named axial, torsional, and lateral vibrations (Hegde et al., 2020). The three types are different in the vibration action and the destructive nature of each mode. The axial vibration is represented by the vertical or longitudinal vibration mode and this might cause the bit damage due to the bounce phenomena. The three vibration modes affect the drilling performance and equipment failure, however, the lateral mode has the least damaging impact (Osnes et al., 2009). The lateral vibration of the drillstring represents the lateral motion from side to side and causes the eccentric rotation for the drillstring (whirl phenomena). The lateral vibration type is the most harmful vibration mode and can cause massive shocks when the BHA hits the wellbore wall. The interaction between the wellbore and BHA contact points might, in some situations, push the system into a backward whirl (Brett et al., 1989). Backward whirl is the most harmful type of vibration, actuating bending moments fluctuations with large magnitude, resulting in high rates of connection fatigue, damaging of bit cutter, and drilling an over-gauged wellbore. Forward whirl might be due to bending of drillstring that happens due to imbalance in BHA and result in wear in BHA from one side. The third vibration mode is the torsional mode where the drillstring is restricted from rotation and this might cause the string twist. In this type, the bit has a periodical rotation and stop cycles due to the rotation restriction. The bit stops (stick) for a certain time, and then the bit rotates (slip) due to the torque increase, and this process is known as stick-slip. The more severe the stick-slip, the longer the stuck period, and in sequence the higher the rotational

accelerations as the bit breaks free. Torsional fluctuations fatigue BHA connections and might damage bits. This vibration is usually expected in environments such as deep wells and high-inclination wells with long lateral (Millan et al., 2019).

Many practical optimizations for the drilling parameters were proposed as solutions to mitigate the drillstring vibrations and consequent problems as drill bit design, utilizing the downhole mud motor, and optimizing the controllable drilling parameters as the rate of penetration (ROP), drilling torque (T), drilling speed rotation (DSR), mud flow rate (Q), and the weight on bit (WOB) (Hegde et al., 2020, 2019; Zhao et al., 2017). The drilling team has to take the effective mitigation approach for each downhole vibration scenario to improve drilling performance and reduce the possibility of adverse outcomes.

CHAPTER 2

LITERATURE REVIEW

2.1 Drilling Vibrations Detection and Machine Learning Applications

The petroleum industry is showing a great trend regarding machine learning applications, in addition, the main objective of the fourth industrial revolution for enhancing the digitization and automation for the industry encouraged the researchers for accomplishing many studies for the machine learning applications in different disciplines and work scopes. The implementation of machine learning succeeded to develop intelligent models for features prediction and operations performance optimization for cost and time savings in different scopes as the drilling performance prediction (Al-Abduljabbar et al., 2020; Mahmoud et al., 2020), rheology estimation for fully automated mud monitoring systems (Alsabaa, A. et al., 2020a; Alsabaa et al., 2020, 2021), predicting different rock petrophysical (Ahmed et al., 2021) and geomechanical characteristics (Gamal et al., 2021; Mahmoud et al., 2022a), in addition to other applications.

A new novel trend toward implementing the use of the surface drilling data and deliver the value from such data for optimizing the drilling performance and mitigating the associated drilling problems was proposed in the literature and showed great outcomes in many studies (Gamal et al., 2020; Gowida et al., 2021; Siddig et al., 2021). It is common in the drilling operation to utilize the surface drilling data that is collected from the rig data sensors to evaluate the drilling performance and manage the drilling process. This includes torque calculation, rotational speed, hook load, block position, flow rate, and many others. Traditionally, drilling engineers use surface torque and rotation speed to track drilling vibrations and in particular, to detect stick-slips. Several methodologies have been developed using only surface measurements or in combination with downhole measurements (Ertas et al., 2014; Lai et al., 2014; Mabile et al., 1996).

Recently, many studies developed a variety of data-driven techniques for detecting downhole vibrations with the application of machine learning. Okoli et al. (Okoli et al., 2019) developed five machine learning (ML) models for classifying the downhole axial and lateral vibrations using the drilling data T, ROP, and WOB. The results showed that the Intra-BHA predicted downhole vibration severity from 50 to 80% accuracy level, while the Inter-BHA predictive accuracies were reduced significantly that was attributed to the different operating and hole conditions. Zhao et al. (Zhao et al., 2017) proposed a modified symbolic aggregate approximation to use drilling data to detect the drilling events anomalies for example stuck pipe, vibration, and fluid loss. Baumgartner and van Oort (Baumgartner and van Oort, 2014) utilize a machine learning technique to analyze and identify downhole vibrations using high-frequency downhole measurements collected by BHA-based sensors. Pollock et al. (Pollock et al., 2018) introduced a system with a neural

network that simulates historical data implemented from the decisions of expert directional drillers with 3% or less error.

Zha and Pham (Zha and Pham, 2019) developed a system to predict stick-slip in real-time from surface parameters only by training a deep neural network. The study used 1400 measurements data set for stick-slip classification from the drilling torque, tension, drilling speed, WOB, and triaxial acceleration data. The model accuracy was 96% and precision of 73%, while the model was further trained on the augmented dataset and showed improved performance with validation accuracy of 99% and precision of 97%. Ignova et al. (Ignova et al., 2019) developed a classification model using K-Means cluster analysis algorithm and principal component analysis (PCA) pattern recognition technique. The model was trained by 2048 measurements data set for classification of good or damaged drilling using high-frequency shock data for the model training process. Wiktorski et al. (Wiktorski et al., 2019) utilized the support vector machines (SVM) tool for developing two models one for detecting the stick-slip and the other model for the lateral vibration by training the models with 260 and 865 measurements for the stick-slip and lateral vibration models respectively. The stick-slip detection model used T, DSR, and WOB for model inputs and the results showed an accuracy of 98% coefficient of determination, while the lateral vibration model was trained using model inputs of T, DSR, and hook load with an accuracy of 93% coefficient of determination. Gupta et al. (Gupta et al., 2019) employed the random forest and gradient boosting ANN for stick-slip classification model using T, ROP, and WOB as model inputs. The overall model accuracy is 62% for detecting the stick-slip pattern.

As shown in the literature, the developed models have some differences in terms of the ML approach, model input parameters, the data set measurements, output parameters, and model accuracy. In addition, there is no complete study for the three types of downhole vibrations (axial, lateral, and torsional). Therefore, this study presents a new contribution toward the prediction of the three classes of downhole vibrations using surface drilling data. The current study used the regression technique for the downhole vibration prediction rather than the classification approach as the regression will provide a trend for the vibration profile as increasing or decreasing and in addition, will provide the benefits of the classification technique as the predicted value shows the level of the vibration as low or high. The study developed a machine learning model using artificial neural networks (ANN) from the surface drilling data WOB, DSR, T, Q, SPP, and ROP as model inputs. The model was trained using a horizontal section drilling operation. Additionally, the study presented an ANN-based equation for detecting downhole vibrations. The outputs from this study will add to the automation process for the drilling operation to close monitor the vibrations and technically help the drilling team to take the efficient decision for mitigating the downhole vibration severity.

The next sections in the paper include the data and ML modeling approach section that provides details about the study approach for building the ML model, and data preparation and analysis. This is followed by the results and conclusion section to present the obtained results from the developed model through training, testing, and validation phases. And conclusions section by the end of the manuscript to summarize the main outcomes from the study with limitations and recommendations.

The petroleum industry is showing a great trend regarding machine learning applications, in addition, the main objective of the fourth industrial revolution for enhancing the digitization and automation of the industry encouraged to research for accomplishing many studies for machine learning applications in different disciplines and work scopes. The implementation of machine learning succeeded to develop intelligent models for features prediction and operations performance optimization for cost and time savings in different scopes as the drilling performance prediction (Al-Abduljabbar et al., 2020; Mahmoud et al., 2020), rheology estimation for fully automated mud monitoring systems (Alsabaa, A. et al., 2020a; Alsabaa et al., 2020, 2021), predicting different rock petrophysical (Ahmed et al., 2021) and geomechanical characteristics (Gamal et al., 2021; Mahmoud et al., 2022a), in addition to other applications.

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Ignova et al. (Ignova et al., 2019) developed a classification model using K-Means cluster analysis algorithm and principal component analysis (PCA) pattern recognition technique. The model was trained by 2048 measurements data set for the classification of good or damaged drilling using high-frequency shock data for the model training process.

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Gupta et al. (Gupta et al., 2019) employed the random forest and gradient boosting ANN for the stick-slip classification model using T, ROP, and WOB as model inputs. The overall model accuracy is 62% for detecting the stick-slip pattern. Another research was done to detect the three modes of vibrations in real time using an artificial neural network and the model evaluation showed great performance for prediction as the statistical metrics proved a higher coefficient of correlation (greater than 0.95) with low errors between actual and predicted values less than 4% average absolute percentage error (Saadeldin et al., 2021).

The developed models among the literature studied the topic from diverse aspects in terms of the ML approach, model input features, the data set measurements, output parameters, and model accuracy. Moreover, there is a shortage of research to study the three types of downhole vibrations (axial, lateral, and torsional) as an integrated modeling approach. Consequently, this study presents a new contribution toward the prediction of downhole

vibrations using surface drilling data from rig sensors for auto-detecting the downhole vibration modes in real-time. The study developed different machine learning models [radial basis function (RBF), support vector machines (SVMs), adaptive neuro-fuzzy inference system (ANFIS), and functional networks (FN)] to evaluate the capabilities of these tools and get the best prediction results from the surface drilling data set. The models were trained using a horizontal section drilling operation. The outputs from this study will greatly add to the drilling operation automation to close monitor the vibrations and technically help the drilling team to take an efficient decision for mitigating the downhole vibration severity.

The petroleum industry is showing a great trend regarding machine learning applications, in addition, the main objective of the fourth industrial revolution for enhancing the digitization and automation of the industry encouraged to research for accomplishing many studies for machine learning applications in different disciplines and work scopes. The implementation of machine learning succeeded to develop intelligent models for features prediction and operations performance optimization for cost and time savings in different scopes as the drilling performance prediction (Al-Abduljabbar et al., 2020; Mahmoud et al., 2020), rheology estimation for fully automated mud monitoring systems (Alsabaa et al., 2021, 2020), predicting different rock petrophysical (Ahmed et al., 2021) and geomechanical characteristics (Gamal et al., 2021; Mahmoud et al., 2022a), in addition to other applications.

A new novel trend toward implementing the surface rig sensor data and delivering the best value from such data for optimizing the drilling performance and mitigating the associated drilling problems was proposed in the literature and showed great outcomes in many studies (Gamal et al., 2020; Gowida et al., 2021; Siddig et al., 2021). It is common in the drilling operation to utilize the surface drilling data that is collected from the rig sensors to evaluate the drilling performance and manage the drilling process. This includes torque calculation, rotational speed, hook load, block position, flow rate, and many others. Traditionally, the drilling team uses surface torque and rotation speed to track drilling vibrations and in particular, to detect stick-slip. Several methodologies have been developed using only surface measurements or in combination with downhole measurements (Ertas et al., 2014; Lai et al., 2014; Mabile et al., 1996).

Recently, many studies developed a variety of data-driven techniques for detecting downhole vibrations with machine learning techniques. Baumgartner and Van Oort (2014) utilized a machine learning technique to analyze and identify downhole vibrations using high-frequency downhole measurements collected by BHA-based sensors (Baumgartner and van Oort, 2014). Zhao et al. (2017) presented a modified symbolic aggregate

approximation to use drilling data to detect the drilling events anomalies for example stuck pipe, vibration, and fluid loss (Zhao et al., 2017).

Pollock et al. (2018) introduced a system with a neural network that simulates historical data implemented from the decisions of expert directional drillers with 3% or less error (Pollock et al., 2018).

Okoli et al. (2019) developed five ML models for classifying the downhole axial and lateral vibrations using the drilling data T, ROP, and WOB. The results showed that the Intra-BHA predicted downhole vibration severity from 50 to 80% accuracy level, while the Inter-BHA predictive accuracies were reduced significantly which was attributed to the different operating and hole conditions (Okoli et al., 2019).

Zha and Pham (2019) developed a system to predict stick-slip in real-time from surface parameters only by training a deep neural network. The study used 1400 data points for stick-slip classification from the drilling torque, tension, drilling speed, WOB, and triaxial acceleration data. The model showed an accuracy of 96% and 73% for model precision, while the model was further fed and trained that caused improving the performance with 99% validation accuracy and 97% for model precision (Zha and Pham, 2019).

Ignova et al. (2019) developed a classification model using K-Means cluster analysis algorithm and principal component analysis (PCA) pattern recognition technique (Ignova et al., 2019). The model was trained by 2048 data set for the classification of good or damaged drilling using high-frequency shock data for the model training process.

Wiktorski et al. (2019) utilized the support vector machines (SVM) tool for developing two models one for detecting the stick-slip and the other model for the lateral vibration by training the models with 260 and 865 measurements for the stick-slip and lateral vibration models respectively. The stick-slip detection model used T, DSR, and WOB for model inputs and the results showed an accuracy of 98% coefficient of determination, while the lateral vibration model was trained using model inputs of T, DSR, and hook load with an accuracy of 93% coefficient of determination (Wiktorski et al., 2019).

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CHAPTER 3

ANN MODEL FOR PREDICTING VIBRATIONS IN HORIZONTAL DRILLING

3.1 Data and ML Modeling Approach

3.1.1 Study Approach

Figure 1 illustrates the different phases of the study approach. The data was gathered from the rig sensors and then the data was forwarded to the data wrangling process for data cleaning and quality enhancement by removing the outliers and performing advanced statistical data analysis to study the data range, distribution, and correlation coefficient. The model building phase started after the full data preprocessing phase and the model building was studied with deep sensitivity for the different learning algorithms and model parameters to provide the best results for the prediction of the downhole vibration. The model was evaluated with statistical metrics to evaluate the model performance and compare the predicted versus actual measurements for the downhole vibration values. The model would be retrained again with different training algorithms or model parameters in case the prediction performance was not accepted till reached the best accuracy level to report the best results and model parameters.

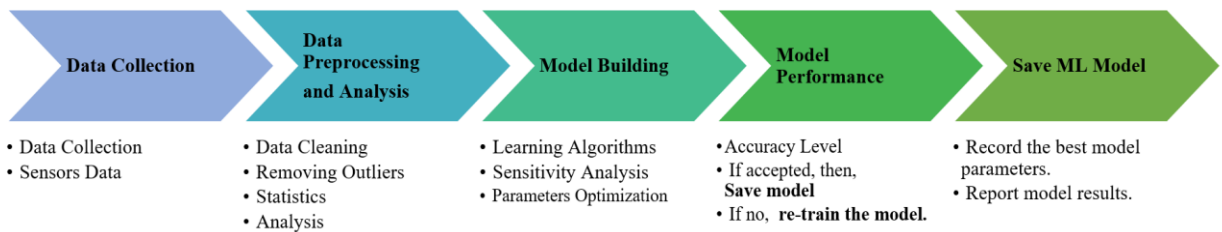


Figure 1: ML development approach.

3.1.2 Data Preparation

A dataset of 13,927 measurements was obtained from drilling a horizontal well through a limestone formation. The drilling parameters are the rate of penetration (ROP), drilling torque (T), drilling speed rotation (DSR), mud rate (Q), standpipe pumping pressure (SPP), and the weight on the drill bit (WOB), while the downhole vibrations were logged using downhole sensors for detecting the downhole drillstring vibrations. These parameters were utilized to feed for the model as inputs for predicting the downhole drillstring vibration modes named axial, lateral, and torsional vibrations as the model predicted outputs. A

different dataset of 9,284 was gathered from a drilling operation for a similar horizontal section in the field that was employed for the validation process after developing the ML models.

3.1.3 Data Analysis

The surface drilling parameters are commonly observed at the surface while drilling and these surface parameters are significantly affected by the interaction between the drillstring and wellbore wall which causes the downhole vibration. The application of statistical analysis to the data gathered demonstrates good variety and representation of the data as it encompasses a wide range of input and output parameters, in addition to, the mean, median, standard deviation, kurtosis, and skewness (Table 1). The minimum and maximum values for each parameter show the data range for this parameter in the dataset and the high range is better as it covers a wide range for the model trained dataset. Skewness is a statistical parameter that reflects the lack of symmetry for data or the distribution over a center point while Kurtosis shows heavy-tailed or light-tailed behavior of the data relative to a normal distribution.

Table 1 Data statistics for the ML model

Model Data	Q , gpm	SPP, psi	DSR, rpm	T, Klbf·ft	WOB, Klbf	ROP, ft/f	Lateral_Vib., g	Axial_Vib., g	Torsional_Vib., deg_per_s_sq
Minimum	230	2279	108	7	10	44	2.67	0.46	1542
Maximum	266	3004	121	12	25	107	7.18	1.25	2152
Range	36	724	12	5	15	63	4.51	0.79	609
Mean	251	2665	118	11	21	65	3.93	0.65	1856
Median	260	2655	118	11	21	63	3.29	0.61	1824
Standard Deviation	11	195	1.4	0.4	1.9	12.4	1.39	0.15	144
Kurtosis	-1.74	-1.21	28.74	12.21	1.27	0.02	0.20	2.19	-0.9
Skewness	-0.28	-0.08	-4.69	-1.87	0.20	0.75	1.39	1.43	0.38

In addition, the coefficient of correlation (R) between the model parameters was determined as shown in Figure 2. The data showed that the lateral vibration had a direct

relationship with Q, WOB, axial and torsional vibration, while had an indirect relationship with SPP, DSR, T, and ROP with a variation in R-value. The axial vibration had an indirect relationship with all inputs except WOB and ROP that showed direct relationship type. The torsional vibration data showed a direct relationship with Q, T, and WOB parameters, while had an indirect relationship with SPP, DSR, and ROP. All three types of vibration data showed a direct relationship that had its maximum R-value between the lateral and torsional vibrations (0.8) while the minimum R was 0.1 between the axial and torsional vibrations. These statistics revealed the complexity between the data and might reveal nonlinear relationships between the parameters, and therefore, the machine learning application for such problems will help to combine and represent the intercorrelations between the parameters for predicting the downhole vibrations based on the learning capabilities from the model data and algorithms.

The interrelations between the drilling parameters and the resultant effect from the downhole vibration are complex and hard to be studied by the statistical analysis only, hence, the machine learning application for such scope is highly required to reveal such problems. WOB and DSR are the most common parameters that can be tuned for mitigating the downhole vibration as remedial action. However, the mitigation mechanism is different for every vibration mode from a practical point of view as increasing the WOB is a remedial action for the axial vibration, increasing DSR is considered an action to mitigate the stick-slip vibration mode, and for the lateral vibration increasing the WOB and decreasing the DSR. Proposing different combinations of drilling parameters tuning might be implemented based on the drilling operation situation and the field experience of the drilling team from the offset wells.

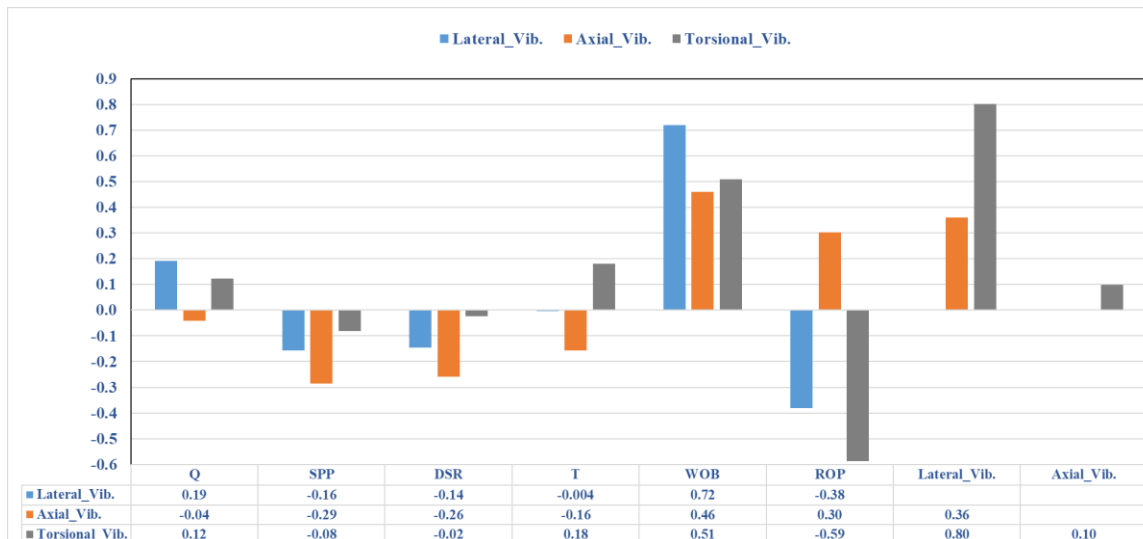


Figure 2: Relative importance between the model parameters.

3.1.4 Artificial Neural Network (ANN)

ANN is considered one of the best common tools for machine learning applications with petroleum data that provides numerous successful contributions regarding prediction purposes. The ANN technique simulated the human biological neural system for learning capabilities for problem thinking (Abbas et al., 2019; Bello et al., 2015). The ANN structure is represented by the main layers named input layer for the model inputs, a hidden layer that might be one or more layers for the processing that contain neurons within the layer, and the output layer for the predictive parameter (Cevik et al., 2011). Figure 3 shows the main structure for the developed ANN model for vibration prediction where the input layer includes the drilling data, hidden layer and its neurons, and the output layer that is the downhole vibrations. The weights and biases are hyperparameters for the model which are connections link between the layers and have a great impact on the model performance (Lippmann, 1987). The model is trained with a learning algorithm that controls the model processing (Graves et al., 2009).

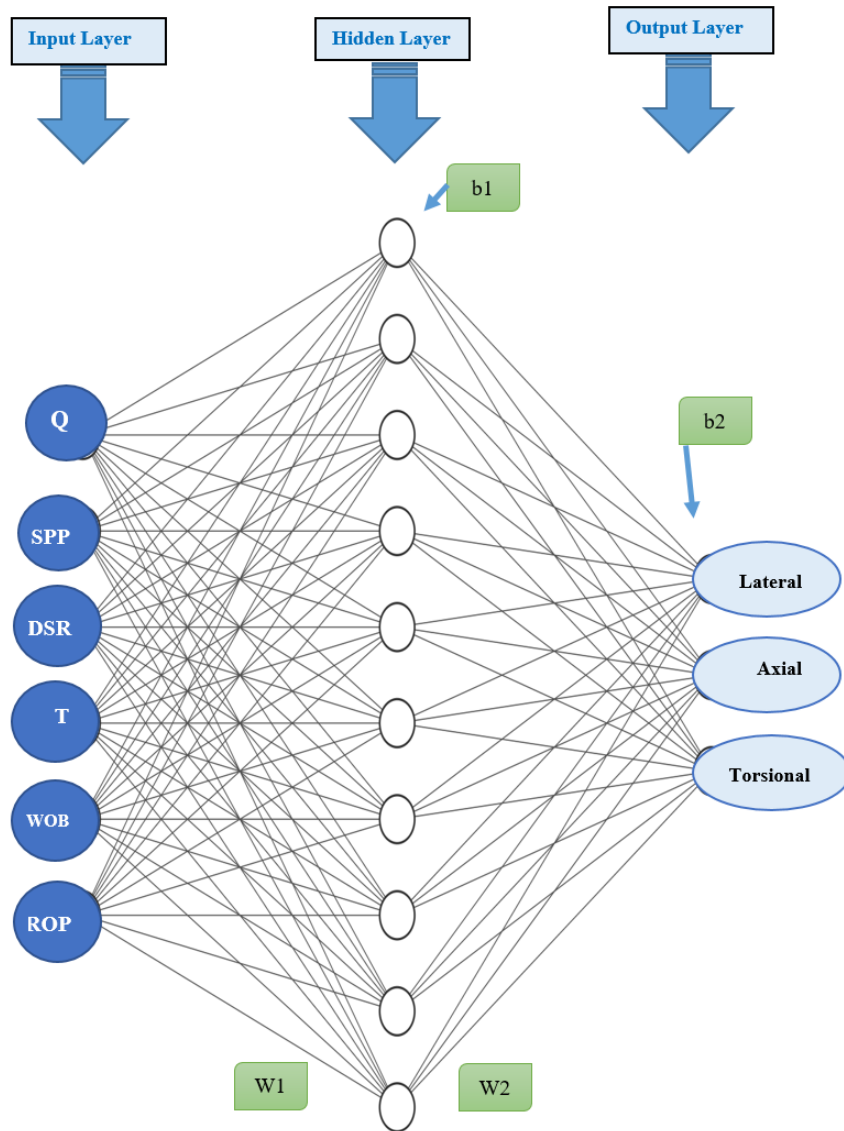


Figure 3: ANN model structure.

