

**REAL-TIME ESTIMATION OF LOST CIRCULATION
RATE WHILE DRILLING USING ARTIFICIAL
INTELLIGENCE TECHNIQUES**

BY

Ahmed Ibrahim Alsaihati

A Thesis Presented to the
DEANSHIP OF GRADUATE STUDIES

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

PETROLEUM ENGINEERING

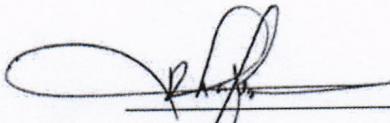
April 2021

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

DHAHRAN- 31261, SAUDI ARABIA

DEANSHIP OF GRADUATE STUDIES

This thesis, written by **AHMED ALSAIHATI** 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**.

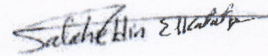


Dr. Dhafer A. Al Shehri
Department Chairman

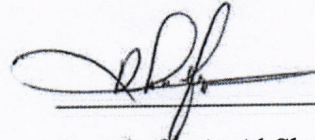


Prof. Suliman Saleh Al-Homidan
Dean of Graduate Studies

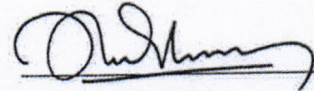
Date



Dr. Salaheldin Elkatatny
(Advisor)



Dr. Dhafer A. Al Shehri
(Member)



Dr. Abdulazeez Abdulraheem
(Member)



© Ahmed Alsaihati

2021

Dedicated to
my parents, my beloved wife and little boy

ACKNOWLEDGMENTS

All praise and thanks be to Almighty Allah, the most Gracious and Merciful. Peace and mercy be upon his Prophet.

I would like to express my special appreciation and thanks to my advisor Dr. Salaheldin Elkatatny for his continuous encouragement and support during my entire master's study at KFUPM. I attribute the level of my master's degree to his encouragement and efforts. Without his assistance, this thesis, would not have been completed. I would like to extend my special appreciation to the committee members Dr. Dhafer Al Shehri and Dr. Abdulazeez Abdulraheem for their valuable comments and suggestions.

I would like to express my gratitude to Saudi Aramco management for the continuous support and motivation through their self-development programs.

Special thanks to my family. Words cannot express how grateful I am to my parents for all of the sacrifices they have made in my life. Your continuous prayers for me were what brought me this far. Last, but not least, I would like to express my appreciation to my beloved wife for her continuous support and patience during my master's program.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	V
TABLE OF CONTENTS	VI
LIST OF TABLES	IX
LIST OF FIGURES	X
LIST OF ABBREVIATIONS	XII
ABSTRACT	XIV
ملخص الرسالة	XVI
CHAPTER 1 INTRODUCTION	1
1.1 Lost Circulation Zone Candidates	3
1.1.1 Natural Losses	3
1.1.2 Induced Losses	4
1.2 The Impact of Lost Circulation	4
1.3 Monitoring of Lost Circulation While Drilling	6
1.4 Different Techniques to Allocate Zones of Lost Circulation	7
CHAPTER 2 LITERATURE REVIEW	8
2.1 Lose Circulation Management	8
2.1.1 Proactive Wellbore Strengthening	8
2.1.2 Corrective Wellbore Strengthening	9
2.2 Classification of LCMs	10
2.2.1 Granular	10
2.2.2 Flaky	11
2.2.3 Fibrous	12
2.2.4 Mixture of LCMs	13
2.2.5 Acid/Water-Soluble	14
2.2.6 High Fluid Loss LCMs Squeeze	15

2.2.7 Swellable/Hydratable LCM Combinations	16
2.2.8 Nanoparticles.....	17
2.3 Laboratory Evaluation of LCMs.....	18
2.3.1 Corrective Treatment Test.....	18
2.3.2 Preventive Treatment Test.....	19
CHAPTER 3 ARTIFICIAL INTELLIGENCE APPLICATIONS IN DRILLING ENGINEERING.....	21
3.1 Artificial Intelligence.....	21
3.2 Machine Learning Techniques	22
3.2.1 Artificial Neural Network	24
3.2.2 Adaptive Neuro-Fuzzy Inference System.....	26
3.2.3 Support Vector Machines	26
3.2.4 Random Forest	28
3.2.5 K-Nearest Neighbor	29
3.2.6 Logistic Regression	30
3.3 Application of AI in the Drilling Industry	31
3.3.1 Application of AI Related to Lost Circulation Problems	35
CHAPTER 4 OBJECTIVE AND METHODOLOGY	38
4.1 The Objective	38
4.2 The Novelty of the Thesis	38
4.3 Research Methods and Materials.....	38
4.3.1 Data Acquisition.....	38
4.3.2 Data Processing	39
4.3.3 Pre-Processing the Outputs	41
4.3.4 Statistical Analysis	43
4.3.5 Dataset Partition	48
4.3.6 Features Importance	49
4.3.7 Models Building.....	51

CHAPTER 5 RESULTS AND DISCUSSION.....	60
5.1 Assessment of the Developed Models	60
5.2 Predictability Comparison of the Developed Models Using Well-8.	73
CHAPTER 6 CONCLUSIONS AND LIMITATIONS	79
REFERENCES.....	81
VITAE.....	95

LIST OF TABLES

Table 1: Types of lost circulation	3
Table 2: Examples of granular LCMs (Alkinani et al., 2018).	11
Table 3: Examples of flaky LCMs (Alkinani et al., 2018).	12
Table 4: Examples of fibrous LCMs (Alkinani et al., 2018).	12
Table 5: Example of LCM mixtures (Alkinani et al., 2018).....	13
Table 6: Examples of acid/water-soluble LCMs (Alkinani et al., 2018).....	14
Table 7: Examples of acid/water-soluble (Alkinani et al., 2018)	16
Table 8: Examples of swellable/hydratable LCMs (Alkinani et al., 2018)	16
Table 9: Wellbore strengthening models (Salehi and Nygaard, 2012).....	20
Table 10: Dummy example of how to identify losses occurrence and estimate the loss rate.....	42
Table 11: Dummy modified dataset with the new variables.....	43
Table 12: Statistical parameters of Well-1 (2,379 data points).	43
Table 13: Statistical parameters of Well-2 (2,117 data points).	44
Table 14: Statistical parameters of Well-3 (2,143 data points).	44
Table 15: Statistical parameters of Well-4 (1,800 data points).	44
Table 16: Statistical parameters of Well-5 (2,375 data points).	45
Table 17: Statistical parameters of Well-6 (996 data points).	45
Table 18: Statistical parameters of Well-7 (2,084 data points).	45
Table 19: Statistical parameters of the training set (11,022 data points).....	48
Table 20: Statistical parameters of the testing set (2,872 data points).....	48

LIST OF FIGURES

Figure 1: Classification of machine learning techniques.....	24
Figure 2: The architecture of an ANN.....	25
Figure 3: SVM Visualization.....	28
Figure 4: Random forest visualization.....	29
Figure 5: K-NN classification visualization.....	30
Figure 6: AI applications in drilling operations.....	32
Figure 7: Box plots of all variables indicating the outliers in the original dataset.	41
Figure 8: Numbers of data points labeled as “Losses” and “No Losses” in each well.....	46
Figure 9: Loss rate profile versus depth for each well.....	47
Figure 10: Numbers of data points labeled as “Losses” and “No Losses” in the training and testing sets.....	49
Figure 11: Comparison of the dependency between the input variables and the binary output. ..	50
Figure 12: Comparison of the dependency between the input and the continuous output loss rate.	51
Figure 13: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum ANN regressor (a) training set, and (b) testing set.	67
Figure 14: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum ANFIS regressor (a) training set, and (b) testing set.....	68
Figure 15: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum SVM regressor (a) training set, and (b) testing set.....	70
Figure 16: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum RF regressor (a) training set, and (b) testing set.	71

Figure 17: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum K-NN regressor (a) training set, and (b) testing set.	73
Figure 18: Numbers of data points labeled as “Losses” and “No Losses” in Well-8.	74
Figure 19: The performance of the developed classifiers using in Well-8.	75
Figure 20: Comparison of the prediction accuracy of ANN, ANFIS, SVM, RF, and K-NN models in predicting loss of circulation rate of Well-8 (1,123 data points).	76
Figure 21: The predicted and actual loss of circulation rate while drilling for Well-8 (1,123 unseen data points) using (a) ANN; (b) ANFIS; (c) SVM; (d) RF; and (e) K-NN.	78

LIST OF ABBREVIATIONS

WBM	:	Water-based mud
OBM	:	Oil-based mud
LCMs	:	Lost circulation materials
NPT	:	Nonproductive time
ECD	:	Equivalent circulation density
WPC	:	Well pressure containment
SCM	:	Stress cage model
FCS	:	Fracture closure stress
HPHT	:	High-pressure high-temperature
PSD	:	Particle size distribution
AI	:	Artificial Intelligence
ANN	:	Artificial neural network
TANSIG	:	Tan sigmoid
LOGSIG	:	Log sigmoid
SVM	:	Support vector machine
RF	:	Random forest
K-NN	:	K-nearest neighbors
ROP	:	Rate of penetration
ANFIS	:	Adaptive neuro-fuzzy inference system
AAPE	:	Absolute average percentage error
R	:	Correlation coefficient
RNN	:	Recurrent neural networks

WOB	:	Weight-on bit
RS	:	Rotary speed
Q	:	Pump flow rate
R²	:	Coefficient of determination
MSE	:	Mean square error
SPP	:	Stand pipe pressure
T	:	Surface drilling torque
MSE	:	Mean square error
RMSE	:	Root mean square error
R²	:	Coefficient of determination
FNN	:	Functional neural network
APV	:	Active pit volume

ABSTRACT

Full Name: Ahmed Ibrahim Alsaihati
Thesis Title: Real-Time Estimation of Lost of Circulation While Drilling Using Artificial Intelligence Techniques.
Major Field: Petroleum Engineering
Date of Degree: April 2021.

Fluid losses into formations is a common operational issue that is frequently encountered when drilling across naturally or induced fractured formations. This could pose significant operational risks, such as well control, that can lead to a blowout and loss of life if not properly controlled, stuck pipe, and wellbore instability, which, in turn, lead to an increase of well duration and cost. Thus, detection of fluid losses during a drilling operation is a standard practice to provide a drilling crew with a quick warning sign to alter the operational parameters and take corrective actions to avoid escalating fluid losses.

Using floating sensors or acoustic reflectors is the most used technique to monitor the level of drilling fluid in the active pit volume. This enables a drilling crew to measure the cumulative volume of the drilling fluid lost into surrounding formations but *only* over a period of time. In addition to this, such sensors or reflectors cannot detect small fluid losses.

This research aims to use and evaluate different artificial intelligence techniques, namely: artificial neural networks, adaptive neuro-fuzzy inference systems, logistic regression, support vector machines, random forests, and K-nearest neighbors in detecting loss of circulation occurrences and estimating the loss of circulation rates in real time while drilling using solely

mechanical surface parameters. Actual field data of seven wells, namely: Well-1, Well-2, Well-3, Well-4, Well-5, Well-6 and Well-7, which had suffered partial or severe loss of circulation, were used to build predictive models, while Well-8 was used to compare the performance of the developed models.

Different performance metrics were used to evaluate the performance of the developed models. Recall, precision, and F1-score measures were used to evaluate the ability of the developed model to detect loss of circulation occurrences, while the root mean square error (RMSE) and correlation coefficient (R) were used to evaluate the performance of the models in predicting the loss of circulation rate in real time. The results showed that K-nearest neighbors outperformed other models in detecting the loss of circulation occurrences in Well-8 with an F1-score of 0.80, and with an RMSE 0.17 and R of 0.90 respectively in predicting the loss of the circulation rate in Well-8.

ملخص الرسالة

الاسم الكامل: أحمد إبراهيم السيهاتي

عنوان الرسالة: التنبؤ في الوقت الحقيقي لفقدان موانع الحفر أثناء الحفر باستخدام أساليب الذكاء الاصطناعي.

التخصص: هندسة البترول

تاريخ الدرجة العلمية: رمضان 1442

يعد فقدان موانع الحفر مشكلة تشغيلية رئيسية يتم مواجهتها بشكل متكرر عند الحفر عبر التكوينات المتصدعة بشكل طبيعي أو مستحث. يمكن أن يشكل هذا مخاطر تشغيلية كبيرة مثل التحكم في البئر الذي يمكن أن يؤدي إلى انفجار وخسارة في الأرواح إذا لم يتم التحكم فيها بشكل صحيح، وتعليق الأنابيب، وعدم استقرار حفرة البئر، مما يؤدي بدوره إلى زيادة مدة البئر وتكلفته. وبالتالي، فإن الكشف عن فقد السوائل أثناء عملية الحفر هو ممارسة اعتيادية لتزويد طاقم الحفر بعلامة تحذير سريعة لتغيير المعلومات التشغيلية واتخاذ الإجراءات التصحيحية لتجنب تصاعد خسائر السوائل.

يعد استخدام المستشعرات العائمة أو العاكسات الصوتية هو الأسلوب الأكثر استخدامًا لمراقبة مستوى سائل الحفر في خزانات التي تحوي موانع الحفر. يتيح ذلك لطاقم الحفر قياس الحجم التراكمي لسائل الحفر المفقود في التكوينات المحيطة ولكن خلال فترة زمنية فقط. بالإضافة إلى ذلك، لا تستطيع هذه المستشعرات أو العاكسات اكتشاف فقد السوائل الصغيرة.

يهدف هذا البحث إلى استخدام تقنيات الذكاء الاصطناعي المختلفة وتقييمها وهي: الشبكة العصبية الاصطناعية (artificial neural network)، ونظام الاستدلال العصبي الغامض التكيفي (adaptive neuro-fuzzy inference system)، والانحدار اللوجستي (Logistic regression)، وآلة ناقلات الدعم (support vector machines)، والغابات العشوائية (random forest)، والجيران الأقرب (K-nearest neighbors) في اكتشاف فقدان حالات موانع الحفر وتقدير فقدان معدل موانع الحفر في الوقت الفعلي أثناء الحفر باستخدام علامات الحفر الميكانيكية فقط. البيانات الحفرية الفعلية لسبعة آبار وهي؛ بئر-1، بئر-2، بئر-3، بئر-4، بئر-5، بئر-6، بئر-7، والتي تعرضت لفقدان جزئي أو شديد لموانع الحفر، لبناء نماذج تنبؤية، بينما تم استخدام بئر-8 لمقارنة أداء التقنيات الذكية المطورة.

تم استخدام مقاييس أداء مختلفة لتقييم أداء التقنيات الذكية المطورة. تم استخدام F1-score لتقييم قدرة النموذج

المطور في اكتشاف فقدان موانع الحفر، بينما تم استخدام جذر متوسط الخطأ التربيعي (RMSE) ومعامل الارتباط (R) لتقييم

أداء النماذج في توقع فقدان معدل فقدان الموائع في الوقت الحقيقي. أظهرت النتائج أن أقرب الجيران تفوق في الأداء على النماذج الأخرى في الكشف عن فقدان حدوث الموائع الحفرية في البئر - 8 مع درجة F1 بلغت 0.80، ومع RMSE بلغ 0.17 و R 0.90 على التوالي في التنبؤ بفقدان معدل موائع الحفر في البئر-8.

CHAPTER 1

INTRODUCTION

A large number of conventional hydrocarbon reservoirs have been depleted due to a significant increase in oil and gas demand which, in turn, has resulted in a reduction in the operational mud weight window and has led to operational challenges, such as lost circulation (Alkinani et al., 2018). Lost circulation can be defined as the partial or complete loss of drilling fluid or cement slurries into the formation at any depth during drilling, circulation, running tubulars, or cementing operations.

Lost circulation events are common occurrences during well construction and have subsequent consequences, such as an increase of overall well construction cost and nonproductive time (NPT), sticking of the drill string, excessive inflow of drilling fluid which can cause reservoir damage and alter its characteristics, and well-control incidents (Howard and Scott, 1951). The economic impact of lost circulation can be significant and, therefore, drilling operators often anticipate a 10% to 20% portion of NPT attributable to lost circulation events.

Lost circulation occurs mainly due to drilling across formations that are naturally fractured, under-pressured (i.e., depleted) or highly permeable (Miranda et al., 2017; Lavrov, 2016; Ramasamy and Amanullah, 2017). The lost circulation treatments that are applied at the rig site can be divided into (Alkinani et al., 2018): (i) corrective lost circulation treatments, which are added either continuously or at regular intervals to the drilling fluid or spotted pills across the lost circulation zone (Kumar et al., 2011; Valverde et al., 2015; White et al., 1956; Jain et al., 2013), and (ii) preventive treatments, which are applied prior to penetrating the lost circulation zones to effectively seal induced fractures and to deliberately increase the fracture gradient and the

operational mud window using the stress cage model (SGM) presented by Alberty and Mclean (2004) and the fracture closure stress (FCS) model developed by Dupriest (Dupriest, 2005).

Lost circulation events are typically caused by (i) a pressure imbalance, wherein the bottom-hole pressure is higher than the formation pore pressure, which results in formation fractures and consequent fluid loss into the induced fractures, and (ii) a pathway for the drilling fluid to enter, such as a natural fracture, cavern, or unconsolidated sand (Ghalambor et al., 2014). Thus, it is required – if possible – to identify all unstable, low-pressure or naturally fractured intervals during the planning phases of drilling a well to drill it safely.

The intensity of lost circulation can be classified into (i) seepage, (ii) partial, (iii) severe, and (iv) complete losses. Seepage loss is a situation when a minimal volume of mud is lost into the formation and which has little effect on the drilling process. Lost circulation is considered seepage when the loss rate starts from 1-10 bbl/hr. for oil-based mud (OBM) and from 1-25 bbl/hr. for water-based mud (WBM) (Sweatman et al., 1997; Nayberg and Petty, 1986; Ghalambor et al., 2014; Nelson and Guillot, 2006; Marinescu et al., 2007; Lost Circulation Guide, 2014). Seepage losses can occur across permeable and porous formations where a low permeable filter cake cannot be achieved (Messenger, 1981). Partial loss is a situation when a moderate volume of mud is lost into the formation. Lost circulation is considered partial when the loss rate starts from 10-20 bbl/hrs. for OBM (Ghalambor et al., 2014; Marinescu et al., 2007; Lake et al., 2006). Some researchers consider a loss rate from 10-50 bbl./hr for OBM to be partial losses (Nayberg and Petty, 1986), while others have defined partial losses to be from 25-100 bbl./hrs. for WBM and from 10-30 bbl./hr. for OBM (Lost Circulation Guide, 2014). This type of loss occurs in unconsolidated sand, horizontal natural fractures, or vertical induced fractures as a result of excessive bottom-hole pressure (Sweatman et al., 1997; Nayberg and Petty, 1986). On the other

hand, lost circulation is classified as severe when a significant volume of mud is lost into the formation. Lost circulation is considered severe when the loss rate ranges from 50-150 bbl./hr. (Sweatman et al., 1997; Ghalambor et al., 2014). Some researchers consider a loss rate of more than 500 bbl./hr. to be classified as severe losses (Nayberg and Petty, 1986; Marinescu et al., 2007; Alkinani et al., 2018), while others have defined severe losses to be more than 30 bbl./hr. for OBM and more than 100 bbl./hr. for WBM (Lost Circulation Guide,2014). Severe losses happen in unconsolidated sand, vugs, shallow caverns, and induced or natural fractures (Nayberg and Petty, 1986). Total loss is a situation where no mud return is detected at the surface (Ghalambor et al., 2014; Nelson and Guillot, 2006; Lost Circulation Guide,2014). It can also be defined as the invisibility of the drilling fluid level in the annulus. On the other hand, total losses happen in cavernous vugs or large fractures (Nayberg and Petty, 1986). Table 1 shows the different types of lost circulation and the common range of the intensity of the loss rate for WBM and OBM (Lost Circulation Guide,2014).

Table 1: Loss of circulation types

Classification	Loss of circulation rate (bbl./hr.)	
	OBM	WBM
Seepage	(0-10]	(0-25]
Partial	(10-40]	(25-100]
Severe	>40	>100
Total	Zero return at surface	Zero return at surface

1.1 Lost Circulation Zone Candidates

1.1.1 Natural Losses

A. Natural Losses Across Pores and Matrices

These occur due to the presence of gravel and coarse sand with high permeability. Gravel and coarse sand can be found mainly at a shallow depth in unconsolidated sands or in depleted reservoirs (Beda and Carugo, 2001). The drilling fluid is lost into nearby formations when the pore size is three times larger than the material size in the drilling fluid.

B. Natural Losses Across Permeable and Naturally Fractured Formations

Natural fractures with apertures measuring from microns to millimeters can occur in many types of formations and cause significant lost circulation incidents (Beda and Carugo, 2001), where the level of the drilling fluid in the annulus falls increasingly. Furthermore, complete loss of circulation can occur if more fractures are exposed as the drilling process continues (Howard and Scott, 1951).

C. Natural Losses Across Cavernous Formations

Natural losses can occur in limestone, dolomites and salts due to the dissolution by water over a period of time; this results in the creation of fractures and caverns with a range of sizes, varying from pinhole to tunnel size (Messenger, 1981; Beda and Carugo, 2001; Lake et al., 2006).

1.1.2 Induced Losses

Loss of circulation in induced fractures can occur when the bottom-hole pressure surpasses the formation fracture pressure (Beda and Carugo, 2001). These losses can be initiated by pressure surges, excessive surface backpressure during well-control killing operations, and excessive drilling parameters (Beda and Carugo, 2001; Messenger, 1981). Induced fractures can also be correlated to poor hole cleaning and wellbore instability (i.e., formation caving), which can cause a sudden increase of the equivalent circulation density (ECD).

1.2 The Impact of Lost Circulation

Lost circulation events cause an increase in NPT as the drilling crew spends excessive time recovering fluid circulation. During drilling in the Gulf of Mexico from 1993-2003, lost circulation events were responsible for more than 10% of NPT (Rehm et al., 2008; Wang et al., 2007). In such

an event, a sidetrack may need to be initiated or a well abandoned if a drilling crew is unable to cure or minimize losses. The economic impact of lost circulation also includes the cost of the drilling fluid lost into the formation and loss of circulation materials (LCMs) used to cure such losses. Generally, the economic impact when drilling with OBM is costlier than when drilling with WBM. Since the cost of drilling fluid represents 25%-40% of the total well construction cost and LCMs are extremely expensive, the impact of loss of circulation on the cost is substantial (Le'colier et al., 2005).

Lost circulation can cause additional drilling problems. A reduction of the drilling fluid level can impair the hole cleaning efficiency, especially in deviated and horizontal profiles, which results in a hole pack-off and mechanical sticking (Abdollahi et al., 2004; Johnson et al., 2000). Lost circulation when drilling a hydrocarbon-bearing zone can cause plugging of the pore structure due to the presence of particles in the drilling fluid, such as weighting agents, drilled solids, or LCMs. Thus, it is necessary to remove the damage caused by these particles not to impair the well productivity, which in turn increases the well cost (Howard and Scott, 1951). A well-control incident is another serious drilling problem that can be caused by severe loss of circulation, where the drilling fluid level falls in the annulus causing the bottom-hole mud hydrostatic pressure acting on the formation face to be lower than the pressure of the drilled formation. This will force a formation fluid (i.e., a kick) into the wellbore and may lead to a blowout if not controlled appropriately (Chilingar and Vorabutr, 1983). Lost circulation in surface holes, where there is no hydrocarbon-bearing zone and formation damage is not expected, can be equally as bad and have negative consequences, such as poor cement jobs and the inability to isolate shallow water aquifers.

1.3 Monitoring of Lost Circulation While Drilling

Monitoring the drilling fluid level in the mud pits with a floating sensor or acoustic reflector is a common technique used to identify drilling fluid losses while drilling (Lavrov, 2016). The floating sensor consists of a buoyant float that is located in the active pit. Most drilling contractors utilize a float that travels along a pole that activates a sequence of reed switches, where the drilling fluid level is related to the electrical signal produced by the status of these magnetic switches. On the other hand, some drilling contractors measure the differences of resistance with a potentiometer that is connected to the buoyant float through a chain mounted on a wheel (Beda and Carugo, 2001). These sensors have been partly replaced by advanced ultrasound sensors. The ultrasound sensor emits a series of ultrasonic pulses which are reflected off the fluid surface and are received by the same sensor. The transit time is proportional to the distance, which enables the system to calculate the drilling fluid levels and volumes in the active or reserve pit tanks.

These techniques provide a quick warning sign of any invasion of a formation fluid (i.e., a kick) or severe loss of circulation but are not accurate enough to identify small losses. Additionally, mud losses over the shale-shakers, the addition of water or mud treatment by a drilling crew, or the drainage of surface lines can cause pit level variations (Beda and Carugo, 2001). High resolution and expensive electromagnetic flowmeters can be used to measure the inlet drilling fluid flow rate (Q_{in}) and the outlet drilling fluid flow rate (Q_{out}) for accurate loss detection (Shafer et al., 1992; Sanfillippo et al., 1997). The principle of the electromagnetic flowmeter is derived from Faraday's law of induction, where conductive drilling fluid can represent the electrical conductor that moves through a magnetic field. The electrical conductor induces a voltage that is perpendicular to the magnetic field and the direction of the flow. The produced voltage is proportional to the flow velocity and, therefore, to the flow rate. These electromagnetic flowmeters are not affected to any degree by the change of viscosity and density of the drilling fluid. For an

electromagnetic flowmeter to work properly, it requires conductive drilling fluids. In addition, a drilling crew has to modify the mud flow system at the surface for proper installation. These two main limitations should be considered before using electromagnetic flowmeters.

1.4 Different Techniques to Allocate Zones of Lost Circulation

Different wireline logs can be deployed at the end of the drilling operation to allocate zones of lost circulation. These include wellbore temperature surveys, spinner surveys, radioactive tracer surveys, and pressure transducer surveys (Beda and Carugo, 2001). The wireline surveys can be costly and difficult to interpret. In addition, such surveys are applicable only when a significant amount of drilling fluid has been lost in the well. Thus, these techniques are rarely implemented as standard practice (Messenger, 1981; Bratton et al., 2001).

CHAPTER 2

LITERATURE REVIEW

2.1 Lose Circulation Management

Loss of circulation when drilling naturally or in induced fractured, cavernous or unconsolidated formations cannot be circumvented completely. However, some proactive and corrective wellbore strengthening techniques can be applied to manage losses.

