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Artificial Intelligent Models for Detection and Prediction of Lost Circulation Events: A Review

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Abstract

Lost circulation or losses in drilling fluid is one of the most important problems in the oil and gas industry, and it appeared at the beginning of this industry, which caused many problems during the drilling process, which may lead to closing the well and stopping the drilling process. The drilling muds are relatively expensive, especially the muds that contain oil-based mud or that contain special additives, so it is not economically beneficial to waste and lose these muds. The treatment of drilling fluid losses is also somewhat expensive as a result of the wasted time that it caused, as well as the high cost of materials used in the treatment such as heavy materials, cement, and others. The best way to deal with drilling fluid losses is to prevent them. Drilling fluid loss is a complex problem that is difficult to predict using simple and traditional methods. Artificial intelligence represents a modern and accurate technology for solving complex problems such as drilling fluid loss. Artificial intelligence through supervised machine learning provides the possibility of predicting these losses before they occur based on field data such as drilling fluid properties, drilling parameters, rock properties, and geomechanical parameters that are related to the loss of circulation of the wells suffered from losses problem located in the same area.

In this paper, several supervised machine learning models have been reviewed that were used for detecting and predicting of loss of drilling fluids during the drilling process. The paper provides an inclusive review of drilling fluid prediction and detection from simplest to more complected intelligent models.

Keywords: Artificial intelligence, Machine learning, Lost circulation prediction, intelligent models, loss of circulation.

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1- Introduction

Drilling fluid loss is a common problem in the petroleum industry. Loss of drilling mud totally or partially within a formation during the drilling process or the return mud from the well is not equivalent to the mud injected into the well is called drilling fluid loss or return loss [1]. Loss of circulation usually happens in highly permeable, depleted reservoirs, natural fissures, cavernous, and fracture formations as shown in Fig. **1** [2]. The loss of drilling fluid leads to an increase in the lost time, which is known as nonproductive time NPT, which is the time needed to treat this problem [3]. During this time, the drilling process stops, which causes a loss of time and an increase in the cost of drilling. Fig. **2** represents causes of delays in drilling time at five sets offshore wells in the Gulf of Mexico. This problem is one of the costliest problems in the oil industry, as it costs 2$ billion annually to treat it also, represents (12% of NPT) according to worldwide oil industry estimation and (46% of NPT) in the Rumaila oil field [3]. Failure to treat the loss of drilling fluid and restore the drilling process normally can lead to stuck pipe or in the worst case to closing the well [4].

There are several methods used to control the loss of circulation. The first one is done by minimizing the density of the drilling mud [5]. The second method is done by using lost circulation materials (LCM) such as peanut shells, mica, cellophane, calcium carbonate, and polymeric materials to bridge over and seal loss zones [5]. These methods are too expensive and time consumption.

Many factors that affecting the loss of drilling fluid, including the petrophysical properties of the rocks (Porosity, Permeability, etc.) and the properties of the drilling fluid itself (MW, ECD, YP, PV, etc.), as well as the drilling parameters (ROP, WOB, RPM, SPM, SSP, TFA, etc.) in addition to (Pore pressure gradient, fracture pressure, etc.) these are some of the well-known factors and there are other unknown factors [6]. Controlling these factors to prevent the loss of drilling fluid is a very difficult task, so it is necessary to have a smart model to predict the occurrence of losses or not, as well as to predict the type of those losses depending on these factors, and therefore some of these factors that can be controlled to prevent or reduce the loss of drilling fluid [7].

Artificial intelligence is one of the most important techniques used in solving complex problems by revealing patterns and complex relationships between the

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causes of the problem and the outcome [8]. Several intelligent models to predict loss of circulation were developed because of the high treatment cost of the losses. Prior to the development of these smart models, the prediction did not provide additional benefits as compared to detection [8, 9].