A deep sensitivity study is required for selecting the best model parameters by comparing the model accuracy for the vibration prediction using two statistical metrics which are the coefficient of correlation and the average absolute percentage error (AAPE). The sensitivity analysis tested a wide range for the data and model parameters in terms of the training to testing ratio from 70:30% to 80:20%, neurons number from 5 to 40 neurons, and several different functions for the network, training, and transfer functions.

The coefficient of correlation (R) is estimated in addition to the average absolute percentage error (AAPE) between the real measurements for the vibration versus

the predicted vibration values for every iteration through the model optimization phase. The two metrics were calculated as:

$$R = \frac{N(\sum_1^N Y_i \hat{Y}_i) - (\sum_1^N Y_i)(\sum_1^N \hat{Y}_i)}{\sqrt{[N \sum_1^N Y_i^2 - (\sum_1^N Y_i)^2] [N \sum_1^N \hat{Y}_i^2 - (\sum_1^N \hat{Y}_i)^2]}} \quad (1)$$

$$AAPE = \left(\frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \times 100 \quad (2)$$

where N is the number of data points, y_i is the real value, $\hat{y}_i$ is the model predicted value, and $\bar{y}$ is the mean value.

3.2 Results and Discussion

The model development approach was designed to deeply study the model performance by optimizing the model parameters. Optimizing the ANN model was performed using different combinations of inputs, shifting randomization, and changing the number of hidden layers, neurons. In addition to selecting different network, training, and transfer functions. The different choices of the ANN parameters tested are shown in Table 2. Parameters with the highest R and lowest AAPE values between the predicted and the observed resultant vibrations have been chosen from the proposed testing range for the model parameters.

The optimized model was trained using the Bayesian regularization back-propagation algorithm to obtain the optimized weights and biases. Hyperbolic tangent sigmoid (tansig) activation function was used as a transfer function to link the input and hidden layer and a linear-type (purelin) activation function was used to link the hidden and output layer. The developed ANN model has three layers: The first layer of the ANN model comprises the input parameters which are Q, SPP, DSR, T, WOB, and ROP; the second layer is the hidden layer of the neurons with optimized weights and bias; finally, the third layer is the output layer, which is resultant vibration mode value.

Table 2 Summary of the optimization process of the developed ANN model

Parameter	Option / Ranges	Optimized parameter
Train to Test Ratio	70:30 to 80:20	70:30
Number of Hidden Layers	1 to 2	1

Number of Neurons in Each layer	1 to 45		15
Network Function	fitnet	newelm	Cascade-forward backpropagation network (newcf)
	newcf	newfit	
	newdtdnn	newlrn	
	newff	newnarxsp	
	newp	newpr	
	newnarx		
Transfer Algorithms	Logsig	Hadlims	Hyperbolic tangent sigmoid (tansig)
	Poslin	Purelin	
	Hardlim	Radbas	
	Saltins	Compet	
	Netlin	Softmax	
	Tribas		
Training Function	Trainbr	Trainlm	Bayesian regularization back-propagation algorithm (trainbr)
	Trainbfg	Traincgb	
	Traincgf	Traincgp	
	Traingda	Traingdx	
	Trainoss	Trainrp	
	Trainscg	trainb	
	Trainr	tansig	

3.2.1 Model Performance

The results of different combinations of the ANN parameters are recorded to list the best model parameter as shown from the summarized results in Table 3. The table shows the change in the model accuracy through the training and testing processes for the three

classes of the vibrations with changing the number of neurons, network, transfer, and training algorithms. It worthy mention that for every run to test a parameter range, all the other parameters are kept fixed (optimized value) to be able to study the effect of this parameter on the model performance. Trials were performed to study the impact on the drilling parameters (that have relatively low correlation coefficient with the vibrations) as inputs for the model and the results showed that including the six inputs will enhance the model accuracy rather than excluding one of the drilling parameters.

Table 3 Summary of the obtained model results with changing the model parameters

Model Parameter		Vibration Mode											
		Lateral				Axial				Torsional			
		Train		Test		Train		Test		Train		Test	
		R	AAP E%	R	AAP E%	R	AAP E%	R	AAP E%	R	AAP E%	R	AAP E%
Number of Neurons	5	0.98	5.02	0.98	5.30	0.95	4.87	0.94	4.88	0.90	2.57	0.90	2.53
	10	0.98	4.25	0.98	4.24	0.97	3.96	0.96	4.07	0.93	2.09	0.94	2.05
	15	0.99	2.4	0.99	2.35	0.99	2.07	0.99	2.12	0.96	1.67	0.95	1.75
Network Function	fitnet	0.99	3.09	0.99	3.27	0.99	2.36	0.99	2.54	0.96	1.75	0.96	1.82
	newff	0.99	3.09	0.99	3.27	0.99	2.36	0.99	2.54	0.96	1.75	0.96	1.82
	newfftd	0.99	3.89	0.98	3.96	0.99	2.65	0.98	2.76	0.95	1.76	0.95	1.81
	newcf	0.99	2.4	0.99	2.35	0.99	2.07	0.99	2.12	0.96	1.67	0.95	1.75
Transfer Function	hardlims	0.88	11.61	0.88	11.61	0.76	9.43	0.76	9.38	0.73	4.20	0.72	4.16
	purelin	0.91	11.80	0.90	11.76	0.65	12.12	0.65	12.16	0.77	4.33	0.77	4.25

	hardlim	0.88	11.57	0.88	11.57	0.81	8.87	0.81	8.77	0.74	4.17	0.73	4.14
	netinv	0.95	6.59	0.94	6.76	0.87	0.07	0.88	0.07	0.88	2.71	0.87	2.72
	tansig	0.99	2.4	0.99	2.35	0.99	2.07	0.99	2.12	0.96	1.67	0.95	1.75
Training Function	traincgb	0.97	5.43	0.97	5.45	0.35	17.91	0.38	17.59	0.91	2.53	0.91	2.49
	traincgf	0.83	16.61	0.81	16.94	0.04	26.42	0.10	25.59	0.85	3.17	0.85	3.12
	traincgp	0.98	5.37	0.98	5.44	0.90	6.81	0.90	6.82	0.89	2.74	0.89	2.72
	traingda	0.86	12.78	0.86	12.81	0.68	11.19	0.68	11.18	0.71	4.40	0.71	4.38
	trainbr	0.99	2.4	0.99	2.35	0.99	2.07	0.99	2.12	0.96	1.67	0.95	1.75
Inputs	Excluding Q	0.96	4.25	0.96	4.32	0.96	3.06	0.96	3.11	0.93	2.01	0.93	2.01
	Excluding SPP	0.96	4.25	0.96	4.32	0.96	3.06	0.96	3.11	0.93	2.01	0.93	2.01
	Drilling parameters	0.99	2.4	0.99	2.35	0.99	2.07	0.99	2.12	0.96	1.67	0.95	1.75

The optimized ANN developed model showed a strong capability for predicting the downhole vibration model with high accuracy based on the two calculated metrics R and AAPE, in addition, the vibrations logs for the predicted and actual measurements that illustrated the high match between the profiles.

The model training results for 9,750 data points showed that R is 0.99 for the axial and lateral vibration prediction, while R is 0.96 for predicting the torsional vibration values. In addition, AAPE is less than 2.4% for predicting the three modes of vibrations as shown in Figure 4.

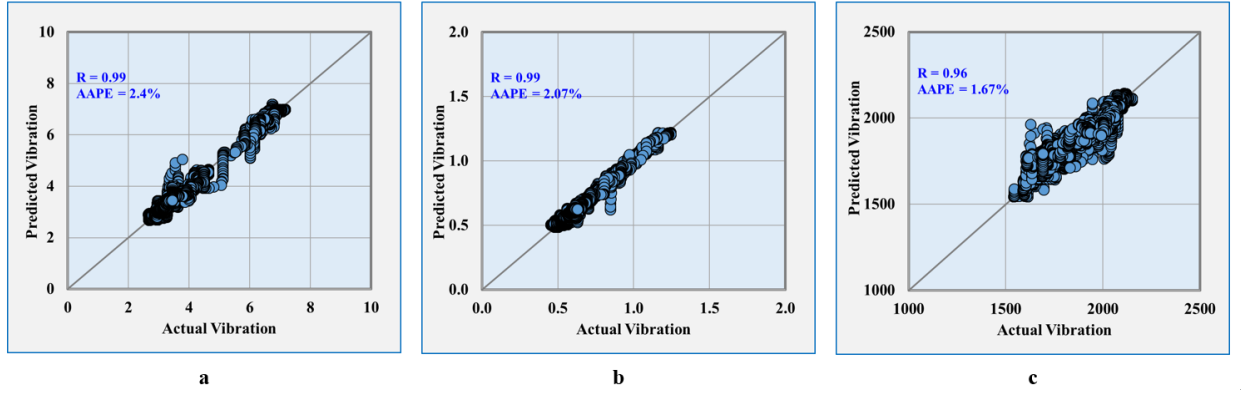


Figure 4 Training results for the developed model. a) Lateral, b) Axial, c) Torsional vibration

The model confirmed the strong prediction even through the testing phase (4,177 data points) as shown in Figure 5 that R is higher than 0.95 and AAPE is below 2.35% for the three modes.

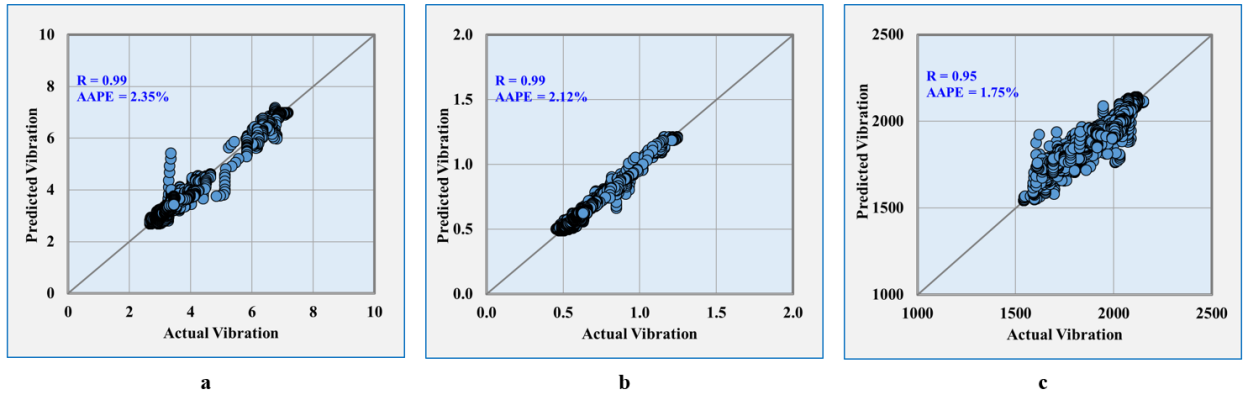


Figure 5 Testing results for the developed model. a) Lateral, b) Axial, c) Torsional vibration

The reason for the high performance of the ANN model through the high level of accuracy for the model results can be attributed to the multivariable ANN parameters that provide several combinations for the ANN structure that can provide the best training for the data as different options for the number of hidden layers, neurons number, training, network, and transfer functions.

3.2.2 Model Validation

For further testing, the developed model was tested with unseen data set of 9,284 measurements that are collected from the field of study from a similar horizontal section drilling operation. The results are plotted in Figure 6 for the three vibrations (lateral, axial, and torsional) and showing that R is 0.99, 0.98, and 0.95, while AAPE is 3.5, 3.0, and 1.89% for lateral, axial, and torsional vibrations respectively. Besides, the plots confirm the high degree of matching between the actual measurements and predicted values.

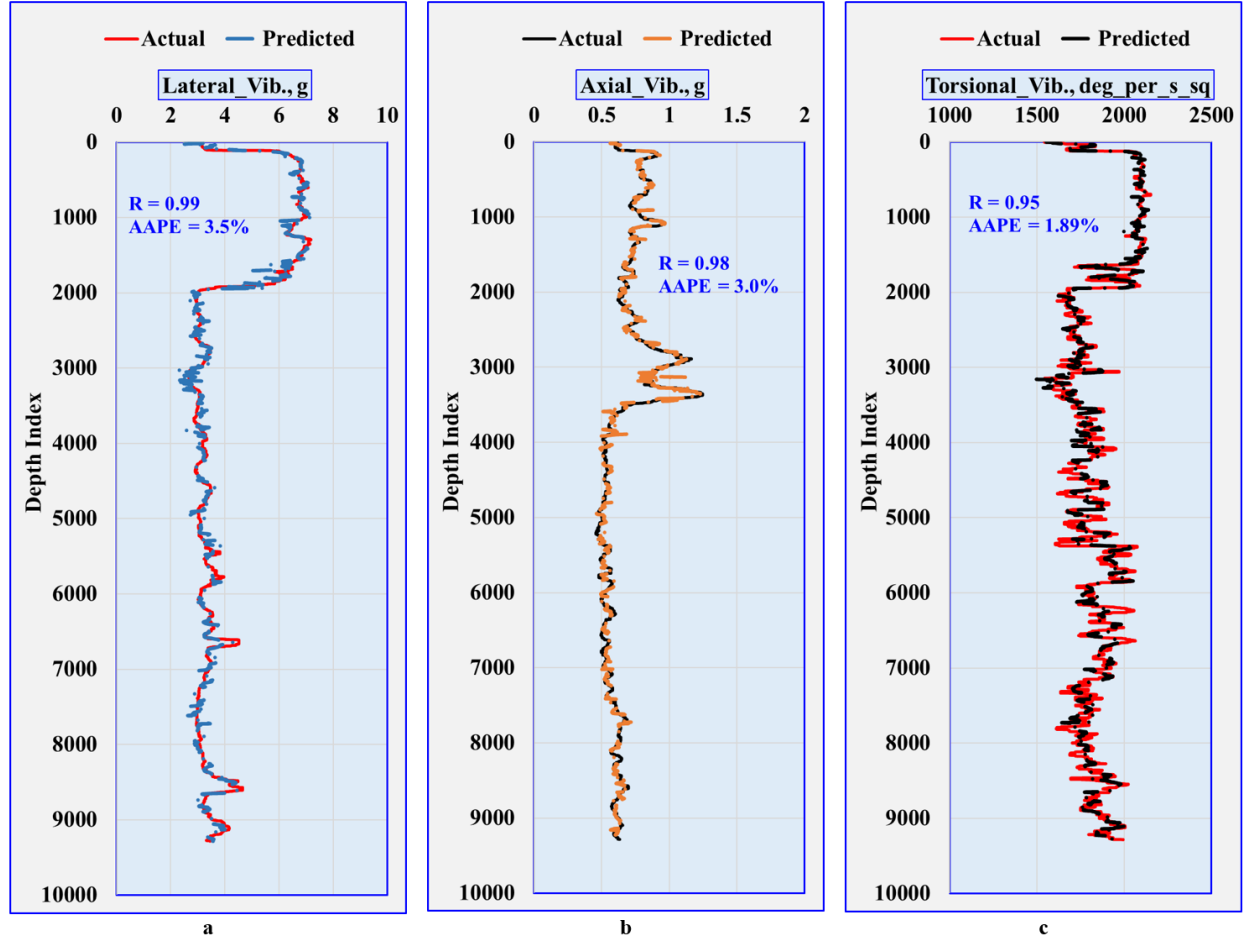


Figure 6 Validation results for the developed model. a) Lateral, b) Axial, c) Torsional vibration

3.2.3 Developed Model-Based Equations

The developed model from the ANN technique was utilized for extracting a model-based equation from the ANN weights and biases along with the transfer function. To utilize the developed equation, the input values should be normalized to be in the range between -1 and 1 as follow:

$$X_{i_{nor}} = 2 * \left(\frac{X_i - X_{i_{min}}}{X_{i_{max}} - X_{i_{min}}} \right) - 1 \quad (3)$$

where, $X_{i_{nor}}$ represents the normalized value for variable X , X_i is the value of variable X , $X_{i_{min}}$ is the minimum value of variable X , $X_{i_{max}}$ is the maximum value of variable X . The minimum and maximum values for each variable that are used for data normalization are presented in Table 1.

The normalized value for the vibration mode can be estimated using Equation 4 as follow:

$$V_{nor} = \left[\sum_{i=1}^N w_{2i} \left(\frac{2}{1 + \exp\left(-2(Q_n * w_{1i,1} + SPP_n * w_{1i,2} + DSR_n * w_{1i,3} + T_n * w_{1i,4} + WOB_n * w_{1i,5} + ROP_n * w_{1i,6} + b_{1,i})\right)} - 1 \right) \right] + b_2 \quad (4)$$

where, V_{nor} is the normalized vibration value for each vibration mode, N is the number of neurons in the hidden layer (N=15), w_{1i} is the weight associated with each feature between the input and the hidden layers, w_{2i} is the weight associated with each feature between the hidden and the output layers, b_{1i} is the bias associated with each neuron in the hidden layer, b_2 is the bias of the output layer.

The weights and biases were extracted from the ANN structure of the developed models after saving the final optimized network for each vibration model and listed in Tables 4, 5, and 6 for the lateral, axial, and torsional vibrations respectively.

Table 4 Weights and biases for lateral vibration estimation

	W1						B1	W2	B2
	Q	SPP	DSR	T	WOB	ROP			
1	7.081	-8.037	0.466	-0.643	3.729	-1.330	-5.433	0.484	-0.629
2	-2.699	1.295	-3.445	3.595	-13.784	-2.202	6.897	-4.858	
3	-6.868	11.205	-11.497	9.965	-15.941	4.541	8.071	0.105	
4	-0.652	-7.229	3.462	2.450	-0.642	-5.750	-3.930	-0.254	
5	11.658	-4.469	0.701	-3.859	6.596	2.219	2.220	0.441	
6	-3.043	1.610	-3.647	3.859	-14.603	-2.224	7.258	4.520	
7	9.676	-0.267	3.515	-7.019	6.841	8.093	-0.397	-0.383	
8	-2.162	-4.534	-24.085	12.975	-4.106	2.547	11.131	-0.074	
9	-1.570	9.246	-5.180	2.588	-0.781	1.325	-0.573	-0.275	
10	4.452	-6.958	1.376	12.063	-3.284	-4.429	-5.303	-0.389	
11	1.089	-0.541	0.801	-0.326	1.742	-0.626	-1.275	-4.315	

12	4.627	-7.073	1.484	8.958	-5.814	-4.047	-2.667	0.521	
13	-9.680	-6.134	-13.300	-34.860	18.785	-9.604	-11.805	-0.382	
14	-4.726	-0.882	1.349	0.485	-2.896	-0.211	2.714	-0.544	
15	-0.779	0.470	-0.744	0.128	-1.696	0.761	1.318	-3.957	

Table 5 Weights and biases for axial vibration estimation

	W1						B1	W2	B2
	Q	SPP	DSR	T	WOB	ROP			
1	2.771	3.826	2.754	7.933	-14.444	-6.942	1.996	0.214	-0.429
2	1.771	2.651	-3.642	5.688	-4.996	1.723	4.944	-0.516	
3	2.065	-2.790	0.577	-1.858	2.344	-1.451	-1.976	-0.531	
4	0.959	0.651	1.253	0.761	-2.013	1.018	-0.606	2.869	
5	0.499	-1.375	-1.636	-0.352	-1.557	-1.396	1.461	-1.110	
6	-3.880	6.200	3.099	2.439	-0.643	4.176	1.301	-0.321	
7	-2.197	-2.605	0.114	-3.653	5.182	-1.662	-3.938	-0.646	
8	-0.622	-0.435	-1.462	-0.241	1.407	-1.025	0.456	2.861	
9	0.685	2.977	0.974	0.079	6.421	3.159	-0.669	-0.324	
10	-0.903	2.562	-0.812	4.708	-11.339	-3.506	3.142	-0.705	
11	-1.994	-2.000	-1.564	-4.461	8.745	-1.614	1.496	0.405	
12	0.424	3.781	0.237	1.237	6.088	3.355	-3.409	-0.428	
13	6.027	-6.864	-6.218	3.589	-4.900	-0.651	2.489	0.183	
14	1.434	-4.305	-17.598	-2.187	-6.860	1.905	10.509	0.318	
15	3.046	-1.128	9.235	4.865	0.643	2.631	-12.328	-0.428	

Table 6 Weights and biases for torsional vibration estimation

	W1						B1	W2	B2
	Q	SPP	DSR	T	WOB	ROP			
1	4.891	10.407	3.881	-0.148	-6.908	-0.423	-11.674	-0.299	0.430
2	1.781	1.211	-0.160	-1.805	0.743	-2.377	1.759	0.549	
3	-3.520	3.153	1.639	0.686	-2.872	1.037	2.310	-2.673	
4	1.216	-2.196	-0.684	4.812	-0.044	-0.447	-2.338	2.012	
5	3.087	-2.240	-1.439	-0.894	2.899	-0.932	-1.992	-2.115	
6	1.927	-3.241	-3.907	0.494	-6.053	5.645	4.979	0.281	
7	-1.028	2.127	1.230	-4.454	0.036	0.127	1.840	2.041	
8	0.575	-1.986	0.292	-1.317	0.291	0.246	-0.393	-1.328	
9	-0.649	-1.458	-1.118	2.645	-3.538	-0.910	-0.226	3.280	
10	0.435	5.380	-1.224	-3.564	1.008	-0.498	0.235	-0.554	
11	-1.465	-0.401	0.196	-1.246	3.676	2.118	2.168	-0.717	
12	0.436	-3.617	2.917	-1.973	1.158	1.444	-2.752	0.748	
13	-0.322	-1.359	-0.812	2.327	-3.217	-1.022	-0.199	-3.409	
14	2.011	11.592	-6.330	4.032	-1.356	4.938	7.316	-0.248	
15	-0.544	8.625	-4.835	-5.274	-1.957	-4.400	1.033	0.417	

The real-time vibrations obtained from the ANN model provide vital information on the durability of drilling BHA. This information is very helpful for directional drillers and drilling engineers. For directional drillers, it can help to identify vibrations then apply correct mitigation for severe condition and gives full control over the bottom hole assembly, also, by tracking the vibrations trends obtained from the model it helps to avoid many tools failure by comparing predicted vibrations versus downhole tools limit such as red zone and continuing drilling without interruption to the well total depth especially while drilling horizontal sections. For drilling engineers, avoiding drilling interruption is required to minimize the non-productive time and in sequence more cost. In addition, giving good readings from

downhole tools to be able to avoid deviations from planned directional plan especially in horizontal sections to be able to hit the targets as per well objectives.