2.1.1 Proactive Wellbore Strengthening

The objective of proactive treatments is to strengthen the wellbore using different techniques to effectively seal off induced fractures and to intentionally increase the fracture gradient and the operational mud window (Withfill, 2008; Salehi and Nygaard, 2011; Salehi and Nygaard, 2012). Treating a drilling fluid with LCMs that have a broad size distribution is beneficial when isolating the fracture tip from wellbore hydrostatic pressure which, in turn, stops fracture propagation (Fuh et al., 1992; Aston et al., 2004). This is often called *stress caging*, where the borehole is strengthened by creating microfractures that are plugged and kept open with particulates to increase the hoop stress around the wellbore (Aston et al., 2004). The ability of LCMs to contain the pressure decreases with the increase in length of the fracture (Deeg and Wang 2004). Thus, the fracture should be sealed as early as possible before it extends significantly in length into the formation.

The SCM was presented by Alberty and Mclean (Alberty and Mclean, 2004) based on a basic linear elastic fracture mechanics model which recommends using LCMs to set at the fracture opening and form a seal to increase the hoop stresses around the wellbore. The FCS model was introduced by Dupriest (2005), which explains how adding LCMs to drilling fluids as a remedial solution can increase the fracture gradient of a formation. It has been stated that the FCS is increased when the fracture is widened and the fracture tip is sealed; this will then compress the

adjacent rocks causing a change in the near wellbore stresses. Additionally, the elastic-plastic fracture model was developed by Aadnoy and Belayneh (Aadnoy and Belayneh, 2004), which allows the fracture gradient to be increased above the predetermined theoretical value. The model states that the fracturing gradient could be improved due to the building of the plastic filter cake deformation at the fracture opening.

2.1.2 Corrective Wellbore Strengthening

The corrective measures are defined as methods that are applied after the occurrence of the losses, where LCMs are added continuously, spotted and soaked as concentrated pills or squeezed into a loss zone if formation fracture pressure allows (Kumar et al., 2011). LCMs should best be designed not only to remain immobile inside the fracture but also to stop drilling fluids from invading it at high wellbore bottom-hole pressures (Deeg, 1999).

There are various corrective loss of circulation treatments that depend on the intensity of the loss rate or the type of formation to be treated. Conventional LCMs blends are added to the drilling fluid system at various concentrations to minimize losses (Wang et al., 2005). On the other hand, pills that have the capability to set, such as engineered cement plugs, advanced gunk plugs, deformable, or soft plugs, are often used to recover circulation in the case of complete losses. Deformable, viscous and cohesive plugs are effective due to their cohesion properties, which support the development of an effective impermeable seal, thus, stopping excessive amounts of drilling fluids from leaking into the loss zone. Such treatments require special planning and blending steps that need to be discussed in detail prior to implementation (Wang et al., 2005).

Natural and induced fractures are the most causative factors of lost circulation, which varies from seepage and partial to complete drilling fluid losses. Therefore, a systematic approach based on field experience and technical knowledge should be applied.

2.2 Classification of LCMs

The need to classify LCMs into different groups is essential because of the availability of the large number of LCMs. LCMs have various physical and chemical properties and, therefore, cataloging them is important in the decision-making process to prevent or cure lost circulation incidents. Their physical properties include their shape and appearance, while their chemical properties include solubility in acids and their ability to swell and react with different chemicals to activate a blend to cure losses (Alkinani et al., 2018).

Canson (1985) classified LCMs based on their appearance as flaky, granular or a mixture of the two. Howard and Scott (1951) categorized LCMs based on their physical properties into four classes: fibrous materials, granular material, lamellated materials and dehydratable materials. White (1956) modified the previous by replacing the dehydratable class with a mixture of LCMs class. Alkinani et al. (2018) updated the classification of LCMs based on the physical and chemical properties to seven classes.

2.2.1 Granular

Granular materials are additives that have the capability of forming a seal at the sand-face of a formation, or within a fracture, to avert losses into the formation (Howard and Scott, 1951; Nayberg and Petty, 1986). A seal within a fracture is preferable because it is a more permanent bridge that cannot be dislodged by pipe movement and rotation or eroded as a result of fluid movement. A mixture of large, medium and small particles or a mixture of relatively large and small particles is most frequently used. The large particles are placed in a formation and form a bridge, while the small particles wedge the smaller openings until the bridge becomes impermeable. The granular LCMs perform better in a system with a high-solids ratio (e.g., cement slurries) (Nayberg and Petty, 1986). Granular materials are mostly used in a proactive wellbore strengthening approach and have a higher crushing resistance force and stiffness than others. In

addition, some types of granular materials are classified as soluble in acid solutions such as calcium carbonate. The most common granular LCMs are presented in Table 2.

Table 2: Examples of granular LCMs (Alkinani et al., 2018)

Description	Commercial name
Ground and walnut shell-sized	WALL-NUT
	MIL-PLUG
	NEW-PLUG
	WALNUT HULLS
	NUTSHELL
	MESUCO-PLUG
Resilient, angular, dual carbon-based, sized graphite	STEELSEAL
	G-SEAL
	C-SEAL
	LC-LUBE
	NEWSEAL
Proprietary natural loss prevention materials (LPM)	SURE-SEAL
	TORQUE-SEAL
Acid-soluble particulates	EZ-PLUG
Ground and marble-sized	BARACARB
	SAFE-CARB
	NEW-CARB
	FLOW-CARB
	MIL-CARB
	W.O.30

2.2.2 Flaky

Flaky materials have a thin flat shape with a relatively large surface area (Schlumberger, 2014). Flaky materials are not stiff but are able to form a mat across a permeable formation (Howard and Scott, 1951; Nayberg and Petty, 1986). Flaky materials can effectively bridge many types of porous media to prevent fluid loss. The most common flaky LCMs are presented in Table 3.

Table 3: Examples of flaky LCMs (Alkinani et al., 2018)

Description	Commercial name
Cellophane	MILFLAKE
	MESUCOFLAKE
Sized grade of Mica	MILMICA
	MESUCO -MICA
Flaked Calcium Carbonate	SOLUFLAKE

2.2.3 Fibrous

Fibrous materials are flexible, long and slender in shape, and are available in different sizes, grades and lengths of fiber (Schlumberger, 2014). Fibrous materials form a mat-like bridge which acts as a filtration medium for particles in the drilling mud to minimize losses into fractures or cavernous formations (Howard and Scott, 1951; Nayberg and Petty, 1986). The mat reduces the size of the openings of the formation which permits the drilling fluid particles to rapidly form a filter cake and completely seal the formation. The performance of the fibrous LCMs depends primarily on the size of the fibers and the size gradation. The chemical and physical nature of the material has limitations in terms of resistance to fragmentation and undergoes degradation when circulated in the drilling fluid system (Nayberg and Petty, 1986). Fibrous materials can be used in both WBM and OBM, and some of them are acid-soluble. However, some materials have limitations when used in OBM. The most common fibrous LCMs are presented in Table 4.

Table 4: Examples of fibrous LCMs (Alkinani et al., 2018)

Description	Commercial name
Natural cellulose fiber	BAROFIBRE
	M-I-X II
	VINSEAL
	CHEK-LOSS
	MESUCOFIBER
	CYBER SEAL

	FIBER SEAL
A proprietary micro cellulosic fiber for WBM	DYNARED
A proprietary micro cellulosic fiber for OBM	DYNA-SEAL
Shredded cedar fibers	M-I CEDAR FIBER
	FIBER PLUG
	PLUG-GIT
	MIL-CEDAR
Acid-soluble extrusion spun mineral fiber	N-Seal
	CAVI-SEAL-AS
	MAGMA FIBER

2.2.4 Mixture of LCMs

A mixture of different LCMs with various properties and sizes performs better in mitigating losses (Nayberg and Petty, 1986; Kumar et al., 2011; Withfill, 2008; Van Oort, 2009). The blend is a mixture of granular, flake, and fibrous materials with various shapes, sizes and stiffness which will penetrate the fracture and effectively seal off extremely permeable zones. The type of LCMs and the particle size distribution are evaluated using different laboratory tests to ensure effective sealing of a wide range of fracture sizes. Table 5 presents different mixtures of LCMs.

Table 5: Examples of LCMs mixtures (Alkinani et al., 2018)

Description	Commercial name
A combination of different LCM types and a wide range of particle sizes	STOPPIT
	PRIMA SEAL
	STOP-FRAC S
	WELL-SEAL
	BARO-SEAL
	STOP-FRAC D

	M-I SEAL
	MIL-SEAL
	CHEM SEAL
	KWIK-SEAL
	MESUCO-SEAL
A blend of acid soluble particulates	EZ-PLUG
A proprietary particulate blend designed to be used with foam wedges	QUIK-WEDGE
A proprietary particulate blends that includes modified natural materials and other additives	STRESS-SHIELD

2.2.5 Acid/Water-Soluble

Conventional LCMs can be a major concern from the reservoir damage perspective. Therefore, the development of non-damaging reservoir LCMs is of prime importance (Sweatman and Scoggins, 1989). Acid/water-soluble LCMs are non-reservoir LCMs that can be used to mitigate losses in reservoir sections. Different acid/water-soluble LCMs are presented in Table 6.

Table 6: Examples of acid/water-soluble LCMs (Alkinani et al., 2018)

Description	Commercial name
A blend of acid-soluble particulates	EZ-PLUG

A non-damaging, cross linkable water-soluble polymer blended with selected sized cellulosic fibers	N-SQUEEZE
Acid-soluble extrusion spun mineral fibers	N-SEAL
	CAVI-SEAL-AS
	MAGMA FIBER
Sized and treated salts	BARAPLUG
Acid-soluble sized calcium carbonate.	BARACARB
	SAFE-CARB
	NEW-CARB
	FLOW-CARB
	MIL-CARB
	W. O. 30
Flaked calcium carbonate.	SOLUFLAKE
Nontoxic fibrous powdered polysaccharide, biodegradable and acid soluble lost circulation material	HOLE-SEAL-II

2.2.6 High Fluid Loss LCMs Squeeze

High fluid loss LCMs are often used for curing severe losses across fractured/induced fractured or highly permeable formations. A plug that seals the lost zone is formed as a result of a filtration process. This type of treatment requires special operational procedures to squeeze a spotted pill into the loss zone at a pressure less than the formation fracture pressure (Lost Circulation Guide,2014). Table 7 shows the different high fluid loss LCM squeezes.

Table 7: Examples of acid/water-soluble LCM (Alkinani et al., 2018)

Description	Commercial name
High fluid loss squeeze	GEO STOP LOSS
High-solids, high fluid loss reactive loss circulation squeeze	DIASEL M
A specially formulated high-solids high fluid loss squeeze	DIAPLUG
A proprietary blend of granular and fibrous materials	X-PRIMA
A blend of granular and fibrous materials	NEW BRIDGE
A micro-sized cellulosic fiber combined with a blend of organic polymers	ULTRA SEAL
A blend of fine particles to promote high fluid loss and other additives in addition to highly compressible and permeable foam rubber chunks	WEDGET-SET
A combination of both resilient graphitic carbon and malleable components	DUO-SQUEEZE

2.2.7 Swellable/Hydratable LCM Combinations

Settable/hydratable LCMs are blended with a highly reactive material, such as a polymer. The settable/hydratable LCMs are activated by chemical reagents or whenever they become in contact with drilling mud or formation fluids. Subsequently, a plug is formed within the loss zone. This type of treatment requires special operational procedures (Lost Circulation Guide, 2014). Table 8 shows examples of swellable/hydratable LCMs.

Table 8: Examples of swellable/hydratable LCMs (Alkinani et al., 2018)

Description	Commercial name
A combination of swelling polymer along with engineered combinations of resilient graphitic carbon and other LCMs	HYDRO-PLUG
Dry powdered/granular materials with synthetic polymers, inorganic minerals, chemical reagents and stabilized organic fillers	SUPER-STOP
A non-damaging, cross-linkable water-soluble polymer blended with selected sized cellulosic fibers	N-SQUEEZE

2.2.8 Nanoparticles

Nanoparticles or ultrafine particles are a mixture of organic and inorganic components, such as silica and iron hydroxide. They are extremely fine in size, between 1 and 200 nanometers in diameter (Contreras et al., 2014). The nanoparticles are prepared by either (Hoelscher et al., 2012; Friedheim et al., 2012; Nwaoji et al., 2013; Contreras et al., 2014) (i) an ex-situ procedure where the nanoparticles are preserved in an aqueous solution and later added to the drilling fluid system, or (ii) an in-situ procedure where precursors are added to form the nanoparticles directly in the drilling fluid. In practical field life, it is recommended to use the in-situ practices to prevent an increase of the water content in the mud (Alkinani et al., 2018). The nanoparticles flow into an unconsolidated formation and build a bridge to bond the grains together, which results in a consolidated formation over a period of time (Espin et al., 3003a; Espin et al., 2003b). Initially, a low fluid viscosity is injected into the formation at a certain displacement rate to displace the

formation fluid. Subsequently, an acidic or naturally consolidated nanoparticle suspension is injected using pressure that must be held for a period of time during the consolidation process (Soroush and Sampaio, 2006).

The nanoparticles are simple and effective in reducing sand production and do not alter the porosity and permeability significantly. Nevertheless, there are disadvantages, such as the inability to increase the rock compressive strength in comparison with conventional LCMs, being unsuitable in long formation intervals with significantly different pore pressures, and the inability to support formations with low permeability (Soroush and Sampaio, 2006).

2.3 Laboratory Evaluation of LCMs

The evaluation of LCMs in a laboratory is important to examine their practicality and stiffness before rig site applications.

2.3.1 Corrective Treatment Test

Particle plugging apparatus (PPA) and high-pressure high-temperature (HPHT) fluid loss apparatus are used to determine the effectiveness of LCMs added to the drilling fluid to bridge either tapered disks that simulate natural/induced fractures or ceramic disks with different sizes that simulate a porous media (Alkinani et al., 2018). The apparatus resembles an HPHT filtration cell that has been modified to operate upside down to remove the effect of the gravitational force.

The drilling fluid that is treated with LCMs passes through a disk under the HPHT. The total fluid loss within 30 minutes and the time required to form a tight seal are measured to evaluate the performance of the tested LCMs. To select the appropriate particle size that will provide an effective seal, based on the pore throat size or the estimated fracture width, a particle size distribution (PSD) analysis is performed (Withfill, 2008). Different PSD models are widely used to select the optimum LCMs, such as Abram's median particle size rule, Vickers method, and the

ideal packing theory. Each model has some limitations and may not be applicable under some conditions, especially when there is a lack of knowledge about the size of pore throat and fracture (Alkinani et al., 2018).

2.3.2 Preventive Treatment Test

The amount of fluid loss collected during the PPA is used to evaluate LCMs where low fluid loss volume is always preferred. However, the fluid loss volume is not a definitive indicator of how effectively LCMs will form a seal because PPA is run under constant pressure and a disk does not simulate the reality of how fluids filtrate across permeable zone (Alkinani et al., 2018). Different laboratory tests are used to study how wellbore strengthening mechanisms work. These laboratory tests can measure an increase of fracture size, spread and re-opening pressures; evaluate LCM sealing effectiveness and how competent the formed seal is; measure an LCM's physical properties, and optimize the PDA for preventive treatments.

Several experiments were performed that have looked at the factors affecting fracture propagation and re-opening pressures (Morita, 1990). The experiments revealed that solids in drilling fluids are significantly related to fracture propagation and re-opening pressures. Later that year, a joint industry project (JIP) was established to investigate how LCMs can improve formation fracture pressure using a hollow core to duplicate the setup of the previous experiments (Van Oort, 2009). To understand the mechanism of how LCMs seal a fracture, an apparatus was developed (Tehrani et al., 2007; Sandres et al., 2008; Van Oort, 2009).

An opposed piston that had two aluminum platens was used to simulate the faces of the fractures. The factors that affect wellbore strengthening, which were presented by Mostafavi et al., 2011, were investigated extensively. The effectiveness of different LCMs in sealing was evaluated using PPA. In addition, cement cores were used to conduct hydraulic fracturing experiments to

study the effect of LCMs in strengthening the wellbore. The results showed that mechanical properties and the concentration of LCMs and PSD are significantly important in wellbore strengthening. Salehi and Nygaard (2012), who performed several hydraulic fracturing experiments by using a hollow cylindrical rock, arrived at similar conclusions.

The improvement of formation fracture pressure is a function of LCMs' physical properties, which include size, shape, strength, crushing resistance and strength. Although these physical properties can be measured, there is no standard method of evaluating the improvement of formation fracture pressure (Alkinani et al., 2018). The effect of the physical properties in wellbore strengthening is a controversial subject. There are models for wellbore strengthening that suggest that the size and strength of the LCMs are not as important as other properties, while other models stress the importance of these factors. Some models emphasize the importance of size and neglect the material's strength. a list of wellbore strengthening models is presented in Table 9.

Table 9: Wellbore strengthening models (Salehi and Nygaard, 2012)

Wellbore strengthening model	Material Size	Material Strength	Authors
Fracture pressure inhibitor	Important	Important	Fuh et al. (1992)
Stress cage	Important	Important	Alberty and Mclean (2004)
FCS	Not important	Not important	Dupriest (2005)
Stress cage	Important	Important	Wang (2007)
Fracture healing	Important	Important	(Aadnoy and Belayneh, 2004)
Fracture propagation resistance (FPR)	Important	Not important	(VanOort, 2009)

CHAPTER 3

ARTIFICIAL INTELLIGENCE APPLICATIONS IN DRILLING ENGINEERING

3.1 Artificial Intelligence

Artificial Intelligence (AI) is one branch of computer science that is capable of creating intelligent machines that simulate the human brain (Kalogirou, 2003). AI has been applied to solve complex practical problems in various fields such as engineering, economics, the medical sector, banking, the military, the marine sector, etc. (Mellit, 2008; Hag, 2014; Babikir, 2019). It has the ability to learn from examples, deal with nonlinear problems, and generalize at a high speed once properly trained (Bello, 2015). AI is widely deployed in many applications due to its symbolic reasoning and flexibility, and its ability to cope with a new situation by processing one or more independent variables to facilitate solving complications that were previously impossible to resolve (Shahab, 2000).

Most AI techniques can potentially solve practical problems with high accuracy by learning from large historical datasets, something that conventional analytical models cannot do (Shahab, 2000; Balaji, 2018). AI has made it clear that the oil and gas industry has to comprehend the applicability of intelligent solutions in overcoming many disciplinary-related problems, such as exploration, production and hydrocarbons management. The applications of AI in drilling operation activities have evolved over recent years due to their flexibility in classification, optimization, prediction and selection (Bello, 2015).

AI aims to use smart machines to predict the likelihood of certain issues occurring based on historical data associated with cost and time. The reliability of the smart machines is dependent on the predictive accuracy and the level of error between the actual and the predicted class labels

or numerical variables of the problem. Various scientific and engineering fields have applied different AI techniques to predict problems. Scientists and engineers refer to AI techniques because of the complexity of most current problems, which are extremely difficult or impossible to resolve by employing hard computing techniques (Bello, 2015). The benefits of AI techniques can be listed as follow (Medsker, 1996; Mellit, 2008; Benghanem, 2012):

- 1- Unlike conventional modeling techniques, AI has the ability to implicitly model complex nonlinear systems without a form of relationship assumption between the independent and dependent variables.
- 2- AI models are more accurate than conventional analytical and empirical models.
- 3- AI has the capability to analyze large datasets to find patterns and derive insights where datasets are incomplete or noisy.
- 4- AI can complete daily tasks more efficiently than a human, with fewer errors.

The petroleum industry is constantly looking for ways to use AI to improve productivity and profitability. However, while there are many benefits, it has its own limitations. There are several key limitations of AI approaches that have an impact on their helpfulness for some tasks and their ability to function in real-world situations. Data availability is one of the main barriers to implementing AI (Bello, 2015). AI models function very well on tasks related to similar data from a training dataset; limitations come to the surface when the model tries to incorporate a new dataset.

3.2 Machine Learning Techniques

Machine learning is an area of AI which involves the construction of complex algorithms that learn from experience whereby the performance of the algorithms improves with each experience. These algorithms operate by detecting patterns in the input variables and building a model to make accurate predictions for a new dataset. The machine learning models identify patterns from large

datasets that provide adequate support for prediction, classification and the decision-making process. The machine learning techniques can be divided into supervised and unsupervised learning.

Supervised machine learning is the task of learning a function to map an independent variable to an output variable based on example input-output pairs. It infers a function from a labeled training dataset that consists of a set of training examples where an optimum scenario allows the machine learning algorithm to correctly predict the class label for unseen data points (Celebi et al., 2013). This requires the machine learning algorithms to generalize from the training datasets to test datasets reasonably. The problems that are solved by supervised machine learning techniques can be categorized as regression and classification problems. In a regression problem, independent variables are mapped onto continuous dependent variables, whereas in a classification problem, dependent variables are mapped onto discrete categories, like “yes” or “no”. The problems that can be solved by supervised machine learning techniques are categorized as: (i) regression problems where independent variables are mapped onto a numerical label, and (ii) classification problems where independent variables are mapped onto a class label.

On the other hand, unsupervised machine learning algorithms employ a mapping function to find patterns and correlation from unlabeled input data with no explicit output. There are two types of unsupervised machine learning: (i) clustering, which involves mainly finding different groups in a dataset, and (ii) density estimation, which aims at summarizing the distribution of a dataset. Additional unsupervised techniques, such as visualization, which involves graphing or plotting data in different ways, and projection methods, like dimensionality reduction, may also be used. Figure 1 shows some of the machine learning algorithms that are widely used. The machine learning models that are used in this study are discussed next.

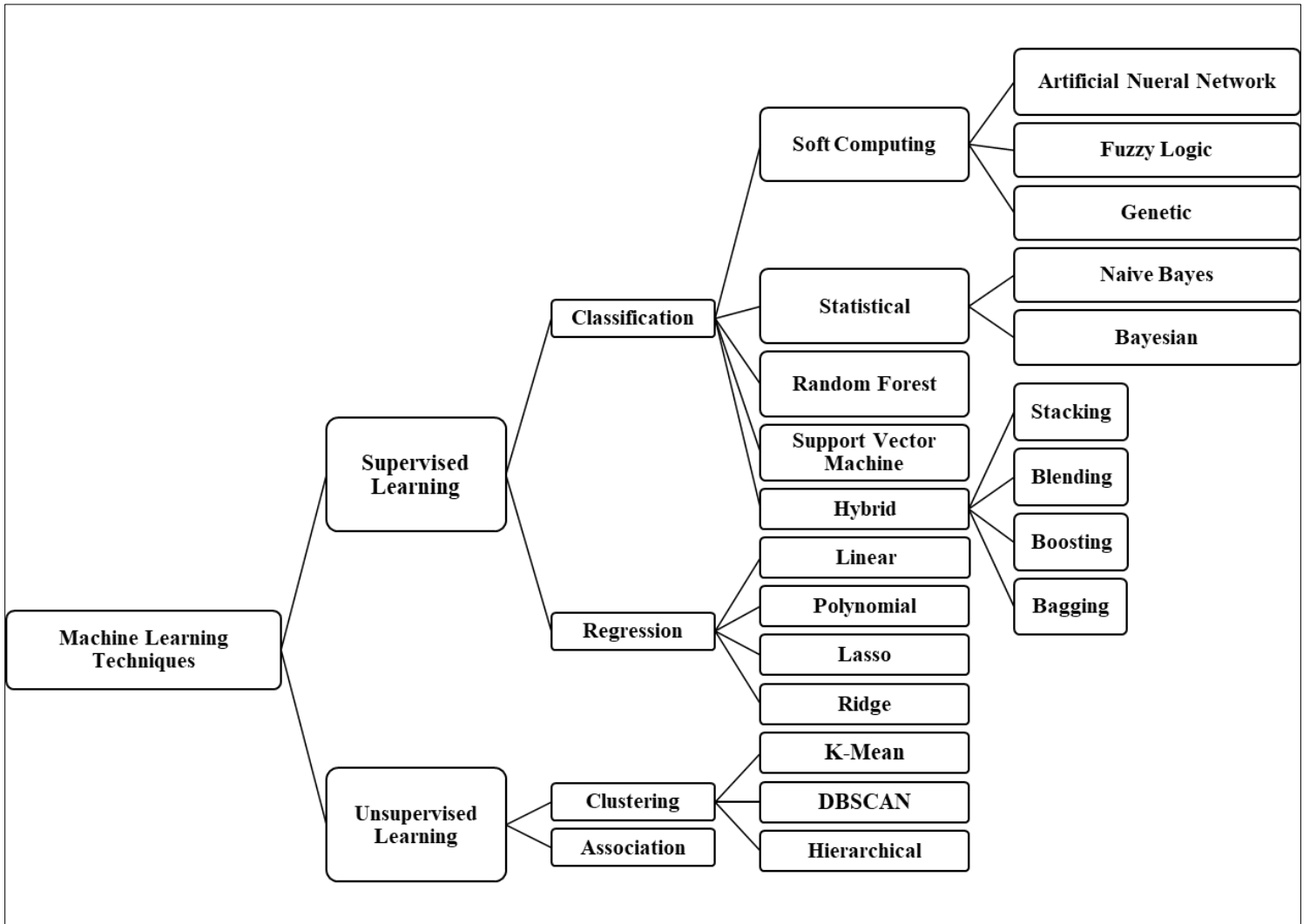


Figure 1: Classification of machine learning techniques

3.2.1 Artificial Neural Network

An artificial neural network (ANN) is an information processing system based on a collection of interconnected artificial neurons that mimic the performance characteristics of the biological human brain. The architecture of an ANN consists of an input layer, hidden layers, and an output layer. The hidden layers in an ANN contain a number of neurons which are made up of four essential components: input data, weights, activation and learning functions, and output values. The input corresponding to each neuron is multiplied by the weights ($\mathbf{W}_{1j}, \mathbf{W}_{2j}, \mathbf{W}_{3j}, \mathbf{W}_{4j} \dots, \mathbf{W}_{nj}$). The summing unit is then fed into an activation function (e.g., PRUELIN, TANSIG, LOGSIG),

which is applied to the weighted inputs of the neurons to produce the final output (Kumar and Thakur, 2012).

An ANN architecture can be classified into two functional groups (Farizawani et al, 2020): (i) feed-forward propagation, and (ii) feedback propagation. In the feed-forward propagation, the information will propagate from input units through the hidden units to the output in one direction. A training algorithm randomly assigns weights and biases, which are then used to transform the input data through each layer until the output is calculated. The error signal of each output is then assessed by comparing an actual output with the calculated one. The error signal of each output is backpropagated from the output layer to each contributed neuron in the hidden layer. The portion of the error signal received by each hidden neuron is based on its influence on the original output. During the feedback propagation, the neural network aims to adjust and modify the weights and bias to minimize the error function. (Mas and Flores, 2007; Kumar and Thakur, 2012; Farizawani et al., 2020). Figure 2 shows the architecture of a single neuron in an ANN network.