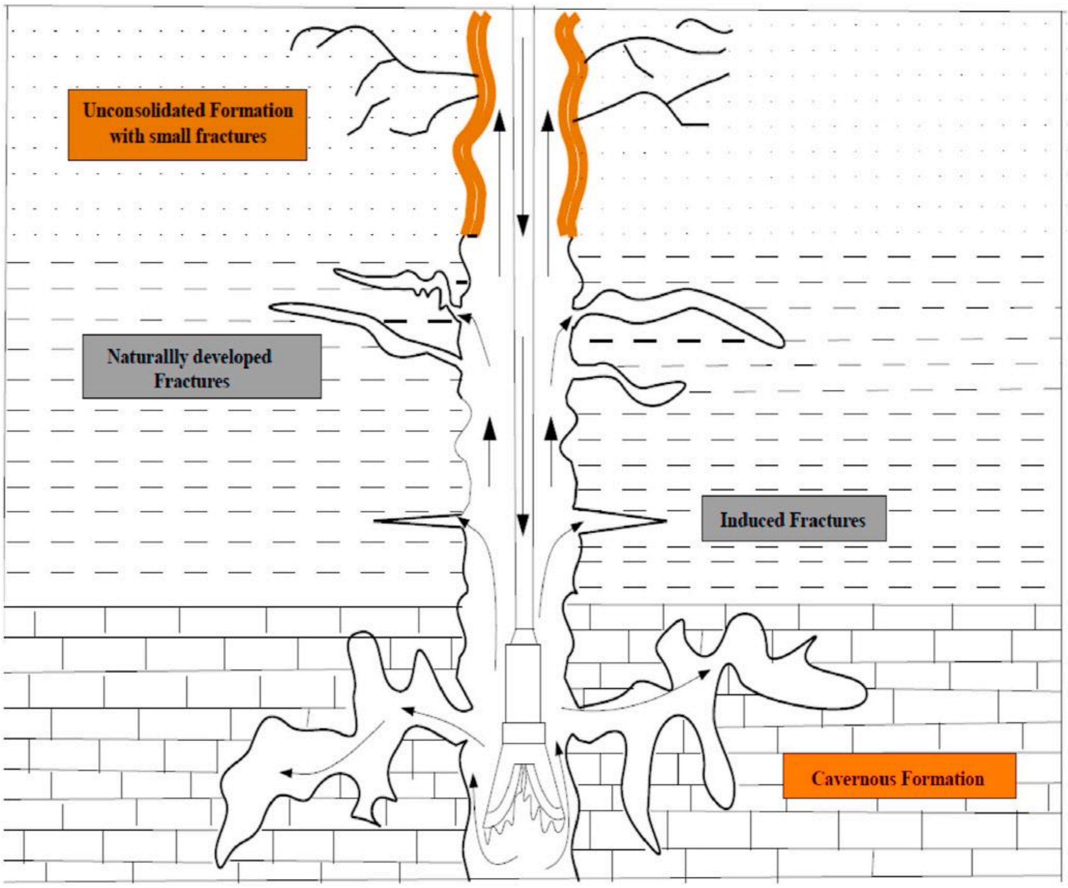

Fig. 1. Various Lost Circulation Zone Types [2]

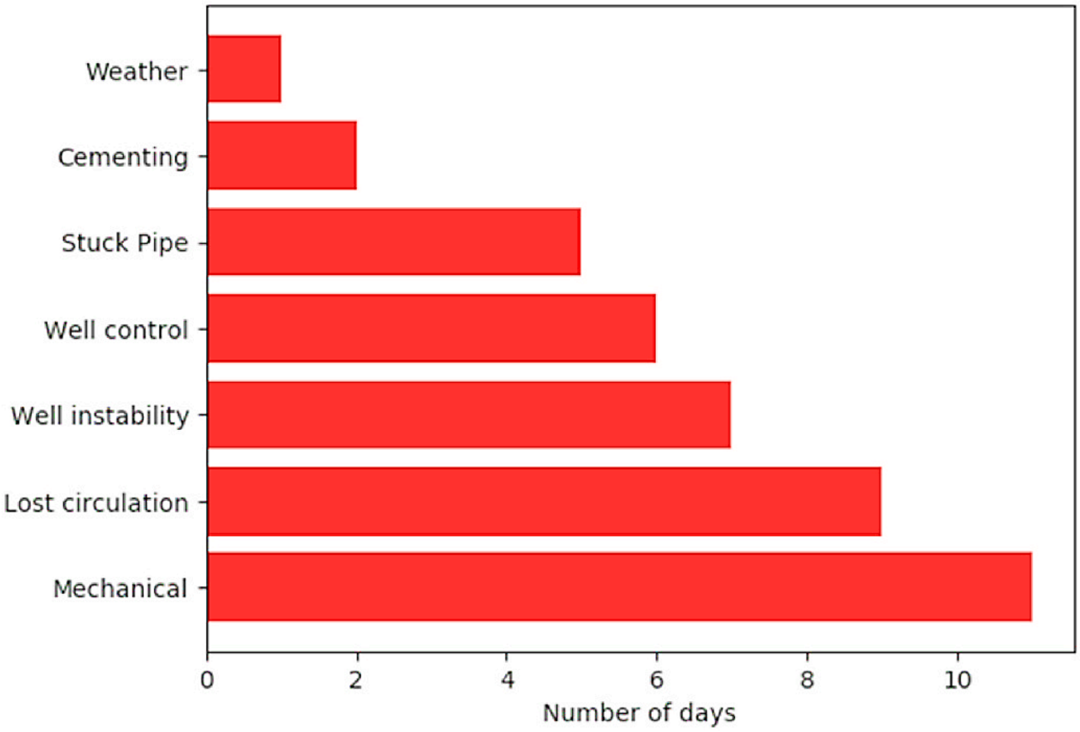

Fig. 2. Days Required to Treat Drilling Problems for Five Sets of Offshore Wells [10]

2- Overview of Prevention of Lost Circulation Problem

The process of compiling the papers related to this topic was divided into three parts, a section that included the compilation of all the papers related to this title represents the first part, and the other part included dividing the papers into prediction and detection, and the last part was to enter deeply into building the models, the data used, and the accuracy of these models as shown in Fig. **3**.