CHAPTER 4

PREDICTING VIBRATIONS IN HORIZONTAL DRILLING BY DIFFERENT ML TECHNIQUES

4.1 Data and Machine Learning Research Approach

4.1.1 Research Approach

The study presented a technical approach that considered the full process for developing the ML models starting from collecting rig sensor data, data preprocessing, building the models, evaluating the accuracy, and finally saving the best results for vibration predictions (Figure 7). The data was gathered from the rig sensors and then the data was forwarded to the data wrangling process for data cleaning and quality enhancement by removing the outliers and performing advanced statistical data analysis to study the data range, distribution, and correlation coefficient. Building the ML models started after the full data preprocessing phase and the model building was studied with deep sensitivity for the different learning algorithms and model parameters to provide the best results for the prediction of the downhole vibrations. The models were evaluated with statistical metrics to evaluate the performance and compare the predicted versus actual measurements for the downhole vibration values. The models would be retrained again with different training algorithms or model parameters in case the prediction performance was not accepted till reached the best accuracy level to report the best results and model parameters. The best prediction results from the optimized ML models were reported to show the models' prediction capabilities.

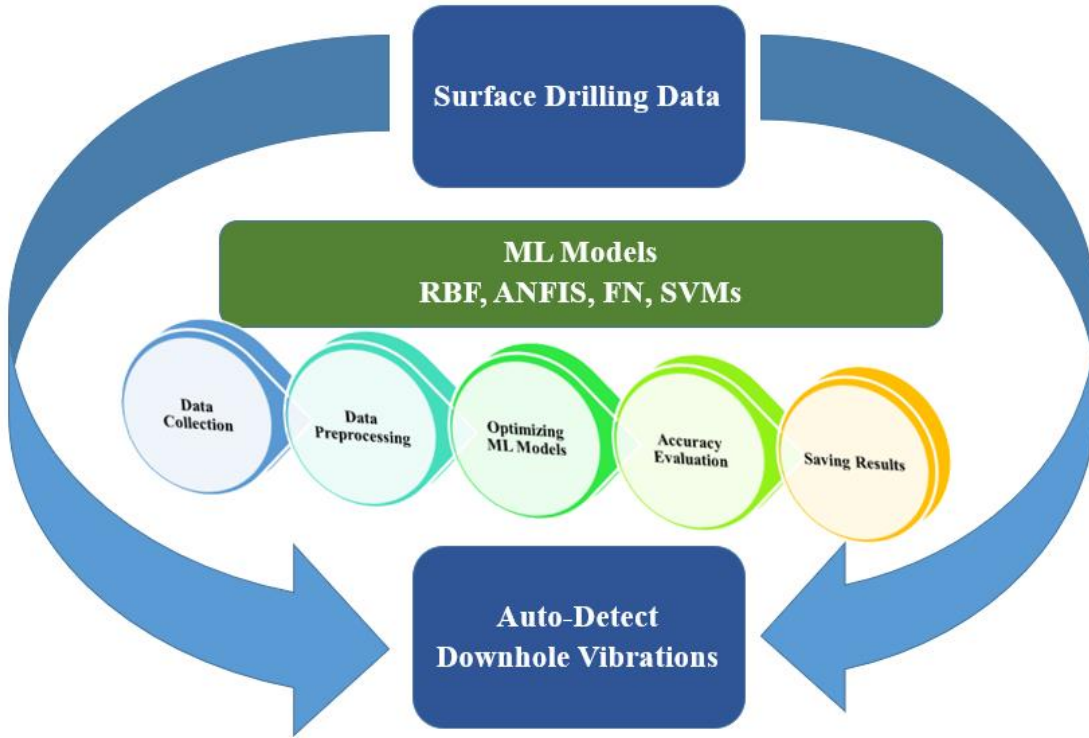


Figure 7 Study approach layout

4.1.2 Data Preprocessing

The current study utilized real field downhole vibration data during drilling horizontal sections to develop the different machine learning models. 5750 data points from a well data that show the surface drilling parameters (that represent the model input features) associated with the downhole vibrations measurements (that show the target parameters of the ML models). Mainly six rig sensors that record the drilling mechanical and hydraulic data are the basic inputs for the models' named rate of penetration (ROP), drilling torque (T), drilling speed rotation (DSR), mud rate (Q), standpipe pumping pressure (SPP), and the weight on the drill bit (WOB), while the downhole vibrations were logged using downhole sensors for detecting the downhole drillstring vibrations (axial, lateral, and torsional vibrations). The developed models were further tested by a validation unseen data set (3950 data points) from a well data during drilling a similar horizontal section within the drilling phase.

The collected drilling data was preprocessed by diverse pipelines to remove the illogic values within the data set as zeros and negative values, remove the parameters outliers, and smooth the drilling data to remove the noise and enhance the data quality. The cleaned data set was then analyzed to explore the interrelationships and data distributions.

4.1.3 Exploratory Data Analysis

The surface drilling parameters are commonly observed at the surface while drilling and these surface parameters are significantly affected by the interaction between the drillstring and wellbore wall which causes the downhole vibration. The application of statistical analysis to the data gathered demonstrates good variety and representation of the data as it encompasses a wide range of input and output parameters (Table 7).

Table 7 Statistical analysis for the models' data set

	Q	SPP	RPM	T	WOB	ROP	Lateral_Vib.	Axial_Vib.	Torsional_Vib.
mean	250.6	2666.3	118.2	11.1	21.2	66.6	3.9	0.7	1843.1
std	10.8	196.8	1.3	0.4	1.9	12.9	1.4	0.2	143.0
min	230.0	2279.4	108.5	7.3	10.4	43.7	2.7	0.5	1543.3
25%	239.1	2489.9	117.8	10.9	20.0	56.8	3.0	0.5	1734.8
50%	259.7	2658.5	118.4	11.1	20.6	63.9	3.3	0.6	1812.7
75%	260.2	2839.3	118.8	11.4	22.4	74.5	3.6	0.7	1929.2
max	265.2	3003.5	120.8	12.2	25.2	106.9	7.2	1.2	2151.9

The pumping rate ranged from 230 to 265.2 ppg, the pumping rate from 2279 to 3003 psi, the drillstring rotation from 108 up to 120 rpm, the drilling torque from 7 up to 12 klbf.ft, the weight on bit from 10 to 25 klbf. and drillability rate from 43 to 106 ft/hr. and the resulting vibrations show a range from 2.7 to 7.2 g, 0.5 up to 1.2 g, and 1543 to 2151 deg_per_s_sq for the lateral, axial, and torsional vibrations respectively.

Figure 8 shows the pair plots for the data set features to represent the correlation of the parameters through visualization and it is clear from the plots that it is a complex nonlinear type of correlation between the drilling parameters and the three modes of downhole vibration.

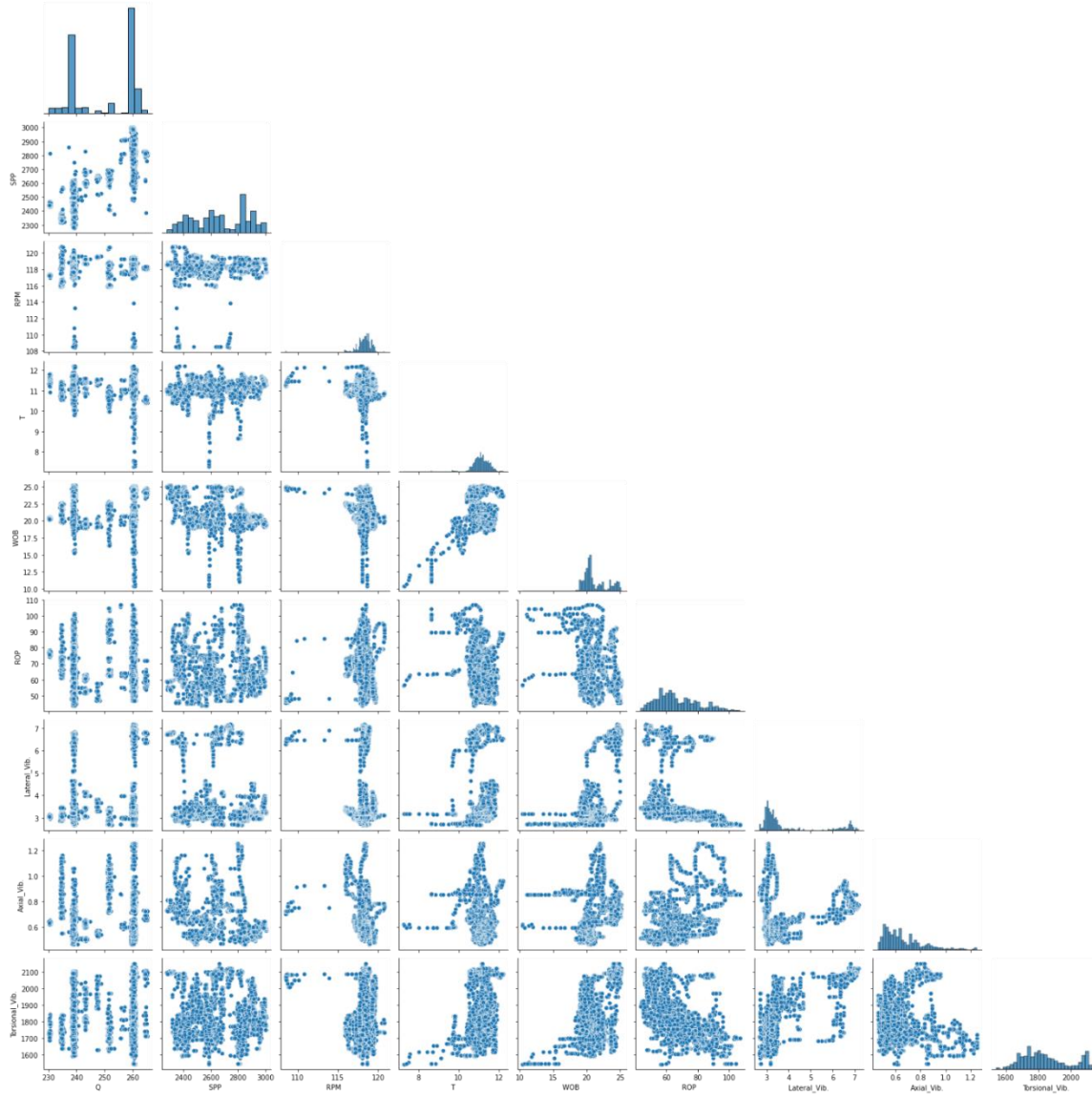


Figure 8 Pair plots for the data set features

Besides, Figure 9 displays the data distribution for the vibration data across the three modes of vibrations where lateral and torsional types showed bimodal distribution while the axial vibration showed positive right-skewed distribution.

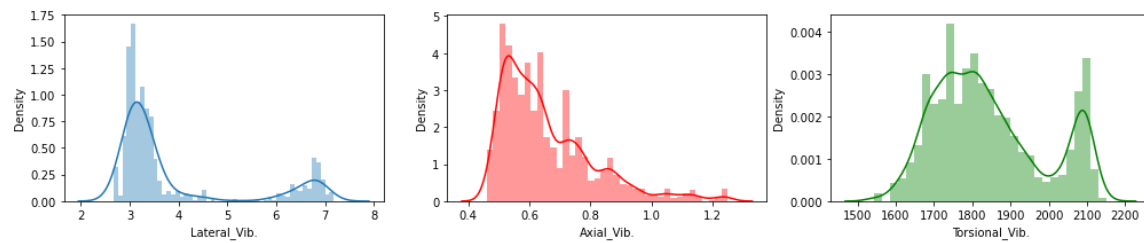


Figure 9 Vibration data distribution

In addition, the coefficient of correlation (R) between the model parameters was determined as shown from the heatmap in Figure 10. The heatmap showed that the lateral vibration had a direct relationship with Q, T, WOB, axial and torsional vibration, while had an indirect relationship with SPP, RPM, and ROP with a variation in R-value. The axial vibration had an indirect relationship with all inputs except WOB and ROP which showed a direct relationship type. The torsional vibration data showed a direct relationship with all parameters except SPP and ROP. All three types of vibration data showed a direct relationship that had its maximum R-value between the lateral and torsional vibrations (0.8) while the minimum R was 0.057 between the axial and torsional vibrations. These statistics revealed the complexity between the data and might reveal nonlinear relationships between the parameters, and therefore, the machine learning application for such problems will help to represent the intercorrelations between the parameters for predicting the downhole vibrations based on the learning capabilities from the model data and algorithms.

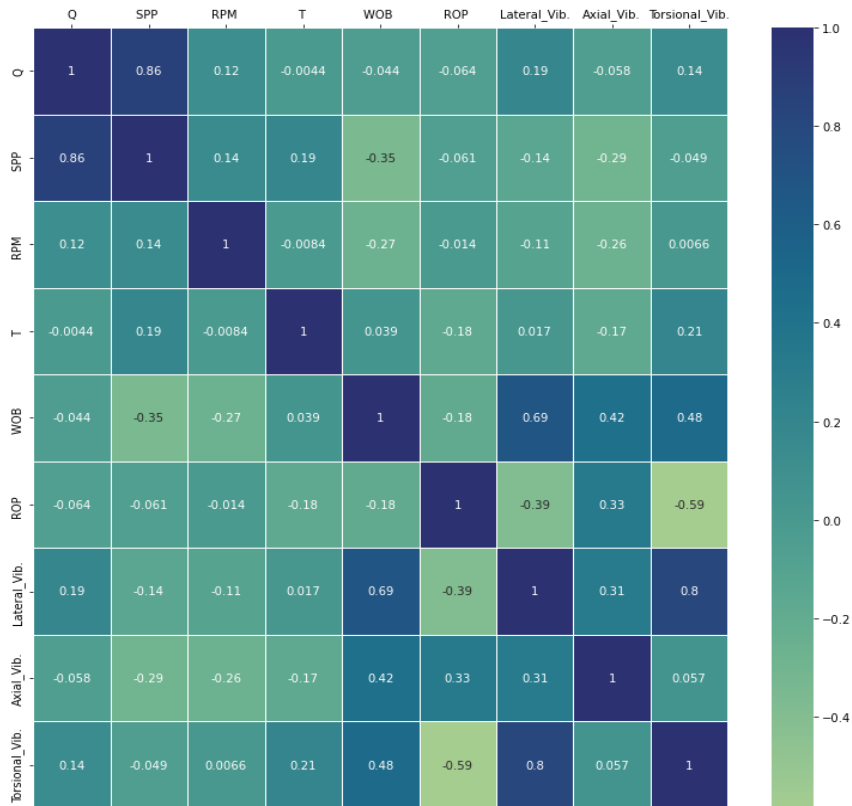


Figure 10 Data heat map

4.1.4 Machine Learning Techniques

The study implemented four techniques to evaluate the capabilities of the algorithms to capture the parameter patterns for autodetecting the downhole vibrations from the surface drilling data. Radial basis function (RBF), support vector machines (SVMs), adaptive

neuro-fuzzy inference system (ANFIS), and functional networks (FN) were utilized and compared during the training and testing for the models. These techniques are now widely applied in ML research applications for petroleum big data (Alsaihati et al., 2022; Mahmoud et al., 2022b).

The RBF is considered to have a simple architecture. Commonly, three layers for the model structure provide a simple way for the training exercise (Tatar et al., 2013). The RBF is found to be a great competent algorithm for modeling the data with a high degree of noise (Rostami et al., 2018). The technique has a non-linear type of transformation that is applied to the hidden layer weighting vector and provides a continuous function for multi-variable prediction by determining the best results for improving the accuracy (Wilamowski and Jaeger, 1996; Li et al., 2011).

ANFIS is one of the ML tools that showed successful applications for solving technical problems with high computational capabilities for prediction purposes in oil and gas (Alsabaa et al., 2020). The tool is considered a modified model that comprises the neural networks and fuzzy interference systems (Jang, 1993) by implementing diverse functions to every node for training the model features in fuzzy interference systems (Noorani et al., 2009). During the algorithm learning progression, changing the membership functions will be done to reach the best results for modeling the problem and this task is commonly controlled by Sugeno systems and Mamdani system as an optimization procedure (Schwenker et al., 2001).

SVM is another ML technique that is used for classification problems and another application for regression purposes. The technique determines the weights and biases from the training data set to figure out the hyperplane which splits the maximum margin of the data (Noble, 2006). The data with a high degree of complexity and dimensionality is found to be modeled by using the Kernel-type technique that has a function for non-linear high dimensional space (Aizerman, 1964; Bottou and Vapnik, 1992).

FN has an architecture of three layers that represent the input layer for the feed input parameters, the output layer for the model prediction, and the processing hidden layer that might be more than one single layer (Rossi et al., 2002). The neurons are connecting these layers and the output is calculated through the identified weights by the learning algorithms as forward or backward propagation types. Finally, the most optimum values for the output are determined (Castillo et al., 2001).

4.1.5 Models Evaluation

The developed models were evaluated during the sensitivity analysis for each model to get the best results for predicting the three models of downhole vibrations. The evaluation was achieved by calculating two statistical metrics as the coefficient of correlation and the average absolute percentage error (AAPE). R and AAPE are estimated between the real

measurements for the vibration versus the predicted vibration values for every iteration through the model optimization phase. The two metrics were calculated as:

$$R = \frac{N(\sum_1^N Y_i \hat{Y}_i) - (\sum_1^N Y_i)(\sum_1^N \hat{Y}_i)}{\sqrt{[N \sum_1^N Y_i^2 - (\sum_1^N Y_i)^2] [N \sum_1^N \hat{Y}_i^2 - (\sum_1^N \hat{Y}_i)^2]}} \quad (1)$$

$$AAPE = \left(\frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \times 100 \quad (2)$$

where N is the total number of points in the data set, y_i represents the real measurement, $\hat{y}_i$ is the model prediction, and $\bar{y}$ is the parameter mean.

4.2 Results and Discussion

Each model was tested during sensitivity analytics for a wide range of every parameter to get the optimized model parameters for the best accuracy and prediction results. This step is exactly performed by evaluating the model prediction accuracy in terms of R and AAPE through each case/run for the model. The optimized parameters for every

4.2.1 Models Optimization

The model performance was determined through model training and testing for the data set. Table 8 presents the optimized parameters for every ML model that is achieved through deep sensitivity analysis across a wide range of parameters of each model. RBF was optimized by using 25 neurons for the network with Bayesian regulation backpropagation training algorithm and Hyperbolic tangent sigmoid transfer function. SVM model had the best results with 10 for kernel options and gaussian kernel function type. ANFIS model with 2 membership functions provided the highest accuracy among the iterations with gaussian type for the input membership function and linear type for the output membership function. FN with functional network forward-backward type and method of nonlinear of degree (2) showed the best results for vibration detection.

Table 8 Sensitivity analysis results for the optimized ML models' parameters

RBF		SVMs		ANFIS		FN	
Neurons No.	25	Kernel option	10	Number of MFs	2	Type	functional network forward-backward

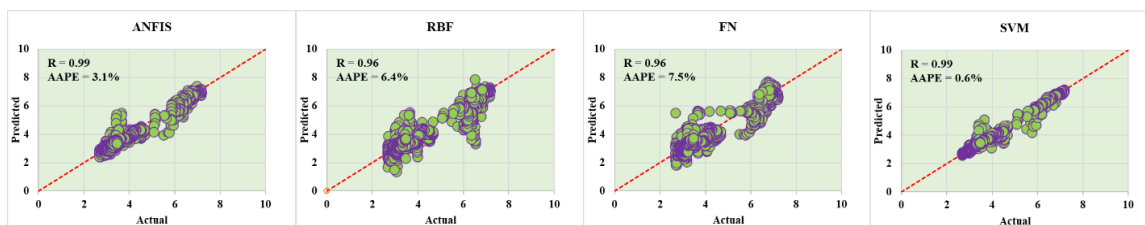
Training Function	Bayesian regulation backpropagation	C	100	InputMF	gaussian	Method	Non-Linear(2)
Transfer Function	Hyperbolic tangent sigmoid	lambda	1e-5	InputMF	Linear		
		epsilon	1e-5				
		verbose	1				
		kernel	gaussian				

It is worth mentioning that the developed models have the same structure for all three models of vibrations, not a separate model for detecting each vibration type and this is one of the challenges during the models' development.

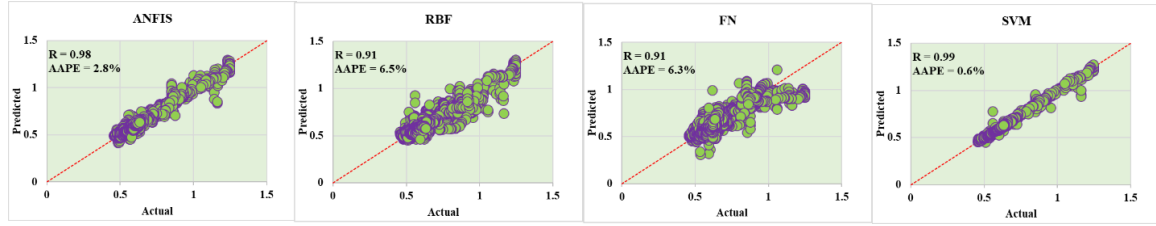
4.2.2 Models Evaluation

Every ML model was trained using 4000 data points (70% of the model data set) and 1750 data points were utilized for testing the model that showed 30% of the total model data set. The next plots show the accuracy delivered by the models for auto-detecting the downhole vibrations in real time for training and testing the models.