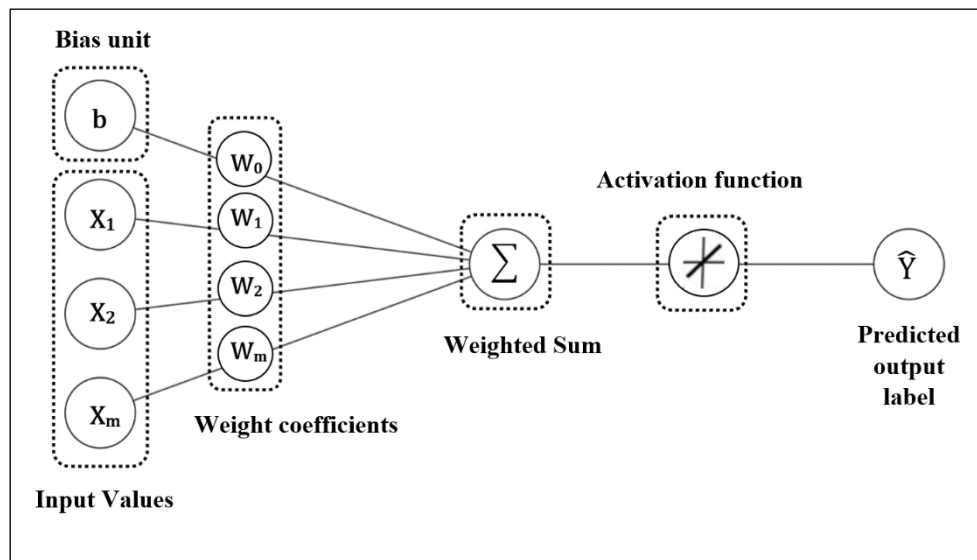


Figure 2: The architecture of an ANN

3.2.2 Adaptive Neuro-Fuzzy Inference System

The adaptive neuro-fuzzy inference system (ANFIS) was developed in the early 1990s (Alsabaa et al., 2020). It is a type of ANN that depends on the Takagi–Sugeno fuzzy inference system (Jang, 1993). The ANFIS inference system uses a set of fuzzy “if-then” rules that is able to learn and optimize nonlinear functions (Abraham, 2005). The architecture of ANFIS comprises four layers [67]. The first layer, called the fuzzification layer, receives the inputs and determines the membership functions (i.e., sigmoid, Gaussian, trapezoidal or straight line), which are used to define the relationship between a truth value and its variable. The second layer, denoted as the rule layer, applies a number of fuzzy “if-then” rules. In the third layer, databases are used in the rules for the membership function, and the decision-making unit is utilized for the operations of inference. In the last layer, the defuzzification interface transfers the fuzzy outputs to crisp results. The latest ANFIS can deal with complex and nonlinear systems by employing adaptive neuro-fuzzy, event-triggered, and additional techniques (Jang and Sun, 1995; Wang et al., 2020; Qiu et al., 2020). ANFIS has the advantages of employing a fuzzy inference system that provides an integrated supervised learning algorithm for data processing by neural networks and fuzzy logic (Jang, 1993; Vilela et al., 2019; Stojčić et al., 2019). ANN was employed for setting the IF-THEN rules in fuzzy logic (Jang, 1996; Tahmasebi and Hezarkhani, 2012), and this integration helped in achieving outstanding performance for the system.

3.2.3 Support Vector Machines

Support vector machines support supervised machine learning that can be used for classification or regression problems (Bello et al., 2015), and can strongly perform in certain applications (Hearst, 1989). Moreover, they have advantages that other algorithms do not, such as the ability to generalize, use fast learning processes, and they possess strong interference capacity (Vapnik,

1995; Anifowose and Abdulraheem, 2011). They work by transferring the data from a low dimension to a high dimension, which is denoted as kernel space, to find a support vector, i.e., a hyperplane that minimizes the number of mispredicted data points (Durka, 2011; Bello et al., 2015). The hyperplane is defined as the plane with the best margin of separation between two classes; the distance between the hyperplane and the nearest data point from either set is called the margin. The data closest to the hyperplane are called support vectors. These are difficult to classify (Durka, 2011), which is why the hyperplane with the maximum margin is the best separator. Figure 3 shows a visualization of an SVM.

To transform the data to a kernel space, SVMs use kernel functions to systematically find the support vector classifiers in higher dimensions. When kernels are used to transform the feature vectors from input space to kernel space for linearly non-separable datasets, the kernel matrix computation requires computational resources. The popular kernel functions are linear kernel functions, polynomial kernel functions, Gaussian, radial basis functions (RBFs), and randomized block analysis of variance (ANOVA RB) kernels (Awad and Khanna, 2015).

The selection of kernel functions is highly dependent on the nature of the dataset. The linear kernel ranks behind the polynomial kernel and is useful in large sparse data vectors. On the other hand, the polynomial kernel is commonly used in image processing, while the ANOVA RB kernel is generally used for regression tasks. The Gaussian RBF is mostly applied if the user lacks prior knowledge (Awad and Khanna, 2015).

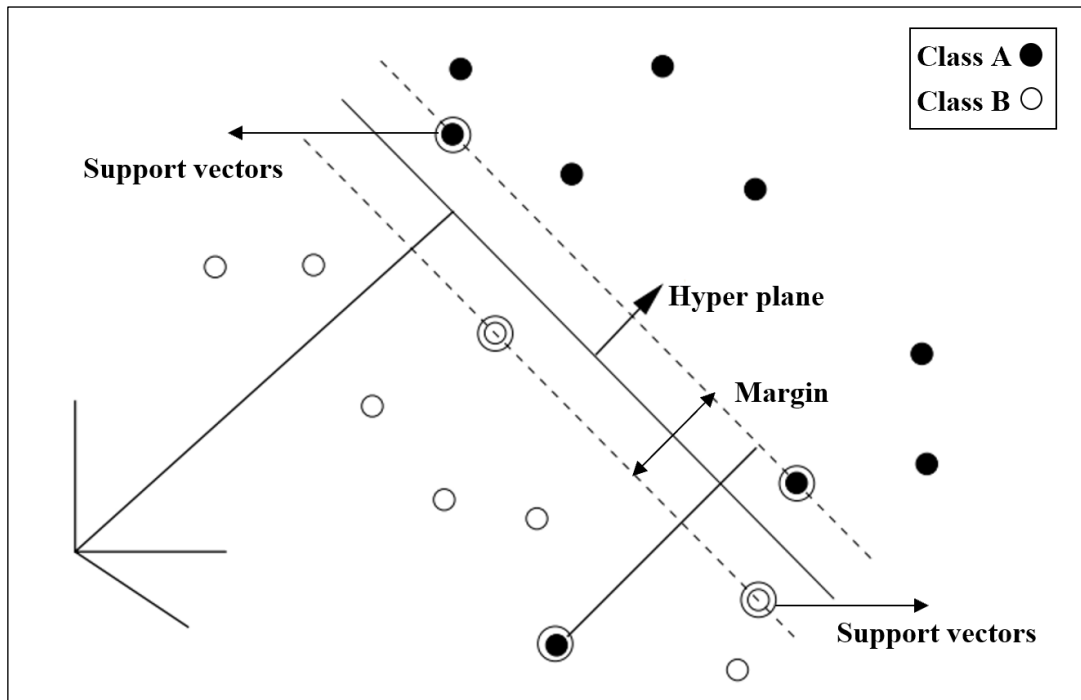


Figure 3: SVM Visualization

3.2.4 Random Forest

Random forest (RF) is an ensemble learning model which can be used to solve classification and regression problems (Hegde and Gray, 2017). The RF operates by constructing hundreds or thousands of decision trees and training each one on a different set of observations. A limited number of independent variables, often determined using cross-validation, are considered during a node splitting process which is called bootstrapping. This is done to eliminate model overfitting and effectively reduce the variance and improve the algorithm performance (Efron, 1982). The final output of the RF is the mode of the predictions of each tree for a classification problem or the average of the predictions of each tree for a regression problem; this process is called aggregation. Some samples are not selected during the bootstrapping process. These samples are called out-of-bag datasets and are beneficial for error estimation of the model. In addition, out-of-bag datasets are used for independent variable importance – a ranking feature – which is useful for model

interpretation (Efron, 1982; Hegde and Gray, 2017; Hegde et al., 2018). The RF outperforms a single decision tree because of its ability to limit overfitting without substantially increasing the margin of error (Hegde and Gray, 2017). Figure 4 shows a visualization of an RF.

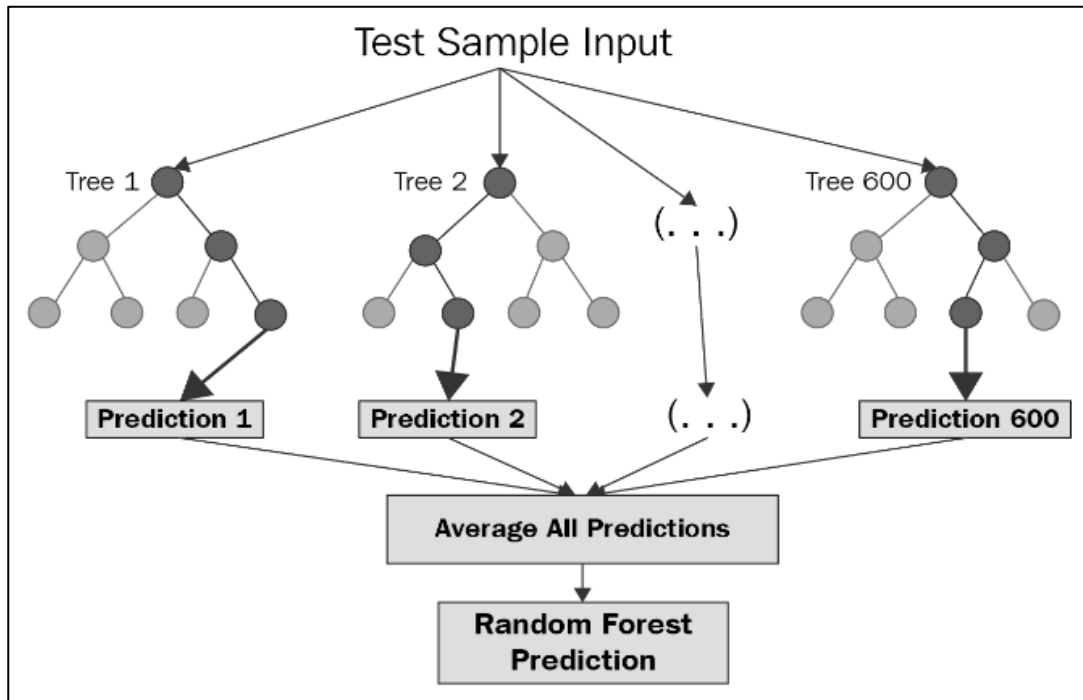


Figure 4: Random forest visualization

3.2.5 K-Nearest Neighbor

K-nearest neighbor (K-NN) is a non-parametric machine learning tool and an instance-based algorithm that can be used for classification and regression problems. The number of neighbors i.e., K in the K-NN model is a user-defined hyperparameter that can be selected using heuristic techniques. The K-NN starts by calculating the distance between a test sample and the training samples. Common metric distances used for continuous variables are Euclidean and Manhattan, while Hamming distance is used for discrete variables. The output of the test sample in a classification problem is a label that is the most frequent among the K-nearest training samples or the average of the K-nearest training samples (Wang, 2019). The K-NN algorithm is often thought of as an algorithm for which no explicit training is needed.

When the class distribution of a dataset is highly skewed (right/left) where training samples of one class dominate the prediction of a new sample because of their large number, a downside of the basic majority of voting occurs (Coomans and Massart, 1982). To resolve this problem, the distance from the test point to each of its nearest neighbors is considered, where the class label or the value in regression problems of each of the K nearest points is multiplied by a weight proportional to the inverse of the distance from that point to the test point.

The K -NN algorithm is considered to be one of the simplest of machine learning algorithms and it is effective when the training dataset is large. However, while there are advantages, the K -NN has some disadvantages, such as the need to determine the value of K , which can be complex, and the high computational cost because of calculating the distances between new test samples to all the training samples. Figure 5 shows a visualization of a K -NN algorithm. The red star is classified as class B if a K of 3 is considered, and it is classified as class A if a K of 5 is considered.

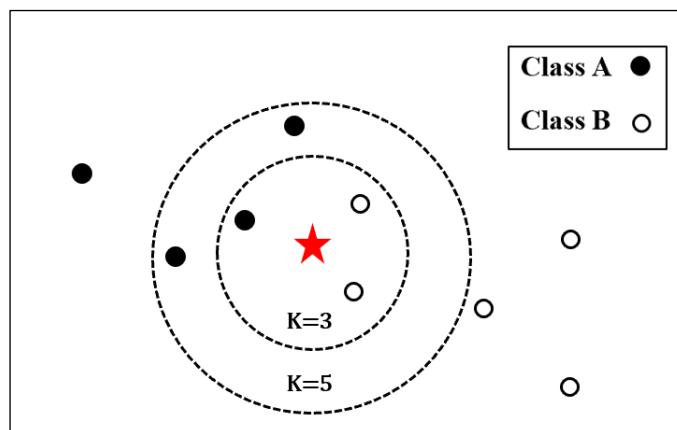


Figure 5: K-NN classification visualization

3.2.6 Logistic Regression

Logistic regression is a statistical model that uses a logistic function to model a binary output variable. It is used to model the probability that an output belongs to the existence of a certain class or event (Hedge et al., 2019). Logistic regression can be extended to model multiple classes or events. Mathematically, a binary logistic model has an output variable with two likely values,

such as yes/no, which is represented by an indicator variable, where the two values are labeled "1" and "0". In a logistic model, the logarithm of the odds for the values labeled "1" is a linear combination of one or more predictors that can be binary or continuous variables. The corresponding probability of the values labeled "1" can vary between 0 and 1. Similar models with a different sigmoid function instead of the logistic function can also be used.

3.3 Application of AI in the Drilling Industry

The drilling operation is a major aspect of the oil and gas industry. It is an extremely expensive operation that requires large daily expenses (Bello, 2015). Therefore, any kind of tools that can enhance the drilling performance at a low cost are vital. AI has been used in the drilling dynamics to predict the likely performance of different factors that contribute to drilling success, such as time and safety. Rate of penetration optimization, abnormalities detection, real-time monitoring of surface and downhole parameters, downhole control of drilling bit and bottom-hole assembly (BHA) behavior, and mitigation of downhole vibrations have been factors of prime importance. Thus, the development of intelligent machines is required to describe a near-accurate imprint of drilling activities when direct and real-time data is not obtainable.

The intelligent decision-making models can also provide a drilling crew with a number of quick and intelligent recommendations on key drilling parameters and proactive or corrective measures to enhance drilling performance (Dashevskiy et al., 1999; Alsaihati et al., 2020). The large number of publications on the application of AI in the drilling industry indicates its ability to reduce drilling costs, enhance drilling efficiency and increase drilling operation safety by learning from previous experiences. The specific applications of AI in drilling operations can be narrowed down to: well planning, procedural decision-making, pattern recognition, well integrity and drilling optimization. See Figure 6.

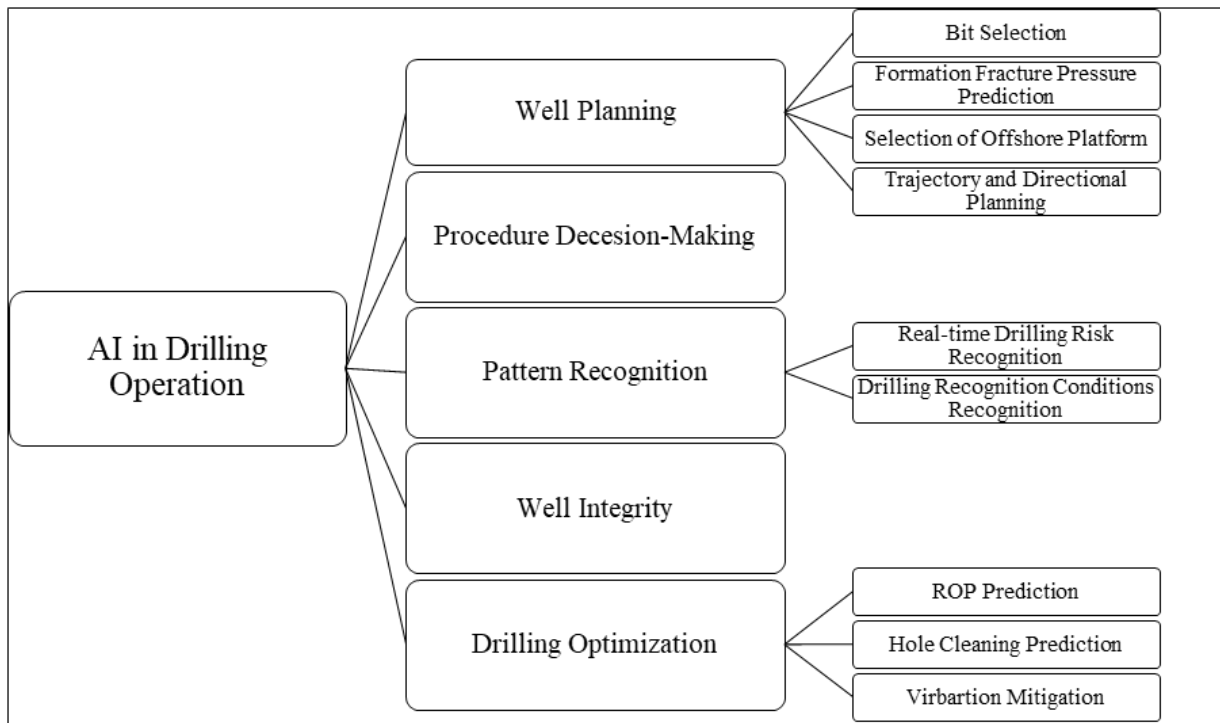


Figure 6: AI applications in drilling operation

The literature review presented here sheds light on several important achievements of AI applications in the drilling industry. Elkatatny (2017) developed ANN, the adaptive neuro-fuzzy inference system (ANFIS) and the SVM models to estimate a continuous profile of the static Poisson's ratio for a carbonate reservoir. A total of 610 core samples and log data, including bulk density, compressional time and shear transit time, were used to build the models. The ANN outperformed the ANFIS and SVM models. The developed ANN model can be used to estimate the Poisson's ratio without obtaining core samples and performing extensive lab work. Elkatatny et al. (2017) used a dataset with 3,333 data points from an actual field to develop their ANN model. The model incorporates drilling fluid and drilling mechanical properties to predict ROP in an intermediate section, i.e., a 16-inch hole size. The ANN model predicted the ROP with an R of 0.993 and an AAPE of 5.6%. Alkinani et al. (2017) collected a large dataset from different fields around the world to develop a deep neural network, i.e., recurrent neural networks (RNN), with

three hidden layers and fourteen neurons to predict the ROP. The independent variables were weight-on-bit (WOB), rotary speed (RS), pump flow rate (Q), plastic viscosity, and yield point. The lowest mean square error (MSE) and highest coefficient of determination (R^2) were obtained using the Levenberg-Marquardt (LM) training algorithm.

Abdelgawad et al. (2019) used an ANN model to estimate the rheological properties of bentonite spud mud. The input variables of the model were mud weight, marsh funnel viscosity, and solid content percentage. The ANN model was coupled with the self-adaptive differential evolution algorithm (SaDE) to optimize the model's parameters. The model was able to predict the rheological properties with an AAPE of less than 5% and an R of more than 95%. Ahmed et al. (2019) used an ANFIS model to predict the ROP in real time while drilling a shale formation across two-hole sizes, 8-3/8-inch and 5-7/8-inch. The model predicted the ROP with an R of 0.934 and an AAPE of 16.946%. The input variables of the model were WOB, stand pipe pressure (SPP), RS, Q, surface drilling torque (T), mud weight, yield point, plastic viscosity, funnel viscosity and solid content percentage. Elkatatny et al. (2019) obtained actual field data to develop an ANN model to predict the depth of the top of four geological formations in real time while drilling. The best performance of the model was obtained when scaled conjugate gradient backpropagation (TRAINSFG) was used as an optimizer, with 20 neurons. The input variables used in the study were the mechanical surface drilling parameters, including ROP, Q, RS, SPP, torque and WOB.

Hedge et al. (2019) used different models - logistic regression, SVM, RF, and Gaussian mixture - to solve a classification problem of the severity of the stick-slip index (SSI) during drilling, where the model's output is low or high. The dataset consisted of surface and downhole drilling parameters, and vibrational measurements acquired from a measurement-while-drilling (MWD) sensor. A threshold of one was used to classify the dataset into two groups: low or high.

If the SSI was greater than 1, the data points were labeled as high, and if it was less than 1, the data points were labeled as low. The results showed that the RF performed better than the logistic regression and SVM models, with an average accuracy of 90%. Abbas et al. (2019) used an ANN model to predict ROP in highly-angled wells. The input variables for the model were depth, WOB, RS, bit type, working hours on the bit, T, Q, SPP, total flow area (TFA) of the nozzles, azimuth, inclination, mud weight, mud rheology (e.g., funnel viscosity, plastic viscosity, yield point), unconfined compressive strength of the rock, vertical stress, maximum horizontal stress, and minimum horizontal stress. The highest value of $R^2 = 0.97$ was obtained using three hidden layers and 30 neurons with TANSIG as a transfer function. Mahmoud et al. (2019) developed a model to estimate the hole cleaning factor (HCF) model. The model incorporates the effect of the drilling fluid rheology, mud weight, Q, hole size, drill pipe size, hole inclination, and ROP to predict the hole cleaning condition. The model was validated on an actual well in North Africa at different depths from 33 to 12,854 ft. The crew members had a stuck pipe incident due to improper hole cleaning at the same depth, as anticipated by the HCF model.

Gurina et al. (2020) adopted an analog search approach to detect accidents while drilling directionally. The study used two types of data: (i) used case accidents obtained from historical wells, including stuck pipe, drill string wash-out, drilling breaks, lost circulation, sloughing shale, and oil and gas show, and (ii) real-time measurements, such as drilling bit depth, T, WOB, SPP, RS, Q, gas content, and hook-load. In addition, the values of the mean, variance, slope angle, deviation, and relative coefficient of the obtained data were calculated and used as input variables for the gradient boosting (GB) classification model. The precision-recall curve was used to check the performance of the model quality since the problem was an unbalanced classification problem. The model achieved a precision-recall curve of 0.6086. Al-AbdulJabbar et al. (2020a) used an

ANN model with one hidden layer and 26 neurons to predict ROP in real time while drilling a carbonate reservoir horizontally. The model achieved a high R and a low AAPE of 0.921 and 5.12%, respectively. The input variables of the model were mechanical drilling parameters and well logs. The drilling parameters were RS, T, and WOB, while the well logs were gamma-ray (GR), deep resistivity (DR), and formation bulk density (RHOB). In another study, Al-AbdulJabbar et al. (2020b) used an ANN to predict the ROP in real time while drilling an s-shaped profile. The developed model had one hidden layer and 29 neurons. The model predicted the ROP with an RMSE of 6.7% and R of 0.0.92. Alsaihati et al. (2020) used SVM, RF and functional network (FNN) models to estimate the ECD while drilling horizontal wells. The input variables were Q, hook-load, ROP, RS, SPP, WOB, and T. The RF model achieved the best results compared to other models, with a root mean square error (RMSE) of 0.35 and a coefficient of determination (R^2) of 0.95.

3.3.1 Application of AI Related to Lost Circulation Problems

Jeirani and Mohebbi (2006) used an ANN to predict the permeability of a filter cake and the amount of filtrate volume. The input variables were time, pressure drop across the filter cake, and water/NaCl weight percent. The developed ANN achieved a high performance with R^2 of 0.9815 and 0.9433 for the filtrate volume and filter cake permeability, respectively. Moazzeni et al. (2010) developed two individual modular neural networks and a particle swarm optimization algorithm to predict the quantity and the severity of loss of circulation using 32 wells in the Maroun oil field. The input parameters included the current depth of the well related to the ground elevation, the current depth of the well related to sea level, drilled depth, time of drilling, length of open hole, the formation's top depth, the north and east coordinates of the well, hole size, Q, SPP, mud density, solid content percentage, viscosity readings, fluid loss, and the number of mud losses

before the considered day. The first model estimated the quantity of losses with an R of 0.944, while the second model predicted the severity of the losses with an R of 0.982.

Jahanbakhshi et al. (2013) used AI to build two ANN models to estimate the lost circulation in naturally fractured reservoirs. The first developed ANN model did not incorporate the geomechanical parameters, while the second model did. They concluded that the model that considered the geomechanical parameters performed better, with an R^2 of 0.94.

Jahanbakhshi and Keshavarzi (2014) used 265 datasets obtained from daily drilling reports, geological information and the geomechanical properties of 21 wells drilled in one of the Iranian oil fields to compare the performance of SVM and ANN models in predicting the amount of loss of circulation. The developed SVM model with a Gaussian kernel function outperformed the ANN model with an R of 0.9851 and an MSE of 766.98.

Toreifi et al. (2014) used a multi-layer perceptron (MLP) network and a modular neural network (MNN) to predict the amount and the severity of loss of circulation in the Maroun oil field. 1756 data points collected from 38 wells were used to develop the models. The input parameters included the east and north coordinates of the well, the current depth, the formation's tip angle, ROP, formation type, annulus capacity, SPP, hydrostatic pressure, Q, filter cake viscosity, plastic viscosity, and yield point. The MNN outperformed the MLP in predicting the losses quantitatively and qualitatively, with R values of 0.944 and 0.982, respectively. Manshad et al. (2017) used an SVM model and an RBF model to address the lost circulation problem. The SVM was used to estimate the amount of lost circulation, while the RBF model was used to predict the severity of the losses in the Maroun oil field. The input parameters were collected from 30 wells and included the north and east coordinates, the loss volume one day prior to the day of interest, and the loss volume during the two days prior to the day of interest. The SVM predicted

the quantity of the losses with a high level of accuracy, while the RBF predicted the severity of the losses with the same.

Far and Hosseini (2017) used an ANN and a genetic algorithm to estimate the amount of losses while drilling in the Asmari formation in an Iranian oilfield. They used a genetic algorithm to determine the optimum pump flow rate, pump pressure, and mud weight to minimize loss severity. The developed model was able to achieve a prediction with an R^2 of 0.9991. Solomon et al. (2017) used an ANN model to estimate the width of an induced fracture to assess the size of LCM required to seal off the fracture. The model was trained and validated using 30 data points. The model predicted the width of the induced fracture with an R^2 of 0.79. Abbas et al. (2019a) used ANN and SVM models to predict the loss of circulation solution across vertical and deviated wells. The dataset they used had 385 actual wells and 19 input parameters. The developed SVM outperformed the ANN with an R^2 values of 0.97 and 0.95 for training and testing datasets, respectively. In the same year, Abbas et al. (2019b) used ANN and SVM algorithms to predict the likelihood of lost circulation occurrences using the same datasets as in their previous study. The SVM performed better than the ANN. Ahmed et al. (2020) compared the performance of three AI models, which were ANN, ANFIS, and FN, in predicting the loss of circulation zones. The input parameters were Q, SPP, WOB, T, and ROP. The ANN outperformed the other models with an R of 0.99 and an RMSE of 0.05.