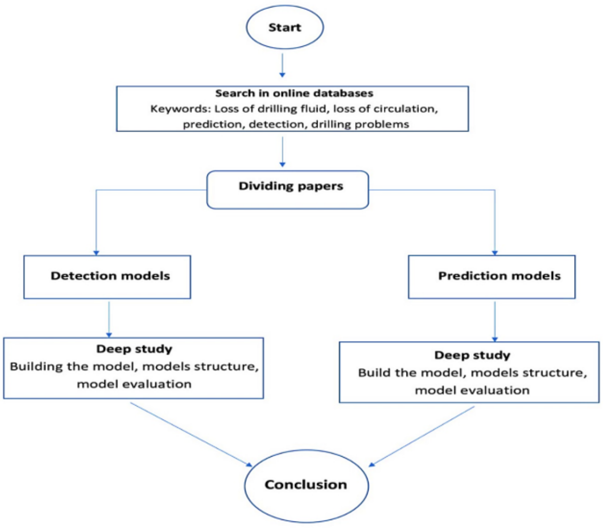

Fig. 3. Scheme Showing the Methodology of Preparing the Research

3- Loss of Circulation Prediction Review

Preventing lost circulation with good planning is a very useful way to stop lost circulation before it happens. Lost recycling prevents lower costs than any other procedure for addressing losses after the fact. Especially with expensive mud like oil-base mud, where it is not economically wise to lose such mud [11]. In this section, models that are used to predict drilling fluid losses will be discussed.

Moazzenii et al. (2010) multilayer Feed_Forward network learned by backpropagation was developed to predict loss circulation events in Maroun oil field, Asmari formation based on drilling reports (D.D.R) of 32 drilled wells Fig. **4**. The structure of the network consisted input layer with a dimension of 18, a hidden layer with 30 neurons, and a target with a dimension of 1. The result of this network with respect to linear correlation coefficient (R) for training, testing, and validation respectively 0.95, 0.76, and 0.82. the result of the network was good in low mud loss but it is bad in severe losses Fig. **5** [6].

Jahanbakhshi et al. (2014) a multilayer perceptron model developed to predict drilling fluid losses and show the effect of geomechanical parameters such as (Minimum horizontal stress, Uniaxial compressive strength, young module, Tensile strength, etc.) on the losses. They built two models for these goals, the first one was developed depending on nongeomechanical parameters such as (drilling fluid properties, drilling parameters, pressures, etc.) only and the other one was created depending on both geomechanical and nongeomechanical parameters. The result shows that the model included geomechanical parameters and was able to predict the losses better than the other one at high accuracy and low error Fig. **6**. The linear correlation coefficient (R) for the first and second models respectively was 0.75 and 0.94 [12].

Toreifi et al. (2014) two Modular Neural Network (MNN) models were built to predict the loss of circulation and a particle swarm optimization (PSO) algorithm was used to optimize different parameters of drilling to reduce the losses. The accuracy of the prediction of the Modular Neural Network models was 94% and 98% respectively. Fig. **7** and Fig. **8** show the two MNN models performance in the prediction loss of circulation [7].

Aljubran et al. (2017) developed several ML and DL models to predict loss of circulation such as (RF, ANN, CNN, and LSTM). The data was drilling parameters gathered from 200 wells suffering from severe or total losses. These data are spilt into 80%,10%, and 10% to train, test and validation the models. The result showed that the CNN model was the best one and this model was able to detect signs leading to seepage and partial losses correctly Table **1** [13].

Sabah et al. (2019) developed several smart systems (MLP, RBF, GA-MLP, DT, ANFIS) to predict loss of circulation in the Maroun oil field. The data was gathered from 61 recently drilled wells for training, testing, and implementing these models. The results show that DT is the best model used for prediction with (R) of 0.9034 and (RMSE) of 0.091 Table **2** [14].

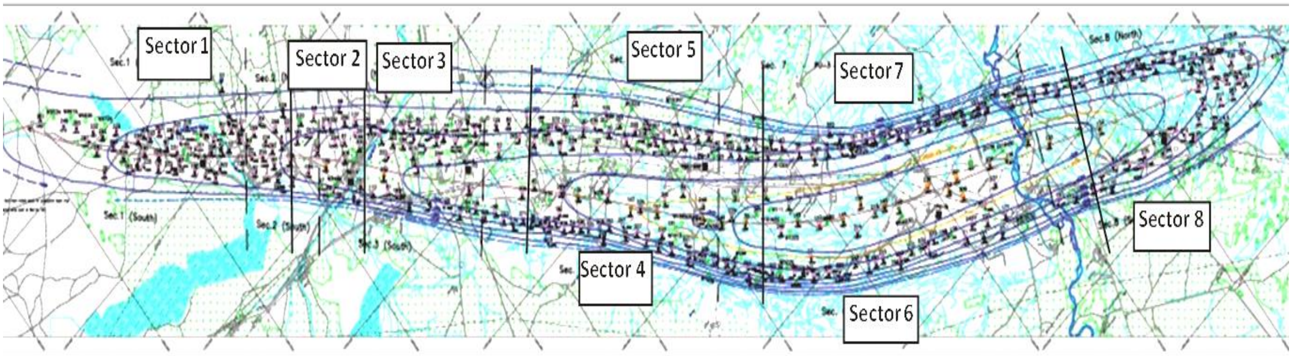

Fig. 4. Maroun Oilfield, South West of Iran [6]