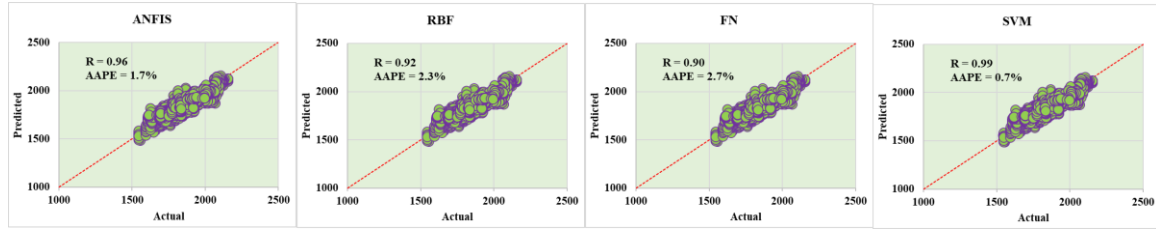
The training results for the developed vibration models are presented in Figure 11 the best-case optimized models. The lateral vibrations show a high degree of prediction especially with SVM-model and ANFIS model and general prediction accuracy is higher than 0.9 for R and a maximum 7.5% AAPE. The other vibration models for the axial and torsional have the same trend with a high degree of match between actual and predicted values for the models' prediction.



a



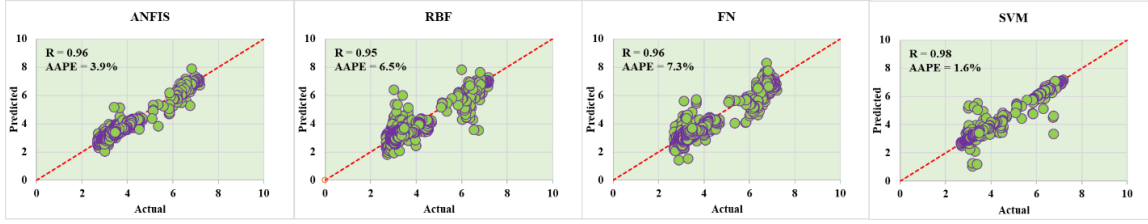
b



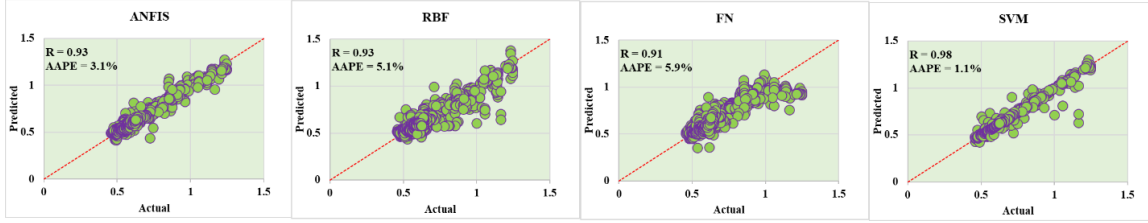
c

Figure 11 Training results for the developed vibration models a) lateral b) axial c) torsional

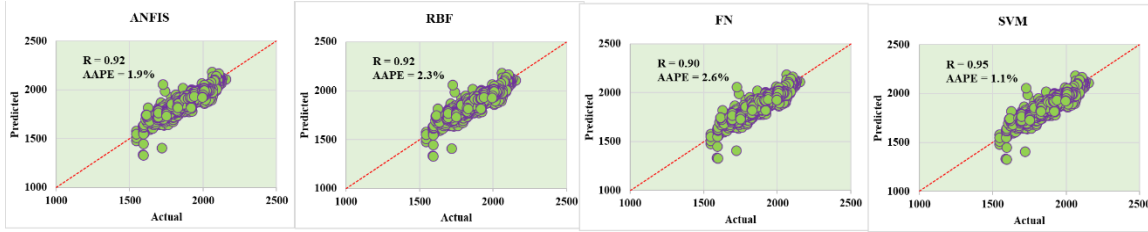
Testing the developed models with the testing data set shows a high degree of accuracy for the vibration predictions as illustrated in Figure 12. The accuracy for the developed models for the three types of vibrations showed that R ranged from 0.91 up to 0.98 with the best minimum AAPE of 1.1% and maximum value of 7.3%.



a



b



c

Figure 12 Testing results for the developed vibration models a) lateral b) axial c) torsional

4.2.3 Models Validation Phase

The four developed models were validated by testing the accuracy over unseen data set to predict the three vibration types in real-time using the well drilling data. The lateral vibration validation results are plotted in Figure 13 to highlight the predicted vibration profiles versus the actual downhole vibrations for the four developed models. The axial and torsional vibration predictions are presented in Figures 14 and 15 respectively. The results showed a high degree of match with the actual downhole measurements for the three types of vibrations with R ranging from 0.9 to 0.98 and AAPE from 1.1 to 6.1%.

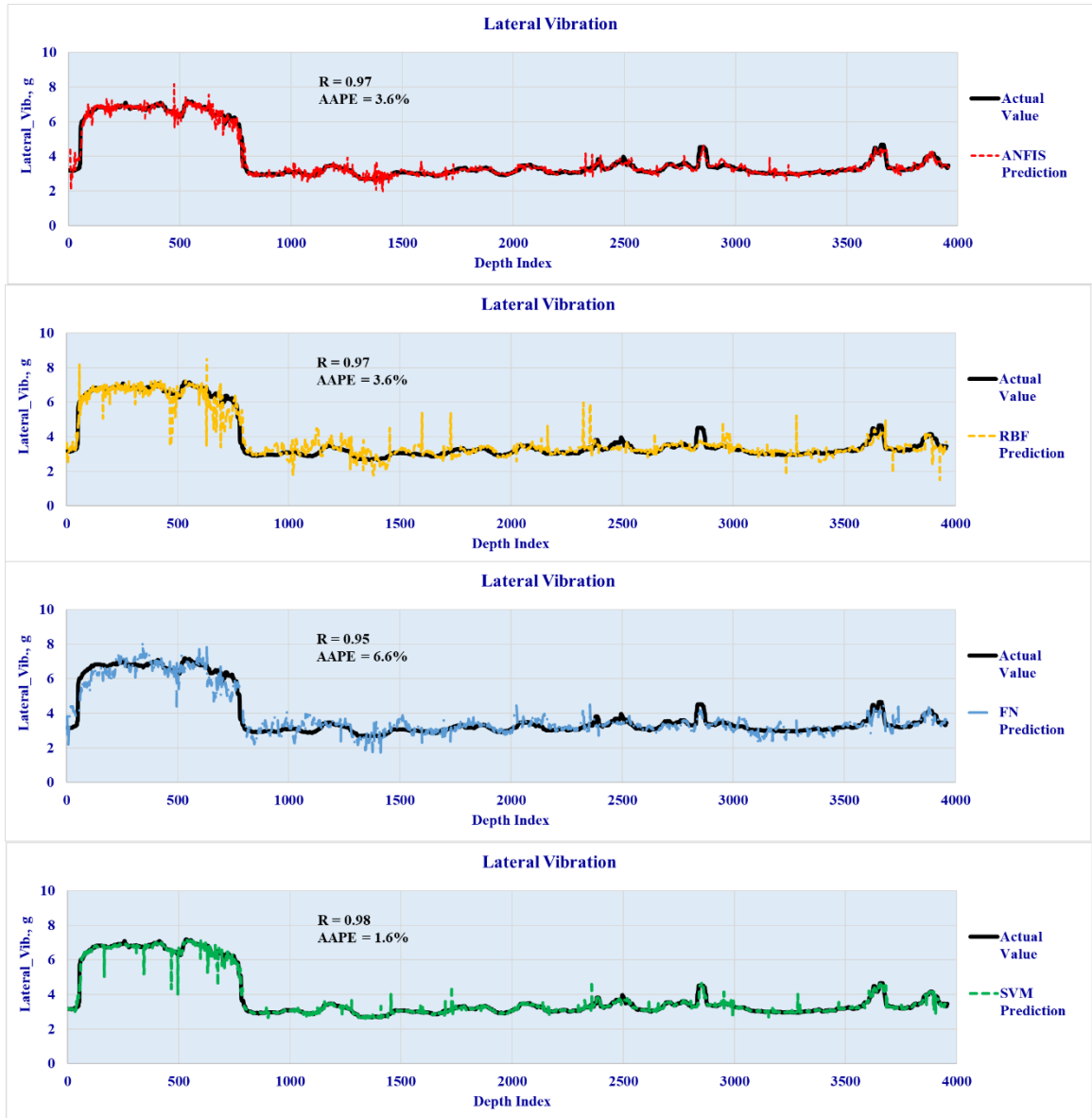


Figure 13 Lateral vibration prediction results (Validation well data set)

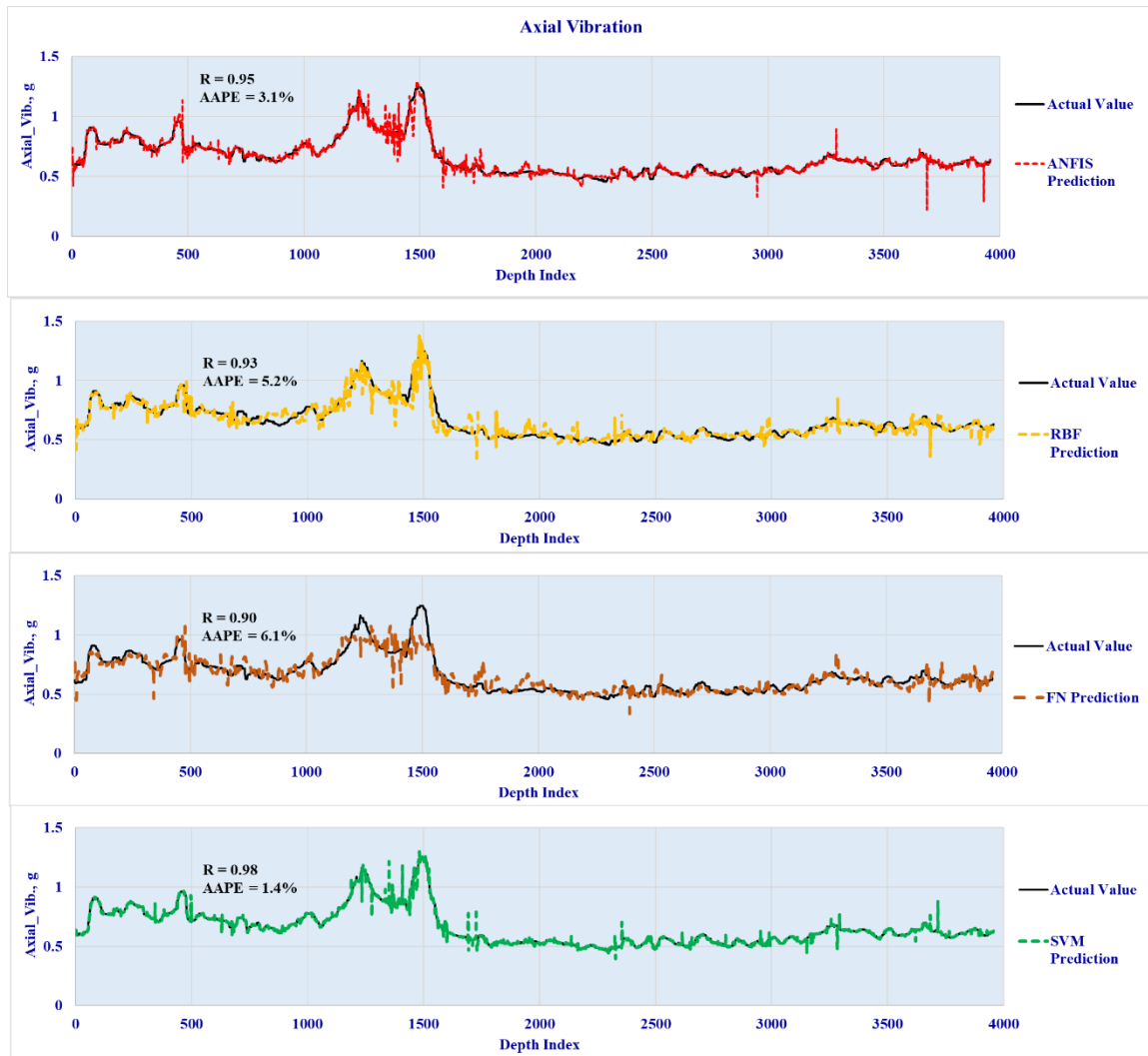


Figure 14 Axial vibration prediction results (Validation well data set)

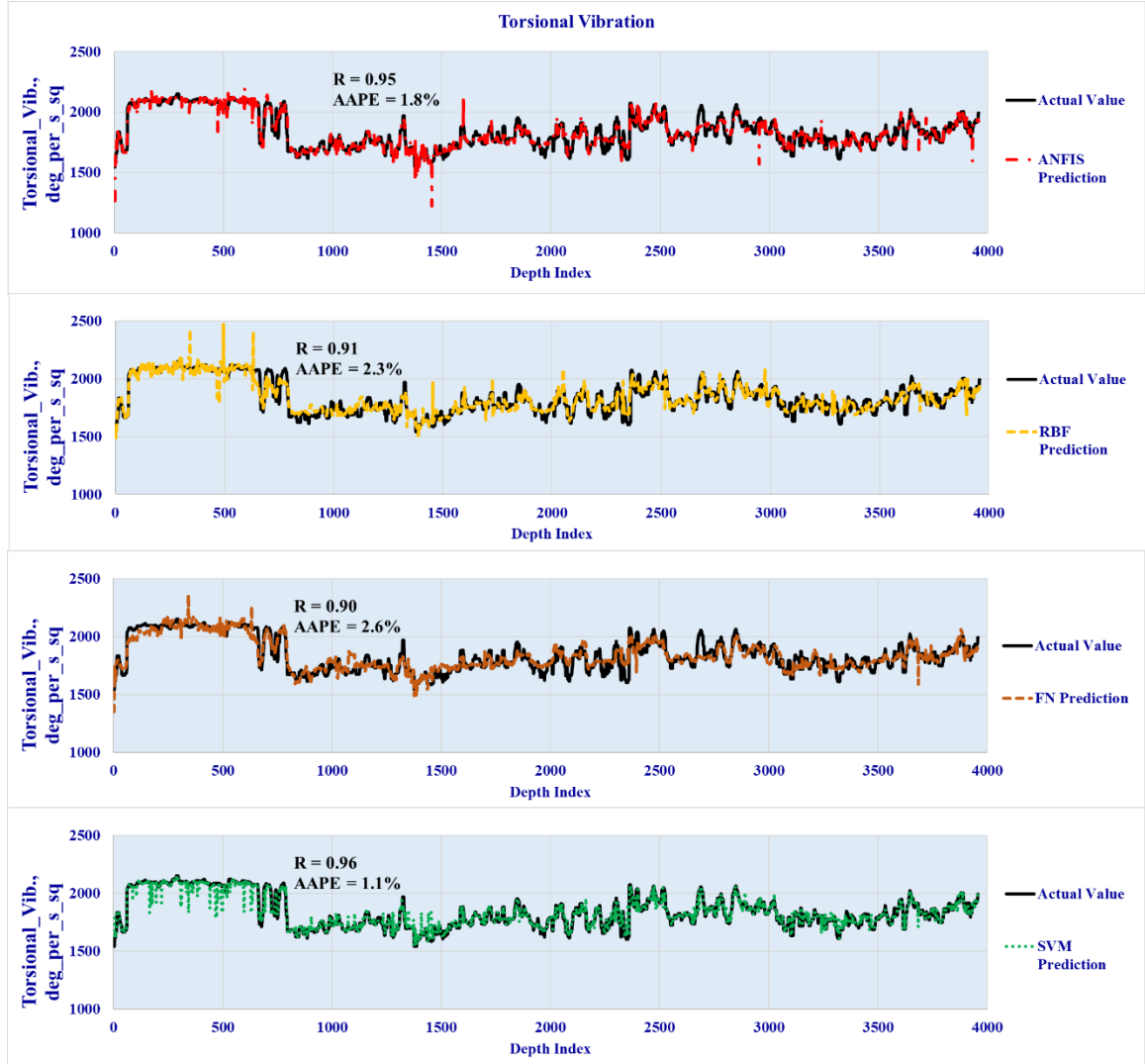


Figure 15 Torsional vibration prediction results (Validation well data set)

The real-time vibrations obtained from the developed ML models provide vital information on the durability of drilling BHA. This information is very helpful for directional drillers and drilling engineers. For directional drillers, it can help to identify vibrations and then apply correct mitigation for severe conditions and gives full control over the bottom hole assembly, also, tracking the vibrations trends obtained from the model it helps to avoid many tools failure by comparing predicted vibrations versus downhole tools limit such as red zone and continuing drilling without interruption to the well total depth especially while drilling horizontal sections. For drilling engineers, avoiding drilling interruption is required to minimize the non-productive time and in sequence more cost. In addition, giving good readings from downhole tools to be able to avoid deviations from the planned directional proposal especially in horizontal sections to be able to hit the targets as per well objectives.

CHAPTER 5

ANN Model For Predicting Vibrations In Curve Section Drilling

5.1 Study Data Description and Machine Learning Modeling

5.1.1 Research Plan

The study presented a technical approach that considered the full process for developing the AI model starting from collecting rig sensor data, data preprocessing, building ANN model, evaluating the accuracy, and finally saving the best results for vibration predictions. The data was gathered from the rig sensors and then the data was forwarded to the data wrangling process for data cleaning and quality enhancement by removing the outliers and performing advanced statistical data analysis to study the data range, distribution, and correlation coefficient. Building the AI-ANN model started after the full data preprocessing phase and the model building was studied with deep sensitivity for the different learning algorithms and model parameters to provide the best results for the prediction of the downhole vibrations. The model was evaluated with statistical metrics to evaluate the performance and compare the predicted versus actual measurements for the downhole vibration values. The model would be retrained again with different training algorithms or model parameters in case the prediction performance was not accepted till reached the best accuracy level to report the best results and model parameters. The best prediction results from the optimized AI-ANN model were reported to show the model prediction capabilities.

5.1.2 Data Description

The current study utilized real field downhole vibration data during drilling curve sections to develop the different machine learning models. 2730 data points from well data that show the surface drilling parameters (that represent the model input features) associated with the downhole vibration measurements (that show the target parameters of the ML model). The main inputs for the developed model are the surface rig sensor data that are the rate of penetration (ROP), drilling torque (T), drilling speed rotation (DSR), mud rate (Q), standpipe pumping pressure (SPP), and the weight on the drill bit (WOB), while the downhole vibrations were logged using downhole sensors for detecting the downhole drillstring vibrations (axial, lateral, and torsional vibrations). The developed models were further tested by a validation unseen data set (blind well data) from a well data during the drilling phase for drilling a similar curve section.

Technically, the curve section is starting with running and setting whipstock across the setting formation followed by cutting a casing window with a rate hole then deploying the drilling bottom hole assembly which consists of an aggressive drill bit, motor / measurement-while-drilling, and drill string to surface with a combination of heavy weight drill pipes and drill pipes. Due to the long radius well profile to build from vertical to 90-degree inclination in around 1,500 – 2,000 feet and to achieve the required dog leg severity, drill collar is avoidable. Usually, the drilling is commenced with a high sliding percentage in shallower formations then gradually decreased while drilling and building deeper formations due to formations lithology however the total sliding percentage for the run is ranging from 30 – 50 % depending on planned dogleg severity, the building tendency in rotary mode, weight transfer efficiency to the drilling bit resulted from friction between drilling BHA and hole walls.

5.1.3 Data Wrangling and Analysis

The collected drilling data was preprocessed by diverse pipelines to remove the illogic values within the data set as zeros and negative values, remove the parameters outliers, and smooth the drilling data to remove the noise and enhance the data quality. The cleaned data set was then analyzed to explore the interrelationships and data distributions.

The surface drilling parameters are commonly observed at the surface while drilling and these surface parameters are significantly affected by the interaction between the drillstring and wellbore wall which causes the downhole vibration. The application of statistical analysis to the data gathered demonstrates good variety and representation of the data as it encompasses a wide range of input and output parameters (Table 1).

The pumping rate ranged from 456.5 to 578.7 ppg, the pumping rate from 1546 to 2729 psi, the drillstring rotation from 187 up to 229 rpm, the drilling torque from 4.9 up to 10.2 klbf.ft, the weight on bit from 6.1 to 27.7 klbf., and the drillability rate from 34.6 to 133 ft/hr. The resulting vibrations show a range from 1.5 to 5.2 g, 0.5 up to 3.9 g, and 602 to 2722 deg_per_s_sq for the lateral, axial, and torsional vibrations respectively.

Figure 16 shows the pair plots for the data set features to represent the correlation of the parameters through visualization and it is clear from the plots that it is a complex type of correlation between the drilling parameters and the three modes of downhole vibration along the curve section drilling.

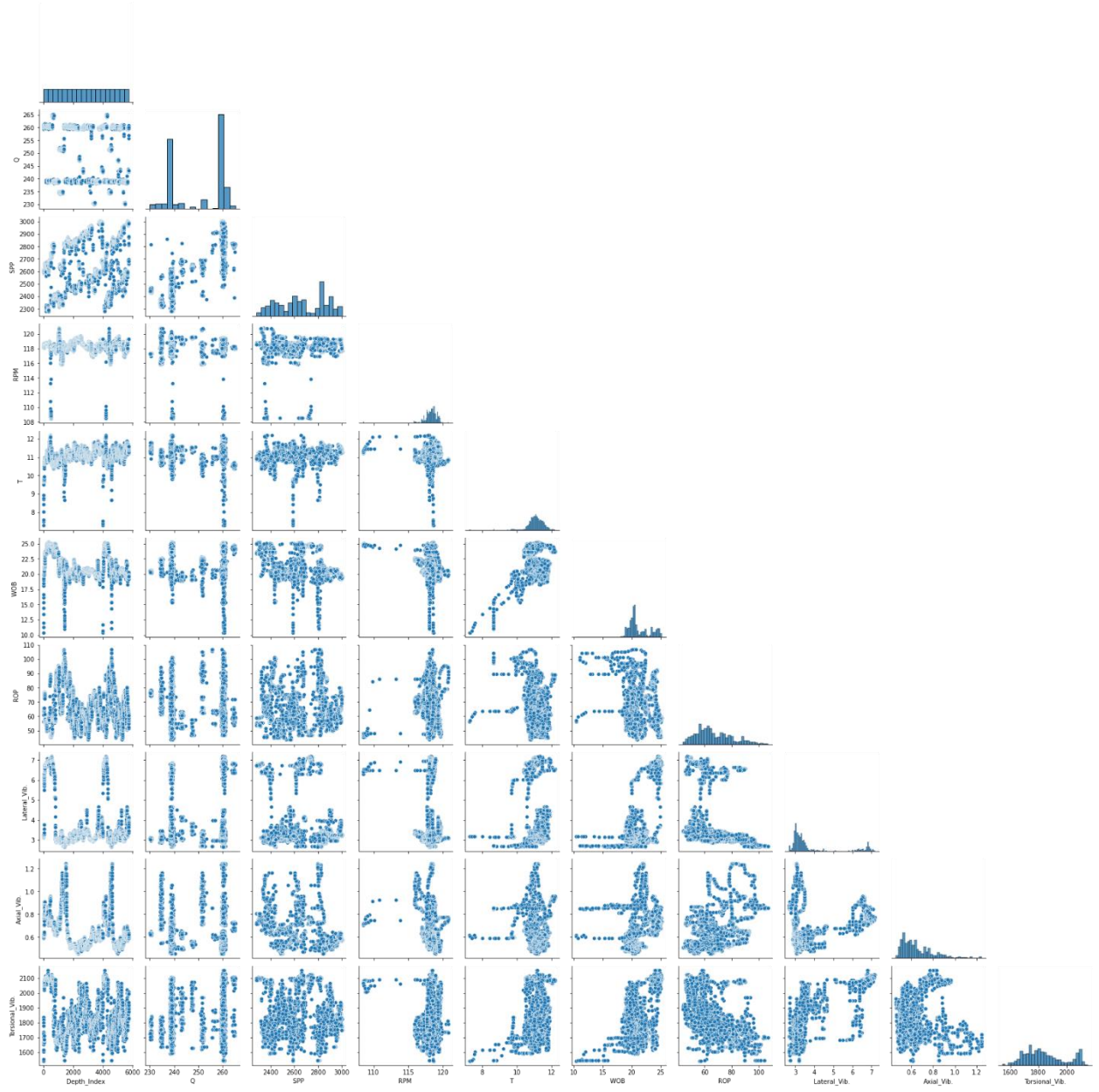


Figure 16 Pair plots for the data set features.