CHAPTER 4

OBJECTIVE AND METHODOLOGY

4.1 The Objective

The main objectives of this research are:

- 1- To use and evaluate the ability of different AI and ML techniques in detecting loss occurrence while drilling in real-time based on drilling surface parameters.
- 2- To use and evaluate the performance of different AI and ML techniques in estimating the loss of circulation rate while drilling in real time based on drilling surface parameters.

This includes the calculation of:

- (a) The actual reduction of active pit volume (APV)
- (b) The theoretical reduction of APV.

4.2 The Novelty of the Thesis

This study documents several key contributions as follow:

- 1- It enables drilling crews to immediately detect a small amount of drilling fluid loss and take corrective actions to minimize the economic impact associated with the loss of circulation.
- 2- It aids drilling engineers to design a pre-drill model with the optimum surface drilling parameters, which are learned from offset wells, before drilling a specific section to lessen drilling fluid losses into formations.
- 3- It permits drillers to spend more time on other critical events and ensure a safe workplace at the rig site.

4.3 Research Methods and Materials

4.3.1 Data Acquisition

This study used field data from an intermediate open-hole section of seven vertical wells. The intermediate section consisted of dolomite/limestone formations that caused partial or severe

loss of circulation due to pore pressure depletion and natural fractures. The original dataset was collected from surface real-time transmitter sensors, which were located in the rig site at different positions. The initial dataset consisted of (i) operational surface drilling parameters, which included Q, SPP, WOB, ROP, RS, and T; and (ii) APV.

Initially, the original dataset comprised all the operational activities, including drilling, taking surveys, making new connections, and tripping and running tubulars. Thus, the original dataset was customized by removing all unnecessary operational activities to make it suitable for the analysis.

4.3.2 Data Processing

Noise in a dataset can significantly impact the predictability accuracy of any machine learning model (Gupta and Gupta, 2019). Therefore, it is essential to use an established technique of the industry known as *smoothing* to reveal the underlying trend in the original dataset. An exponential moving average (EMA) technique was applied to the original dataset with a damping factor of 0.9 which is used most often in time-series data (Brown, 1959; Winters, 1960; Holt, 2004). EMA can be applied using Eq. 1.

$$Y_t = \gamma X_{t-1} + (1 - \gamma)Y_{t-1} \quad (1)$$

where,

Y_t = the smoothed observaton of variable a at time (t)

γ = the damping factor, unitless

X_{t-1} = the unsmoothed observation of variable a at time (t-1)

Y_{t-1} = the smoothed observation of variable a at time (t-1).

The outliers that could have affected the accuracy of the model's prediction were removed from the dataset using interquartile range (IQR), also technically called H-spread. The H-spread is a

measure of statistical dispersion that is equal to the difference between the upper quartile (Q_3) and the lower quartile (Q_1). For the H-spread, any value below $Q_1 - 1.5 \times \text{IQR}$ or above $Q_3 + 1.5 \times \text{IQR}$ is considered an outlier. Figure 7 shows the box plots of all the variables in the original datasets before removing the outliers.

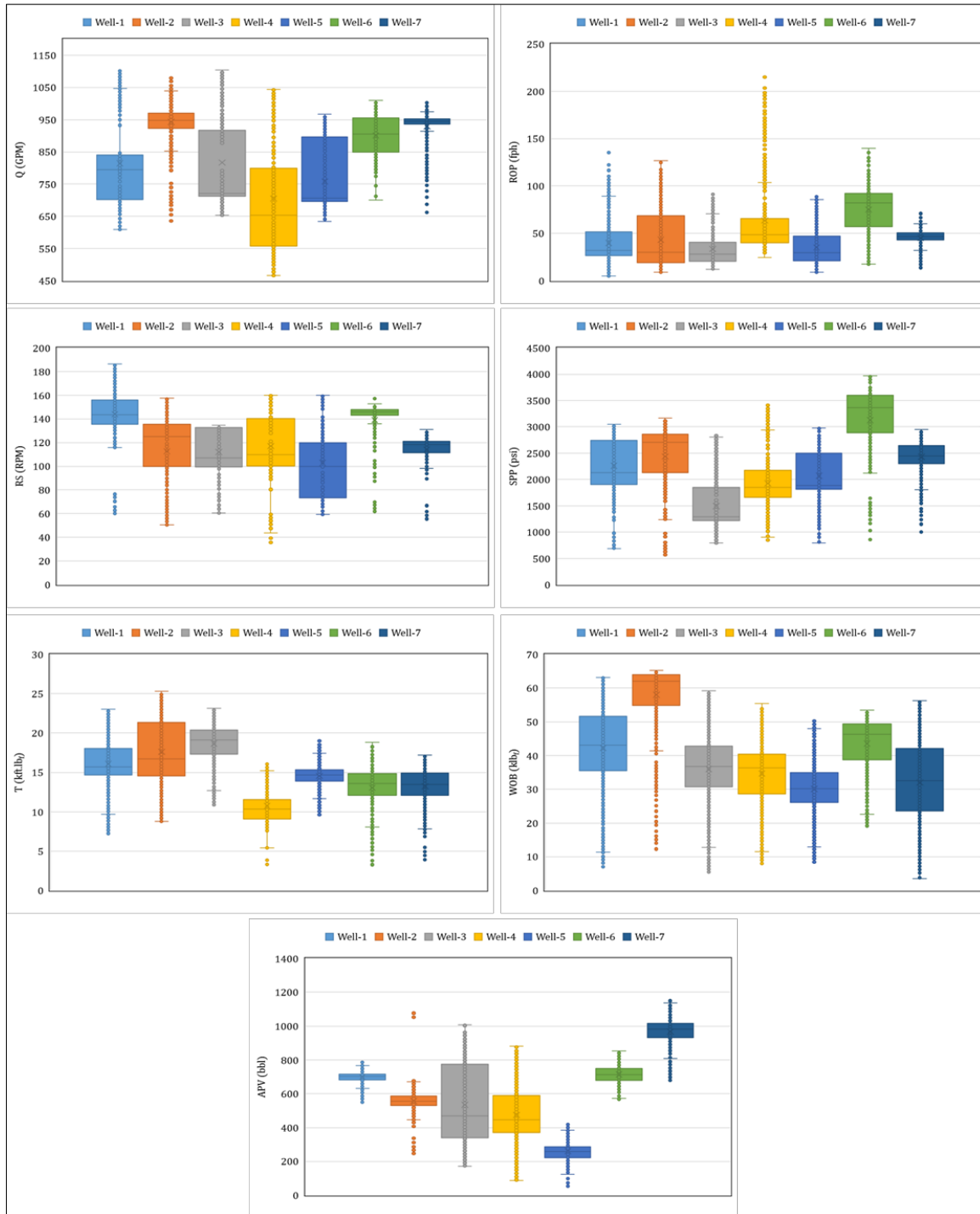


Figure 7: Box plots of all variables indicating the outliers in the original dataset

4.3.3 Pre-Processing the Outputs

Three important quantities were calculated manually to be able to identify the loss of circulation occurrence and estimate the loss rate while drilling for each observation in the original dataset: (i) the actual reduction of the APV, (ii) the theoretical reduction of the APV, and (iii) the difference between the actual and theoretical reduction. These quantities can be calculated using Eq 2,3, and 4.

$$\text{Actual reduction of APV (bbl.)} = \text{APV}_{t-1} - \text{APV}_t \quad (2)$$

$$\text{Theoretical reduction of APV (bbl.)} = \left[\frac{\text{OH}^2 - (\text{OD}^2 - \text{ID}^2)}{1029.4} \times (\Delta D) \right] \quad (3)$$

$$\text{Difference between the actual and theoretical reduction (bbl.)} \quad (4)$$

$$= \text{Actual reduction of APV} - \text{Theoretical reduction of APV}$$

where,

APV_t = the active pit volume at the current time, bbl

APV_{t-1} = the active pit volume at the previous time, bbl

OH = the open-hole size of the drilled section, inch

OD = the outer diameter of the BHA, inch

ID = the inner diameter of the BHA, inch

ΔD = $\text{Depth}_{(t)} - \text{Depth}_{(t-1)}$, ft

Theoretically, if the difference between the actual reduction and theoretical reduction is greater than zero, the data point is labeled as LOSSES “1”, and if the difference is equal to zero, the data point is labeled as NO_LOSSES “0”. Also, if the difference is less than zero, the data point is labeled as NO_LOSSES “0”. This indicates the need for either a treatment for the drilling fluid or

the addition of further mud volume due to the loss. In this study, a threshold of 0.5 was used instead to account for the mud loss over the surface solid control equipment. The loss rate was calculated next, using Eq. 5.

$$\text{Loss rate (bbl./min)} = \frac{\text{Difference between actual and theoretical reduction}}{\Delta T} \quad (5)$$

where,

ΔT = the incremental time between two consecutive data points, min

Table 10 shows a dummy example of how to identify loss of circulation occurrence and estimate the loss rate for a particular observation in a dataset.

Table 10: Dummy example of how to identify loss occurrence and estimate the loss rate.

Time (Min)	Depth (ft)	Q (GPM)	SPP (psi)	WOB (Klbr)	ROP (fph)	RS (RPM)	T (Kft.lbr)	APV (bbl.)	Actual Reduction of APV (bbl.)	Theoretical Reduction of APV (bbl.)	Difference of Actual and Theoretical (bbl.)	Loses (Yes/No)	Lose Rate (bbl./Min)
0	0	###	###	###	###	###	###	600	----	----	----	----	----
1	10	###	###	###	###	###	###	597	3	3*	0	0	0
2	20	###	###	###	###	###	###	592	5	2*	3	1	3
:	:	:	:	:	:	:	:	:	:	:	:	:	:
:	:	:	:	:	:	:	:	:	:	:	:	:	:
100	1000	###	###	###	###	###	###	420	7	7	0	0	0

*These values are assumed, not calculated, in this particular example.

The new variables (i.e., loss occurrence and loss rate) were calculated to be able to accomplish our objectives by building a machine learning classifier for the real-time prediction of the loss occurrence, and a regressor for the real-time prediction of loss rate. Table 11 presents a dummy modified dataset with the new variables of interest that will be used for building machine learning models.

Table 11: Dummy modified dataset with the new variables

Q (GPM)	SPP (Psi)	WOB (klbf)	ROP (fph)	RS (RPM)	T (kft.lbf)	Losses (Yes/No)	Loss Rate (bbl./Min)
###	###	###	###	###	###	0	0
###	###	###	###	###	###	1	2
###	###	###	###	###	###	0	0
###	###	###	###	###	###	0	0

4.3.4 Statistical Analysis

The prepared dataset consisted of seven wells with data points of 13,894. A statistical analysis was performed on the prepared dataset for each well to study the range and the degree of distortion from the normal distribution of each variable in the dataset. Tables 12-18 show the descriptive statistics for Well-1, Well-2, Well-3, Well-4, Well-5, Well-6, and Well-7. Figure 8 shows the number of data points labeled as “Losses” and “No Losses” in each well. Figure 8 shows that Well-3 has the highest number of data points of 1,650 labeled as “Losses”, while Well-6 has the lowest number of data points of 570 labeled as “Losses”. Figure 9 shows a loss rate profile versus the depth for each well.

Table 12: Statistical parameters of Well-1 (2,379 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lbf)	WOB (klbf)	Loss rate (bbl./min)
Min	609.1	4.9	60.3	682.8	7.3	7.1	0.0
Max	1105.7	135.2	186.7	3045.7	23.0	63.1	8.1
Range	496.5	130.3	126.4	2362.9	15.8	56.1	8.1
Mean	814.5	39.9	144.0	2260.4	16.1	42.2	0.5
Standard deviation	143.5	21.4	19.6	472.1	2.8	11.2	1.1
Kurtosis	-0.53	1.45	4.33	-0.30	0.47	0.15	8.68
Skewness	0.95	1.27	-1.32	-0.20	-0.05	-0.66	2.74

Table 13: Statistical parameters of Well-2 (2,117 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lbf)	WOB (klbf)	Loss rate (bbl./min)
Min	635.9	8.9	50.5	566.6	8.8	12.3	0.0
Max	1086.8	126.7	157.5	3161.9	25.3	65.2	8.1
Range	450.9	117.7	106.9	2595.3	16.6	52.9	8.1
Mean	942.8	43.3	112.7	2436.3	17.6	58.0	0.9
Standard deviation	66.5	28.8	27.1	561.9	3.9	8.8	1.3
Kurtosis	2.34	-0.75	-0.55	1.20	-1.14	4.71	4.55
Skewness	-1.08	0.69	-0.68	-1.25	0.16	-2.04	2.06

Table 14: Statistical parameters of Well-3 (2,143 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lbf)	WOB (klbf)	Loss rate (bbl./min)
Min	653.9	12.2	60.5	791.5	10.9	5.4	0.0
Max	1104.4	91.9	134.7	2837.7	23.2	59.3	8.0
Range	450.5	79.8	74.2	2046.2	12.3	53.8	8.0
Mean	816.7	33.7	112.1	1493.4	18.7	36.0	1.7
Standard deviation	154.3	18.4	17.3	479.8	2.4	11.5	1.5
Kurtosis	-0.75	1.35	-0.15	0.32	1.35	0.22	1.25
Skewness	1.01	1.47	-0.30	1.15	-1.03	-0.54	1.01

Table 15: Statistical parameters of Well-4 (1,800 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lbf)	WOB (klbf)	Loss rate (bbl./min)
Min	466.6	24.5	35.7	845.9	3.3	8.0	0.0
Max	1044.1	215.1	159.8	3446.0	16.4	55.4	10.0
Range	577.5	190.6	124.2	2600.1	13.1	47.4	10.0
Mean	705.3	63.7	117.1	1927.6	10.7	34.7	1.6
Standard deviation	169.1	38.3	24.4	509.3	2.2	9.2	1.8
Kurtosis	-0.76	2.11	-0.60	1.11	0.18	-0.26	4.06
Skewness	0.67	1.74	0.42	0.85	0.69	-0.21	1.97

Table 16: Statistical parameters of Well-5 (2,375 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lbf)	WOB (klbf)	Loss rate (bbl./min)
Min	633.7	9.0	59.2	797.4	9.6	8.5	0.0
Max	967.7	90.7	160.0	2980.0	19.2	50.5	12.9
Range	333.9	81.7	100.8	2182.6	9.6	42.0	12.9
Mean	758.0	35.0	102.8	2068.9	14.5	30.1	0.7
Standard deviation	102.6	19.2	26.6	509.2	1.5	8.4	1.4
Kurtosis	-0.94	-0.06	-0.46	-0.77	1.33	0.10	21.21
Skewness	0.89	0.93	0.43	0.05	-0.38	-0.10	4.04

Table 17: Statistical parameters of Well-6 (996 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lbf)	WOB (klbf)	Loss rate (bbl./min)
Min	700.2	17.4	62.0	857.6	3.3	19.2	0.0
Max	1010.3	140.0	157.5	3964.2	18.8	53.5	9.9
Range	310.0	122.5	95.5	3106.7	15.5	34.3	9.9
Mean	900.7	75.1	139.1	3125.9	13.1	43.5	0.9
Standard deviation	60.7	25.8	21.5	645.8	2.6	7.9	1.3
Kurtosis	-0.84	-0.41	6.36	0.88	0.90	0.77	6.00
Skewness	-0.12	-0.58	-2.77	-1.27	-1.05	-1.18	2.07

Table 18: Statistical parameters of Well-7 (2,084 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lbf)	WOB (klbf)	Loss rate (bbl./min)
Min	662.3	13.8	55.6	998.9	3.9	3.5	0.0
Max	1003.1	72.0	130.9	2953.3	17.2	56.3	12.2
Range	340.8	58.2	75.4	1954.4	13.3	52.8	12.2
Mean	929.7	45.2	114.1	2433.3	13.2	32.0	0.8
Standard deviation	48.5	7.4	13.2	317.4	2.1	11.9	1.4
Kurtosis	8.17	3.55	8.08	2.14	0.97	-0.89	9.93
Skewness	-2.83	-1.60	-2.81	-1.15	-0.87	-0.24	2.83

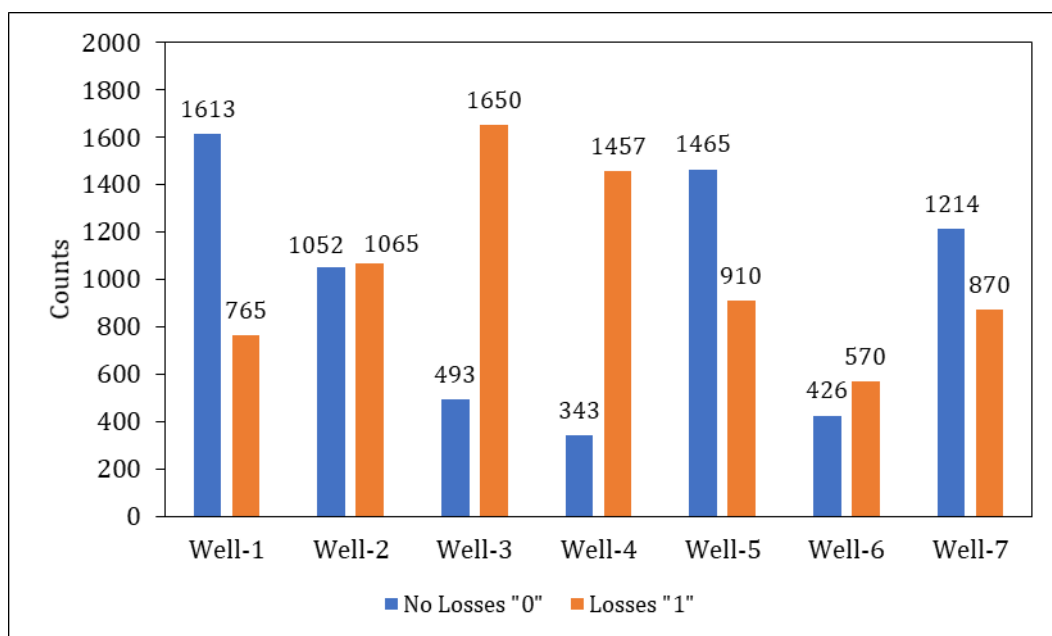


Figure 8: Numbers of data points labeled as “Losses” and “No Losses” in each well

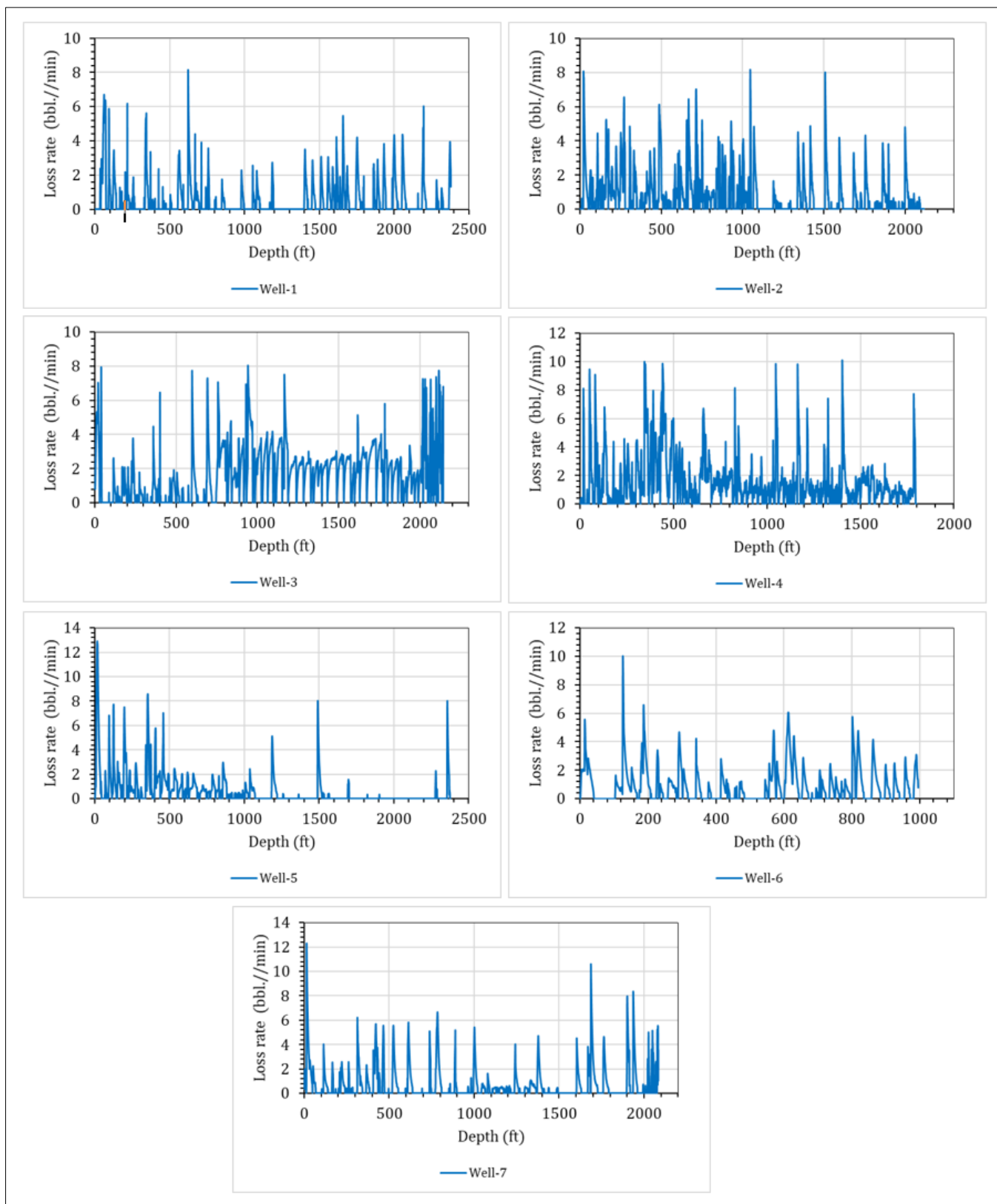


Figure 9: Loss rate profile versus depth for each well

4.3.5 Dataset Partition

In this study, the dataset was split in a ratio of 80:20. Eighty percent of the data was selected for training to ensure that the models captured most of the loss behaviors while drilling. The training set had 11,022 data points, while the testing set had 2,872 data points. The descriptive statistics for the training and testing sets are presented in Tables 19 and 20. Figure 10 shows the number of data points labeled as “Losses” and “No Losses” in the training and testing sets. Figure 10 indicates that there were 4,721 data points labeled as “No Losses” and 6,301 data points labeled as “Losses” in the training set. On the other hand, there were 852 data points labeled as “No Losses” and 2,020 data points labeled as “Losses” in the testing set

Table 19: Statistical parameters of the training set (11,022 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lbf)	WOB (klbf)	Loss rate (bbl./min)
Min	466.9	4.9	35.7	566.6	3.3	3.5	0.0
Max	1105.7	149.9	186.7	3964.2	25.3	65.2	12.9
Range	638.8	145.0	151.0	3397.6	22.1	61.6	12.9
Mean	832.5	44.1	118.7	2184.3	15.1	39.2	1.0
Standard deviation	143.7	24.4	25.9	644.4	3.6	13.6	1.5
Kurtosis	-0.91	1.05	-0.27	-0.53	-0.16	-0.54	6.92
Skewness	-0.11	1.10	-0.28	0.03	0.18	0.00	2.29

Table 20: Statistical parameters of the testing set (2,872 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lbf)	WOB (klbf)	Loss rate (bbl./min)
Min	466.6	5.0	39.4	577.9	3.4	4.6	0.0
Max	1104.6	149.6	186.3	3963.5	25.0	65.1	12.7
Range	638.0	144.6	146.9	3385.6	22.0	60.5	12.7
Mean	832.4	43.4	118.6	2180.3	15.0	39.0	0.9
Standard deviation	142.5	23.8	25.7	643.6	3.6	13.9	1.4
Kurtosis	-0.90	1.22	-0.23	-0.45	-0.16	-0.55	7.92
Skewness	-0.08	1.11	-0.29	0.01	0.17	-0.02	2.38

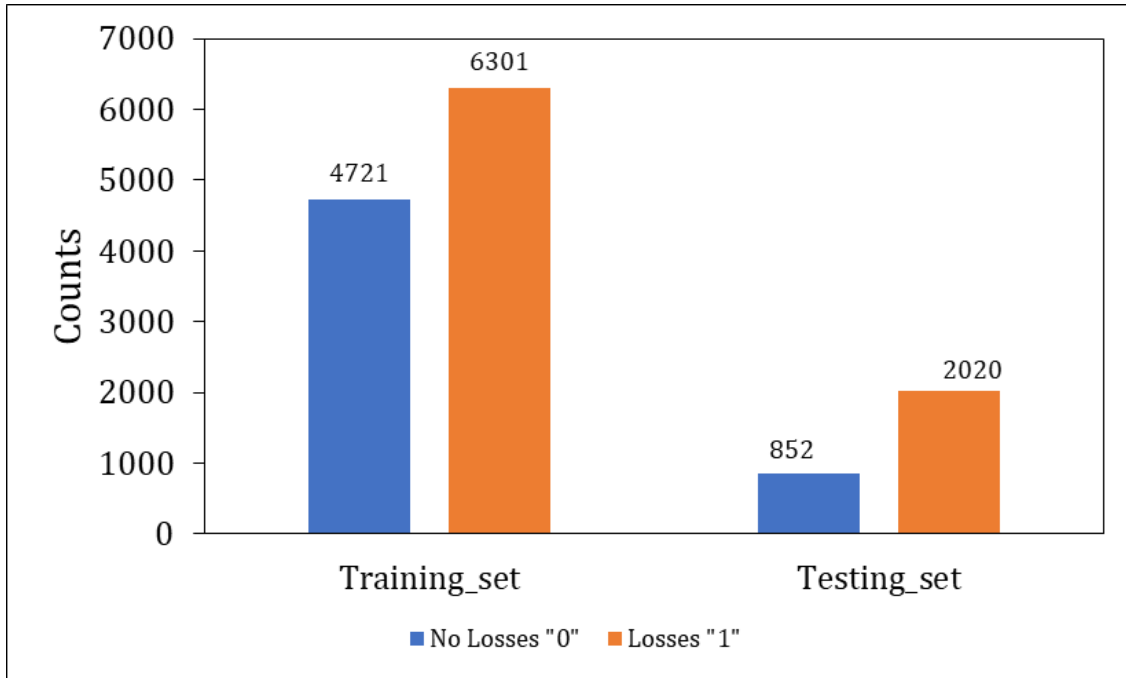


Figure 10: Numbers of data points labeled as “Losses” and “No Losses” in the training and testing sets

4.3.6 Features Importance

Understanding the influence of input variables on output variables is imperative when developing AI and ML models because including more inputs than required can result in the curse of dimensionality and can decrease learning speed and efficiency (Abbas et al., 2019). Mutual information (MI), which is a statistical quantity that measures the amount of information between two variables, was used to study the relationship between the input and output variables. The MI is a dimensionless quantity and it is always greater than or equal to zero. The MI can be thought of as a reduction of uncertainty about one variable given knowledge of another. A high MI value indicates a large reduction in uncertainty, while a low MI value indicates a small reduction in uncertainty; zero MI indicates that the variables are independent. (Batina et al., 2010). The MI of two jointly variables X and Y can be calculated using Eq.5 (Cover and Thomas, 1991).

$$MI(X, Y) = \int_y \int_x P[X = x, Y = y] \cdot \log \left(\frac{P[X = x, Y = y]}{P[X = x] \cdot P[Y = y]} \right) dx dy \quad (5)$$

where,

MI = mutual information

X = random variable

Y = random variable

P(X) = the marginal probability density function of variable X

P(Y) = the marginal probability density function of variable Y

- **Classification Task**

Figure 11 compares the dependency between the input parameters and the binary output variable.