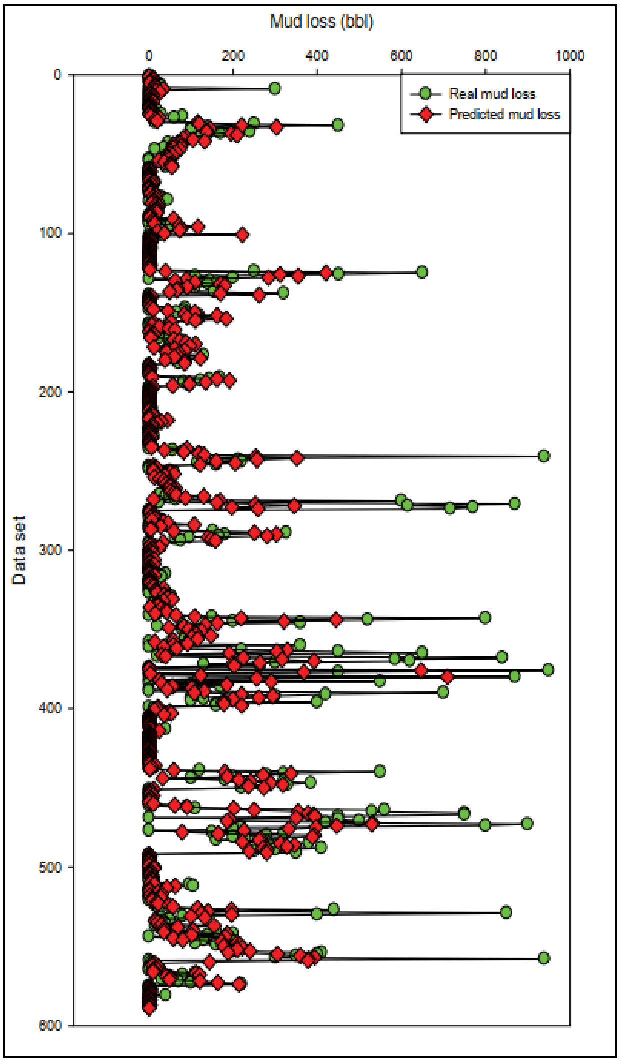

Fig. 5. Predicted and Real Mud Losses in Maroun Oil Field [6]

Table 1. Model's Results

Algorithm	Test accuracy (%)	Validation accuracy (%)
RF (standard normalization)	80.96	78.50
ANN (standard normalization)	89.15	78.17
RF (window normalization)	88.40	80.67
ANN (window normalization)	90.74	79.39
CNN (window normalization)	92.55	82.33
LSTM (window normalization)	92.45	87.64

Table 2. Performance Indices

Model	**Data set**	**R2**	**RMSE**
Decision tree	Train	0.97	0.052
	Test	0.93	0.091
MLP	Train	0.92	0.094
	Test	0.90	0.099
ANFIS	Train	0.90	0.1163
	Test	0.88	0.1087
RBF	Train	0.85	0.1172
	Test	0.84	0.1315
GA-MLP	Train	0.83	0.132
	Test	0.84	0.137

Abbas et al. (2019) two intelligent models were developed to predict loss of circulation in southern Iraqi oil fields. The data used to train, test, and implement these two models were collected from wells well in the southern oil fields of Iraq. The first model was a support vector machine (SVM) show good results than the second one which was ANN. The accuracy of SVM was 92% & 91% of training and testing respectively [8].

Geng et al. (2019) applied machine learning algorithms to correlate the losses risk with the seismic data. Support vector machine, logistic regression, and random forest were used to predict loss of circulation events by using seismic data. Predictive results showed the cross-validation accuracy of 0.8 which was a satisfactory outcome [9].

Alkinani et al. (2019) artificial neural networks (ANNs) were developed to estimate losses in induced fracture formations. The data used to build this model was drilling operation parameters and drilling fluid properties collected from 1500 wells and divided into 60%, 20%, and 20% to train, test, and implement the model. The result showed that the best algorithm to train the ANN was Levenberg-Marquardt (LM) which gives better accuracy with R2 equal to 0.92 [15].

Agin et al. (2019) developed Adaptive Neuro Fuzzy Inference System (ANFIS) to predict the losses of drilling fluid in the Maroun oilfield based on drilling data such as Drilling operation parameters, drilling fluid properties, and amount of lost circulation. The result shows the root mean square error of ANFIS of training, testing, and validation equal to 0.08, 0.09, and 0.15 respectively. The results suggest that the ANFIS method can be successfully applied to establish a lost circulation prediction model Fig. **9** [16].