In addition, Figure 17 displays the data distribution for the vibration data across the three modes of vibration where lateral and torsional modes showed bimodal distribution while the torsional vibration showed right-skewed distribution. The data skew shows the data distortion degree from the normal distribution, and hence, represents the data distribution over the range. The joint plots as shown in Figure 18 reveal the interrelationships between the three modes of vibrations, and from the plots, there is no clear trend for the vibration profiles over the model data.

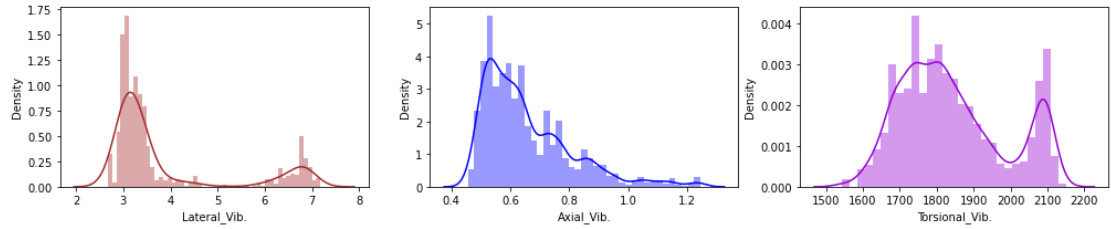


Figure 17 Data distribution for the vibration modes

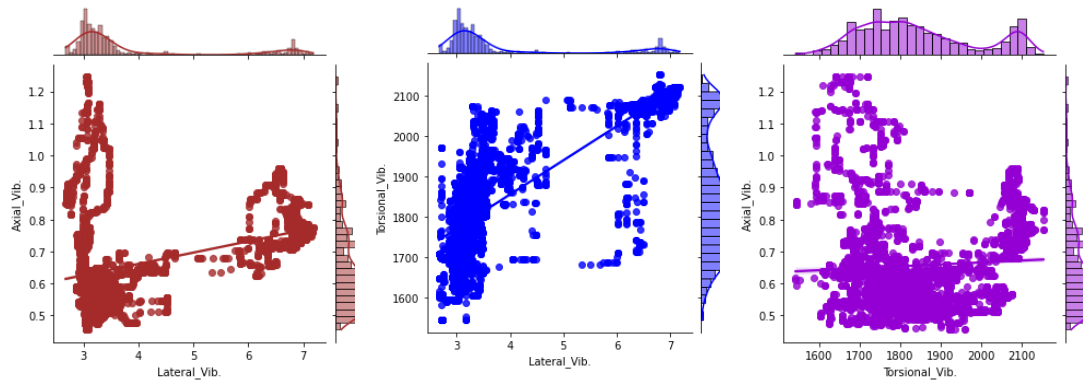


Figure 18 Joint plots for the vibration modes

In addition, the coefficient of correlation (R) between the model parameters was determined as shown from the heatmap in Figure 19. Torsional vibration was found to have a direct relationship with all drilling parameters except SPP and ROP, while axial mode showed an indirect relationship with drilling parameters except a direct relationship with WOB and ROP, besides, the lateral mode of vibration had a direct relationship with Q, T, and WOB, with an indirect type of relationship with other three parameters (SPP, RPM, and ROP). All statistics showed a variation in R -value. It was found that torsional and lateral modes had a strong linear relationship (0.95) as clear also from the data plots (Figure 18).

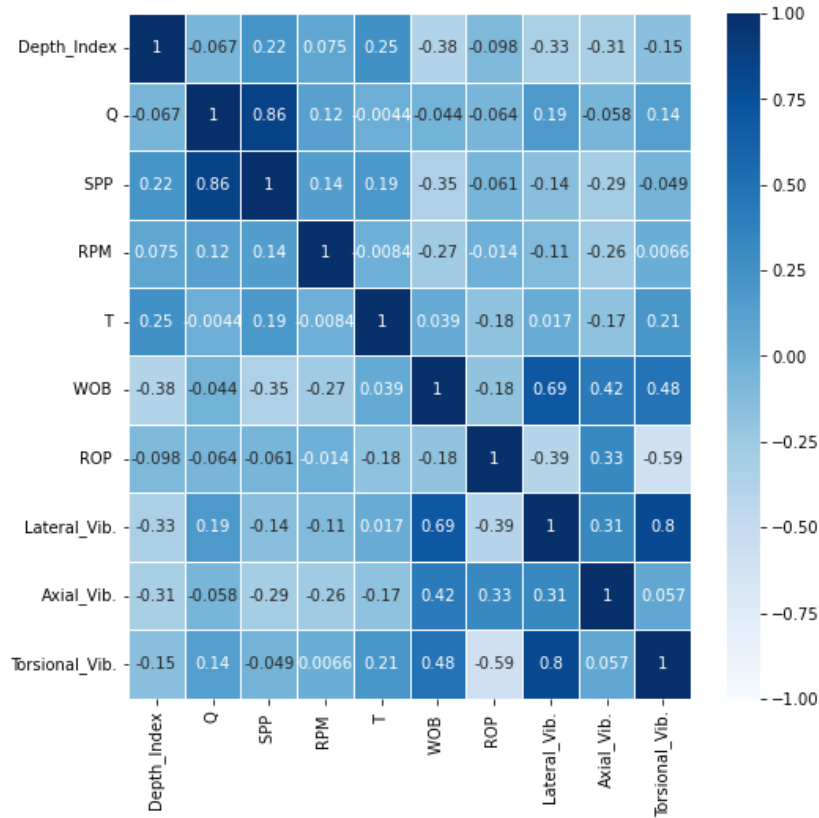


Figure 19 Data heat map

These statistics revealed the complexity between the data and might reveal nonlinear relationships between the parameters, and therefore, the machine learning application for such problems will help to represent the intercorrelations between the parameters for predicting the downhole vibrations based on the learning capabilities from the model data and algorithms.

5.1.4 AI-ANN Model

The study implemented four techniques to evaluate the capabilities of the algorithms to capture the parameter patterns for autodetecting the downhole vibrations from the surface drilling data. Artificial neural networks (ANN), Radial basis function (RBF), support vector machines (SVMs), adaptive neuro-fuzzy inference system (ANFIS), and functional networks (FN) were utilized and compared during the training and testing for the models. These techniques are now widely applied in ML research applications for petroleum big data (Alsabaa, A. et al., 2020b; Alsaihati et al., 2022; Mahmoud et al., 2022b).

ANN is considered one of the best common tools for machine learning applications with petroleum data that provides numerous successful contributions regarding prediction purposes. The ANN technique simulated the human biological neural system for learning capabilities for problem thinking (Abbas et al., 2019; Bello et al., 2015). The ANN structure is represented by the main layers named the input layer for the model inputs, a hidden layer that might be one or more layers for the processing that contain neurons within the layer, and the output layer for the predictive parameter (Cevik et al., 2011). The weights and biases are hyperparameters for the model which are connections linked between the layers and have a great impact on the model performance (Lippmann, 1987). The model is trained with a learning algorithm that controls the model processing (Graves et al., 2009). The main structure of the developed ANN model for vibration prediction is represented by the input layer includes the drilling data, the hidden layer and its neurons, and the output layer which is the downhole vibrations. Figure 20 showed the developed ANN vibration model structure.

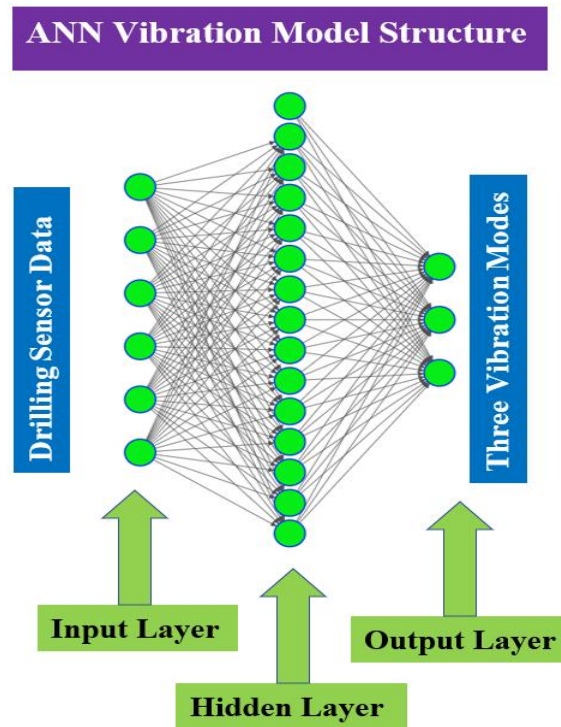


Figure 20 ANN Vibration Model Structure

5.1.5 Model Evaluation Metrics

The developed models were evaluated during the sensitivity analysis for each model to get the best results for predicting the three models of downhole vibrations. The evaluation was achieved by calculating two statistical metrics [the coefficient of correlation (R) and the

average absolute percentage error (AAPE)]. R and AAPE are estimated between the real measurements for the vibration versus the predicted vibration values for every iteration through the model optimization phase. The two metrics were calculated as:

$$R = \frac{N(\sum_1^N Y_i \hat{Y}_i) - (\sum_1^N Y_i)(\sum_1^N \hat{Y}_i)}{\sqrt{[N \sum_1^N Y_i^2 - (\sum_1^N Y_i)^2][N \sum_1^N \hat{Y}_i^2 - (\sum_1^N \hat{Y}_i)^2]}} \quad (1)$$

$$AAPE = \left(\frac{1}{N} \sum_{i=1}^N \left| \frac{y_i - \hat{y}_i}{y_i} \right| \right) \times 100 \quad (2)$$

where N is the total number of points in the data set, y_i represents the real measurement, $\hat{y}_i$ is the model prediction, and $\bar{y}$ is the parameter mean.

5.2 Results and Discussion

ANN model was tested during sensitivity analytics for a wide range of every parameter to get the optimized model parameters for the best accuracy and prediction results. Once reached the best accuracy for the optimized model parameter, the model structure was saved with the reported results besides the ANN-based equation for real-time estimating of the downhole vibrations while drilling the curve section. The following parts showed in deep detail how the optimization process with the best prediction results.

5.2.1 Models Optimization

Optimizing the model parameters is a crucial step for getting the best prediction result through the model training and testing phases, and this step is commonly achieved through deep sensitivity trials for all the model parameters that affect the prediction performance. Many automated trials and error runs were done to evaluate the impact of every model parameter on the predicted values of vibrations. Table 2 presents the final optimized parameters for the ANN vibration model that is achieved across a wide range of parameters of each model. It is worth mentioning that the developed models have the same structure for two models of vibrations (lateral and axial) with only 1 hidden layer of 25 neurons, pattern recognition network function, Bayesian regularization as a training function, and hyperbolic tangent sigmoid transfer function. Whereas the torsional model had changes in only two parameters (35 neurons and Log-sigmoid transfer function).

5.2.2 Models Accuracy (Training and Testing Phases)

ANN vibration model was trained using 1910 data points (70% of the model data set) and 820 data points were utilized for testing the model that showed 30% of the total model data set. The next plots show the accuracy delivered by the models for auto-detecting the downhole vibrations in real time for training and testing the models.

The training and testing results for the developed ANN vibration model are presented in Figure 21 for the best-case optimized models. ANN model accuracy was higher than 0.98 for the three modes of vibration prediction (with AAPE not higher than 1.8% for axial and lateral vibrations with 4.4% AAPE for the torsional vibrations).

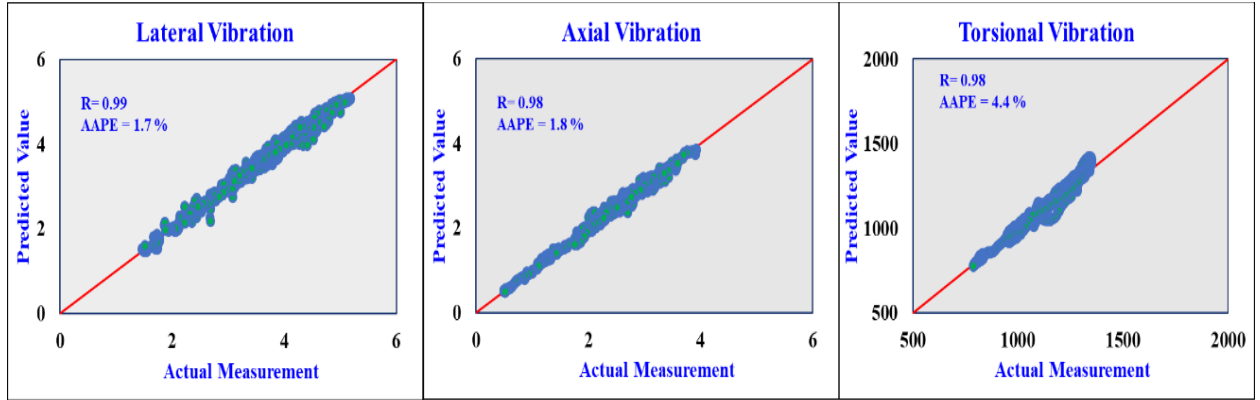


Figure 21 ANN-Vibration prediction model training results

The testing phase for the developed vibrations model showed that the models are capable to predict the downhole vibrations with high accuracy for the testing data set as presented in Figure 22. The model accuracy is generally accepted with R greater than 0.96 and AAPE does not exceed 2.6%. It is worth mentioning that the torsional vibration is very challenging especially for the curve section drilling operation.

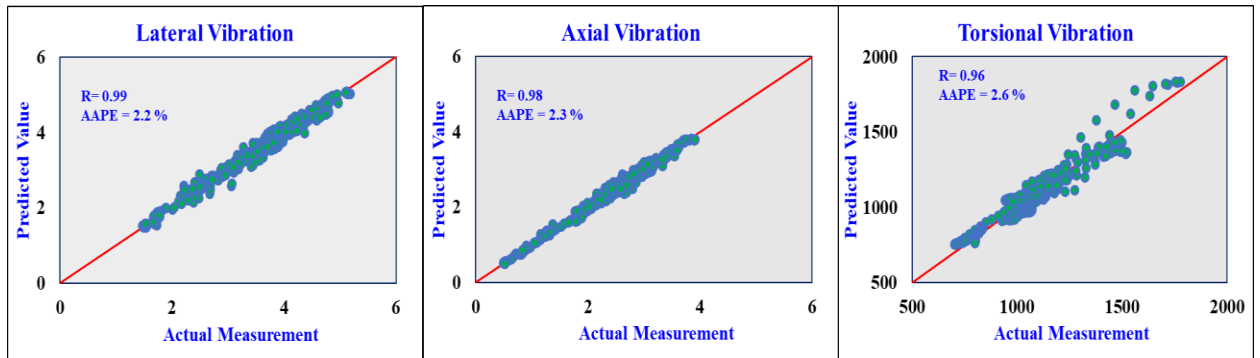


Figure 22 ANN-Vibration prediction model testing results

5.2.3 ANN-Developed Equation

A newly developed ANN-based equation was extracted from weights and biases of the ANN-vibration model network. The ANN-based equation is easy to be used in real-time on the rig site using the input values of the drilling data. To utilize the equation, firstly the input and output parameters should be normalized to be in the range of -1 to 1:

$$X_{i\text{ nor}} = 2 * \left(\frac{X_i - X_{i\text{ min}}}{X_{i\text{ max}} - X_{i\text{ min}}} \right) - 1 \quad (1)$$

Where, $X_{i\text{ nor}}$ represents the normalized value for parameter X; X_i is parameter X value at each data point; $X_{i\text{ min}}$ is the minimum value for parameter X; $X_{i\text{ max}}$ is the maximum value of parameter X. The minimum and maximum values for each parameter for data normalization using Equation 1 are listed in Table 1.

Equation 2 represents the formula that can be used for lateral and axial vibration prediction in the normalized form while Equation 3 is for the torsional vibration mode, and the correlation uses weights and biases that are shown in Tables 3, 4, and 5 (Appendix A). To get the real denormalized value, Equation 1 can be used to convert back the obtained normalized value from vibration predictions.

$$\text{Valn}_i = \left[\sum_{i=1}^N w_{12,i} \left(\frac{2}{\left[1 + e^{-2 * (w_{1i,1}(Qn) + w_{1i,2}(SPPn) + w_{1i,3}(RPMn) + w_{1i,4}(Tn) + w_{1i,5}(WOBn) + w_{1i,6}(ROPn) + b_{1i})} \right]} - 1 \right) \right] + b_2 \quad (2)$$

$$\text{Vtn}_i = \left[\sum_{i=1}^N w_{12,i} \left(\frac{1}{\left[1 + e^{-(w_{1i,1}(Qn) + w_{1i,2}(SPPn) + w_{1i,3}(RPMn) + w_{1i,4}(Tn) + w_{1i,5}(WOBn) + w_{1i,6}(ROPn) + b_{1i})} \right]} \right) \right] + b_2 \quad (3)$$

Where N represents the hidden layer neurons number, W_1 shows the weights between the input parameters and the hidden layer, W_2 shows the weights between the hidden layer and the output layer, b_1 shows the biases of the hidden layer, and b_2 shows the biases of the output layer.

5.2.4 Validation Phase (Unseen Well Data)

The developed ANN-model was validated by evaluating the accuracy of unseen well data to predict the three vibration types in real-time using the well drilling data. The three types of vibrations for the validation results are plotted in Figure 23 to highlight the predicted vibration profiles versus the actual downhole vibrations for the developed model. The axial and torsional vibration predictions are showing an accuracy of 0.97 for R with 3.4% AAPE. The torsional vibration profile showed a good degree of match with the actual measured downhole values with 0.92 for R and 3.6% AAPE.

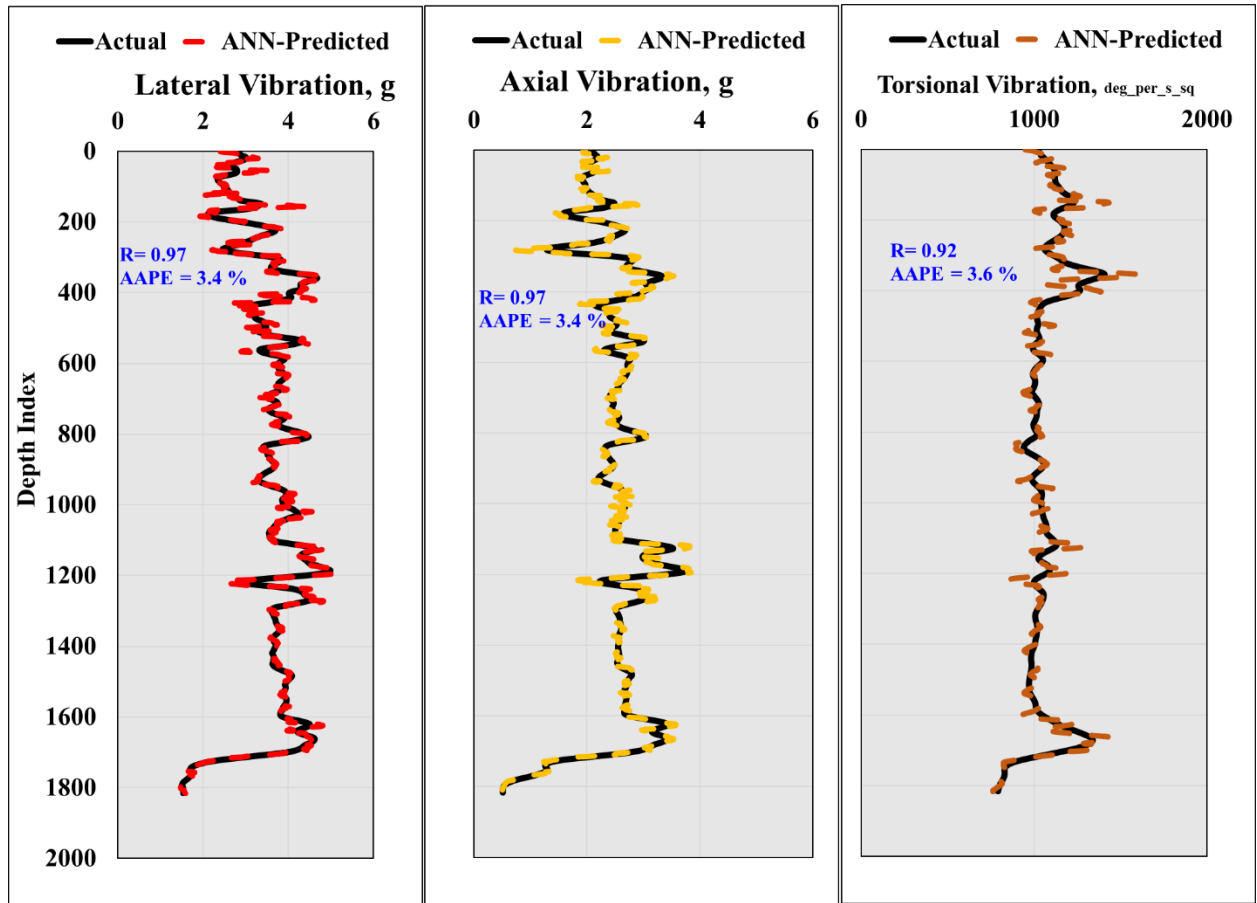


Figure 23 Vibration prediction results (Validation well data set)

By comparison between the prediction results, it is obvious that the prediction of torsional vibration is not on the high level as well as the axial and/or torsional vibrations prediction. This observation is mainly attributed to the existence of the downhole mud motor in the BHA which consists of a rotor that rotates inside a stator that might negatively affect on having the clear pattern between surface parameters and torsional vibration.

The real-time vibrations obtained from the developed ANN model provides vital information on the durability of drilling BHA. This information is very helpful for directional drillers and drilling engineers. For directional drillers, it can help to identify vibrations and then apply correct mitigation for severe conditions and gives full control over the bottom hole assembly, also, tracking the vibrations trends obtained from the model will help to avoid many tools failure by comparing predicted vibrations versus downhole tools limit such as red zone and continuing drilling without interruption to the well total depth especially while drilling curve sections. For drilling engineers, avoiding drilling interruption is required to minimize the non-productive time and in sequence more cost. In addition, giving good readings from downhole tools to be able to avoid deviations from the

planned directional proposal especially in curve sections to be able to hit the targets as per well objectives.

CHAPTER 6

Predicting Vibrations In Curve section Drilling BY DIFFERENT ML TECHNIQUES

6.1 Data Description and Machine Learning

6.1.1 Study Approach

The study presented a technical approach that considered the full process for developing the ML models starting from collecting rig sensor data, data preprocessing, building the models, evaluating the accuracy, and finally saving the best results for vibration predictions (Figure 24). The data was gathered from the rig sensors and then the data was forwarded to the data wrangling process for data cleaning and quality enhancement by removing the outliers and performing advanced statistical data analysis to study the data range, distribution, and correlation coefficient. Building the ML models started after the full data preprocessing phase and the model building was studied with deep sensitivity for the different learning algorithms and model parameters to provide the best results for the prediction of the downhole vibrations. The models were evaluated with statistical metrics to evaluate the performance and compare the predicted versus actual measurements for the downhole vibration values. The models would be retrained again with different training algorithms or model parameters in case the prediction performance was not accepted till reached the best accuracy level to report the best results and model parameters. The best prediction results from the optimized ML models were reported to show the models' prediction capabilities.