Figure 11 shows that Q, RS, and SPP have MI values of 0.13, 0.14 and 0.11 respectively, while ROP and T have values of MI of 0.03 and 0.04, respectively. On the other hand, WOB has a low value of MI of 0.02.

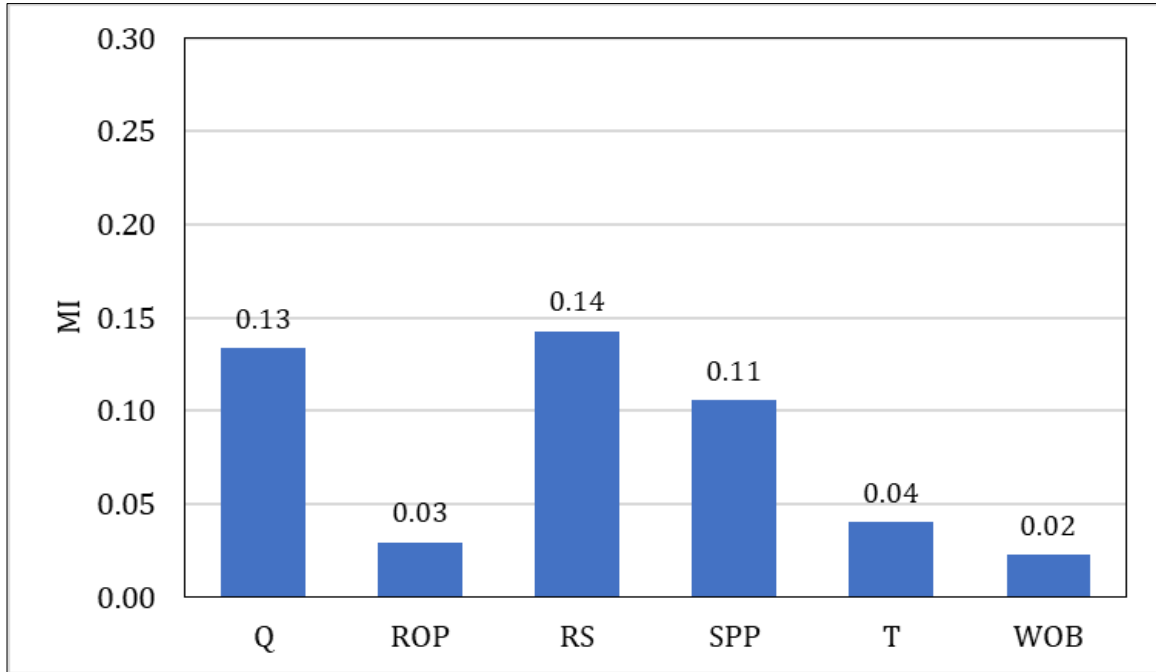


Figure 11: Comparison of the dependency between the input variables and the binary output

- **Regression Task.**

Figure 12 compares the dependency between the input parameters and the continuous output variable, the loss rate. Figure 12 shows that Q, RS, and SPP have high MI values of 1.0, 0.96 and 0.82 respectively, while ROP and T have moderate values of MI of 0.41 and 0.45, respectively. On the other hand, WOB has a low value of MI of 0.31.

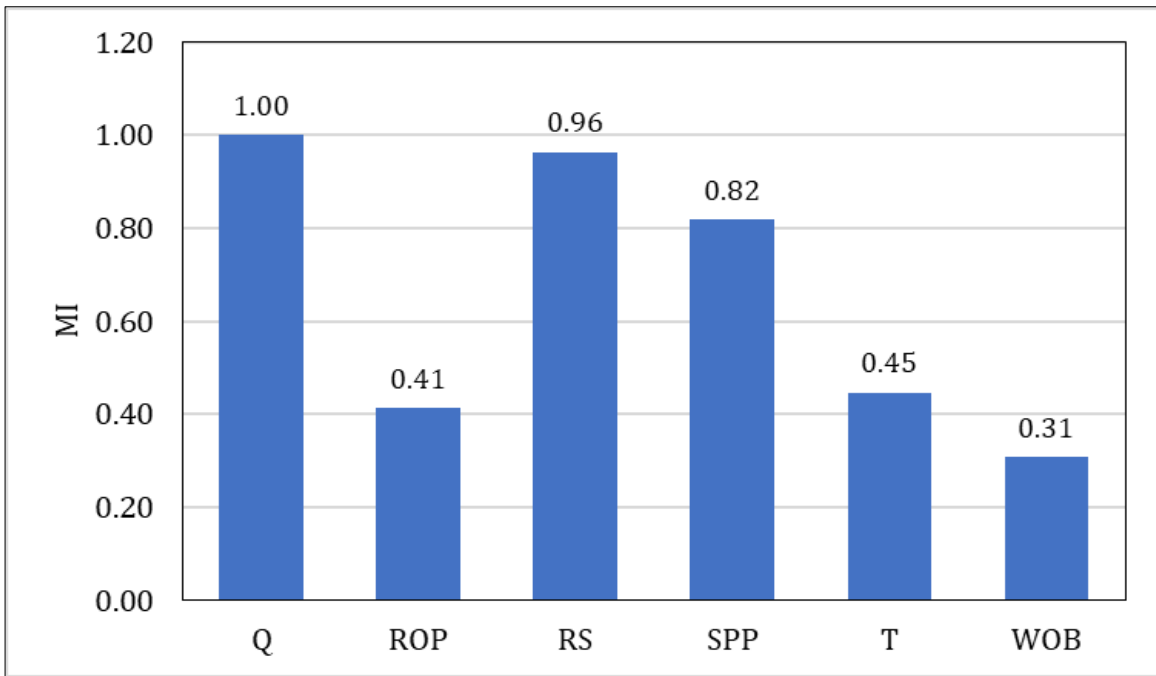


Figure 12: Comparison of the dependency between the input variables and the continuous output, the loss rate

4.3.7 Models Building

- **Classification Task**

Five AI tools were used to build a classification model for the prediction of loss occurrence using mechanical surface parameters, which included Q, ROP, RS, SPP, T, and WOB.

1. **ANN Classifier**

An ANN classifier was built for predicting loss occurrence while drilling using mechanical surface parameters. The optimum number of hidden layers in the ANN architecture was determined by

increasing the number from 1 to 3. Generally, increasing the number of hidden layers improves the accuracy of the model. However, in this case, using more than one hidden layer increased the elapsed time for training the network, especially with the large dataset and, therefore, it was avoided. The weights and biases were initialized using a random function, which generates random values from -1 to 1. The interaction between different optimizers, such as Bayesian regularization backpropagation (TRAINBR) and LM backpropagation (TRAINLM), with the two activation functions, i.e., tan sigmoid (TANSIG) and SoftMax, were evaluated. In addition, a different number of neurons was tuned from 1 to 30 to find their optimum number. Furthermore, the learning rate, which was a hyperparameter (Krzywanski et al., 2018), with a value from 0 to 1 and which is used to control how quickly or slowly the convergence of an error occurs, was tuned to find the optimum number.

2. Logistic Regression

Python's Scikit-Learn® was used to build a logistic regression model for losses occurrence prediction. There are different hyperparameters in a logistic regression model that can be optimized to enhance the predictive power. The inverse regularization parameter C, which is a controllable parameter that retains the strength modification of the regularization by being inversely positioned to the lambda regulator, was tuned using the GridSearchCV algorithm to find the optimum value. The C parameter controls the variance-bias trade-off to perform better on unseen datasets. The penalty is another important parameter, which used for tuning the function by adding an additional penalty term in the error function. Different options of penalty parameter can be used, such as L1, L2, and elastic-net. However, the default option, i.e., L2, was used.

The logistic regression chooses the class that has the largest probability based on a default threshold of 0.5. Thus, if $P(Y=\text{No Losses "0"}) > 0.5$ then that specific data point is classified as

No Losses “0”, while it is classified as Loss “1” if $(Y = \text{Losses “1”}) > 0.5$. Different thresholds were evaluated using GridSearchCV algorithm to find the value that optimizes the model performance.

3. SVM Classifier

Python’s Scikit-Learn® was used to build an SVM classifier for loss occurrence prediction. Different kernel functions (i.e., linear, RBF, polynomial) were applied to map the original nonlinear dataset onto a higher-dimensional space to become separable. Similar to logistic regression, C is an important parameter in an SVM model, used to control the variance-bias trade-off to generalize well on unseen data. The performance of the SVM classifier with different C values using linear and kernel functions was evaluated. In the case of a polynomial kernel function, different degrees from 3 to 10 were assessed. The gamma parameter, which signifies the influence of points either near or far away from the hyperplane, was also tuned using the GridSearchCV algorithm. A low value of gamma means that the influence of the training reaches far away, while a high value means the influence reaches nearby. Two options for gamma in an SVM classifier (i.e., scale or auto) were evaluated.

4. RF Classifier

Python’s Scikit-Learn® was used to build an RF classifier model. The hyperparameters in an RF are either used to enhance the predictive power or to make the model run quicker. The `n_estimators` is a hyperparameter; this is the number of trees that an RF builds before computing the average of predictions. The `n_estimators` was tuned from 1 – 150 using the GridSearchCV algorithm to find the optimal value. A high number of `n_estimators` enhances the performance of the model and makes the prediction more stable, but it slows down the process of computation. `Max_features` is another hyperparameter; this is the number of features to be considered to split a

node in each decision tree. If the max_features is Sqrt, then the number of features to be considered is the square root of the number of input variables in a dataset. If the max_features is Log₂, then the number of features to be considered is the base-2 logarithm of the number of input variables in a dataset. Both max_features types were tried during the construction of the RF to find the optimum performance.

Max_depth is another important hyperparameter; this represents the depth of each tree in a forest. In practice, deep trees can capture more information about the dataset, but they can cause model overfitting. Therefore, the max_depth, in this case, was tuned from 1– 32 using the GridSearchCV algorithm to find the optimum value.

5. K-NN Classifier

Python's Scikit-Learn® was used to build a K-NN classifier. Different combinations of odd numbers of K and distance metrics (i.e., Euclidean and Manhattan) were used to evaluate the performance of the model. Even numbers of K were not used during the model development to avoid having a tie in the samples at the decision boundaries.

- **Regression Task**

Five AI tools were used to build a regression model for the prediction of loss of circulation rate using mechanical surface parameters. These were Q, ROP, RS, SPP, T, and WOB.

1. ANN Regressor

An ANN regressor was built for the real-time prediction of loss of circulation rate while drilling using mechanical surface parameters. The number of the hidden layer was limited to a single layer due to the increase in the elapsed time required to train the neural network. The weights and biases were initialized using a random function that generates random values from -1 and 1. The interaction between different optimizers, such as the Bayesian regularization backpropagation

(TRAINBR) and the LM backpropagation (TRAINLM), with three activation functions, i.e., log sigmoid (LOGSIG), tan sigmoid (TANSIG), and RBF, were evaluated. In addition, different numbers of neurons were evaluated from 1 to 30 to find the optimum number. Furthermore, the learning rate was tuned to find the optimum value.

2. ANFIS Regressor

The ANFIS model was built using a subtractive clustering technique. The subtractive clustering technique was used to cluster the data and create a fuzzy inference system with a minimum number of rules. Different values of the radius of the cluster of 0.2, 0.3, 0.4, and 0.5 were tried, as were various numbers of epochs from 100 to 300, to find the optimum model parameters.

3. SVM Regressor

Python's Scikit-Learn® was used to build an SVM regressor for the prediction of loss of circulation rate in real time. Different kernel functions (i.e., linear, RBF, polynomial) with different C values and gamma options were evaluated during model development. In the case of a polynomial kernel function, different degrees, from 3 to 10, were assessed.

4. RF Regressor

Python's Scikit-Learn® was used to build an RF regressor model for loss of circulation rate prediction. The n_estimators were tuned from 1 – 150 using the GridSearchCV algorithm to find the optimal value. Both max_features types were tried during the construction of the RF to find the optimum performance. The max_depth was tuned from 1– 32 using GridSearchCV to find the optimum value.

5. K-NN Regressor

Python's Scikit-Learn® was used to build a K-NN regressor for the real-time prediction of loss of circulation rate. Several combinations of different K and distance metrics (i.e., Euclidean and

Manhattan) were used to evaluate the performance of the model. Unlike with the K-NN classifier, odd and even numbers of K were used during model development since the output i.e., loss circulation rate, is a continuous variable.

4.3.6 Models Assessment

The evaluation of models is an important component in AI projects which aim to estimate the ability of a developed model to generalize on future unseen datasets. Model evaluation metrics are required to quantitatively measure the performance of a developed model. The selection of evaluation metrics depends on the type of machine learning problem in question, such as classification, regression, clustering, etc.

- **Classification Task**

In a statistical classification, a confusion matrix is a table layout that provides a picture of the developed model performance (Stehman, 1997). In this study, the confusion matrix is a table with two dimensions (actual and predicted), and two sets of classes (Losses and No Losses) in both dimensions. The actual classifications are the columns and the predicted ones are the rows or vice versa (Powers, 2011). The confusion matrix itself is not a performance measure as such, but almost all of the performance metrics are calculated based on the numbers inside it. Table 21 describes a confusion matrix for a classification model in our case.

Table 21: Description of a confusion matrix

Actual classes Predicted classes	No Losses “0”	Losses “1”
	No Losses “0”	Losses “1”
No Losses “0”	True Negative (TN)	False Positive (FP)
Losses “1”	False Negative (FN)	True Positive (TP)

There are four possibilities when a classification model is used to predict the class of a data test:

A. True Negative (TN)

True negative is the case when the actual class of a data point was labeled as No Losses “0” and the model classified it as No Losses “0”.

B. True Positive (TP)

True positive is the case when the actual class of a data point was labeled as Losses “1” and the model classified it as Losses “1”.

C. False Positive (FP)

False positive is the case when the actual class of a data point was labeled as No Losses “0” and the model classified it as Losses “1”.

D. False Negative (FN)

False negative is the case when the actual class of a data point was labeled as Losses “1” and the model classified it as No Losses “0”.

There are important performance metrics for a classification model derived from a confusion matrix:

A. Recall (Sensitivity or True Positive Rate)

The recall is defined as the ratio between the number of positive samples correctly classified as positive to the total number of positive samples. The recall is concerned only with how the positive samples are classified. The mathematical expression of the recall is presented in Eq. 6.

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (6)$$

B. Precision

Precision is calculated as the ratio between the number of positive samples correctly classified as positive to the total number of samples classified as positive either correctly or incorrectly. Precision measures the model's ability to classify a sample as positive. The mathematical expression of precision is presented in Eq. 7.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (7)$$

C. F1-Score

It is preferred to combine recall and precision in a single performance metric to evaluate a classification model. This can be achieved using a harmonic mean called the F1-score. The F1-score can reach a value of 1 when a classifier is at its best and can reach 0 when it is at its worse. It should be noted that, if it is desired to minimize false negatives, recall should be as close as it can be to 1 without precision being very low. On the other hand, if it desired to minimize the false positives, the precision should be close as it can be to 1 without recall being very low. If it is desired to minimize both false negatives and false positives, the F1-score should be close to 1. The F1-score can be calculated using Eq.8.

$$\text{F1 Score} = 2 * \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (8)$$

- **Regression Task**

The models' performance is evaluated using an RMSE and R. The RMSE is one way of quantifying the difference between the values implied by the predicted and actual values. The RMSE values may indicate how well the model output values fit the desired output values, but it is often useful to investigate the model performance by calculating R. The RMSE and R can be calculated as:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2} \quad (9)$$

$$R = \frac{n(\sum_1^n Y_i \hat{Y}_i) - (\sum_1^n Y_i)(\sum_1^n \hat{Y}_i)}{\sqrt{[n \sum_1^n Y_i^2 - (\sum_1^n Y_i)^2] [n \sum_1^n \hat{Y}_i^2 - (\sum_1^n \hat{Y}_i)^2]}} \quad (10)$$

where n is the number of samples in the dataset, Y_i is the actual output, and $\hat{Y}_i$ is the predicted output.

CHAPTER 5

RESULTS AND DISCUSSION

This research aimed to detect the loss of circulation occurrence and predict the amount of loss of circulation in real time. This chapter presents the technical results of the developed AI and ML models.

5.1 Assessment of the Developed Models

- **Classification Task**

- 1- **ANN Classifier**

The performance of the ANN classifier was evaluated by calculating the precision, recall, and F1-scores. Table 22 shows the performance of the ANN classifier in predicting the occurrence of the loss of circulation with two different optimizers, i.e., TRAINBR and TRAINLM, and their optimal number of neurons and learning rate when using an activation function, TANSIG. The analysis shows that the ANN classifier with the optimizer, TRAINBR, had an F1-score of 0.83 and 0.80 in the training set and testing set, respectively. On the other hand, the ANN classifier with the optimizer, TRAINLM, had an F1-score of 0.83 and 0.79 in the training set and testing set, respectively.

Similarly, Table 22 shows the performance of the ANN classifier in predicting the occurrence of loss of circulation with two different optimizers, i.e., TRAINBR and TRAINLM, and their optimal number of neurons and learning rate when using an activation function, SoftMAX. The analysis shows that the ANN classifier with the optimizer, TRAINBR, had an F1-score of 0.75 and 0.50 in the training set and testing set, respectively. On the other hand, the ANN classifier with the optimizer, TRAINLM, had an F1-score of 0.82 and 0.80 in the training set and testing set, respectively. The results presented in Tables 21 and 22 show that the ANN classifier

with TRAINBR as a learning function and TANSIG as an activation function with the number of neurons at 30 had the best results in predicting the loss of circulation occurrence.

Table 21: The performance of the ANN classifier using two different optimizers with the TANSIG activation function and one hidden layer

Training function	NO. Neurons	Learning rate	Training set			Testing set		
			Precision	Recall	F1-Score	Precision	Recall	F1-Score
TRAINBR	*30	0.12	0.84	0.83	0.83	0.81	0.78	0.80
TRAINLM	29		0.83	0.82	0.83	0.80	0.79	0.79

* Best results

Table 22: The performance of the ANN classifier using two different optimizers with the SoftMax activation function and one hidden layer

Training function	NO. Neurons	Learning rate	Training set			Testing set		
			Precision	Recall	F1-Score	Precision	Recall	F1-Score
TRAINBR	30		0.77	0.74	0.75	0.52	0.49	0.50
TRAINLM	29	0.12	0.80	0.84	0.82	0.78	0.82	0.80

2- Logistic Regression

The performance of the logistic regression model with different thresholds from 0.4 to 0.6 is presented in Table 23. Table 23 shows an improvement in the F1-score as the threshold increases. However, after a threshold of 0.5, the F1-score starts decreasing. The model with a threshold of 0.5 achieved its best performance with an F1-score of 0.658 and 0.654 in the training set and testing set, respectively.

Table 23: The performance of the logistic regression model with different thresholds

C	Penalty	Threshold	Training set			Testing set		
			Precision	Recall	F1-Score	Precision	Recall	F1-Score
10	L2	0.4	0.615	0.604	0.583	0.607	0.598	0.577
		0.425	0.624	0.619	0.609	0.625	0.621	0.611
		0.45	0.634	0.633	0.629	0.634	0.633	0.629
		0.475	0.642	0.642	0.640	0.640	0.640	0.638
		*0.5	0.658	0.658	0.658	0.654	0.655	0.654
		0.525	0.657	0.656	0.657	0.648	0.647	0.647

0.55	0.659	0.653	0.652	0.655	0.649	0.649
0.57	0.665	0.655	0.652	0.659	0.648	0.646
0.6	0.669	0.650	0.644	0.662	0.642	0.636

* Best results

3- SVM Classifier

The SVM classifier performance with different parameters (C, gamma, kernel function) was evaluated. Table 24 presents the results of the SVM classifier when RBF was used as a kernel function with different values of C. Table 24 shows that a value of C equal to 1 and a gamma option of “auto” were the best combined model parameters, yielding an F1 score of 0.91 and 0.83 in the training set and testing set respectively when RBF was used as a kernel.

Table 25 shows the results of the SVM classifier when linear was selected as a kernel function. The option of gamma when linear was used had no effect on the SVM classifier. Table 25 shows that the SVM classifier with a linear kernel function had its highest F1 score of 0.60 in both training and testing sets when the C value was 0.01.

Table 26 presents the results of the SVM classifier with a polynomial kernel function. Table 26 shows that, as the degree of the polynomial increased above two, the F1-score decreased. The SVM classifier had its highest F1-score of 0.61 in both training and testing sets when a polynomial of degree 2 was used as a kernel function. The results show that the SVM classifier with an RBF kernel function outperformed other SVM classifiers with different kernel functions, with a high F1-score of 0.91 and 0.83 in the training set and testing set, respectively.

Table 24: The performance of the SVM classifier with the RBF kernel function

		Training set			Testing set		
C	Gamma	Precision	Recall	F1-score	Precision	Recall	F1-score
0.001	Auto	0.89	0.89	0.89	0.81	0.81	0.81
0.01		0.89	0.87	0.87	0.80	0.78	0.77
0.1		0.83	0.76	0.74	0.73	0.67	0.64

*1		0.91	0.91	0.91	0.83	0.83	0.83
10		0.80	0.66	0.62	0.69	0.58	0.52
100		0.79	0.62	0.57	0.68	0.55	0.47
1000		0.77	0.55	0.46	0.66	0.52	0.41
0.001		0.33	0.42	0.34	0.33	0.42	0.35
0.01		0.33	0.42	0.34	0.33	0.42	0.35
0.1		0.57	0.56	0.52	0.56	0.56	0.51
1	Scale	0.30	0.41	0.33	0.31	0.41	0.33
10		0.46	0.51	0.39	0.59	0.54	0.48
100		0.33	0.42	0.34	0.34	0.42	0.35
1000		0.57	0.56	0.52	0.57	0.56	0.51

* Best results

Table 25: The performance of the SVM classifier with the linear kernel function

		Training set			Testing set		
C	Gamma	Precision	Recall	F1-score	Precision	Recall	F1-score
0.001		0.54	0.54	0.54	0.53	0.53	0.53
0.01		0.60	0.60	0.60	0.61	0.60	0.60
0.1	Auto/	0.39	0.40	0.39	0.38	0.39	0.38
1	Scale	0.50	0.51	0.48	0.52	0.52	0.49
10		0.39	0.39	0.39	0.38	0.38	0.38
100		0.39	0.39	0.39	0.38	0.38	0.38
1000		0.39	0.39	0.39	0.38	0.38	0.38

Table 26: The performance of the SVM classifier with the polynomial kernel function

Training set				Testing set		
Degree	Precision	Recall	F1-score	Precision	Recall	F1-score
2	0.60	0.60	0.60	0.61	0.61	0.61
3	0.60	0.59	0.59	0.61	0.60	0.59
4	0.59	0.58	0.56	0.60	0.58	0.56
5	0.57	0.57	0.56	0.57	0.57	0.56
6	0.42	0.42	0.40	0.57	0.57	0.56
7	0.27	0.52	0.36	0.27	0.52	0.36
8	0.27	0.52	0.36	0.27	0.52	0.36
9	0.27	0.52	0.36	0.27	0.52	0.36
10	0.27	0.52	0.36	0.27	0.52	0.36

4- RF Classifier

Table 27 shows the performance of the RF classifier with `n_estimators` of 100 and different `max_depth` values in predicting the loss of circulation occurrence. Table 26 shows the performance of the RF classifier improves as the `max_depth` increases. However, increasing the `max_depth` more than it is supposed to be can lead to a model overfitting. Thus, a `max_depth` of 16 was selected as an optimum value since there was no significant improvement when the `max_depth` went beyond it. It is worth mentioning that different options of `max_features` had no effect on the performance of the model. The optimum RF classifier predicted the loss of circulation occurrence with an F1-score of 0.989 and 0.910 in the training set and testing set, respectively.

Table 27: The performance of the RF classifier with different `max_depth` values

Max_depth	Training set			Testing set		
	Precision	Recall	F1-score	Precision	Recall	F1-score
1	0.803	0.465	0.465	0.786	0.448	0.571
2	0.806	0.476	0.476	0.790	0.458	0.580
3	0.745	0.661	0.661	0.730	0.637	0.680
4	0.746	0.676	0.676	0.735	0.664	0.698
5	0.772	0.693	0.693	0.756	0.677	0.714
6	0.803	0.724	0.724	0.781	0.700	0.738
7	0.826	0.759	0.759	0.803	0.729	0.764
8	0.837	0.798	0.798	0.812	0.758	0.784
9	0.863	0.841	0.841	0.825	0.787	0.806
10	0.892	0.879	0.879	0.839	0.822	0.830
11	0.915	0.897	0.897	0.856	0.834	0.845
12	0.932	0.922	0.922	0.862	0.861	0.862
13	0.953	0.954	0.954	0.877	0.892	0.884
14	0.969	0.969	0.969	0.887	0.901	0.894
15	0.982	0.984	0.984	0.896	0.916	0.906
*16	0.989	0.989	0.989	0.901	0.920	0.910
17	0.995	0.992	0.992	0.902	0.924	0.913
18	0.998	0.995	0.995	0.905	0.928	0.916
19	0.999	0.997	0.997	0.908	0.929	0.918
20	1.000	0.998	0.998	0.908	0.929	0.918

* Best results

4- K-NN Classifier

Table 28 shows the performance of the K-NN classifier with different K values when Manhattan was used as a distance metric. Table 27 shows that the K-NN model with a K value of 3 achieved its best performance with an F1-score of 0.955 and 0.908 in the training set and testing set respectively when Manhattan was used as a metric distance. Similarly, Table 29 shows the performance of the K-NN classifier with different values of K and the Euclidian distance was slightly better than when Manhattan was used as a metric distance. Table 27 shows that the K-NN model with a K value of 3 achieved its best performance with an F1-score of 0.955 and 0.912 in the training set and testing set respectively when Euclidian was used as a metric distance.