Hou et al. (2020) ANN model was built to predict the loss of circulation in Yingqiong Basin one of the offshore HTHP regions in the world. The data used for training and testing the model were drilling parameters, drilling fluid properties, and formation properties. The model was created to predict six types of losses (micro, small, middle, large, severe, and no losses). The accuracy after the 50-epoch iterative process was 93% and 92% for the training and testing respectively. The performance of the ANN to predict six lost circulation types is good. The proposed model satisfies the need for drilling engineering and can provide guidance for the estimation of lost circulation risks prior to drilling [17].

Ahmed et al. (2020) three artificial intelligence techniques developed (Artificial Neural Network ANN, Fuzzy Logic FL, and Functional Network FN) to predict the losses in high-pressure, high-temperature (HPHT) wells. They used three wells in this work Well A to train and test the models and well B and C to implement these models. Drilling parameters are used to build these models. ANN was the better model with a Correlation coefficient of 0.99 and RMSE 0.05 and was able to predict the lost circulation zones in the unseen Wells [18].

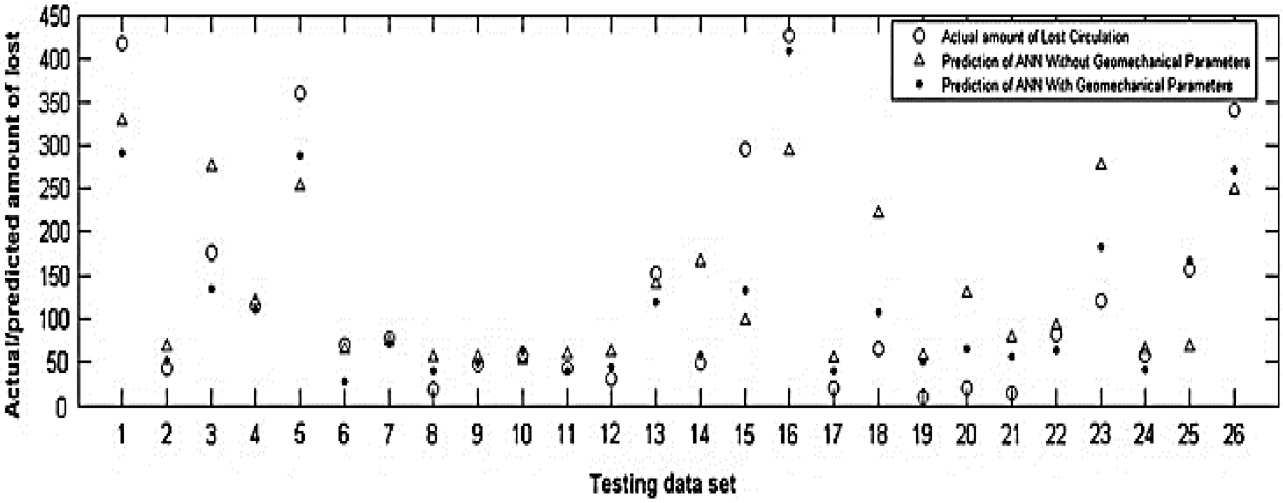

Fig. 6. Comparative Plot of ANN Performance [12]

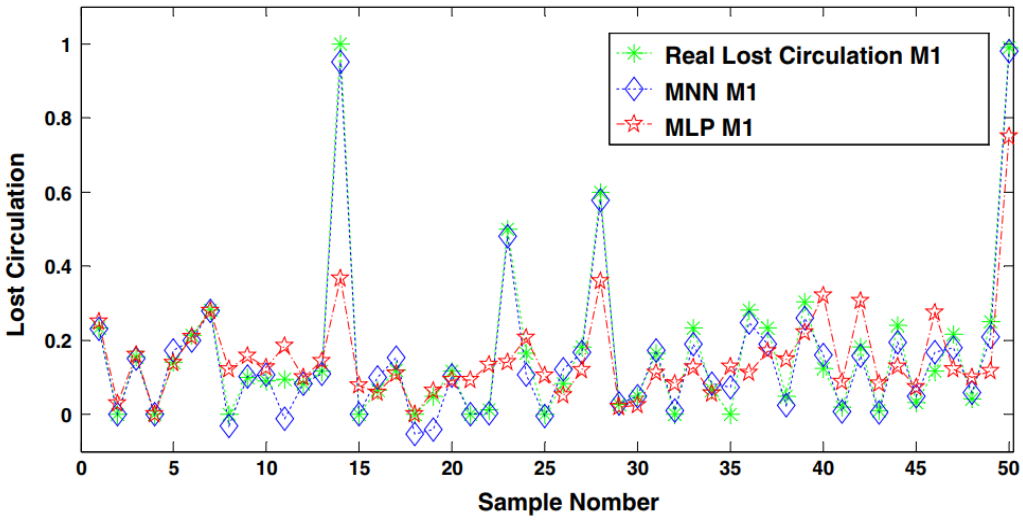

Fig. 7. Comparison of the Estimated Values of the First Model and the Real Losses [7]