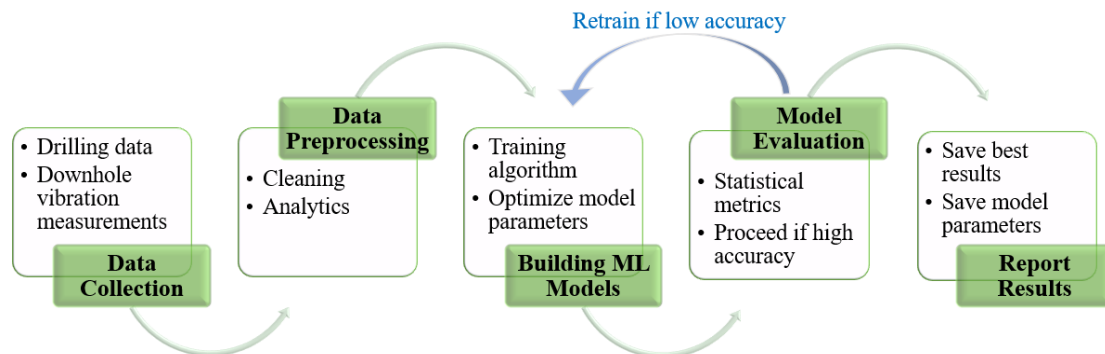


Figure 24 ML model layout.

6.1.2 Data Description

The current study utilized real field downhole vibration data during drilling curve sections to develop the different machine learning models. 2730 data points from well data that show the surface drilling parameters (that represent the model input features) associated with the downhole vibrations measurements (that show the target parameters of the ML models). Mainly six rig sensors that record the drilling mechanical and hydraulic data are the basic inputs for the models' named rate of penetration (ROP), drilling torque (T), drilling speed rotation (DSR), mud rate (Q), standpipe pumping pressure (SPP), and the weight on the drill bit (WOB), while the downhole vibrations were logged using downhole sensors for detecting the downhole drillstring vibrations (axial, lateral, and torsional vibrations). The developed models were further tested by a validation unseen data set (1810 data points) from a well data during drilling a similar curve section within the drilling phase.

Technically, the curve section is starting with running and setting whipstock across the setting formation followed by cutting a casing window with a rate hole then deploying the drilling bottom hole assembly which consists of an aggressive drill bit, motor / measurement-while-drilling (MWD), and drill string to surface with a combination of heavy weight drill pipes and drill pipes. Due to the long radius well profile to build from vertical to 90-degree inclination in around 1,500 – 2,000 feet and to achieve the required dog leg severity, drill collar is avoidable. Usually, the drilling is commenced with a high sliding percentage in shallower formations then gradually decreased while drilling and building deeper formations due to formations lithology however the total sliding percentage for the run is ranging from 30 – 50 % depending on planned dogleg severity, the building tendency in rotary mode, weight transfer efficiency to the drilling bit resulted from friction between drilling BHA and hole walls.

6.1.3 Data Preprocessing and Analytics

The collected drilling data was preprocessed by diverse pipelines to remove the illogic values within the data set as zeros and negative values, remove the parameters outliers, and smooth the drilling data to remove the noise and enhance the data quality. The cleaned data set was then analyzed to explore the interrelationships and data distributions.

The surface drilling parameters are commonly observed at the surface while drilling and these surface parameters are significantly affected by the interaction between the drillstring and wellbore wall which causes the downhole vibration. The application of statistical analysis to the data gathered demonstrates good variety and representation of the data as it encompasses a wide range of input and output parameters (Table 9).

Table 9 Statistical analysis for the models' data set

	Q	SPP	RPM	T	WOB	ROP	Lateral_Vib.	Axial_Vib.	Torsional_Vib.
Minimum	456.5	1546.6	187.2	4.9	6.1	34.6	1.5	0.5	602.4
Maximum	578.7	2729.0	229.1	10.2	27.7	133.1	5.2	3.9	2722.0
Mean	533.6	2367.5	212.1	8.1	21.1	82.5	3.6	2.5	1055.0
Standard Deviation	25.8	201.2	11.8	1.5	4.3	13.6	0.7	0.6	194.6

The pumping rate ranged from 456.5 to 578.7 ppg, the pumping rate from 1546 to 2729 psi, the drillstring rotation from 187 up to 229 rpm, the drilling torque from 4.9 up to 10.2 klbf.ft, the weight on bit from 6.1 to 27.7 klbf., and the drillability rate from 34.6 to 133 ft/hr. The resulting vibrations show a range from 1.5 to 5.2 g, 0.5 up to 3.9 g, and 602 to 2722 deg_per_s_sq for the lateral, axial, and torsional vibrations respectively.

Figure 25 shows the pair plots for the data set features to represent the correlation of the parameters through visualization and it is clear from the plots that it is a complex type of correlation between the drilling parameters and the three modes of downhole vibration.

Besides, Figure 26 displays the data distribution for the vibration data across the three modes of vibration where lateral and axial types showed almost similar left-skewed data distribution while the torsional vibration showed less positive right-skewed distribution. The data skew shows the data distortion degree from the normal distribution and hence, represents the data distribution over the range.

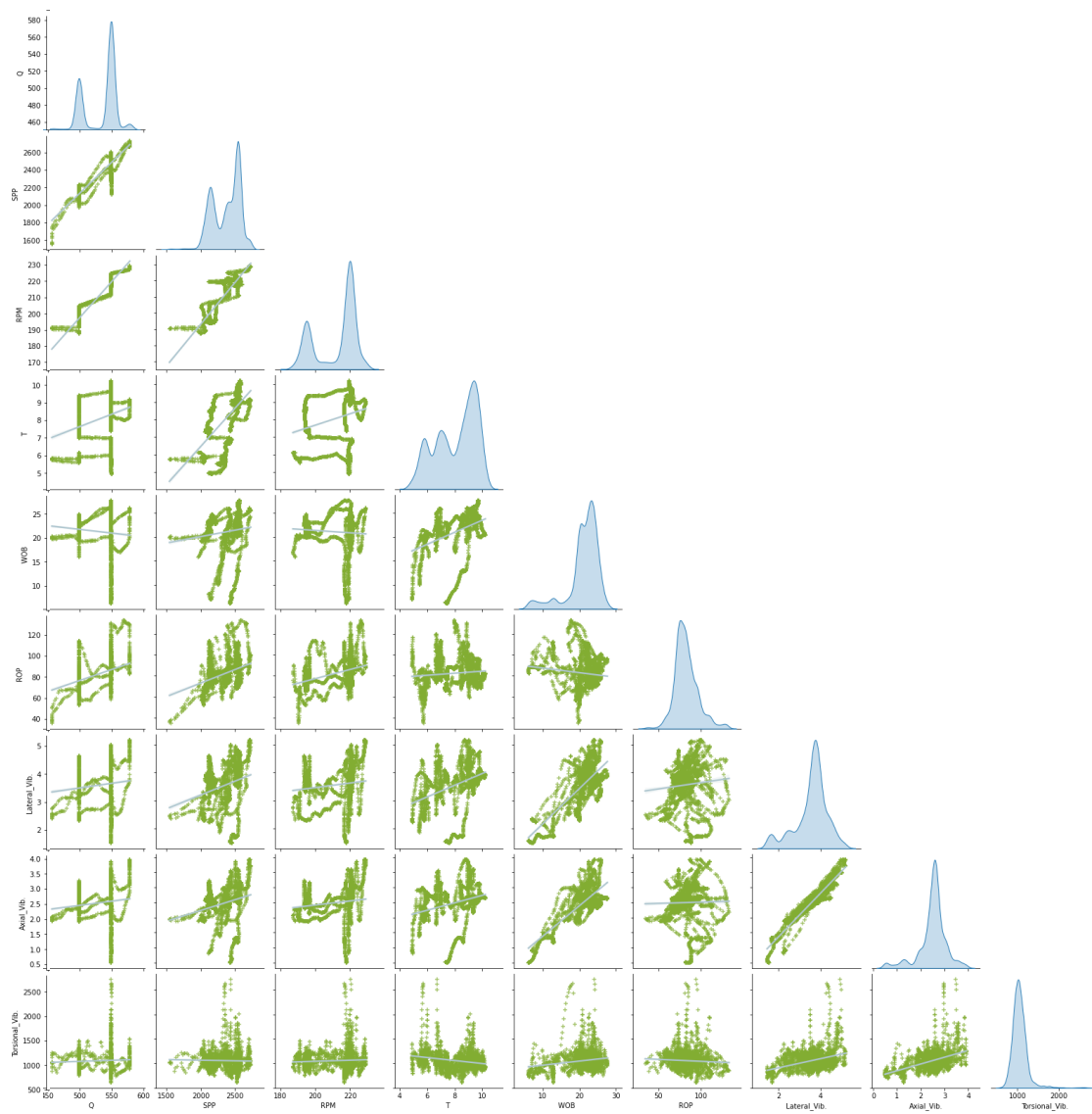


Figure 25 Pair plots for the data set features

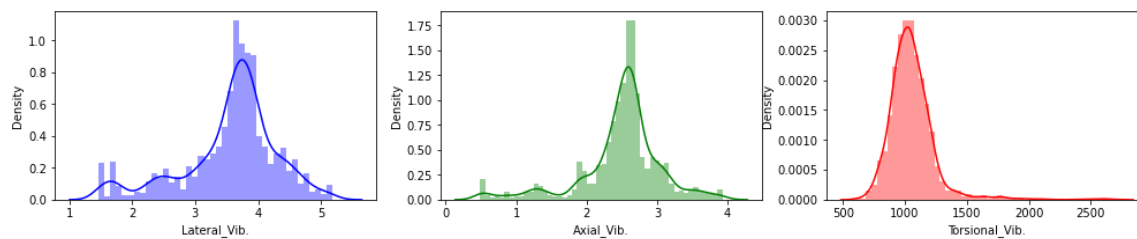


Figure 26 Vibration data distribution

In addition, the coefficient of correlation (R) between the model parameters was determined as shown from the heatmap in Figure 27. The heatmap showed that the axial and lateral vibrations had a direct relationship with all drilling data, besides the torsional vibration as well. It was found that axial and lateral modes had a strong linear relationship (0.95) as clear also from the data plots (Figure 25). Torsional vibration was found to have an indirect relationship with SPP, T, and ROP with a variation in R-value. These statistics revealed the complexity between the data and might reveal nonlinear relationships between the parameters, and therefore, the machine learning application for such problems will help to represent the intercorrelations between the parameters for predicting the downhole vibrations based on the learning capabilities from the model data and algorithms.

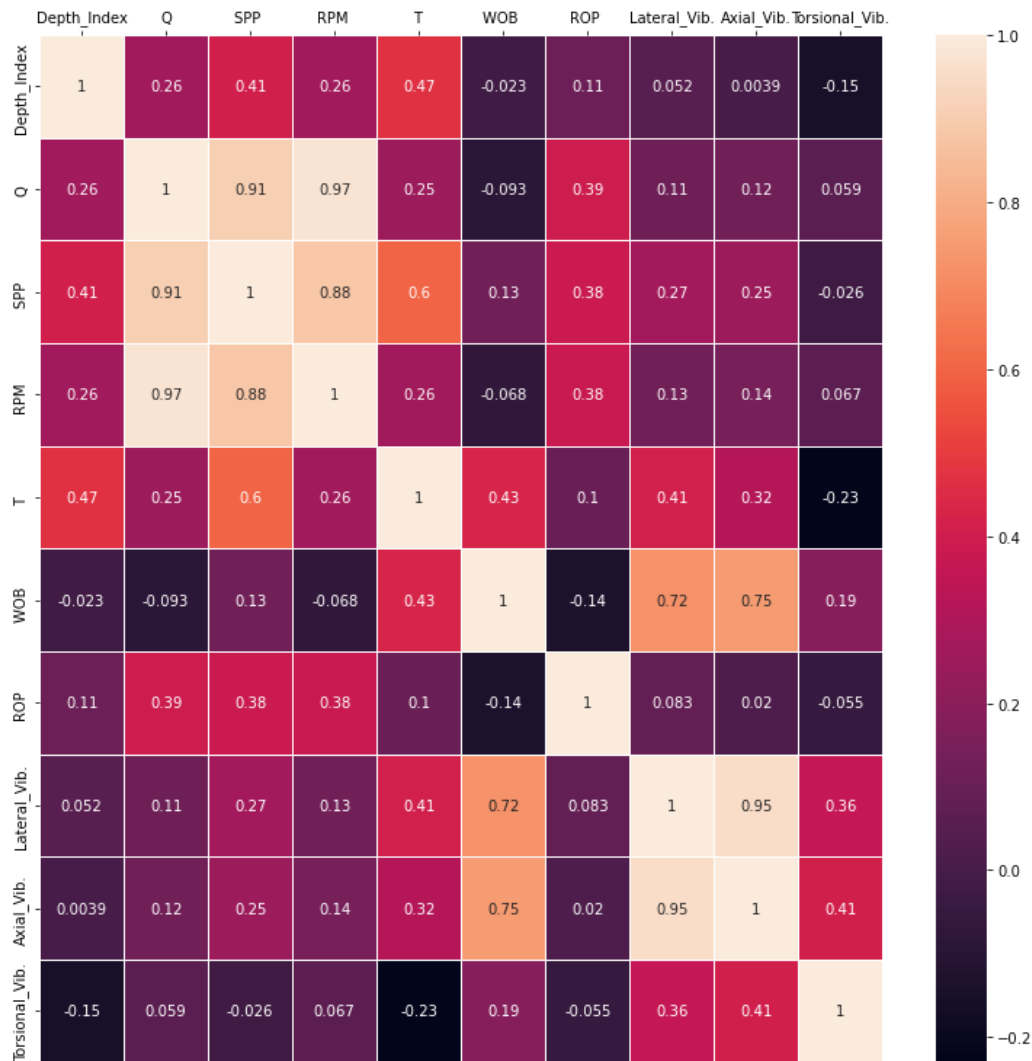


Figure 27 Data heat map

6.1.4 Machine Learning Models

The study implemented four techniques to evaluate the capabilities of the algorithms to capture the parameter patterns for autodetecting the downhole vibrations from the surface drilling data. Radial basis function (RBF), support vector machines (SVMs), adaptive neuro-fuzzy inference system (ANFIS), and functional networks (FN) were utilized and compared during the training and testing for the models. These techniques are now widely applied in ML research applications for petroleum big data (Alsaihati et al., 2022; Mahmoud et al., 2022b).

ANFIS is one of the ML tools that showed successful applications for solving technical problems with high computational capabilities for prediction purposes in oil and gas (Alsabaa et al., 2020). The tool is considered a modified model that comprises the neural networks and fuzzy interference systems (Jang, 1993) by implementing diverse functions to every node for training the model features in fuzzy interference systems (Noorani et al., 2009). During the algorithm learning progression, changing the membership functions will be done to reach the best results for modeling the problem and this task is commonly controlled by Sugeno systems and Mamdani system as an optimization procedure (Schwenker et al., 2001).

RBF is considered to have a simple architecture. Commonly, three layers for the model structure provide a simple way for training exercises (Tatar et al., 2013). The RBF is found to be a great competent algorithm for modeling the data with a high degree of noise (Rostami et al., 2018). The technique has a non-linear type of transformation that is applied to the hidden layer weighting vector and provides a continuous function for multi-variable prediction by determining the best results for improving the accuracy (Wilamowski and Jaeger, 1996; Li et al., 2011).

FN has an architecture of three layers that represent the input layer for the feed input parameters, the output layer for the model prediction, and the processing hidden layer that might be more than one single layer (Rossi et al., 2002). The neurons are connecting these layers and the output is calculated through the identified weights by the learning algorithms as forward or backward propagation types. Finally, the most optimum values for the output are determined (Castillo et al., 2001).

SVM is another ML technique that is used for classification problems and another application for regression purposes. The technique determines the weights and biases from the training data set to figure out the hyperplane which splits the maximum margin of the data (Noble, 2006). The data with a high degree of complexity and dimensionality is found to be modeled by using the Kernel-type technique that has a function for non-linear high dimensional space (Aizerman, 1964; Bottou and Vapnik, 1992).

6.1.5 Accuracy Evaluation

The developed models were evaluated during the sensitivity analysis for each model to get the best results for predicting the three models of downhole vibrations. The evaluation was achieved by calculating two statistical metrics [the coefficient of correlation (R) and the average absolute percentage error (AAPE)]. R and AAPE are estimated between the real measurements for the vibration versus the predicted vibration values for every iteration through the model optimization phase. The two metrics were calculated as:

$$R = \frac{N(\sum_1^N Y_i \hat{Y}_i) - (\sum_1^N Y_i)(\sum_1^N \hat{Y}_i)}{\sqrt{[N \sum_1^N Y_i^2 - (\sum_1^N Y_i)^2] [N \sum_1^N \hat{Y}_i^2 - (\sum_1^N \hat{Y}_i)^2]}} \quad (1)$$

$$AAPE = \left(\frac{1}{N} \sum_{i=1}^N \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \right) \times 100 \quad (2)$$

where N is the total number of points in the data set, y_i represents the real measurement, $\hat{y}_i$ is the model prediction, and $\bar{y}$ is the parameter mean.

6.2 Results and Discussion

Each model was tested during sensitivity analytics for a wide range of every parameter to get the optimized model parameters for the best accuracy and prediction results. This step is exactly performed by evaluating the model prediction accuracy in terms of R and AAPE through each case/run for the model. The optimized parameters for every

6.2.1 Models Optimization

Optimizing the model parameters is a crucial step for getting the best prediction result through the model training and testing phases, and this step is commonly achieved through deep sensitivity trials for all the model parameters that affect the prediction performance. Many automated trials and error runs were done to evaluate the impact of every model parameter on the predicted values of vibrations. Table 10 presents the optimized parameters for every ML model that is achieved across a wide range of parameters of each model. RBF was optimized by using 25 neurons for the network with Bayesian regulation backpropagation training algorithm and linear transfer function. ANFIS model with 2 membership functions provided the highest accuracy among the iterations with gaussian type for the input membership function and linear type for the output membership function. FN with functional network forward-backward type and method of nonlinear of degree (2) showed the best results for vibration detection. The SVM model had the best results with the gaussian kernel function type, kernel options of (10, and 3), and C regularization (100 and 3000) for lateral, axial, and torsional respectively.

It is worth mentioning that the developed models have the same structure for all three models of vibrations (except for only two SVM parameters), not a separate model for

detecting each vibration type and this is one of the challenges during the models' development.

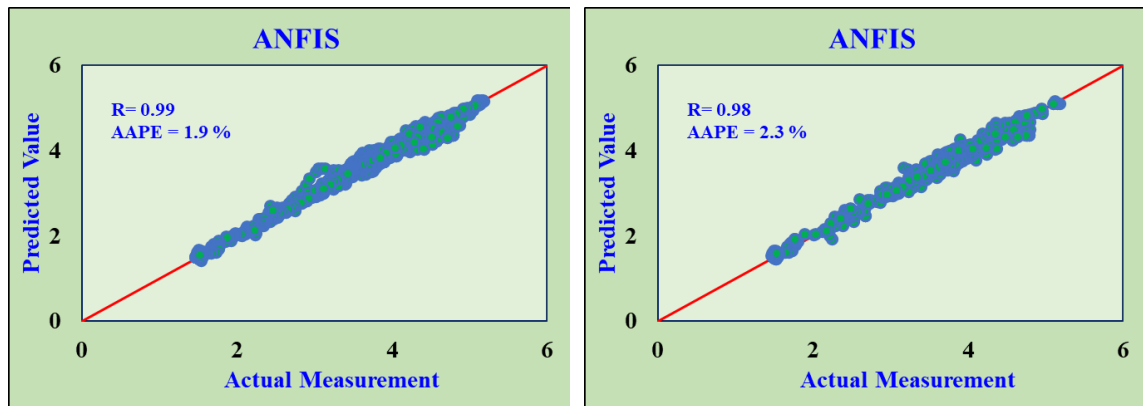
Table 10 Sensitivity analysis results for the optimized ML models' parameters

RBF Vibration Model			
Parameter	Lateral	Axial	Torsional
Neurons No.	25		
Training Function	Bayesian regulation backpropagation		
Transfer Function	linear		
SVM Vibration Model			
Kernel option	10	10	3
C Regularization	100	100	3000
lambda	1e-5		
epsilon	1e-5		
verbose	1		
kernel	gaussian		
ANFIS Vibration Model			
Number of MFs	2		
Input MF	gaussian		
Input MF	linear		
FN Vibration Model			
Type	Non-Linear(2)		
Method	Functional network backward-forward method		

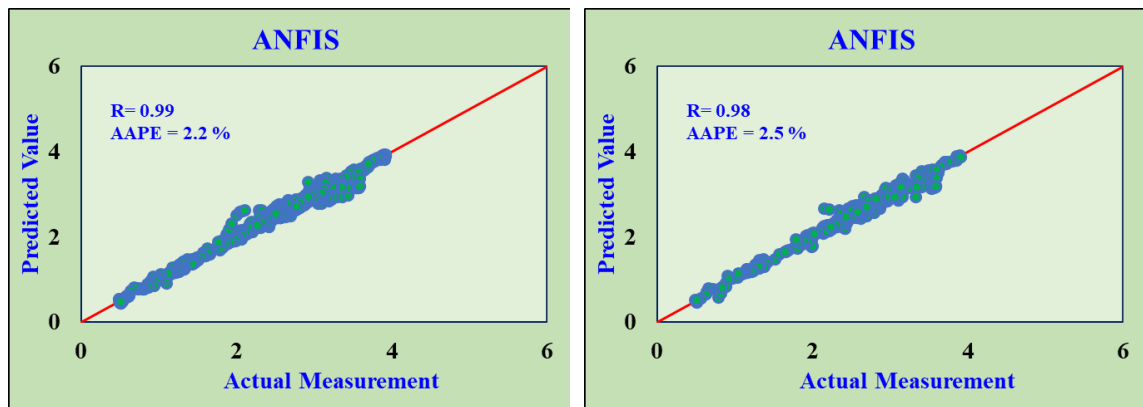
6.2.2 Models Accuracy (Training and Testing Phases)

Every ML model was trained using 1910 data points (70% of the model data set) and 820 data points were utilized for testing the model that showed 30% of the total model data set. The next plots show the accuracy delivered by the models for auto-detecting the downhole vibrations in real time for training and testing the models.