Table 28: The performance of the K-NN classifier with Manhattan distance

K	Distance	Training set			Testing set		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
3	Manhattan	0.946	0.964	0.955	0.895	0.922	0.908
5		0.924	0.952	0.937	0.879	0.910	0.894
7		0.905	0.939	0.921	0.861	0.901	0.880
9		0.890	0.927	0.908	0.850	0.886	0.868
11		0.874	0.921	0.897	0.836	0.879	0.857
13		0.862	0.911	0.886	0.824	0.873	0.848
15		0.851	0.901	0.875	0.817	0.858	0.837
17		0.846	0.892	0.868	0.815	0.848	0.831
19		0.835	0.885	0.859	0.807	0.826	0.816

Table 29: The performance of the K-NN classifier with Euclidian distance

K	Distance	Training set			Testing set		
		Precision	Recall	F1-Score	Precision	Recall	F1-Score
*3	Euclidian	0.946	0.964	0.955	0.900	0.924	0.912
5		0.924	0.952	0.937	0.882	0.916	0.899
7		0.905	0.939	0.921	0.869	0.909	0.889
9		0.890	0.927	0.908	0.855	0.889	0.872
11		0.874	0.921	0.897	0.842	0.890	0.865
13		0.862	0.911	0.886	0.829	0.879	0.853
15		0.851	0.901	0.875	0.822	0.867	0.844
17		0.846	0.892	0.868	0.819	0.857	0.838
19		0.835	0.885	0.859	0.812	0.844	0.827

* Best results

- **Regression Task**

1- ANN Regressor

The performance of the ANN model was evaluated by calculating the RMSE and R. Table 30 shows the performance of the ANN model in predicting the loss of circulation rate with three different optimizers, i.e., TRAINBR and TRAINLM, and with the optimal number of neurons and learning rate when using an activation function, TANSIG. The analysis shows that the RMSE reached its lowest value of 1.12 and 1.14 with 30 neurons and one hidden layer in the training set and testing set respectively when using the optimizer TRAINBR to predict the loss of circulation rate. Table 31 shows that the performance of the ANN model in predicting the loss of circulation rate with TRAINBR and TRAINLM when using an activation function LOGSIG was poor.

Table 32 shows the performance of the ANN model in predicting the loss of circulation rate with TRAINBR and TRAINLM, and their optimal number of neurons and learning rate when using an activation function, RBF. The RMSE reached its lowest value of 1.12 and 1.15 with 29 neurons and one hidden layer in the training set and testing set respectively when using the optimizer TRAINBR to predict the loss of circulation rate. Figure 13(a) and 13(b) show the cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum ANN model.

Table 30: The performance of the ANN regressor using two different optimizers with TANSIG activation function and one hidden layer

Training function	NO. Neurons	Learning rate	Training set		Testing set	
			RMSE	R	RMSE	R
TRAINBR	*30		1.12	0.67	1.14	0.61
TRAINLM	30	0.12	1.17	0.62	1.18	0.58

* Best results

Table 31: The performance of the ANN regressor using two different optimizers with LOGSIG activation function and one hidden layer

Training function	NO. Neurons	Learning rate	Training set		Testing set	
			RMSE	R	RMSE	R
TRAINBR	14	0.12	5.66	0.06	5.69	0.10
TRAINLM	11		5.66	0.05	5.69	0.08

Table 32: The performance of the ANN regressor using two different optimizers with RBF activation function and one hidden layer

Training function	NO. Neurons	Learning rate	Training set		Testing set	
			RMSE	R	RMSE	R
TRAINBR	29	0.12	1.12	0.66	1.15	0.61
TRAINLM	30		1.15	0.64	1.16	0.60

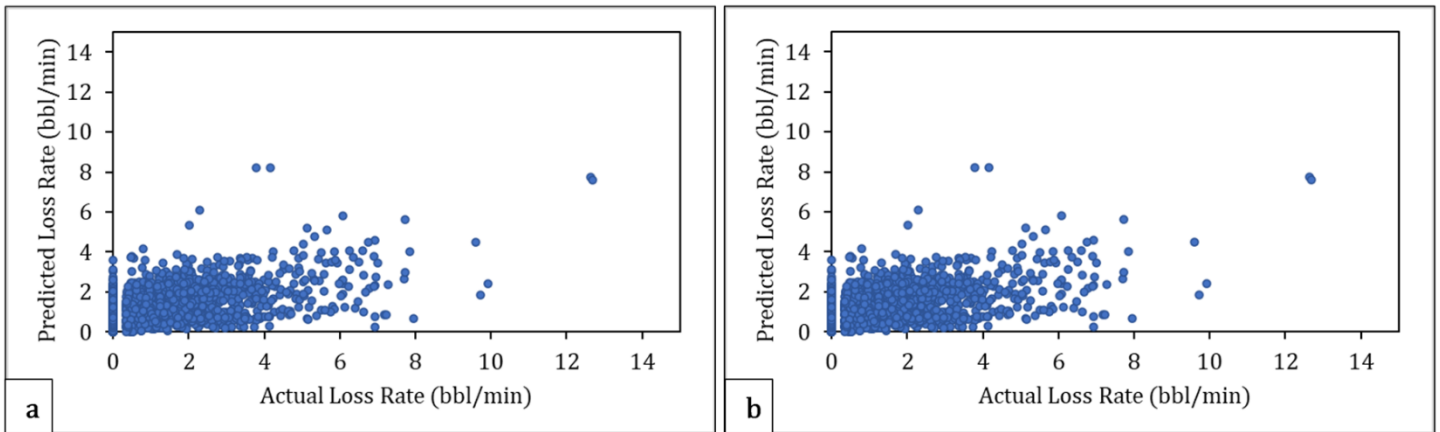


Figure 13: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum ANN regressor (a) training set and (b) testing set

2- ANFIS Regressor

The performance of the ANFIS model with different cluster radiuses and a different number of epochs is presented in Table 33. The results of the sensitivity analysis showed that the cluster radius of 0.2 and 300 epochs achieved the optimum results with an RMSE of 1.14 and an R of 0.64 in the training set, while the RMSE and R were 1.17 and 0.58 respectively in the testing set. Figure

14(a) and 14(b) show cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum ANFIS model.

Table 33: The performance of the ANFIS in predicting the loss of circulation rate with different cluster radius and epochs

Radius	Epochs	Training set		Testing set	
		RMSE	R	RMSE	R
0.2	100	1.17	0.62	1.19	0.56
0.3		1.25	0.54	1.26	0.49
0.4		1.31	0.47	1.30	0.43
0.5		1.33	0.45	1.32	0.41
0.2	200	1.16	0.63	1.18	0.58
0.3		1.20	0.59	1.24	0.52
0.4		1.27	0.52	1.28	0.46
0.5		1.30	0.48	1.30	0.44
*0.2	300	1.14	0.64	1.17	0.58
0.3		1.17	0.62	1.21	0.55
0.4		1.25	0.54	1.26	0.49
0.5		1.29	0.49	1.29	0.44

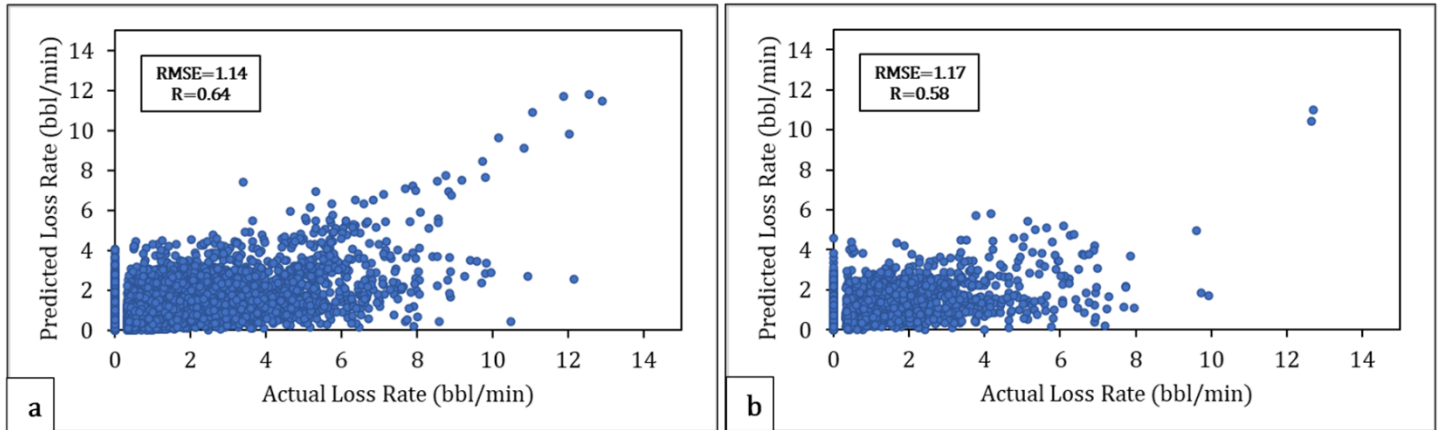


Figure 14: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum ANFIS regressor (a) training set, and (b) testing set

3. SVM Regressor

The SVM regressor performance with different parameters (C, gamma, kernel function) was evaluated. Table 34 shows the results of the SVM regressor when RBF was used as a kernel function with different values of C. Table 34 shows that a value of C equal to 1 and a gamma

option of “auto” are the best-combined model’s parameters that had an RMSE and an R of 0.91 and 0.79 in the training set. On the other hand, the RMSE and R were 1.22 and 0.53 respectively in the case of the testing set. The model with a value of C of 10 produced a high R in the training set of 0.97 but a low value of 0.65 in the testing set which indicate model overfit.

The results showed that the SVM regressor with linear and polynomial kernel functions did not perform well, and therefore were not presented here. Figure 15(a) and 15(b) show cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum SVM model.

Table 34: The performance of the SVM regressor with the RBF kernel function

C	Gamma	Training set		Testing set	
		RMSE	R	RMSE	R
0.001	Auto	1.62	0.43	1.56	0.42
0.01		1.61	0.42	1.56	0.41
0.1		1.50	0.12	1.49	0.27
*1		0.91	0.79	1.22	0.53
10		0.14	0.97	1.10	0.65
100		0.10	0.98	1.11	0.64
1000		0.10	0.98	1.11	0.63
0.001	Scale	1.55	0.29	1.49	0.27
0.01		1.46	0.18	1.42	0.18
0.1		1.45	0.22	1.41	0.21
1		1.44	0.25	1.40	0.23
10		1.42	0.29	1.39	0.26
100		1.41	0.31	1.39	0.27
1000		1.42	0.31	1.39	0.25

* Best results

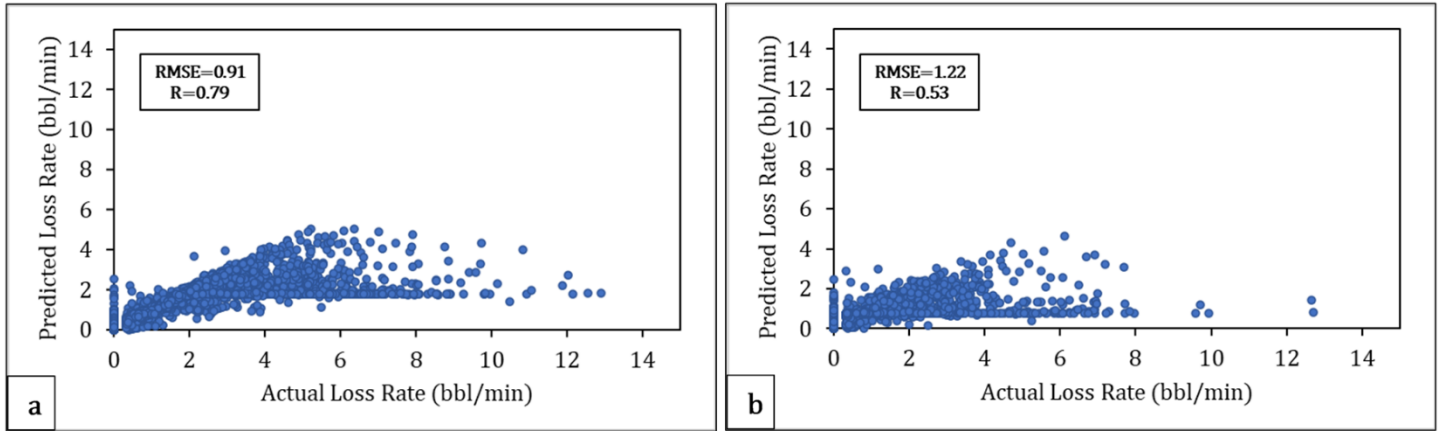


Figure 15: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum SVM regressor (a) training set, and (b) testing set

4. RF Regressor

Table 35 shows the performance of the RF regressor with different max_depth values in predicting the loss of circulation rate. Table 35 shows the performance of the RF regressor improves as the max_depth increases. The max_depth of 24 was selected as an optimum value since there was no significant improvement when the max_depth went beyond it. It is worth mentioning that different options of max_features had no effect on the performance of the model. The optimum RF regressor predicted the loss of circulation rate with an RMSE of 0.26 and an R of 0.99 in the training set, while the RMSE and R were 0.60 and 0.92 respectively in the testing set. Figure 16(a) and 16(b) show cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum RF model.

Table 35: The performance of the RF regressor with different Max_depth

Max_Depth	Training		Testing	
	RMSE	R	RMSE	R
1	1.40	0.39	1.37	0.36
2	1.36	0.44	1.33	0.41
3	1.31	0.49	1.30	0.45
4	1.26	0.55	1.26	0.49
5	1.21	0.60	1.22	0.54
6	1.15	0.65	1.18	0.59

7	1.09	0.70	1.13	0.63
8	1.03	0.74	1.09	0.67
9	0.96	0.78	1.04	0.71
10	0.88	0.83	0.98	0.75
11	0.81	0.86	0.93	0.78
12	0.75	0.88	0.87	0.81
13	0.67	0.91	0.82	0.84
14	0.58	0.94	0.78	0.86
15	0.54	0.95	0.74	0.87
16	0.46	0.96	0.71	0.88
17	0.42	0.97	0.68	0.89
18	0.37	0.98	0.66	0.90
19	0.34	0.98	0.64	0.90
20	0.31	0.98	0.63	0.91
21	0.29	0.99	0.62	0.91
22	0.28	0.99	0.61	0.91
23	0.27	0.99	0.61	0.91
*24	0.26	0.99	0.60	0.92
25	0.26	0.99	0.60	0.92
27	0.26	0.99	0.60	0.91
30	0.25	0.99	0.60	0.92
26	0.25	0.99	0.60	0.92
34	0.25	0.99	0.60	0.91
29	0.25	0.99	0.60	0.91
31	0.25	0.99	0.60	0.92
32	0.25	0.99	0.60	0.91
33	0.25	0.99	0.60	0.91
28	0.25	0.99	0.59	0.92

*Best results

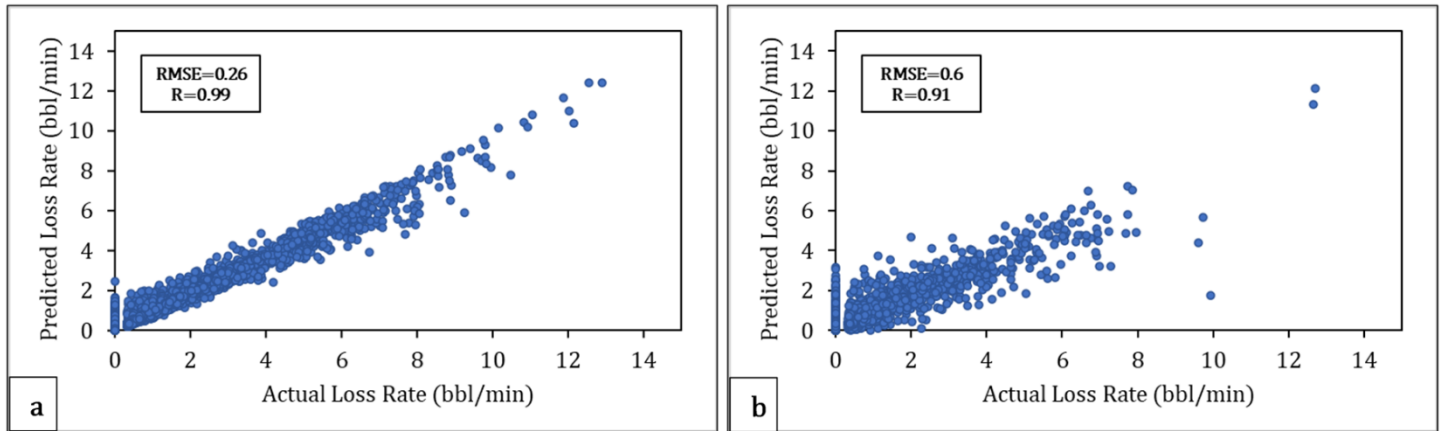


Figure 16: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum RF regressor (a) training set, and (b) testing set

5. K-NN Regressor

Table 36 shows the performance of the K-NN regressor with different K values when Manhattan was used as a distance metric. Table 36 shows that the K-NN model with a K value of 2 achieved its best performance with an RMSE of 0.35 and an R of 0.97 in the training set, while the RMSE and R were 0.69 and 0.94, respectively. Similarly, Table 37 shows the performance of the K-NN model with different values of K when Euclidian was used as a distance metric. Table 37 shows that the K-NN model with a K value of 2 achieved its best performance with an RMSE of 0.37 and an R of 0.97 in the training set, while the RMSE and R were 0.73 and 0.87, respectively. The results show that the K-NN model with Manhattan distance slightly outperformed the K-NN model with Euclidian distance. Figure 17(a) and 17(b) show cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum K-NN model.

Table 36: The performance of the K-NN regressor with Manhattan distance

K	Distance	Training		Testing	
		RMSE	R	RMSE	R
*2	Manhattan	0.35	0.97	0.69	0.94
3		0.44	0.95	0.73	0.88
4		0.52	0.94	0.75	0.87
5		0.57	0.92	0.78	0.85
6		0.62	0.91	0.83	0.83
7		0.66	0.90	0.86	0.82
8		0.70	0.88	0.89	0.80
9		0.74	0.87	0.92	0.79
10		0.77	0.86	0.95	0.77
11		0.80	0.84	0.97	0.76
12		0.82	0.83	1.00	0.75
13		0.85	0.82	1.01	0.74
14		0.88	0.81	1.03	0.72
15		0.90	0.80	1.05	0.71
16		0.92	0.79	1.07	0.70
17		0.93	0.78	1.08	0.69
18		0.95	0.77	1.10	0.68
19		0.96	0.76	1.11	0.67
20		0.98	0.76	1.12	0.66

* Best results

Table 37: The performance of the K-NN regressor with Euclidian distance

K	Distance	Training		Testing	
		RMSE	R	RMSE	R
2	Euclidian	0.37	0.97	0.73	0.88
3		0.47	0.95	0.75	0.87
4		0.54	0.93	0.78	0.86
5		0.61	0.91	0.81	0.84
6		0.65	0.90	0.85	0.82
7		0.69	0.89	0.89	0.80
8		0.73	0.87	0.91	0.79
9		0.77	0.86	0.94	0.78
10		0.80	0.84	0.97	0.76
11		0.83	0.83	0.99	0.75
12		0.85	0.82	1.01	0.74
13		0.87	0.81	1.03	0.72
14		0.89	0.80	1.05	0.71
15		0.91	0.79	1.07	0.70
16		0.93	0.78	1.08	0.69
17		0.95	0.77	1.10	0.68
18		0.96	0.76	1.11	0.67
19		0.98	0.76	1.12	0.66
20		0.99	0.75	1.13	0.65

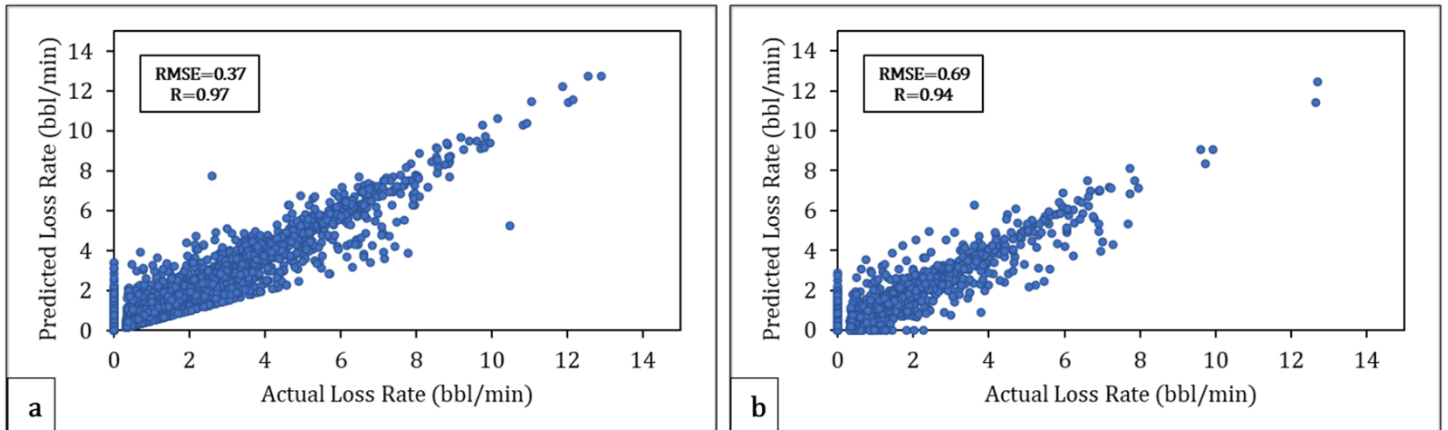


Figure 17: Cross-plots of the actual loss of circulation rate versus the predicted loss of circulation rate of the optimum K-NN regressor (a) training set, and (b) testing set

5.2 Predictability Comparison of the Developed Models Using Well-8.

Well-8, with more than 1,123 unseen data points, was used to compare the capability of the base with the developed models in predicting the loss of circulation occurrence and rate in real time.

The compatibility of the input parameters in Well-8 was checked to ensure they were in the same range as the dataset which was used to train the models. The descriptive statistics for the dataset of Well-8 is presented in Table 38. Figure 18 shows the number of data points labeled as “Losses” and “No Losses” in Well-8. Figure 18 indicates that there were 569 data points labeled as “No Losses” and 554 data points labeled as “Losses” in the training set.

Table 38: Statistical parameters of Well-8 (1,123 data points)

Statistical parameters	Q (GPM)	ROP (fph)	RS (RPM)	SPP (psi)	T (kft.lb _f)	WOB (klb _f)	Loss rate (bbl./min)
Min	584.9	9.7	68.7	1345.4	3.4	20.4	0.00
Max	988.4	93.0	151.2	3523.4	21.1	55.0	2.79
Range	403.5	83.3	82.5	2177.9	17.7	34.6	2.79
Mean	889.3	27.4	128.4	2953.5	12.9	41.1	0.15
Standard deviation	88.9	14.0	17.7	521.1	2.9	6.6	0.39
Kurtosis	0.253	7.127	1.292	-0.253	-0.01	0.020	16.386
Skewness	-0.939	2.334	-0.669	-0.948	0.39	-0.473	3.757

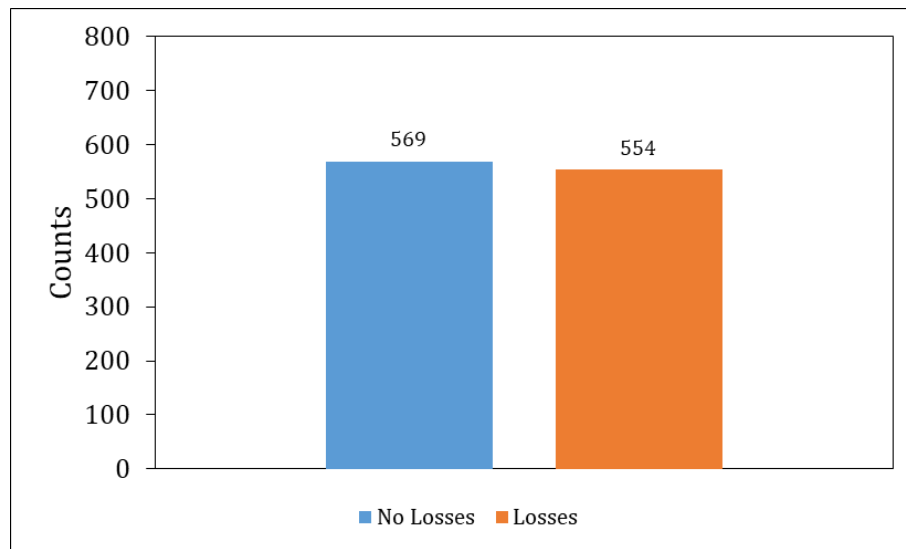


Figure 18: Numbers of data points labeled as “Losses” and “No Losses” in Well-8

- **Classification Task**

Figure 19 compares the performance of the developed models in predicting the occurrence of losses in Well-8. Figure 19 shows that the K-NN classifier outperformed the other models with an

F1-score of 0.80. The K-NN performed consistently in terms of precision and recall, with 0.80 and 0.81, respectively. The RF classifier did not perform well and had a low F1-score of 0.43. The RF classifier had a high precision of 0.69 and a low recall of 0.31. This means that the RF classifier missed some of the “Losses” observations (i.e., a high FN), but those predicted as positive were indeed positive (i.e., a low FP). Similarly, the ANN classifier had a high precision of 0.52 and a low recall of 0.31. The ANN classifier had a high precision of 0.52 and a low recall of 0.31.