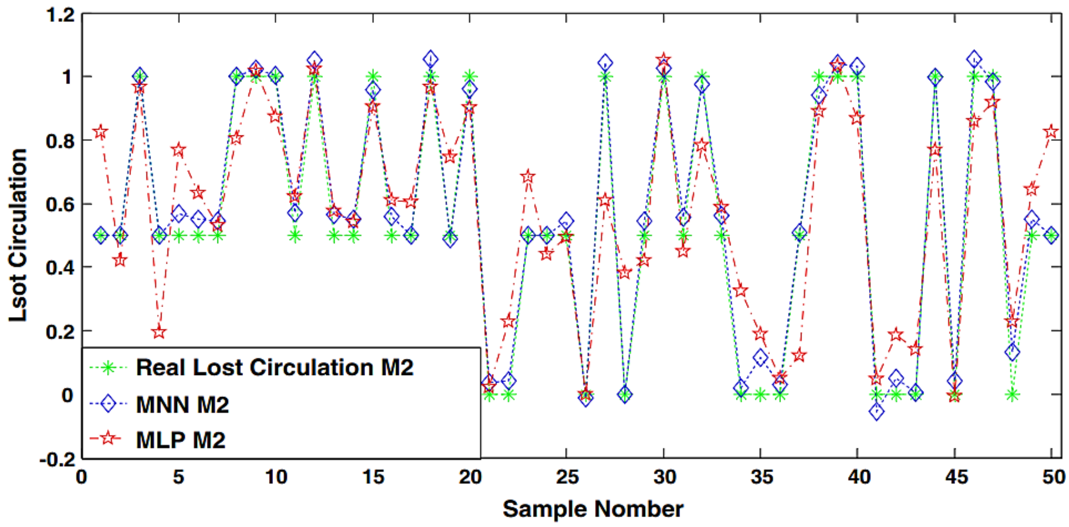

Fig. 8. Comparison of the Estimated Values of the Second Model and the Real Losses [7]

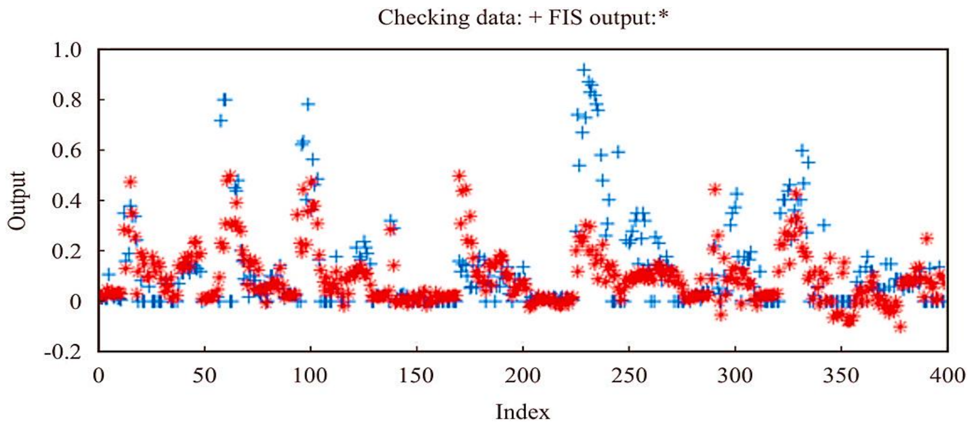

Fig. 9. Comparison of Real and ANFIS Outputs in Checking Data [16]

4- Loss of Circulation Detection Review

The methods or technology used for loss circulation detection are divided into two types the first one is called conventional and the second called intelligent methods. Conventional methods include (Pit volume monitoring, Delta flow, etc.). There are other tools used for this target like (Survey tools, PWD tools, and Geostatistics-based). In this section, we will focus on the Intelligent method which is most useful and has fewer errors than humans.

Yamaliev et al. (2009) developed deep drilling equipment technical condition recognition system is based on the images classification acting to the neural network that helped to understand and identify bit technological conditions based on pressure and bit weight which can help to improve drilling efficiency and solve any problems that can happen in the future Fig. **10** [19].

Lian Z. et al. (2010) developed a fuzzy reasoning method to estimate the downhole conditions and monitor the control parameters which subsequently assisted in improving the drilling efficiency [20].

Zhao J. et al. (2017) developed an unsupervised ML method such as (SAX, hierarchical clustering, dynamic time warping, pattern recognition, and classification) for detecting various drilling anomalies depending on drilling data. This method can automatically inform the driller or remote center of the changes of operational parameters when unusual drilling events occur using drilling data to build the model such as bottom hole parameters, rheological properties, and geometric data of the well to predict various drilling anomalies (pipe stuck, change in ECD, fluid losses, etc.) [21].

Unrau and Torrione (2017) developed supervised ML models such as (support vector machines, regression models, etc.) these models help in checking for the false alarm and that’s will help incorrect detection of fluid losses or gain during the drilling process [22].