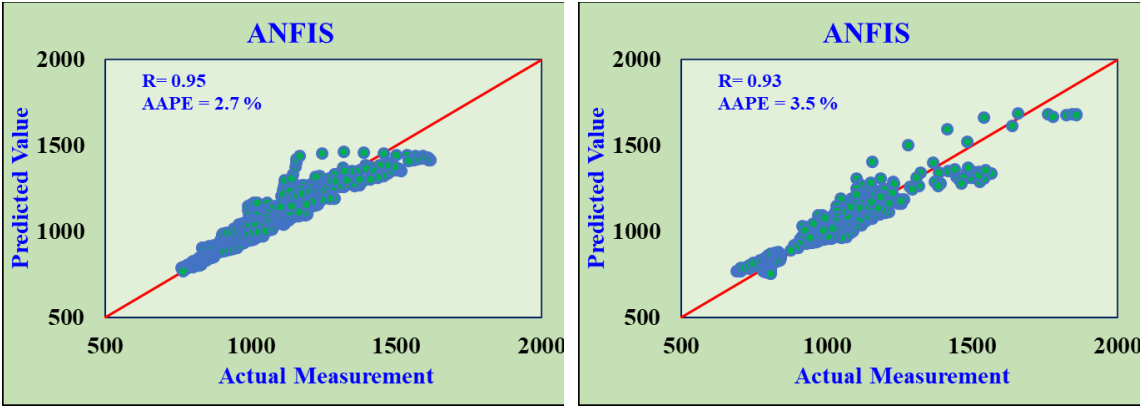
The training and testing results for the developed ANFIS-vibration model are presented in Figure 28 for the best-case optimized models. ANFIS model accuracy was higher than 0.99 for the axial and lateral prediction (with AAPE less than 2.2%) and R was 0.95 for the torsional mode prediction with 2.7% AAPE for the training set. For the testing set, R was 0.98 with an AAPE of less than 2.5% for axial and lateral vibration predictions and R of 0.93 and AAPE of 3.5% for predicting the torsional vibration mode.



a



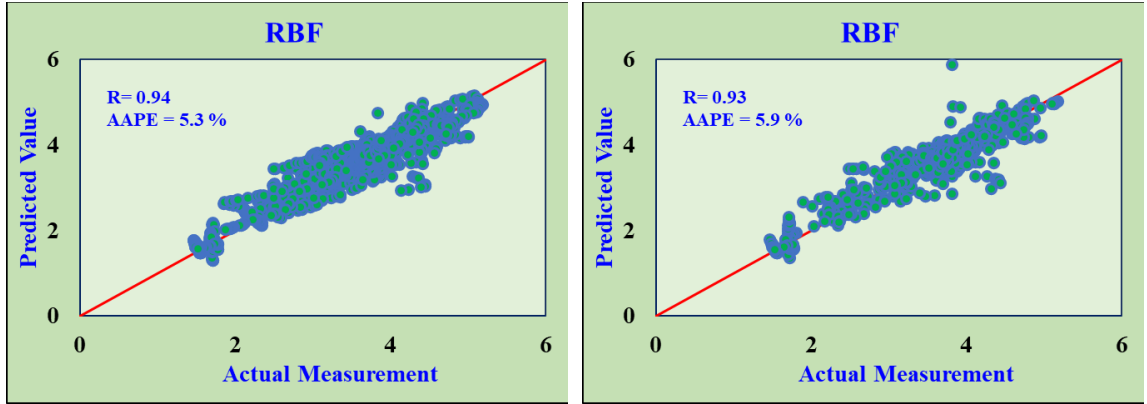
b



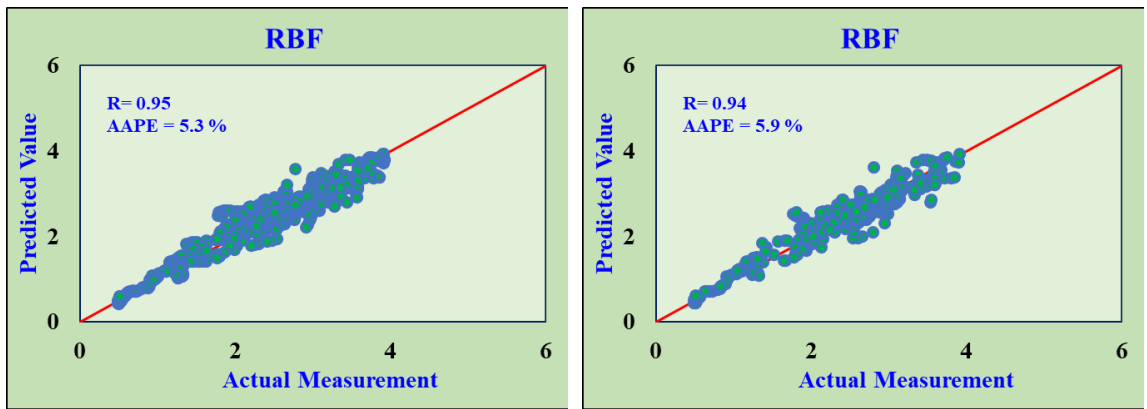
c

Figure 28 ANFIS-Vibration prediction model results, a) lateral b) axial c) torsional. [Left is train and right is test phase]

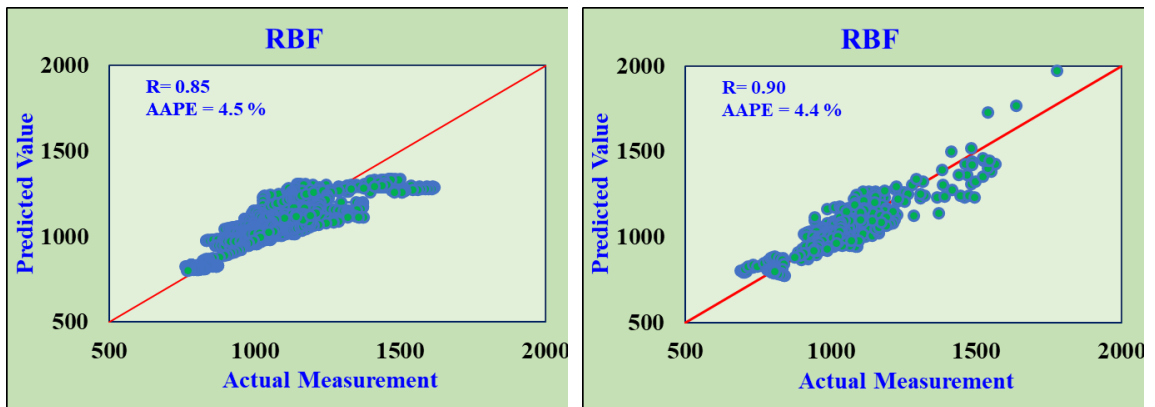
The developed RBF-vibration model results are presented in Figure 29 for the best-case optimized models through training and testing phases. RBF model accuracy was higher than 0.93 for the axial and lateral prediction (with AAPE less than 5.9%) during training and testing. While the accuracy for the torsional vibration is lower than the other two modes of vibrations. R showed higher than 0.85 with an AAPE of 4.5% for predicting the torsional vibration over the training and testing data sets.



a



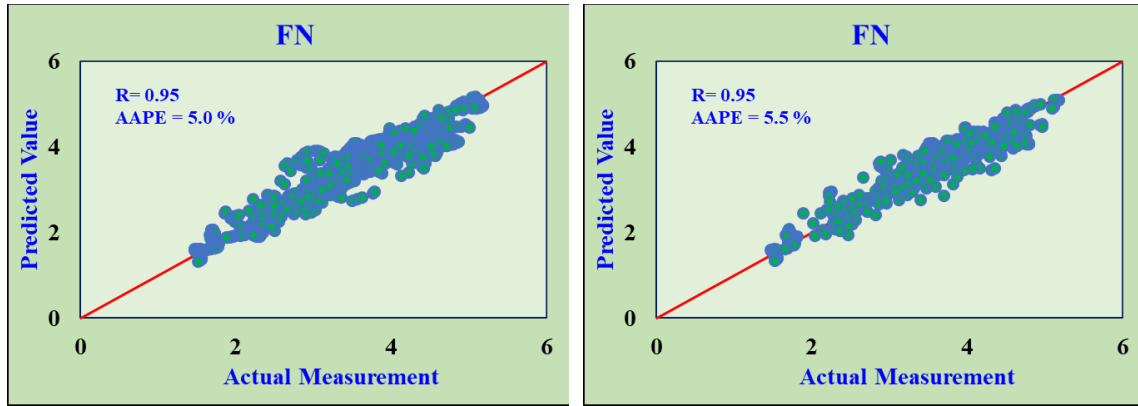
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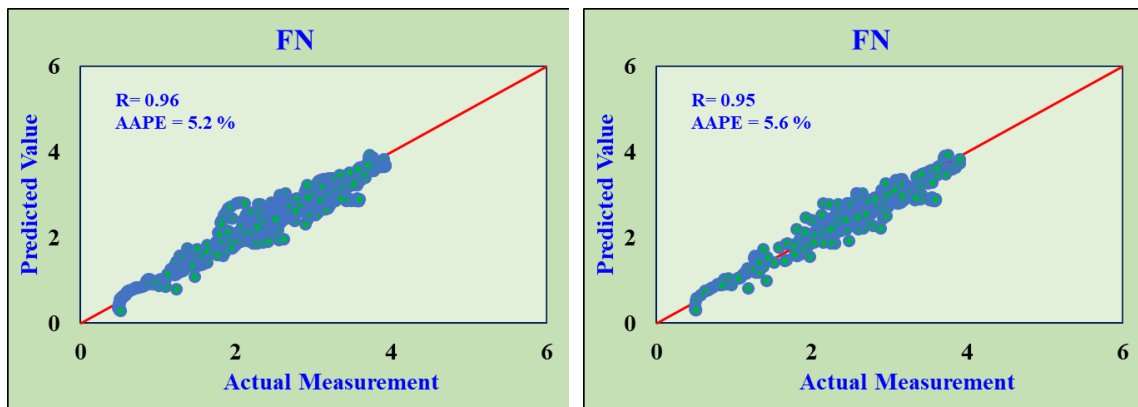
c

Figure 29 RBF-Vibration prediction model results. a) lateral b) axial c) torsional. [Left is train and right is test phase]

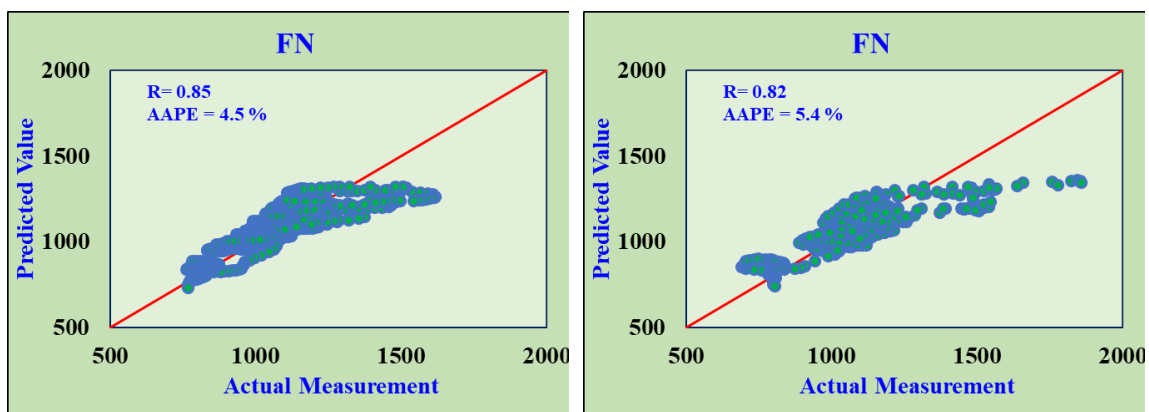
The FN model accuracy was close to the RBF as it showed high accuracy for predicting the axial and lateral vibrations (R is higher than 0.95 and AAPE less than 5.6%) while it showed low accuracy (R is higher than 0.82 and AAPE less than 5.4%) for the torsional vibration detection by the model over the training and testing sets as shown in Figure 30.



a



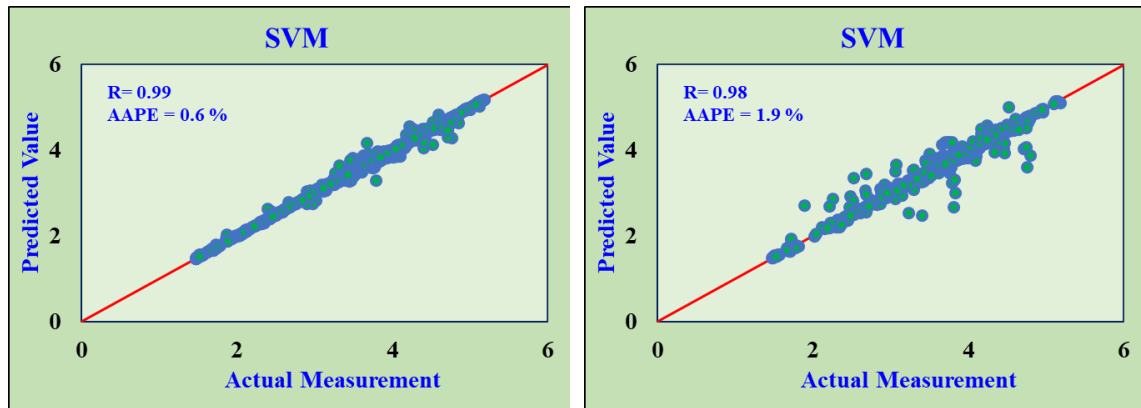
b



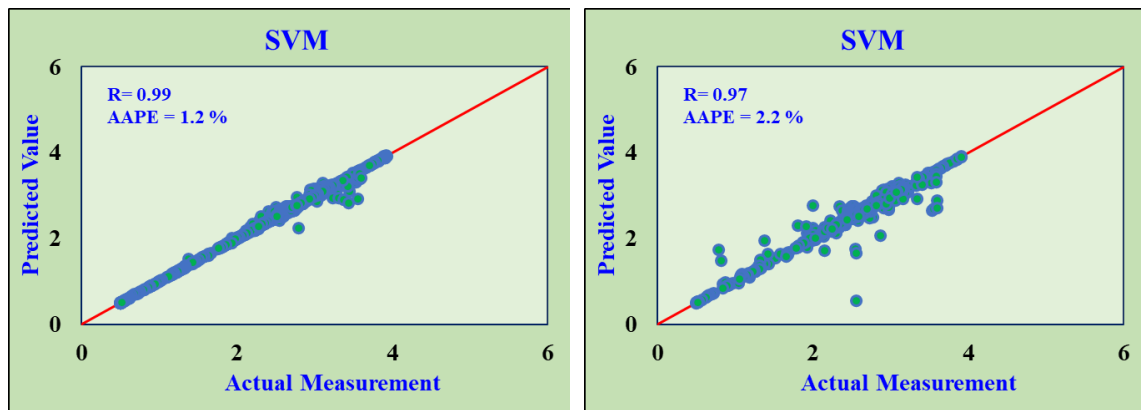
c

Figure 30 FN-Vibration prediction model results. a) lateral b) axial c) torsional. [Left is train and right is test phase]

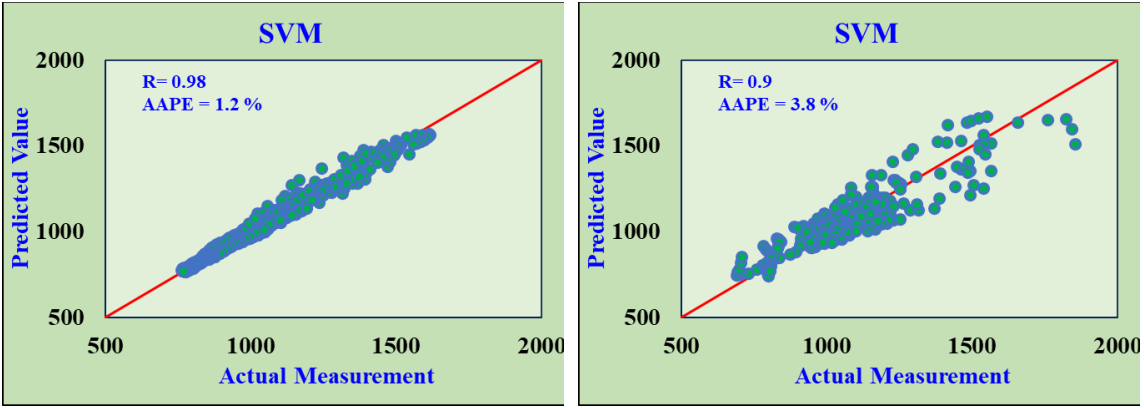
Figure 31 represents the SVM model accuracy that is close to the ANFIS prediction (R is higher than 0.97 and AAPE less than 2.2%) for predicting the three vibration models over the training and testing sets. Only predicting the torsional vibration for the testing set showed prediction accuracy (R of 0.9 with 3.8% AAPE).



a



b



c

Figure 31 SVM-Vibration prediction model results. a) lateral b) axial c) torsional. [Left is train and right is test phase]

6.2.3 Validation Phase (Unseen Well Data)

The four developed models were validated by evaluating the accuracy over unseen well data to predict the three vibration types in real-time using the well drilling data. The lateral validation results are plotted in Figure 32 to highlight the predicted vibration profiles versus the actual downhole vibrations for the four developed models. The axial and torsional vibration predictions are presented in Figures 33 and 24 respectively. The overall accuracy recorded showed R higher than 0.93 and AAPE less than 2.8% for SVM and ANFIS models while FN and RBF showed R between 0.82 to 0.95 and AAPE less than 5.7% for predicting the three vibrations. SVM and ANFIS models showed the highest accuracy over FN and RBF models.

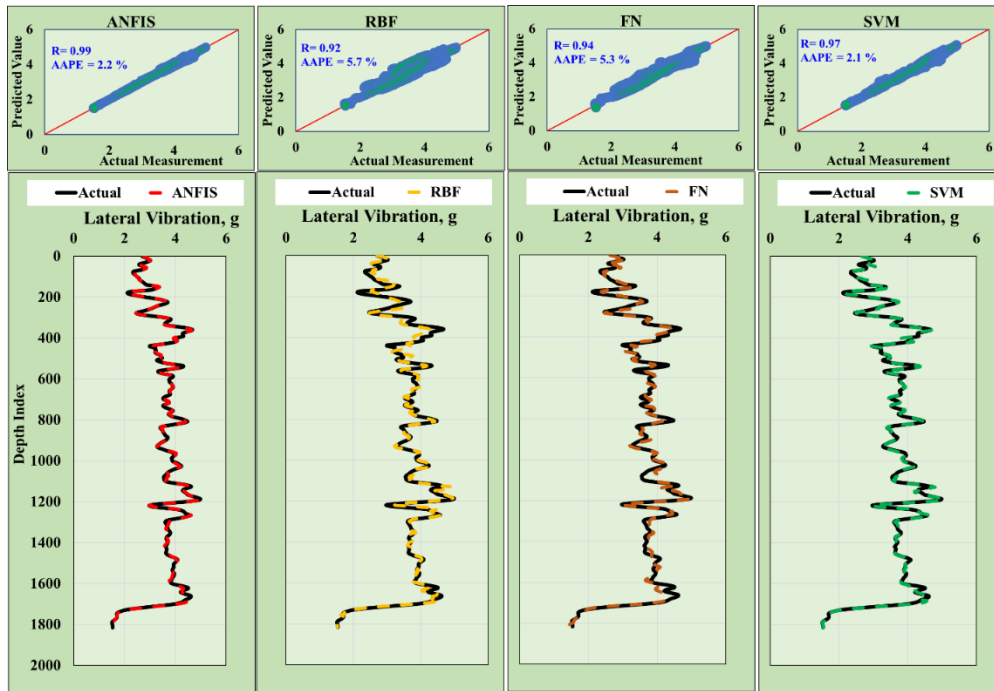


Figure 32 Lateral vibration prediction results (Validation well data set)

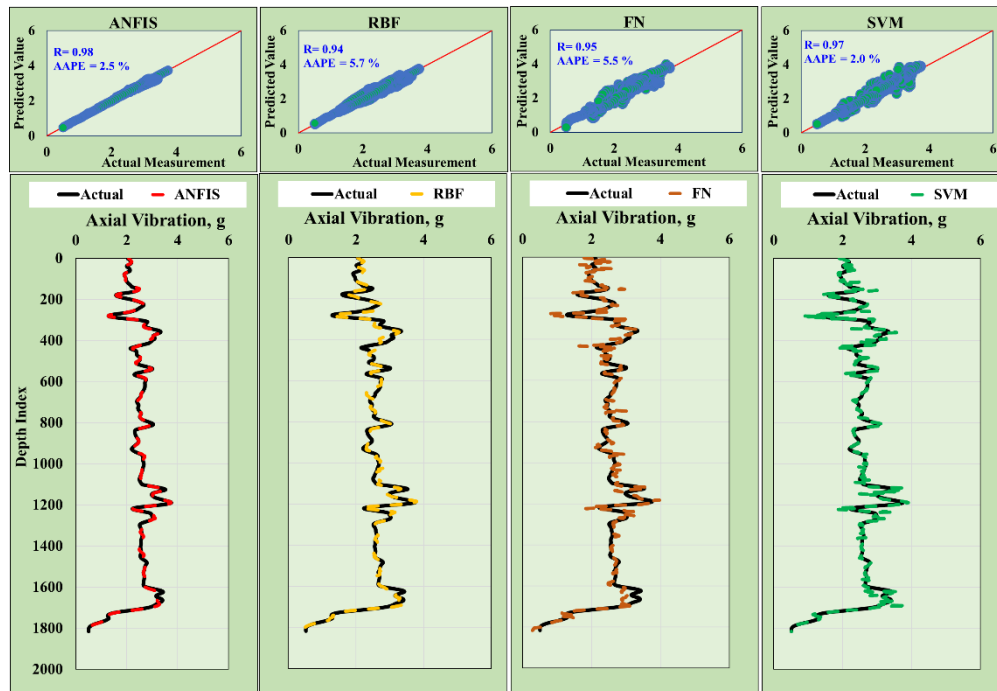


Figure 33 Axial vibration prediction results (Validation well data set)

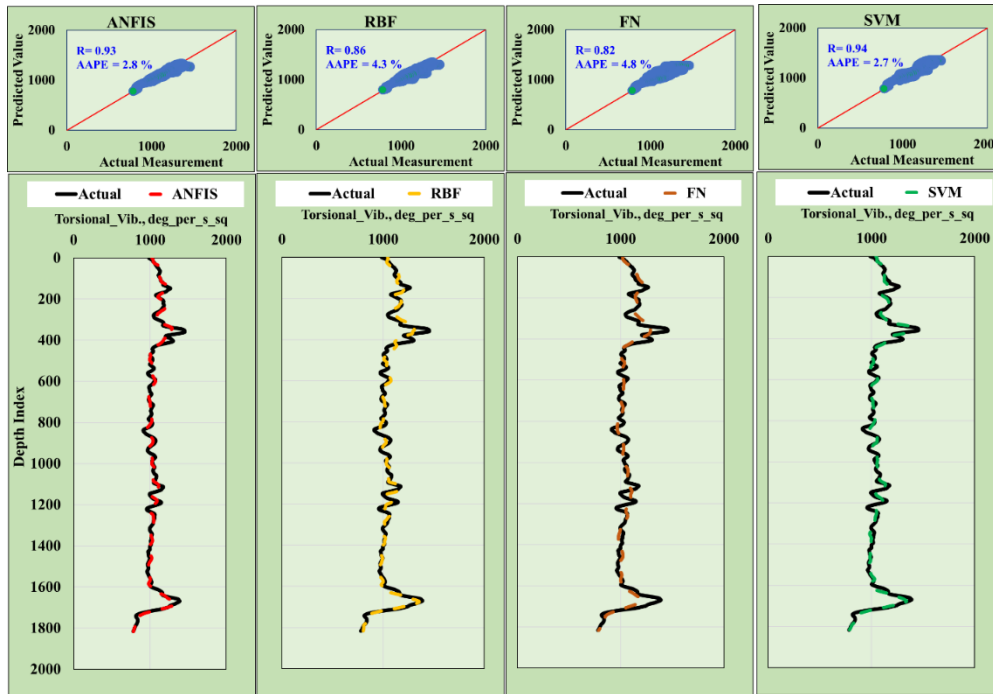


Figure 34 Torsional vibration prediction results (Validation well data set)

By comparison between machine learning models, it is obvious that the prediction of torsional vibration is not on the high level as well as the axial and/or torsional vibrations prediction. This observation is mainly attributed to the existence of the downhole mud motor in the BHA which consists of a rotor that rotates inside a stator that might negatively affect on having the clear pattern between surface parameters and torsional vibration.