The SVM classifier was the second-best model in terms of F1-score with 0.45, but this was still considered a low F1-score. The SVM classifier had a low precision of 0.45 and a high recall of 0.55. This means that most of the “Losses” observations were correctly recognized (i.e., a low FN) but there were some FP observations. On the other hand, the logistic regression model had a poor performance, with an F1-score of 0.12. The logistic regression had an extremely high precision value of 0.85 and a very low recall of 0.06, which indicates that the model missed a lot of the “Losses” observations (i.e., a high FN). The results showed that the K-NN was the best classifier with a consistent performance.

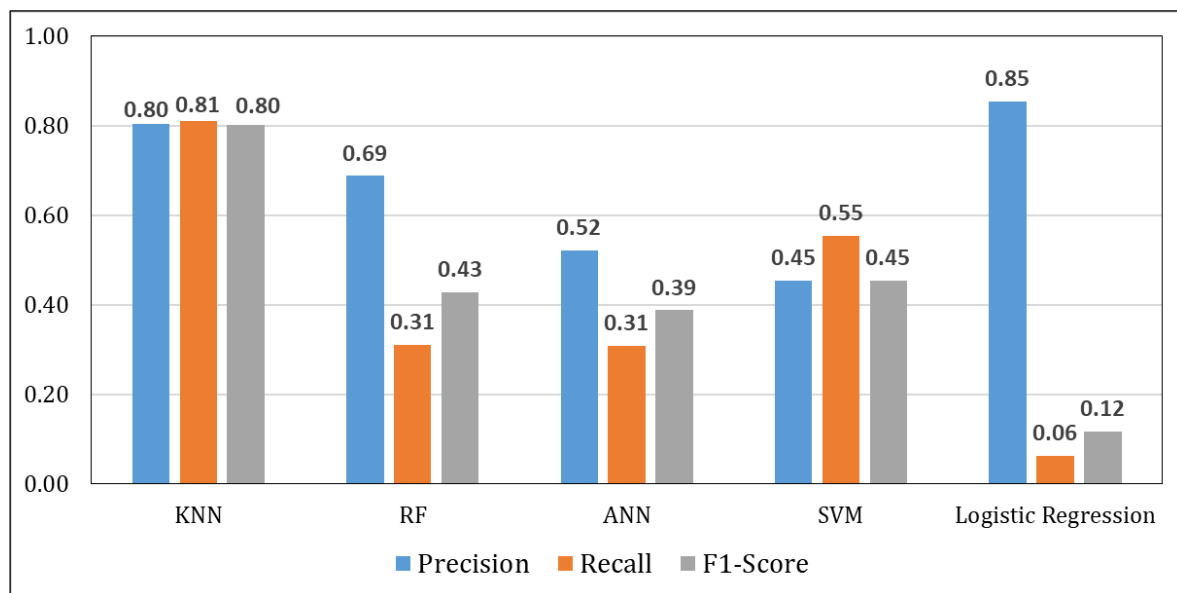


Figure 19: The performance of the developed classifiers used in Well-8

- **Regression Task**

Figure 20 shows the performance of the developed models in the prediction of the loss of circulation rate in real time. Figure 20 shows that the K-NN regressor outperformed the other models with a small RMSE of 0.17 and a high R of 0.90. The SVM had a relatively small RMSE of 0.41 but an extremely low value of R of 0.14. The ANFIS and ANN had high RMSE values of 2.24 and 2.23 with very low R values of 0.05 and 0.10, respectively. The RF, on the other hand, had a slightly better value of R of 0.16 compared to the ANN, ANFIS, and SVM models, but it is still considered to be an extremely low value of R.

Figure 21 shows the actual and predicted loss of circulation rate in Well-8 using the developed models versus the adjusted depth. The adjusted depth is used to hide the actual well depth. These results show that the K-NN's performance was very satisfactory, whereas the ANN, ANFIS, RF, and SVM models were not able to accurately predict the loss of circulation rate.

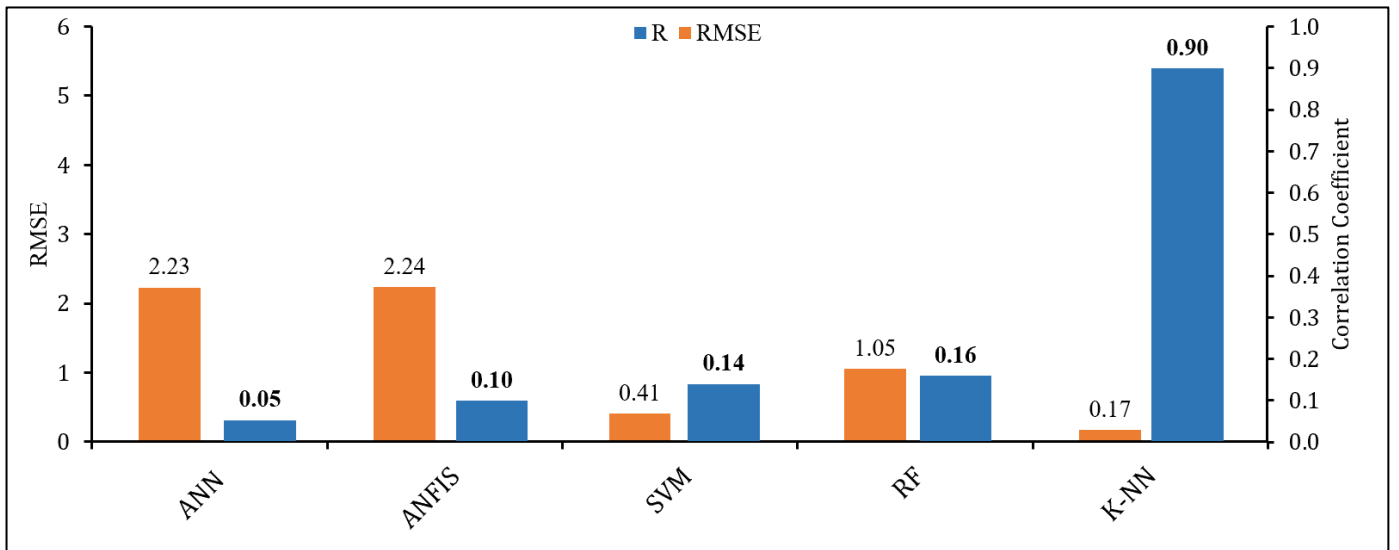


Figure 20: Comparison of the prediction accuracy of ANN, ANFIS, SVM, RF, and K-NN models in predicting loss of circulation rate of Well-8 (1,123 data points)

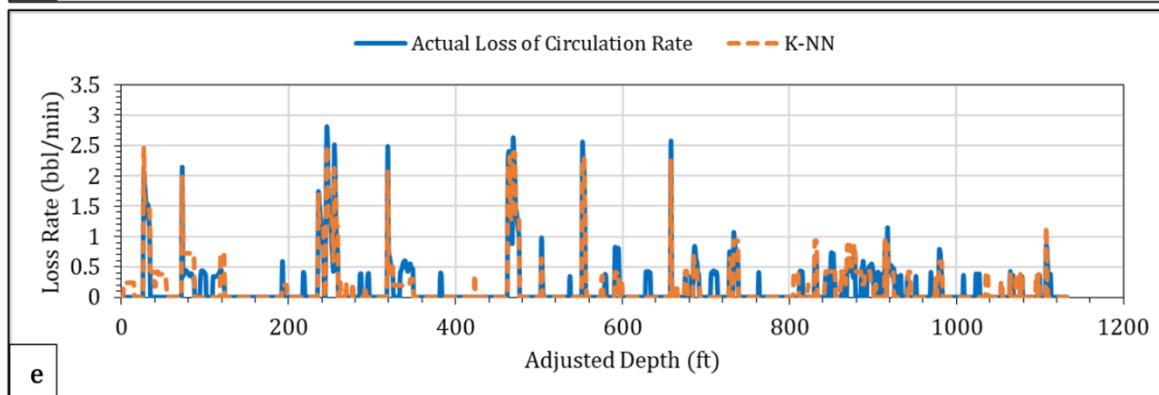
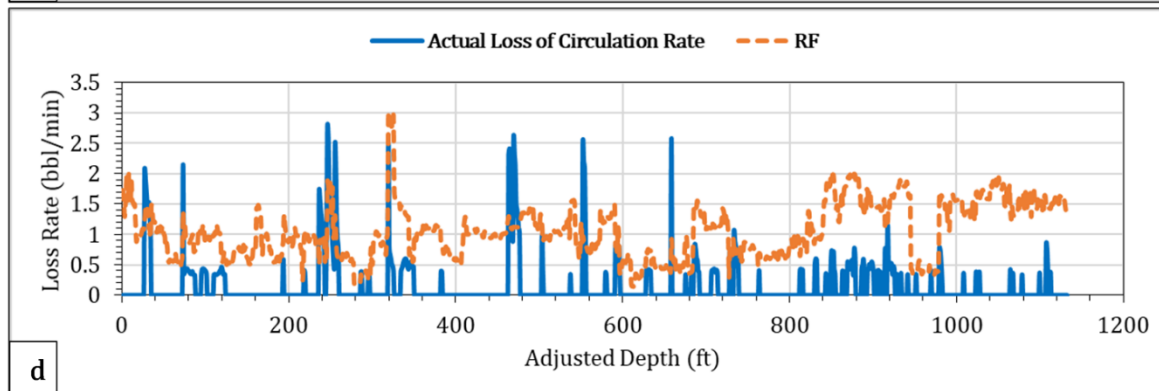
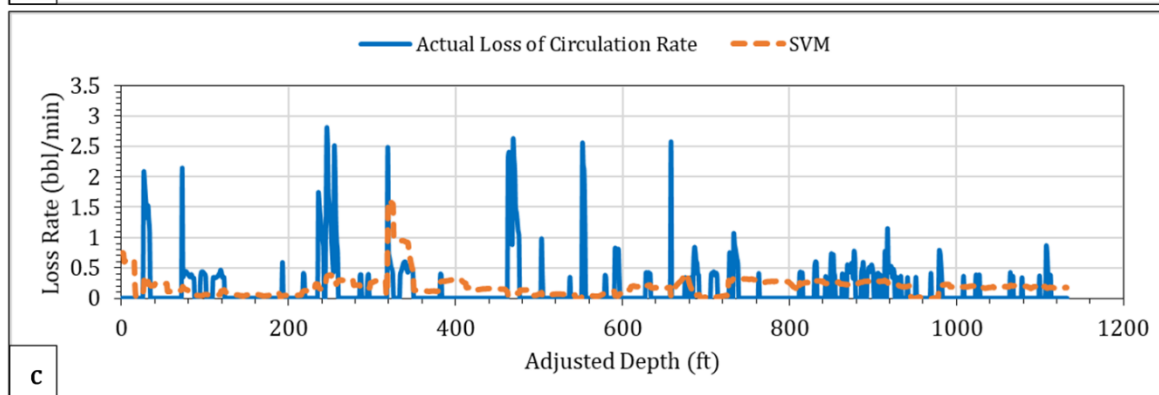
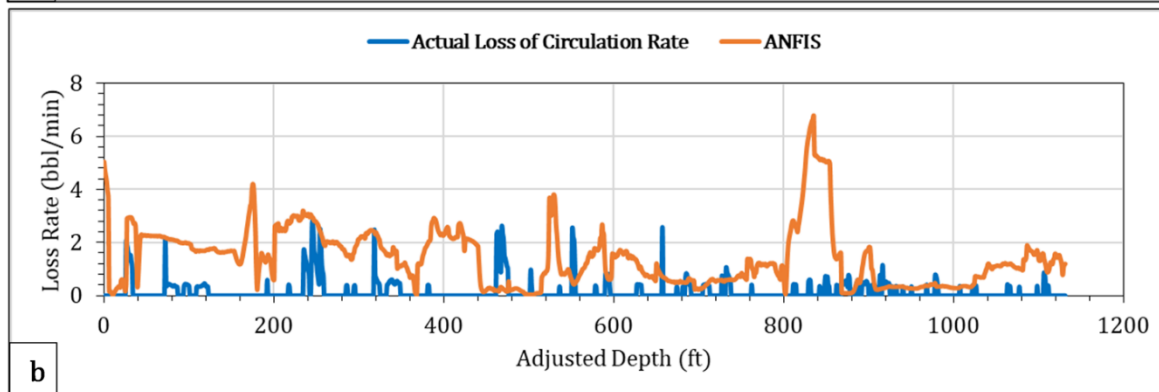
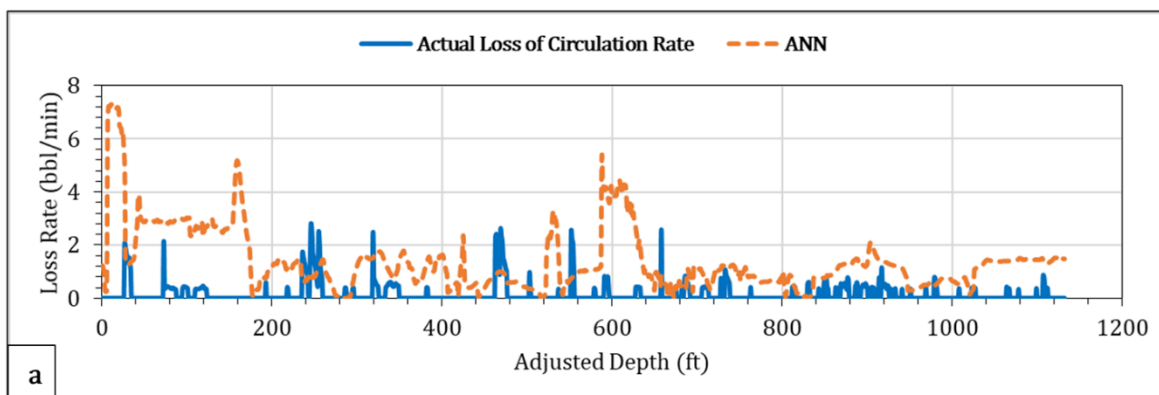


Figure 21: The predicted and actual loss of circulation rate while drilling for Well-8 (1,123 unseen data points) using (a) ANN; (b) ANFIS; (c) SVM; (d) RF; and (e) K-NN

CHAPTER 6

CONCLUSIONS AND LIMITATIONS

Modern drilling involves several interconnecting operational activities. Therefore, acquiring real-time insightful information about drilling operation is of prime importance for safety and efficiency. This research aimed to evaluate the ability of different AI and ML techniques in detecting loss occurrence and predicting the loss of circulation rate in real time based on drilling surface parameters, including Q, SPP, WOB, ROP, RS, and T. To achieve that, actual field data of seven wells were used to build five intelligent models. Well-8, with unseen data points amounting to 1,123, was used to compare the performance of the models. The classifiers were compared based on the established performance metrics. The following can be concluded based on the obtained results:

- The K-NN classifier achieved a high F1-score in detecting loss of circulation occurrence, compared to the other developed models, of 0.912 in the testing set, while the RF was the second-best classifier with almost the same F1-score of 0.910.
- The SVM with an RBF kernel function achieved an F1-score of 0.83, while the ANN classifier with a training function, TRAINBR, and an activation function, TANSIG, had an F1-score of 0.80 in predicting the loss of circulation occurrence in the testing set.
- The logistic regression model was the least accurate classifier in detecting loss of circulation occurrence, with an F1-score of 0.654 in the testing set.
- The K-NN classifier outperformed the other models in detecting the loss of circulation occurrences in Well-8 with an F1-score of 0.80.

- The K-NN and RF regressors predicted the loss of circulation rate with R values of 0.94 and 0.92 respectively, while the RMSEs were 0.69 and 0.60 respectively in the testing set.
- The ANN with a training function, TRAINBR, and an activation function, TANSIG, predicted the loss of circulation with an R of 0.61 and an RMSE of 1.14 in the testing set, while the R and RMSE were 0.58 and 1.17 respectively in the case of ANFIS model.
- The SVM model was the least accurate model with an R of 0.53 and an RMSE of 1.22 in the testing set.
- The K-NN predicted the loss of circulation rate in Well-8 with an R of 0.90 and an RMSE of 0.17, while the other models did not perform well.

There are some limitations associated with the data-driven models used in this study that can be summarized as follow:

- The dataset was collected from specific hole section and a range of input parameters, as discussed in 4.3.3. Therefore, the models would need to be retrained if a well is to be drilled with different well profiles and mechanical drilling parameters.
- Data-driven models are extremely dependent on data quality. Often, sensors are exposed to harsh environmental conditions, such as mechanical shocks, temperature changes, humidity, etc. Therefore, it is essential to establish a recalibration cycle as inaccurate data can mislead the drilling crew.

References

1. Alkinani, H.H., Al-Hameedi, A., Flori, R., Norman, S., Hilgedick, S., Alsaba, M. Updated Classification of Lost Circulation Treatments and Materials with an Integrated Analysis and their Application. Presented at the SPE Western Regional Meeting, Garden Grove, California, USA. 22-26 April 2018. SPE-190118-MS. 15– 16 April. <https://doi.org/10.2118/190118-MS>
2. Howard, G., Scott, P. (1951). An Analysis and the Control of Lost Circulation. *Journal of Petroleum Technology*, 3(06), 171-182. <https://doi.org/10.2118/951171-G>.
3. Miranda, C.R., Oliveira, J.L., Cavalcante, G.M.S., d’Almeida, A.R., Pereira, R.F.L., Santos, R.L.L., Surmas, R. Materials for Controlling Severe Lost Circulation—Laboratory Evaluation. Presented at SPE Latin America and Caribbean Petroleum Engineering Conference, Buenos Aires, Argentina, 17–19 May 2017. SPE-185582-MS. <https://doi.org/10.2118/185582-MS>.
4. Lavrov, A. *Lost Circulation Mechanisms and Solutions*, 1st ed.; Gulf Professional Publishing: Amsterdam, The Netherlands, 2016. ISBN: 9780128039410.
5. Ramasamy, J., Amanullah, M. Novel Fibrous Lost Circulation Materials Derived from Deceased Date Tree Waste. Presented at SPE Kingdom of Saudi Arabia Annual Technical Symposium and Exhibition, Dammam, Saudi Arabia, 24–27 April 2017. SPE-187989-MS. <https://doi.org/10.2118/187989-MS>
6. Kumar, A.; Savari, S.; Jamison, D.E.; Whitfill, D.L. Lost Circulation Control and Wellbore Strengthening: Looking Beyond Particle Size Distribution. Presented at AADE National Technical Conference and Exhibition, Houston, TX, USA, 12–14 April 2011. AADE-11-NTCE-21.
7. Valverde, E.; Goodwin, A. Radio Frequency Identification (RFID)-Enabled Circulation Sub Precisely Spots Loss Circulation Material in Critical Interval. Presented at SPE Annual Technical Conference and Exhibition, Houston, TX, USA, 28–30 September 2015. SPE-174950-MS. <https://doi.org/10.4043/26970-MS>
8. White, R.J. Lost-circulation Materials and their Evaluation. 1956. Presented at Drilling and Production Practice, New York, NY, USA, 1 January. API-56-352.
9. Jain, B.; Khattak, M.A.; Mesa, A.M.; Al Kalbani, S.; Meyer, A.; Aghbari, S.; Al-Salti, A., Hennette, B., Khaldi, M., Al-Yaqoubi, A., et al. Successful Implementation of Engineered Fiber-

Based Loss Circulation Control Solution to Effectively Cure Losses While Drilling, Cementing and Work over Operations in Oman. Presented at the SPE Annual Technical Conference and Exhibition, Society of Petroleum Engineers, New Orleans, LA, USA, 30 September–2 October 2013. SPE-166529-MS. <https://doi.org/10.2118/166529-MS>.

10. Alberty, M. W. and McLean, M. R. 2004. A Physical Model for Stress Cages. Presented at the SPE Annual Technical Conference and Exhibition, Houston, USA, 26-29 September. SPE-90493-MS. <https://doi.org/10.2118/90493-MS>.

11. Dupriest, F. E. 2005. Fracture Closure Stress (FCS) and Lost Returns Practices. Presented at the SPE/IADC Drilling Conference, Amsterdam, Netherlands, 23-25 February. SPE-92192-MS. <https://doi.org/10.2118/92192-MS>.

12. Ghalambor, A., Salehi, S., Shahri, M. P., Karimi, M. Integrated Workflow for Lost Circulation Prediction. 2014. Presented at the SPE International Symposium and Exhibition on Formation Damage Control, Society of Petroleum Engineers, Lafayette, Louisiana, USA, 26–28 February. SPE-168123-MS. <https://doi.org/10.2118/168123-MS>.

13. Sweatman, R. E., Kessler, C. W., Hillier, J. M. New Solutions to Remedy Lost Circulation, Crossflows, and Underground Blowouts. Presented at SPE/IADC Drilling Conference, Amsterdam, Netherlands, 4-6 March 1997. SPE-37671-MS. <https://doi.org/10.2118/95895-MS>.

14. Nayberg, T. M. and Petty, B. R. 1986. Laboratory Study of Lost Circulation Materials for use in Both Oil-base and Water-base Drilling Muds. IADC/SPE 14723, IADC/SPE Drilling Conference, Dallas, USA, 10-12 February.

15. Nelson, E.B., Guillot, D. Well Cementing, 2nd ed.; Schlumberger: Sugar Land, TX, USA, 2006. ISBN 0978853008.

16. Marinescu, P., Oswald, R.J, Vlasceanu, P. Uniquely Characteristics Mixed-Metal Oxide (MMO) Fluid Cure Lost Circulation While Meeting European Environmental Regulations. Presented at Asia Pacific Oil and Gas Conference and Exhibition, Jakarta, Indonesia. 30 October –1 November 2007. SPE-110341-MS. <https://doi.org/10.2118/110341-MS>.

17. Chevron Phillips Chemical Company. 2014. Lost Circulation Guide. <http://www.cpchem.com/bl/drilling/en-us/Documents/LostCirculationGuide.pdf>. Accessed 26 January 2021.

18. Messenger, J. Lost Circulation, PennWell Publishing Company, 1981. ISBN-13: 9780878141753.

19. Lake, L., Fanchi, J., Mitchell, R., Arnold, K., Clegg, J., Holstein, E., & Warner, H. (2006). Petroleum Engineering Handbook. [Richardson, TX.]: Society of Petroleum Engineers. ISBN: 1555631142.
20. Ferron, D.J., Smiley, B.E., Reneau, W.P., Ledbetter, S.B., Stephens, M.L., Murray, D., Fidan, E., Babadagli, T., and Kuru, E. 2004. Use of Cement As Lost Circulation Material Field Case Studies. Presented at the IADC/SPE Asia Pacific Drilling Technology Conference and Exhibition, Kuala Lumpur, Malaysia, 13-15 September. SPE-88005-MS.
21. Beda, G., and Carugo, C. 2001. January 1. Use of Mud Microloss Analysis While Drilling to Improve the Formation Evaluation in Fractured Reservoir. Presented at the SPE Annual Technical Conference and Exhibition held in New Orleans, Louisiana, 30 September–3 October. SPE-71737-MS. <https://doi.org/10.2118/71737-MS>.
22. Rehm, B., Schubert, J., Haghshenas, A., Paknejad, A.S., Hughes J., editors. Managed pressure drilling. Houston (TX): Gulf Publishing Company; 2008.
23. Wang, H., Towler, B.F., Soliman, M.Y. 2007. Fractured Wellbore Stress Analysis: Sealing Cracks to Strengthen a Wellbore. Presented at the SPE/IADC Drilling Conference, Amsterdam, The Netherlands, 20-22 February. SPE-104947-MS. <https://doi.org/10.2118/104947-MS>
24. Le'colier E, Herzhaft B, Ne'au L, Quillien B, Kieffer J. 2005. Development of a nanocomposite gel for lost circulation treatment. Presented at the SPE European Formation Damage Conference held in Scheveningen, The Netherlands, 25-27 May. SPE- 94686-MS. <https://doi.org/10.2118/94686-MS>.
25. Abdollahi, J., Carlsen, I.M., Mjaaland, S., Skalle, P., Rafiei, A., Zarei, S. 2004. Underbalanced drilling as a tool for optimized drilling and completion contingency in fractured carbonate reservoirs. Presented at the SPE/IADC Underbalanced Technology Conference and Exhibition held in Houston, Texas, USA, 11-12 October. SPE-91579-MS. <https://doi.org/10.2118/91579-MS>.
26. Johnson, L., Murphy, P., Arsanious, K. 2000. Improvements in Lost-Circulation Control During Drilling Using Shear-Sensitive Fluids. Presented at the 2000 Petroleum Society's Canadian International Petroleum Conference held in Calgary, Canada, 4-8 June. PETSOC-2000-062-P.
27. Chilingar, G., and Vorabutr, P.1983. Drilling and drilling fluids. Amsterdam: Elsevier. ISBN: 978-0444421777

28. Sanfillippo, F., Brignoli, M., Santarelli, F. J., and Bezzola, C. 1997. Characterization of Conductive Fractures While Drilling. Presented at the 1997 SPE European Formation Damage Conference held in Hague, The Netherlands, 2-3 June. SPE-38177-MS. <https://doi.org/10.2118/38177-MS>.
29. Shafer, D.M., Loeppke, G.E., Glowka, D.A. and Scott, D.D. 1992. An Evaluation of Flowmeters for the Detection of Kick and Lost Circulation During Drilling. presented at the IADC/SPE Drilling Conference, 18–21 February. SPE-23935-MS. <https://doi.org/10.2118/23935-MS>.
30. Bratton, T. R., Rezmer-Cooper, I. M., Desroches, J., Gille, Y.-E., Li, Q., McFayden, M. 2001. How to diagnose drilling-induced fractures in wells drilled with oil-based muds with real-time resistivity and pressure measurements. Presented at SPE/IADC Drilling Conference, Amsterdam, Netherlands, 27 February–1 March. SPE-67742-MS. <https://doi.org/10.2118/67742-MS>.
31. Withfill, D. L. 2008. Lost Circulation Material Selection, Particle Size Distribution and Fracture Modeling with Fracture Simulation Software. Presented at the IADC/SPE Asia Pacific Drilling Technology Conference and Exhibition, Jakarta, Indonesia, 25-27 August. SPE-115039-MS. <https://doi.org/10.2118/115039-MS>.
32. Salehi, S. and Nygaard, R. 2012. Numerical Modeling of Induced Fracture Propagation: A Novel Approach for Lost Circulation Materials (LCM) Design in Borehole Strengthening Applications of Deep Offshore Drilling. Presented at the SPE Annual Technical Conference and Exhibition, San Antonio, USA, 8-10 October. SPE-135155-MS. <https://doi.org/10.2118/135155-MS>.
33. Salehi, S. and Nygaard, R. 2011. Evaluation of New Drilling Approach for Widening Operational Window: Implications for Wellbore Strengthening. Presented at the SPE Production and Operations Symposium, Oklahoma City, USA, 27-29 March. SPE-140753-MS. <https://doi.org/10.2118/140753-MS>.
34. Fuh, G.F., Morita, N., Boyd, P.A., and McGoffin, S.J. 1992. A New Approach to Preventing Lost Circulation While Drilling. Presented at the SPE Annual Technical Conference and Exhibition, Washington, DC, 4–7 October. SPE-24599-MS. <https://doi.org/10.2118/24599-MS>.