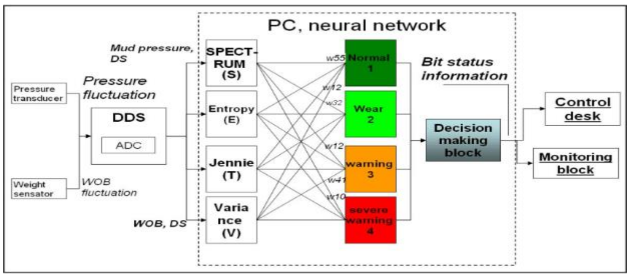

Fig. 10. The Neural Network Variant of the Deep Drilling Equipment

Table 3. Summary of Detection Studies

No.	The author	Objective of the study	Model	Inputs	Model Structure	Outputs	Performance
1	Yamaliev et al. (2009)	Understanding and identifying bit conditions	Neural networks	Dispersion, entropy, Jinny coefficient, and spectrum	4-4-1	Describe bit status	-
2	Lian et al. (2010)	Estimating the downhole conditions	Fuzzy reasoning	Logging data such as: total HC, total pit volume, temperature, conduction, density, hook load	--	Detecting of various drilling problems	The application results of some cases showed accurate and reliable result
3	Zhao J. et al. (2017)	Detecting of several drilling anomalies	Un-supervised ML	Hole parameters, Rheological properties, and geometric properties of the well	--	pipe stuck, change in ECD, fluid losses, etc.	This method used to inform the driller any change of drilling operational parameters when drilling events occur.
4	Unrau and Torrione (2017)	Checking for false alarm	supervised ML models such as (support vector machine, regression models, etc.)	Pit volume, flowing in, Flowing out	-	Accurate alarm of fluid losses	The result was satisfactory

Table 4. Summary of Prediction Studies

No.	The author	Objective of the study	Model	Inputs	Model Structure	Outputs	Performance
1	Moazzani et al. (2010)	Prediction of Lost circulation	ANN	Well depth, pump flow rate, pump pressure, bit size, mud weight, solids content, PHI600, PHI300, drilling time, volume loss, physical properties of the rocks	18-30-1	Losses	R^2 of ANN model 0.95, 0.82, 0.76 for training, testing and validation respectively
2	Jahanbekhshi et al. (2014)	Prediction of Lost Circulation	ANN	Non-geomechanical: Hole deepness, ϕ, Permeability, SSP, EcD, PV, gel strength, viscosity, solids content, temperature. Geomechanical: tensile strength, uniaxial strength, horizontal stress, E-modulus	11-15-1 16-1-9-1	Losses	R^2 are 0.75 and 0.94 for models 1 and 2
3	Toreifi et al. (2014)	Prediction of Lost circulation	MNN-PSO	Depth, top of the formation, SSP, type of the formation, pump flow rate, ROP, pump pressure, solids content, plastic viscosity, gel strength, annuls volume, ϒP	/	Losses	R^2 is 0.944 and MSE is 0.0047
4	Aljubran et al. (2017)	Prediction of Lost circulation	RF, CNN, ANN, LSTM	SURFACE DRILLING PARAMETERS: WOB, HKHT, HKL, TQ, SPP, FLWIN, FLWOUT, ROP, RPM, PVT.	CNN 16-4	Losses	CNN was the best model with an accuracy of 92.55%
5	Sabah et al. (2019)	Prediction of Loss circulation	ANFIS, DT, MLPNN, RBF-NN and GA-MLP	Hole diameter and depth, Pp, FFP, mud pressure, ROP, CP, solid content, WOB, PV, RPM, ϒP, mud viscosity, Gel 10 min, gel strength, MD, hole diameter, SSP, phi600, phi300, mud rate	ANFIS: 28 -Measurable functions -normalization - defuzzification - final outputs MLPNN: single layer input and output RBFNN: one layer for input, output, and hidden. MLP-GA: Input-10-10-1	Losses	DT was the best with (R^2) of 0.935and (RMSE) of 0.091
6	Abbas A. et al.(2019)	Prediction of Lost circulation	SVM and ANN	lithology, mud weight, pump rate, ROP, CP, solid content, WOB, PV, RPM, ϒP, mud viscosity, Gel 10 min, gel strength, MD, hole diameter	ANN: 18-40-40-1	Losses	ANN training and testing accuracy are 0.87 and 0.83
7	Geng Z. et al. (2019)	Prediction of Loss circulation using seismics data	LRC, RFC, and SVC	Variance, sweetness, attenuation, and RMS amplitude	-	Detecting fluid loss hazard	Cross-validation accuracy 0.8
8	Alkinani et al. (2019)	Prediction of Lost circulation	ANN	MW, WOB, ϒP, PV, TFA, ECD, pump flow rate	1-10-1	Volume of Losses	R^2 equal 0.925
9	Agin et al. (2019)	Prediction of Lost circulation	ANFIS	Drilling footage, hole size, WOB, RPM, pump rate, pump pressure, PV, ϴ600, ϴ300, solid percent, mud velocity, pore pressure, gel strength, drilling time, SSP, losses	ANFIS: -17 inputs -measurable functions - 12 if-then fuzzy -Output of 12 clusters -final outputs	Losses	RMSE of ANFIS 0.08,0.09 and 0.15 of training, testing, and validation respectively
10	Hou et al. (2020)	Prediction of Lost circulation	ANN	Drilling fluid properties: MW, YP, PV, Solid content Drilling operation parameters: pump rate, RPM, ROP, WOB, SPP, TFA, MD Geology parameters: Lithology	15-(6-15)- 6	Six lost circulation types	ANN accuracy 93% and 92% of training and testing
11	Ahmed et al. (2020)	Loss Circulation Prediction binary classification	FN, FL, and ANN	Depth, HKHT, HKL, FPWPMP, ROP, RPM, SPP, TORQUE, WOB	ANN: 6-5-2	Losses	ANN is the best model with R 0.99 and RMSE 0.05