The real-time vibrations obtained from the developed ML models provide vital information on the durability of drilling BHA. This information is very helpful for directional drillers and drilling engineers. For directional drillers, it can help to identify vibrations and then apply correct mitigation for severe conditions and gives full control over the bottom hole assembly, also, tracking the vibrations trends obtained from the model will help to avoid many tools failure by comparing predicted vibrations versus downhole tools limit such as red zone and continuing drilling without interruption to the well total depth especially while drilling curve sections. For drilling engineers, avoiding drilling interruption is required to minimize the non-productive time and in sequence more cost. In addition, giving good readings from downhole tools to be able to avoid deviations from the planned directional proposal especially in curve sections to be able to hit the targets as per well objectives.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

7.1 CONCLUSIONS

7.1.1 Prediction of vibration in Horizontal section using ANN

In this research, different ANN models were developed for predicting downhole drillstring vibrations based on the measurement of surface drilling parameters Q, SPP, DSR, T, WOB, and ROP. Recorded data points (13,927 field data points for a horizontal well) were used to build the model. The summary of this work can be concluded as follows:

- The optimization process of the ANN parameters show that the optimized parameters are 15 neurons for only one hidden layer, Cascade-forward backpropagation as network function, Bayesian regularization back-propagation algorithm of learning rate 0.12 for training algorithm, a hyperbolic tangent sigmoid activation function linking the input and hidden layers, and a linear function linking the hidden and output layers.
- The optimized ANN model can predict vibrations with high accuracy that showed R higher than 0.95 and AAPE below 2.4% between the predicted and the observed vibrations values during the training and testing phases
- The developed models were assessed with a validation data set of 9,284 measurements where they yielded a high accuracy of prediction (R higher than 0.95 and AAPE below 3.5% for the three modes of vibration).
- White-box model-based equation was acquired by extracting a new correlation equation through the ANN model to estimate different types of vibration.

The system proposed in this paper can be deployed on drilling rig site to provide real-time monitoring of drilling dynamics and be a trigger for the automated advisory system, in addition, is helpful for directional drillers and drilling engineers for drilling optimization and better well planning.

The study has some limitations as any developed model regarding the model data base that is for drilling a horizontal well through a limestone formation and the range for the data set of the developed model. Therefore, the study recommended applying the same approach for different formations, well profiles, data set ranges, and different ML techniques.

7.1.2 Prediction of vibration in horizontal section using ML techniques

This research provided a technical approach for developing ML models for auto-detecting the downhole vibrations (lateral, axial, and torsional) in real-time based on the rig sensors' surface data. The training data set was collected during the drilling horizontal section that comprised drilling data with downhole vibration measurements. The summary of this work can be concluded as follows:

- 5750 measurements data set was used to train four different techniques to predict the three modes of vibrations from drilling surface parameters named rate of penetration, drilling torque, drilling speed rotation, mud rate, standpipe pumping pressure, and the weight on the drill bit.
- The models parameters optimization process was achieved through sensitivity analysis for each model parameters with performance evaluation using two statistical metrics R and AAPE.
- The optimized models showed strong prediction capabilities during the training and testing phases with overall accuracy for the three types of vibrations of R ranging from 0.91 up to 0.98 with a best minimum AAPE of 1.1% and maximum value of 7.3%. Besides, ANFIS and SVM models had the best-in-class accuracy performance.
- The developed ML models were validated with unseen data set (3950 measurements well data) collected from the same field and environment to check the overall accuracy of the developed models that reported R ranged from 0.9 to 0.98 and AAPE from 1.1 to 6.1%.

The system proposed in this paper can be deployed on a drilling rig site to provide real-time monitoring of drilling dynamics and be a trigger for the automated advisory system, in addition, is helpful for directional drillers and drilling engineers for drilling optimization and better well planning.

7.1.3 Prediction of vibration in Curve section using ANN

Detecting the downhole drilling vibrations through artificial intelligence was provided through this research with a high degree of accuracy (lateral, axial, and torsional) in a real-time based on the rig sensors' surface data. The training data set was collected during the drilling curve section that comprised drilling data with downhole vibration measurements. The summary of this work can be concluded as follows:

- 2730 measurements data set was used to train and test ANN different learning algorithms to predict the three modes of vibrations from drilling surface parameters named rate of penetration, drilling torque, drilling speed rotation, mud rate, standpipe pumping pressure, and the weight on the drill bit.

- The parameters optimization process of ANN model parameters was achieved through sensitivity analysis with performance evaluation using two statistical metrics R and AAPE.
- The optimized models showed strong prediction capabilities during the training and testing phases with overall accuracy for the three types of vibrations and the best-in-class accuracy performance (R higher than 0.96 and AAPE less than 4.4%).
- The developed ANN model was validated with an unseen data set (1810 measurements of unseen well data) and the overall accuracy recorded showed R higher than 0.92 and AAPE less than 3.6% for predicting the three vibrations.
- A developed ANN-based equation for the model weights and biases to be utilized for real-time estimating of the vibrations without using the code.

The ANN model proposed in this paper can be deployed as an intelligent solution on a drilling rig site to provide real-time monitoring of drilling vibrations and be a trigger for the automated advisory system, in addition, is helpful for directional drillers and drilling engineers for drilling optimization and better well planning.

7.1.4 Prediction of vibration in Curve section using ML techniques

Detecting the downhole drilling vibrations through machine learning was provided through this research with a high degree of accuracy (lateral, axial, and torsional) in a real-time based on the rig sensors' surface data. The training data set was collected during the drilling curve section that comprised drilling data with downhole vibration measurements. The summary of this work can be concluded as follows:

- 2730 measurements data set was used to train and test four different techniques to predict the three modes of vibrations from drilling surface parameters named rate of penetration, drilling torque, drilling speed rotation, mud rate, standpipe pumping pressure, and the weight on the drill bit.
- The parameters optimization process of every ML model was achieved through sensitivity analysis with performance evaluation using two statistical metrics R and AAPE.
- The optimized models showed strong prediction capabilities during the training and testing phases with overall accuracy for the three types of vibrations as ANFIS and SVM models had the best-in-class accuracy performance (R higher than 0.9 and AAPE less than 3.8%), while RBF and FN models showed R ranged from 0.82 to 0.96 and AAPE less than 5.9%.
- The developed ML models were validated with unseen data set (1810 measurements of unseen well data) and The overall accuracy recorded showed R higher than 0.93 and AAPE less than 2.8% for SVM and ANFIS models while

FN and RBF showed R between 0.82 to 0.95 and AAPE less than 5.7% for predicting the three vibrations.

The ML models proposed in this paper can be deployed as an intelligent solution on a drilling rig site to provide real-time monitoring of drilling vibrations and be a trigger for the automated advisory system, in addition, is helpful for directional drillers and drilling engineers for drilling optimization and better well planning.

7.2 RECOMMENDATIONS

Developing physical and cloud platform that can receive, sort, analyze and optimize drilling parameters to mitigate downhole drilling vibrations using the following:

1. Develop data process that is connected to wellsite in a real time using local computer that help in decrease latency and optimize network bandwidth cost.
2. Create an intermediate real time platform using cloud computers that connects data from multiple resources to and from rig system that enables giving recommendations and interact live with drilling operations thus enhancing well plan activities.

References

1. Abbas, A.K., Rushdi, S., Alsaba, M., Al Dushaishi, M.F., 2019. Drilling Rate of Penetration Prediction of High-Angled Wells Using Artificial Neural Networks. *Journal of Energy Resources Technology, Transactions of the ASME* 141. <https://doi.org/10.1115/1.4043699>
2. Ahmed, A., Elkatatny, S., Gamal, H., Abdulraheem, A., 2021. Artificial Intelligence Models for Real-Time Bulk Density Prediction of Vertical Complex Lithology Using the Drilling Parameters. *Arabian Journal for Science and Engineering* 1–14. <https://doi.org/10.1007/s13369-021-05537-3>
3. Aizerman, M.A., 1964. Theoretical Foundations of the Potential Function Method in Pattern Recognition Learning. *Automation and Remote Control*.
4. Al-Abduljabbar, A., Gamal, H., Elkatatny, S., 2020. Application of artificial neural network to predict the rate of penetration for S-shape well profile. *Arabian Journal of Geosciences* 13, 1–11. <https://doi.org/10.1007/s12517-020-05821-w>
5. Alsabaa, A., Gamal, H., Elkatatny, S., Abdulraheem, A., 2021. New correlations for better monitoring the all-oil mud rheology by employing artificial neural networks. *Flow Measurement and Instrumentation* 101914. <https://doi.org/10.1016/j.flowmeasinst.2021.101914>
6. Alsabaa, A., Gamal, H., Elkatatny, S., Abdulraheem, A., 2020. Real-time prediction of rheological properties of invert emulsion mud using adaptive neuro-fuzzy inference system. *Sensors (Switzerland)* 20, 1669. <https://doi.org/10.3390/s20061669>
7. Alsabaa, A., Gamal, H.A., Elkatatny, S.M., and Abdulraheem, A., 2020a. Real-Time Prediction of Rheological Properties of All-Oil Mud Using Artificial Intelligence. *American Rock Mechanics Association*. <https://www.onepetro.org/conference-paper/ARMA-2020-1645>
8. Alsabaa, A., Gamal, H.A., Elkatatny, S.M., and Abdulraheem, A., 2020b. Real-Time Prediction of Rheological Properties of All-Oil Mud Using Artificial Intelligence. *American Rock Mechanics Association*. <https://www.onepetro.org/conference-paper/ARMA-2020-1645>
9. Alsaihati, A., Elkatatny, S., Gamal, H., 2022. Rate of penetration prediction while drilling vertical complex lithology using an ensemble learning model. *Journal of Petroleum Science and Engineering* 208, 109335. <https://doi.org/10.1016/J.PETROL.2021.109335>
10. Bailey, J.R., Biediger, E., Gupta, V., Ertas, D., Elks, W.C., Dupriest, F.E., 2008. Drilling Vibrations Modeling and Field Validation. *SPE/IADC Drilling Conference, Proceedings* 2, 825–839. <https://doi.org/10.2118/112650-MS>
11. Baumgartner, T., van Oort, E., 2014. Pure and Coupled Drill String Vibration Pattern Recognition in High Frequency Downhole Data. *Proceedings - SPE Annual Technical Conference and Exhibition* 7, 4950–4972. <https://doi.org/10.2118/170955-MS>
12. Bello, O., Holzmann, J., Yaqoob, T., Teodoriu, C., 2015. Application Of Artificial Intelligence Methods In Drilling System Design And Operations: A Review Of The State Of The Art. *Journal of Artificial Intelligence and Soft Computing Research* 5, 121–139. <https://doi.org/10.1515/jaiscr-2015-0024>

13. Bottou, L., Vapnik, V., 1992. Local Learning Algorithms. *Neural Computation* 4, 888–900. <https://doi.org/10.1162/neco.1992.4.6.888>
14. Brett, J.F., Warren, T.M., Behr, S.M., 1989. Bit Whirl: A New Theory of PDC Bit Failure. *All Days*. <https://doi.org/10.2118/19571-MS>
15. Castillo, E., Gutiérrez, J.M., Hadi, A.S., Lacruz, B., 2001. Some Applications of Functional Networks in Statistics and Engineering. *Technometrics* 43, 10–24. <https://doi.org/10.1198/00401700152404282>
16. Cevik, A., Sezer, E.A., Cabalar, A.F., Gokceoglu, C., 2011. Modeling of the uniaxial compressive strength of some clay-bearing rocks using neural network, in: *Applied Soft Computing Journal*. Elsevier, pp. 2587–2594. <https://doi.org/10.1016/j.asoc.2010.10.008>
17. Ertas, D., Bailey, J.R., Wang, L., Pastusek, P.E., 2014. Drillstring Mechanics Model for Surveillance, Root Cause Analysis, and Mitigation of Torsional Vibrations. *SPE Drilling & Completion* 29, 405–417. <https://doi.org/10.2118/163420-PA>
18. Gamal, H., Alsaihati, A., Elkatatny, S., Haidary, S., Abdulraheem, A., 2021. Rock Strength Prediction in Real-Time While Drilling Employing Random Forest and Functional Network Techniques. *Journal of Energy Resources Technology* 143. <https://doi.org/10.1115/1.4050843>
19. Gamal, H., Elkatatny, S., Abdulraheem, A., 2020. Rock drillability intelligent prediction for a complex lithology using artificial neural network. *Society of Petroleum Engineers - Abu Dhabi International Petroleum Exhibition and Conference 2020, ADIP 2020*.
20. Gowida, A., Elkatatny, S., Gamal, H., 2021. Unconfined compressive strength (UCS) prediction in real-time while drilling using artificial intelligence tools. *Neural Computing and Applications* 7. <https://doi.org/10.1007/s00521-020-05546-7>
21. Graves, A., Liwicki, M., Fernández, S., Bertolami, R., Bunke, H., Schmidhuber, J., 2009. A novel connectionist system for unconstrained handwriting recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 31, 855–868. <https://doi.org/10.1109/TPAMI.2008.137>
22. Gupta, S., Chatar, C., Celaya, J.R., 2019. Machine Learning Lessons Learnt in Stick-Slip Prediction. *Society of Petroleum Engineers - Abu Dhabi International Petroleum Exhibition and Conference 2019, ADIP 2019*. <https://doi.org/10.2118/197584-MS>
23. Hegde, C., Millwater, H., Gray, K., 2019. Classification of drilling stick slip severity using machine learning. *Journal of Petroleum Science and Engineering* 179, 1023–1036. <https://doi.org/10.1016/J.PETROL.2019.05.021>
24. Hegde, C., Pyrcz, M., Millwater, H., Daigle, H., Gray, K., 2020. Fully coupled end-to-end drilling optimization model using machine learning. *Journal of Petroleum Science and Engineering* 186, 106681. <https://doi.org/10.1016/J.PETROL.2019.106681>
25. Ignova, M., Matheus, J., Amaya, D., Richards, E., 2019. Recognizing Abnormal Shock Signatures During Drilling with Help of Machine Learning. *SPE Middle East Oil and Gas Show and Conference, MEOS, Proceedings 2019-March*. <https://doi.org/10.2118/194952-MS>

26. Jang, J.S.R., 1993. ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Transactions on Systems, Man and Cybernetics* 23, 665–685. <https://doi.org/10.1109/21.256541>
27. Lai, S.W., Wood, M., Eddy, A., Holt, T., Bloom, M., 2014. Stick-slip detection and friction factor testing using surface-based torque and tension measurements. *Proceedings - SPE Annual Technical Conference and Exhibition* 1, 609–626. <https://doi.org/10.2118/170624-ms>
28. Li, L., Wei, X., Shifan, Z., Wan, Z., 2011. Reservoir Property Prediction Using the Dynamic Radial Basis Function Network. Presented at the 2011 SEG Annual Meeting, OnePetro.
29. Lippmann, R.P., 1987. An Introduction to Computing with Neural Nets. *IEEE ASSP Magazine* 4, 4–22. <https://doi.org/10.1109/MASSP.1987.1165576>
30. Mabile, C., Desplans, J.P., Pavone, D., 1996. A New Way of Using Surface Measurements to Detect Down Hole Vibrations. *All Days*. <https://doi.org/10.2118/36883-MS>
31. Mahmoud, A.A., Elkatatny, S., Al-AbdulJabbar, A., Moussa, T., Gamal, H., Shehri, D. Al, 2020. Artificial neural networks model for prediction of the rate of penetration while horizontally drilling carbonate formations, in: 54th U.S. Rock Mechanics/Geomechanics Symposium.
32. Mahmoud, A.A., Gamal, H., Elkatatny, S., Alsaihati, A., 2022a. Estimating the Total Organic Carbon for Unconventional Shale Resources During the Drilling Process: A Machine Learning Approach. *Journal of Energy Resources Technology* 144. <https://doi.org/10.1115/1.4051737>
33. Mahmoud, A.A., Gamal, H., Elkatatny, S., Chen, W., 2022b. Real-time evaluation of the dynamic Young's modulus for composite formations based on the drilling parameters using different machine learning algorithms. *Frontiers in Earth Science* 10, 1034704. <https://doi.org/10.3389/feart.2022.1034704>
34. Millan, E., Ringer, M., Boualleg, R., Li, D., 2019. Real-Time Drillstring Vibration Characterization Using Machine Learning. *SPE/IADC Drilling Conference, Proceedings 2019-March*, 5–7. <https://doi.org/10.2118/194061-MS>
35. Noble, W.S., 2006. What is a support vector machine? *Nat Biotechnol* 24, 1565–1567. <https://doi.org/10.1038/nbt1206-1565>
36. Noorani, R., Kordi, H., Ghazvinian, A.H., 2009. An Adaptive Neuro-Fuzzy Inference System for Uniaxial Compressive Strength of Rocks. Presented at the ISRM Regional Symposium - EUROCK 2009, OnePetro.
37. Okoli, P., Cruz Vega, J., Shor, R., 2019. Estimating Downhole Vibration via Machine Learning Techniques Using Only Surface Drilling Parameters. *SPE Western Regional Meeting Proceedings 2019*, 195334. <https://doi.org/10.2118/195334-MS>
38. Osnes, S.M., Amundsen, P.A., Weltzin, T., Nyrnes, E., Grindhaug, G., 2009. Vibration Measurements: A Time for Standardisation. *SPE/IADC Drilling Conference, Proceedings 2*, 1112–1118. <https://doi.org/10.2118/119877-MS>
39. Pollock, J., Stoecker-Sylvia, Z., Veedu, V., Panchal, N., Elshahawi, H., 2018. Machine Learning for Improved Directional Drilling. *Proceedings of the Annual Offshore Technology Conference* 4, 2496–2504. <https://doi.org/10.4043/28633-MS>

40. Rossi, F., Conan-Guez, B., Fleuret, F., 2002. Functional data analysis with multi layer perceptrons, in: Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02 (Cat. No.02CH37290). Presented at the Proceedings of the 2002 International Joint Conference on Neural Networks. IJCNN'02 (Cat. No.02CH37290), pp. 2843–2848 vol.3. <https://doi.org/10.1109/IJCNN.2002.1007599>
41. Rostami, A., Kalantari-Meybodi, M., Karimi, M., Tatar, A., Mohammadi, A.H., 2018. Efficient estimation of hydrolyzed polyacrylamide (HPAM) solution viscosity for enhanced oil recovery process by polymer flooding. *Oil and Gas Science and Technology* 73, 22. <https://doi.org/10.2516/ogst/2018006>
42. Saadeldin, R., Gamal, H., Elkatatny, S., Abdulaheem, A., 2021. Intelligent Model for Predicting Downhole Vibrations Using Surface Drilling Data During Horizontal Drilling. *Journal of Energy Resources Technology* 144. <https://doi.org/10.1115/1.4052794>
43. Schwenker, F., Kestler, H.A., Palm, G., 2001. Three learning phases for radial-basis-function networks. *Neural Networks* 14, 439–458. [https://doi.org/10.1016/S0893-6080\(01\)00027-2](https://doi.org/10.1016/S0893-6080(01)00027-2)
44. Siddig, O., Gamal, H., Elkatatny, S., Abdulaheem, A., 2021. Applying Different Artificial Intelligence Techniques in Dynamic Poisson's Ratio Prediction Using Drilling Parameters. *Journal of Energy Resources Technology* 1–15. <https://doi.org/10.1115/1.4052185>
45. Tatar, A., Shokrollahi, A., Mesbah, M., Rashid, S., Arabloo, M., Bahadori, A., 2013. Implementing Radial Basis Function Networks for modeling CO₂-reservoir oil minimum miscibility pressure. *Journal of Natural Gas Science and Engineering* 15, 82–92. <https://doi.org/10.1016/j.jngse.2013.09.008>
46. Wiktorski, E., Geekiyanage, S., Løken, E., Sui, D., 2019. Comparative study of surface and downhole drillstring vibrations measurements on a laboratory-scale drilling rig. *Society of Petroleum Engineers - SPE Norway One Day Seminar 2019*. <https://doi.org/10.2118/195610-ms>
47. Wilamowski, B.M., Jaeger, R.C., 1996. Implementation of RBF type networks by MLP networks, in: Proceedings of International Conference on Neural Networks (ICNN'96). Presented at the Proceedings of International Conference on Neural Networks (ICNN'96), pp. 1670–1675 vol.3. <https://doi.org/10.1109/ICNN.1996.549151>
48. Zha, Y., Pham, S., 2019. Monitoring downhole drilling vibrations using surface data through deep learning. 2018 SEG International Exposition and Annual Meeting, SEG 2018 2101–2105. <https://doi.org/10.1190/segam2018-2964198.1>
49. Zhao, J., Shen, Y., Chen, W., Zhang, Z., Johnston, S., 2017. Machine Learning–Based Trigger Detection of Drilling Events Based on Drilling Data. *SPE Eastern Regional Meeting 2017-October*, 187512. <https://doi.org/10.2118/187512-MS>

Vitae



Ramy Saadeldin Mohamed



34421 Pearl Compound, Ar Rawabi Dist, Khobar,
Saudi Arabia



(+966) 543446968



(+20) 1221544124



Ramy.welleng@gmail.com



Education



[Suez, Egypt]



[Cairo, Egypt]



[Cairo, Egypt]



[Dhahran, KSA]



Roles Played

- Night Wellsite leader: GUPCO (Egypt, Gulf of Suez "Offshore")
- Drilling & Operation Engineer: GUPCO (Egypt, Cairo)
- Senior Drilling & Operation Engineer: GUPCO (Egypt, Cairo)
- Wellsite Leader: GUPCO (Egypt, Gulf of Suez "Offshore")
- Senior Well Engineer (Plan & Ops): Halliburton (KSA, Dhahran) & Aramco (KSA, WOED)
- Engineering Team Leader: Halliburton (KSA, Dhahran) & Aramco (KSA, WOED)
- Shadow Project Manager: Halliburton (KSA, Dhahran)



1- Peer-Reviewed Published and Under Review Journal Papers

- 1) **Saadeldin, R.**, Gamal, H., Elkatatny, S. and Abdulraheem, A., 2021. Intelligent Model for Predicting Downhole Vibrations Using Surface Drilling Data During Horizontal Drilling. Journal of Energy Resources Technology, pp.1-19.
<https://doi.org/10.1115/1.4052794>

Under Review

- 2) Autodetecting Downhole Vibrations By Artificial Intelligence For Curve Section Drilling. Under review for Scientific Reports.
- 3) Detecting Downhole Vibrations Through Drilling Horizontal Sections: Machine Learning Study. Under review for ACS Omega.
- 4) Machine Learning Solution for Predicting Vibrations While Drilling Curve Section. Under review for PEPT.

3- Conference Papers (Accepted and Published)

- 1) Ramy Saadeldin, Hany Gamal, Salaheldin Elkatatny, Abdulazeez Abdulraheem, Dhafer Alshehri, Intelligent Prediction of Downhole Drillstring Vibrations in Horizontal Wells by Employing Artificial Neural Network. IPTC 2023