35. Aston, M.S., Alberty, M.W., McLean, M.R., de Jong, H.J., Armagost, K. 2004. Drilling Fluids for Wellbore Strengthening. Presented at the IADC/SPE Drilling Conference, Dallas, 2–4 March. SPE-87130-MS. <https://doi.org/10.2118/87130-MS>.
36. Deeg, W. and Wang, H. 2004. Changing Borehole Geometry and Lost Circulation Control. GulfRock, Houston, 7–9 June. ARMA/NARMS 04-577.
37. Aadnoy, B., and Belayneh, M. 2004. Elasto-plastic fracturing model for wellbore stability using non-penetrating fluids. Journal of Petroleum Science and Engineering, 45(3-4), 179-192. <https://doi.org/10.1016/j.petrol.2004.07.006>.
38. Deeg, W.F.J. 1999. High Propagation Pressures in Transverse Hydraulic Fractures: Cause, Effect, and Remediation. Presented at the SPE Annual Technical Conference and Exhibition, Houston, 3–6 October. SPE- 56598-MS. <https://doi.org/10.2118/56598-MS>.
39. Wang, H., Sweatman, R. E., Engelman, R. E., Deeg, W. F. J. and Whitfill, D. L. 2005. The Key to Successfully Applying today's Lost Circulation Solutions. Presented at the SPE Annual Technical Conference and Exhibition, Dallas, Texas, USA, 9-12 October. SPE-95895-MS. <https://doi.org/10.2118/95895-MS>.
40. Canson, B. E. 1985. Lost Circulation Treatment for Naturally Fractured, Vugular, or Cavernous Formations. Presented at the SPE/IADC Drilling Conference, New Orleans, USA, 5-8 March. SPE-13440-MS. <https://doi.org/10.2118/13440-MS>.
41. Schlumberger. 2014. Oil Field Glossary, <http://www.glossary.oilfield.slb.com> (Accessed 24 January, 2021).
42. VanOort, E., Friedheim, J., Pierce, T., Lee, J. 2009. Avoiding Losses in Depleted and Weak Zones by Constantly Strengthening Wellbores. Presented at the SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, USA, 4-7 October. SPE-125093-PA. <https://doi.org/10.2118/125093-PA>.
43. Sweatman, R. E., and Scoggins, W. C. 1988. Acid-Soluble Magnesia Cement: New Applications in Completion and Workover Operations. Presented at the SPE Annual Technical Conference and Exhibition, Houston, USA, 2-5 October. SPE-18031-PA. <https://doi.org/10.2118/18031-PA>.
44. Contreras, O., Hareland G., Husein, M., Nygaard, R., Alsaba, M. 2014. Application of In-House Prepared Nanoparticles as Filtration Control Additive to Reduce Formation Damage.

Presented at the SPE International Symposium and Exhibition on Formation Damage, Lafayette, Louisiana, USA, 26-28 February. SPE-168116-MS. <https://doi.org/10.2118/168116-MS>.

45. Hoelscher, K. P., De Stefano, G., Riley, M, Young, S. 2012. Application of Nanotechnology in Drilling Fluids. Presented at the SPE International Oilfield Nanotechnology Conference and Exhibition, Noordwijk, Netherlands, 12-14 June. SPE-157031-MS. <https://doi.org/10.2118/157031-MS>.

46. Nwaoji, C.O., Hareland, G., Husein, M., Nygaard, R., Zakaria, M.F. 2013. Wellbore Strengthening-Nano-Particle Drilling Fluid Experimental Design Using Hydraulic Fracture Apparatus. Presented at the SPE/IADC Drilling Conference and Exhibition, Amsterdam, the Netherlands, 5 – 7 March. SPE-163434-MS. <https://doi.org/10.2118/163434-MS>.

47. Friedheim, J. E., Young, S., De Stefano, G. L, J., and Guo, Q. 2012. Nanotechnology for Oilfield Applications – Hype or Reality? Presented at the SPE International Oilfield Nanotechnology Conference and Exhibition, Noordwijk, Netherlands, 12-14 June. SPE-157032-MS. <https://doi.org/10.2118/157032-MS>.

48. Espin, D., Chavez, J.C. and Ranson, A. 2003. Method for consolidation of sand formations using nanoparticles. United State patent 6513592, Issued on 4th of February.

49. Espin, D., Chavez, J.C. and Jimenez, M.A. 2003. Method for treating drilling fluid using nanoparticles. United States Patent 6579832, Issued on 17th of June.

50. Soroush, H., Sampaio, J.H.B. 2006. Investigation into Strengthening Methods for Stabilizing Wellbores in Fractured Formations. presented at the SPE Annual Technical Conference and Exhibition, 24–27 September. SPE-101802-MS. <https://doi.org/10.2118/101802-MS>.

51. Morita, N., Black, A. D., and Fuh, G. F. 1990. Theory of Lost Circulation Pressure. Presented at the SPE Annual Technical Conference and Exhibition, New Orleans, Louisiana, USA, 23- 26 September. SPE-20409-MS. <https://doi.org/10.2118/20409-MS>.

52. Tehrani, A., Friedheim, J., Cameron, J. and Reid, R. 2007. Designing Fluids for Wellbore Strengthening – Is It an Art? Presented at the National Technical Conference and Exhibition, Houston, Texas, USA, 10-12 April. AADE-07- NTCE-75

53. Sanders, M. W., Young, S. and Friedheim, J. 2008. Development and Testing of Novel Additives for Improved Wellbore Stability and Reduced Losses. presented at the SPE Annual Technical Conference and Exhibition, 21–24 September. SPE-116139-MS. <https://doi.org/10.2118/116139-MS>.

54. Mostafavi, V., Hareland, G., Belayneh, M. and Aadnoy, B. S. 2011. Experimental and Mechanistic Modeling of Fracture Sealing Resistance with Respect to Fluid and Fracture Properties. Presented at the 45th US Rock Mechanics Symposium, San Francisco, USA, 26-29 June. ARMA 11-98.
55. Wang, H. 2007. Near Wellbore Stress Analysis for Wellbore Strengthening. PhD dissertation, Department of Chemical and Petroleum Engineering, University of Wyoming. 2007.
56. Aadnoy, B., Belayneh, M., Arriado Jorquera, M., and Flateboe, R. 2008. Design of Well Barriers to Combat Circulation Losses. SPE Drilling & Completion, 23(03), 295-300. <https://doi.org/10.2118/105449-PA>.
57. Kalogirou, S. 2003. Artificial intelligence for the modeling and control of combustion processes: a review. Progress in Energy and Combustion Science, 29(6), pp.515-566. [https://doi.org/10.1016/S0360-1285\(03\)00058-3](https://doi.org/10.1016/S0360-1285(03)00058-3).
58. Mellit, A. 2008. Artificial Intelligence technique for modelling and forecasting of solar radiation data: a review. International Journal of Artificial Intelligence and Soft Computing, 1(1), 52. <https://doi.org/10.1504/IJAISC.2008.021264>.
59. Hag Elsafi, S., 2014. Artificial Neural Networks (ANNs) for flood forecasting at Dongola Station in the River Nile, Sudan. Alexandria Engineering Journal 53, 655–662. <https://doi.org/10.1016/j.aej.2014.06.010>.
60. Babikir, H.A., Abd Elaziz, M., Elsheikh, A.H., Showaib, E.A., Elhadary, M., Wu, D., and Liu, Y., 2019. Noise prediction of axial piston pump based on different valve materials using a modified artificial neural network model. Alexandria Engineering Journal 58, 1077–1087. <https://doi.org/10.1016/j.aej.2019.09.010>.
61. Bello, O., Holzmann, J., Yaqoob, T. and 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(2), pp.121-139. <https://Doi.org/10.1515/jaiscr-2015-0024>.
62. Shahab, M. 2000. Virtual-Intelligence Applications in Petroleum Engineering: Part 1—Artificial Neural Networks. Journal of Petroleum Technology, 52(9). <https://doi.org/10.2118/58046-JPT>.

63. Balaji, K., Rabiei, K., Suicmez, V., Canbaz, C., Agharzeyva, Z., Tek, S., Bulut, U., and Temizel, C. 2018. Status of Data-Driven Methods and Their Applications in Oil and Gas Industry. Presented at 80th EAGE Conference and Exhibition held in Copenhagen, Denmark, 11-14 June. SPE-190812-MS. <https://doi.org/10.2118/190812-MS>.
64. Medsker, L. 1996. Microcomputer applications of hybrid intelligent systems. *Journal of Network and Computer Applications*, 19(2), 213-234. <https://doi.org/10.1006/jnca.1996.0015>.
65. Mellit, A. 2008. Artificial Intelligence technique for modelling and forecasting of solar radiation data: a review. *International Journal of Artificial Intelligence and Soft Computing*, 1(1), 52. <https://doi.org/10.1504/IJAISC.2008.021264>.
66. Benghane, M. 2012. Artificial intelligence techniques for prediction of solar radiation data: a review. *International Journal of Renewable Energy Technology*, 3(2), 189. <http://dx.doi.org/10.1504/IJRET.2012.045626>.
67. Celebi, M., Kingravi, H., Vela, P. 2013. A comparative study of efficient initialization methods for the k-means clustering algorithm. *Expert Systems with Applications*, 40(1), 200-210. <https://doi.org/10.1016/j.eswa.2012.07.021>.
68. Kumar, K. and Thakur, G., 2012. Advanced Applications of Neural Networks and Artificial Intelligence: A Review. *International Journal of Information Technology and Computer Science*, 4(6), pp.57-68. DOI: [10.5815/ijitcs.2012.06.08](https://doi.org/10.5815/ijitcs.2012.06.08).
69. Farizawani, A., Puteh, M., Marina, Y. and Rivaie, A., 2020. A review of artificial neural network learning rule based on multiple variants of conjugate gradient approaches. *Journal of Physics: Conference Series*, 1529, p.022040. [doi:10.1088/1742-6596/1529/2/022040](https://doi.org/10.1088/1742-6596/1529/2/022040).
70. Alsabaa, A., Gamal, H., Elkatatny, S. and Abdulraheem, A., 2020. Real-Time Prediction of Rheological Properties of Invert Emulsion Mud Using Adaptive Neuro-Fuzzy Inference System. *Sensors*, 20(6), p.1669. <https://doi.org/10.3390/s20061669>.
71. Jang, J.-S.R. 1993. "ANFIS: adaptive-network-based fuzzy inference system". *IEEE Transactions on Systems, Man and Cybernetics*. 23 (3): 665–685. <https://psycnet.apa.org/doi/10.1109/21.256541>.
72. Abraham A. 2005. Adaptation of Fuzzy Inference System Using Neural Learning. In: Nedjah N., Macedo Mourelle L. (eds) *Fuzzy Systems Engineering. Studies in Fuzziness and Soft Computing*, vol 181. Springer, Berlin, Heidelberg. https://doi.org/10.1007/11339366_3.

73. Jang, J.S. and Sun, C.T., 1995. Neuro-fuzzy modeling and control. *Proceedings of the IEEE*, 83(3), pp.378-406. <https://doi.org/10.1109/5.364486>.
74. Wang, T., Ma, M., Jianbin, Q., Gao, H., 2020. Event-Triggered Adaptive Fuzzy Tracking Control for Pure-Feedback Stochastic Nonlinear Systems with Multiple Constraints. *IEEE Transactions on Fuzzy Systems*. <https://doi.org/10.1109/TFUZZ.2020.2979668>.
75. Qiu, J., Ma, M. and Wang, T., 2020. Event-Triggered Adaptive Fuzzy Fault-Tolerant Control for Stochastic Nonlinear Systems via Command Filtering. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*. <https://doi.org/10.1109/TSMC.2020.3013744>.
76. Vilela, M., Oluyemi, G. and Petrovski, A., 2019. A fuzzy inference system applied to the value of information assessment for the oil and gas industry. *Decision Making: Applications in Management and Engineering*, 2(2), pp.1-18. <https://doi.org/10.31181/DMAME1902001V>.
77. Stojčić, M., Stjepanović, A. and Stjepanović, Đ., 2019. ANFIS model for the prediction of generated electricity of photovoltaic modules. *Decision Making: Applications in Management and Engineering*, 2(1), pp.35-48. <https://doi.org/10.31181/DMAME1901035S>.
78. Jang, J.S., 1996, September. Input selection for ANFIS learning. In *Proceedings of IEEE 5th International Fuzzy Systems (Vol. 2, pp. 1493-1499)*. <https://doi.org/10.1109/FUZZY.1996.552396>.
79. Tahmasebi, P., Hezarkhani, A. A hybrid neural networks-fuzzy logic-genetic algorithm for grade estimation. *Comput. Geosci.* 2012, 42, 18–27, <https://doi.org/10.1016/j.cageo.2012.02.004>.
80. Mas, J. and Flores, J., 2007. The application of artificial neural networks to the analysis of remotely sensed data. *International Journal of Remote Sensing*, 29(3), pp.617-663. <https://doi.org/10.1080/01431160701352154>.
81. Hearst, M.A. 1998. Support Vector Machines. *IEEE Intelligent Systems and Their Applications*, July/August 1998, Vol. 13, Issue 4, pp. 18-28, ISSN. <https://doi.org/10.1109/5254.708428>.
82. Vapnik. V, *The Nature of Statistical Learning Theory*. 2nd ED, New York, Springer p.1-314, 1995.
83. Anifowose, F., Abdulraheem, A. 2011. Fuzzy Logic Driven and SVM-Driven Hybrid Computational Intelligence Models Applied to Oil and Gas Reservoir Characterization. *Journal of Natural Gas Science and Engineering*. <https://doi.org/10.1016/j.jngse.2011.05.002>.

84. Durka, B. 2011. A Classification Algorithm Using Mahalanobis Distance Clustering of Data with Applications on Biomedical Data Sets. MSc dissertation, Middle East Technical University, Ankara, Turkey.
85. Hegde, C. and Gray, K. 2017. Use of machine learning and data analytics to increase drilling efficiency for nearby wells. *Journal of Natural Gas Science and Engineering*, 40, pp.327-335. <https://doi.org/10.1016/j.jngse.2017.02.019>.
86. Efron, B. 1982. The jackknife, the bootstrap and the other resampling plans. Philadelphia, Pa., Society for Industrial and Applied Mathematics.
87. Hedge, C., Wallace, S., and Gray, K. 2015. Using Trees, Bagging, and Random Forest to Predict Rate of Penetration During Drilling. Presented at the SPE Middle East Intelligence Oil and Gas Conference and Exhibition held in Dubai, UAE, 15-16 September. SPE-176792-MS. <https://doi.org/10.2118/176792-MS>.
88. Wang, L. 2019. Research and Implementation of Machine Learning Classifier Based on KNN. *IOP Conference Series: Materials Science and Engineering*, 677, 052038. [doi: 10.1088/1757-899x/677/5/052038](https://doi.org/10.1088/1757-899x/677/5/052038).
89. Coomans, D., and Massart, D. 1982. Alternative k-nearest neighbor rules in supervised pattern recognition. *Analytica Chimica Acta*, 138, 153-165. [https://doi.org/10.1016/S0003-2670\(01\)85298-3](https://doi.org/10.1016/S0003-2670(01)85298-3).
90. Hegde, C., Millwater, H. and Gray, K. 2019. Classification of drilling stick slip severity using machine learning. *Journal of Petroleum Science and Engineering*, 179, pp.1023-1036. [doi: 10.1016/j.petrol.2019.05.02](https://doi.org/10.1016/j.petrol.2019.05.02).
91. Dashevskiy, D., Dubinsky, V., Macpherson, J.D. 1999. Application of Neural Networks for Predictive Control in Drilling Dynamics. presented at the SPE Annual Technical Conference and Exhibition, 3–6 October. SPE-56442-MS. <https://doi.org/10.2118/56442-MS>.
92. Alsaihati, A., Elkatatny, S., Mahmoud, A.A. and Abdulraheem, A., 2020. Use of Machine Learning and Data Analytics to Detect Downhole Abnormalities While Drilling Horizontal Wells, With Real Case Study. *Journal of Energy Resources Technology*, 143(4). <https://doi.org/10.1115/1.4048070>.
93. Elkatatny, S. 2017. Application of Artificial Intelligence Techniques to Estimate the Static Poisson's Ratio Based on Wireline Log Data. *Journal of Energy Resources Technology*, 140(7). <https://doi.org/10.1115/1.4039613>.

94. Alkinani, H.H., Al-Hammed, A.T, Dunn-Norman, S., Flori, R.E., Al-Alwani, M.A., and Mutar, R.A. 2017. Dynamic Neural Network Model to Predict the Rate of Penetration Prior to Drilling. This paper was presented at the 53rd US Rock Mechanics /Geomechanics Symposium held in New York, NY, USA, 23-26 June. ARMA-19-509. pp.1-11.
95. Ahmed, A.A., Elkatatny, S., Abdulwahab, Z., Mahmoud, M., and Abdulraheem, A. 2019. Rate of Penetration Prediction in Shale Formation Using Fuzzy Logic. Paper presented at the International Petroleum Technology Conference held in Beijing, China, 26-28 March. IPTC-19548-MS.pp.1-9. <https://doi.org/10.2523/IPTC-19548-MS>.
96. Elkatatny, S., Al-AbdulJabbar, A. and Mahmoud, A. 2019. New Robust Model to Estimate Formation Tops in Real Time Using Artificial Neural Networks (ANN). Petrophysics – The SPWLA Journal of Formation Evaluation and Reservoir Description, 60(6), pp.825-837. doi.org/10.30632/pjv60n6-2019a7.
97. Abbas, A., Rushdi, S., Alsaba, M. and Al Dushaishi, M. 2019. Drilling Rate of Penetration Prediction of High-Angled Wells Using Artificial Neural Networks. Journal of Energy Resources Technology, 141(11). <https://doi.org/10.1115/1.4043699>.
98. Mahmoud, A., Elzenary, M. and Elkatatny, S., 2019. New Hybrid Hole Cleaning Model for Vertical and Deviated Wells. Journal of Energy Resources Technology, 142(3). DOI: [10.1115/1.4045169](https://doi.org/10.1115/1.4045169).
99. Gurina, E., Klyuchnikov, N., Zaytsev, A., Romanenkova, E., Antipova, K., Simon, I., Makarov, V. and Koroteev, D. 2020. Application of machine learning to accidents detection at directional drilling. Journal of Petroleum Science and Engineering, 184, p.106519. DOI: [10.1016/j.petrol.2019.106519](https://doi.org/10.1016/j.petrol.2019.106519).
100. Al-AbdulJabbar, A., Elkatatny, S., Abdulhamid Mahmoud, A., Moussa, T., Al-Shehri, D., Abughaban, M. and Al-Yami, A. 2020a. Prediction of the Rate of Penetration while Drilling Horizontal Carbonate Reservoirs Using the Self-Adaptive Artificial Neural Networks Technique. Sustainability, 12(4), p.1376. <https://doi.org/10.3390/su12041376>.
101. Al-Abduljabbar, A., Gamal, H. and Elkatatny, S. 2020b. Application of artificial neural network to predict the rate of penetration for S-shape well profile. Arab J Geosci 13, 784. <https://doi.org/10.1007/s12517-020-05821-w>.

102. Alsaihati, A., Elkatatny, S. and Abdulraheem, A., 2020. Real-Time Prediction of Equivalent Circulation Density for Horizontal Wells Using Intelligent Machines. ACS Omega, 6(1), pp.934-942. <https://doi.org/10.1021/acsomega.0c05570>.
103. Jeirani, Z., and Mohebbi, A. 2006. Estimating the initial pressure, permeability and skin factor of oil reservoirs using artificial neural networks. Journal of Petroleum Science and Engineering, 50(1), 11-20. [DOI: 10.1016/j.petrol.2005.09.002](https://doi.org/10.1016/j.petrol.2005.09.002).
104. Moazzeni, A. R., Nabaei, M., Jegarluei, S. G. 2010. Prediction of Lost Circulation Using Virtual Intelligence in one of the Iranian Oilfields. presented at the Nigeria Annual International Conference and Exhibition, Tinapa - Calabar, Nigeria 31 July- 7 August. SPE-136992-MS. <https://doi.org/10.2118/136992-MS>.
105. Jahanbakhshi, R., Keshavarzi, R., Jalili, S. 2013. Artificial neural network-based prediction and geomechanical analysis of lost circulation in naturally fractured reservoirs: a case study. European Journal of Environmental and Civil Engineering, 18(3), 320-335. <https://doi.org/10.1080/19648189.2013.860924>.
106. Jahanbakhshi, R., and Keshavarzi, R. 2014. Quantitative and qualitative analysis of lost circulation in natural and induced fractured formations: the integration of operational conditions and geomechanical parameters. European Journal of Environmental and Civil Engineering, 19(4), 418-444. <https://doi.org/10.1080/19648189.2014.949872>.
107. Manshad, Abbas., Rostami, Habib., Niknafs, Hassan., Mohammadi, Amir. (2017). Integrated Lost Circulation Prediction in Oil Field Drilling Operation. ResearchGate. 978-1-53610-852-1.
108. Toreifi, H., Rostami, H., Manshad, A. K. 2014. A new method for prediction and solving the problem of drilling fluid loss using modular neural network and particle swarm optimization algorithm. Journal of Petroleum Exploration and Production Technology, 4(4), 371-379. <https://doi.org/10.1007/s13202-014-0102-5>
109. Far, P. B., and Hosseini, P. (2017). Estimation of lost circulation amount occurs during under balanced drilling using drilling data and neural network. Egyptian Journal of Petroleum, 26(3), 627-634. [doi:10.1016/j.ejpe.2016.09.004](https://doi.org/10.1016/j.ejpe.2016.09.004).
110. Solomon, O., Adewale, D., Anyanwu, C. (2017). Fracture Width Prediction and Loss Prevention Material Sizing in Depleted Formations Using Artificial Intelligence. presented at the

SPE Nigeria Annual International Conference and Exhibition, Lagos, Nigeria, 31 July-2 August 2017. SPE-189068-MS. <https://doi.org/10.2118/189068-MS>.

111. Abbas, A., Al-haideri, N., Bashikh, A. 2019a. Implementing artificial neural networks and support vector machines to predict lost circulation. *Egyptian Journal of Petroleum*, 28(4), 339-347.

<https://doi.org/10.1016/j.ejpe.2019.06.006>.

112. Abbas, A., Bashikh, A., Abbas, H., Mohammed, H. (2019b). Intelligent decisions to stop or mitigate lost circulation based on machine learning. *Energy*, 183, 1104-1113.

<https://doi.org/10.1016/j.energy.2019.07.020>.

113. Ahmed, A., Elkatatny, S., Ali, A., Abughaban, M., Abdulraheem, A. 2020. Application of Artificial Intelligence Techniques in Predicting the Lost Circulation Zones Using Drilling Sensors. *Journal of Sensors*, 2020, 1-18. <https://doi.org/10.1155/2020/8851065>.

114. Gupta, S. and Gupta, A. 2019. Dealing with Noise Problem in Machine Learning Datasets: A Systematic Review. *Procedia Computer Science*, 161, pp.466-474.

<https://doi.org/10.1016/j.procs.2019.11.146>.

115. Brown, R. (1959). *Statistical forecasting for inventory control*. New York [etc.]: McGraw-Hill Book Company.

116. Winters, P. 1960. Forecasting Sales by Exponentially Weighted Moving Averages. *Management Science*, 6(3), 324-342. <https://doi.org/10.1287/mnsc.6.3.324>.

117. Holt, C. 2004. Author's retrospective on 'Forecasting seasonals and trends by exponentially weighted moving averages. *International Journal of Forecasting*, 20(1), 11-13.

<https://doi.org/10.1016/j.ijforecast.2003.09.015>.

118. Batina, L., Gierlichs, B., Prouff, E., Rivain, M., Standaert, F., Veyrat-Charvillon, N. 2010. Mutual Information Analysis: A Comprehensive Study. *Journal of Cryptology*, 24(2), 269-291.

<https://doi.org/10.1007/s00145-010-9084-8>.

119. Cover, T., and Thomas, J. 1991. *Elements of information theory*. New York, N.Y.: Wiley.

120. Krzywanski, J., Fan, H., Feng, Y., Shaikh, A., Fang, M. and Wang, Q. 2018. Genetic algorithms and neural networks in optimization of sorbent enhanced H₂ production in FB and CFB gasifiers. *Energy Conversion and Management*, 171, pp.1651-1661.

<https://doi.org/10.1016/j.enconman.2018.06.098>.

121. Stehman, S. 1997. Selecting and interpreting measures of thematic classification accuracy. *Remote Sensing of Environment*, 62(1), 77-89. [https://doi.org/10.1016/S0034-4257\(97\)00083-7](https://doi.org/10.1016/S0034-4257(97)00083-7).
122. Powers, D. 2011. Evaluation: From Precision, Recall and F-Measure to ROC, Informedness, Markedness & Correlation. *Journal of Machine Learning Technologies*.

Vitae

Name	Ahmed Ibrahim Alsaihati
Nationality	Saudi
Email	Ahmed.i.saihati.4@gmail.com
Address	King Faisal Street Saihat Saudi Arabia 32437 6783
Academic Background	M.S. in Petroleum Engineering, 2021, King Fahad University of Petroleum and Minerals. B.S. in Petroleum Engineering, 2012, King Fahad University of Petroleum and Minerals.
Publication	Alsaihati, A., Elkatatny, S., Mahmoud, A.A. and Abdulraheem, A. (2020). Use of Machine Learning and Data Analytics to Detect Downhole Abnormalities While Drilling Horizontal Wells, With Real Case Study. Journal of Energy Resources Technology, 143(4). https://doi.org/10.1115/1.4048070. Alsaihati, A., Elkatatny, S. and Abdulraheem, A. (2020). Real-Time Prediction of Equivalent Circulation Density for Horizontal Wells Using Intelligent Machines. ACS Omega, 6(1), pp.934-942. https://doi.org/10.1021/acsomega.0c05570 Ahmed, A., Alsaihati, A., Elkatatny, S. (2020). An Overview of the Common Water-Based Formulations Used for Drilling Onshore Gas Wells in the Middle East. Arabian Journal for Science and Engineering. doi: 10.1007/s13369-020-05107-z. Altowilib, A., AlSaihati, A., Alhamood, H., Alafnan, S., and Alarifi, S. (2020). Reserves Estimation for Coalbed Methane Reservoirs: A Review. Sustainability, 12(24), 10621. doi: 10.3390/su122410621.