5- Conclusion

The problem of losing drilling fluid is a difficult and complex problem that is difficult to detect easily and costs the oil industry a lot of money, and it is difficult to predict using traditional techniques until after it occurs. Modern technologies such as artificial intelligence have provided a great service to the oil industry in predicting cases of drilling fluid loss, thus this problem can be avoided using these techniques, and that lead to reduce NPT, costs incurred to treat this problem, and increased drilling efficiency. It is clear by reviewing these techniques that there is no specific technique to solve this problem. If we assume that one of the techniques works perfectly in a certain area, it works horribly in another area.

Several smart models have been reviewed, most of the models are built based on the properties of the drilling fluid (mud weight, plastic viscosity, yield point, etc.), and drilling parameters (pressure, weight on bit, rate of penetration, etc.) without the petrophysical properties of the rocks (porosity, permeability, etc.) due to the difficulty of obtaining them in the area where the drilling fluid losses occur.

The accuracy of the model depends on the accuracy of the obtained data and its relevance to the problem, and the selection of data depends on experience to the greatest extent. The models in which rock properties are used showed higher accuracy than other models.

Depending on the study, the most important parameter influencing the drilling fluid loss process which was drilling fluid properties such as equivalent circulating density (ECD) that means the possibility of preventing or reducing the possibility of this problem occurring by controlling the value of the most important factors causing this problem.

Moreover, these techniques require a lot of time and data for the purpose of developing them, as most of these techniques discover all kinds of problems during the drilling process, which makes determining the main cause of these problems difficult.

Nomenclature

Acronym	Definition
AI	Artificial Intelligence
ANFIS	Adaptive Neuro Fuzzy Interface System
ANN	Artificial Neural Networks
CNN	Convolutional Neural Networks
FN	Functional Networks
FL	Functional Language
MLP	Multi-Layer Perceptron
HKHT	Hook Height
GA-MLP	Genetic Algorithm Multilayer perceptron
LRC	Logistic Regression Classifier
LSTM	Long Short-Term Memory
MLP	Multilayer perceptron
MLP-NN	Multilayer perceptron Neural Network
MSE	Mean-Square Error
MD	Measure Depth
MNN	Modular-Neural Network
NPT	Non-Production Time
PV	Plastic viscosity
PSO	Particle Swarm Optimization
R	Linear Correlation Coefficient
R2	Square Linear Correlation Coefficient
RBF	Radial basis function
RF	Random Forest
RFC	Random Forest Classification
RPS	Round Per Seconds
RMSE	Root mean square error
SVC	Support Vector machine Classification
SVM	Support Vector Machine

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نماذج ذكية للكشف والتنبؤ بأحداث فقدان سائل الحفر: مراجعة

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الخلاصة

يعد الفقدان اوالنقصان في سائل الحفر من أهم المشاكل في صناعة النفط والغاز، وظهر في بداية هذه الصناعة، مما تسبب في العديد من المشاكل أثناء عملية الحفر، والتي قد تؤدي إلى إغلاق البئر ووقف عملية الحفر. إن طين الحفر غالي الثمن نسبيًا، خاصةً الطين الذي يحتوي على نفط أو الذي يحتوي على إضافات خاصة، لذلك فهو غير مفيد اقتصاديًا إهدار هذه الأطيان وفقدانها. كما أن معالجة خسائر سوائل الحفر باهظة الثمن إلى حد ما نتيجة للوقت الضائع الذي تسبب فيه، فضلاً عن التكلفة العالية للمواد المستخدمة في المعالجة مثل المواد المثقلة والأسمنت وغيرها. أفضل طريقة للتعامل مع فقد سائل الحفر هو منع حدوثها. يوفر الذكاء الاصطناعي من خلال التعلم الآلي الخاضع للإشراف إمكانية التنبؤ بهذه الخسائر قبل حدوثها بناءً على البيانات الميدانية مثل خصائص سائل الحفر، ومعايير الحفر، وخصائص الصخور، والمعايير الجيوميكانيكية المتعلقة بالآبار التي عانت من مشكلة الخسائر الموجودة في نفس المنطقة.

في هذا البحث، تمت مراجعة العديد من نماذج التعلم الآلي الخاضعة للإشراف والتي تم استخدامها للكشف عن فقدان سوائل الحفر والتنبؤ به أثناء عملية الحفر. تقدم الورقة مراجعة شاملة للتنبؤ بسائل الحفر واكتشافه من النماذج الذكية الأبسط إلى الأكثر تجميعًا.

الكلمات الدالة: الذكاء الاصطناعي, خسارة سائل الحفر, التنبؤ, مشاكل عملية الحفر, نموذج ذكي, اطيان الحفر.