01 Dec 2019

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Recommended Citation

H. H. Alkinani et al., "Application of Artificial Neural Networks in the Drilling Processes: Can Equivalent Circulation Density Be Estimated Prior to Drilling?," *Egyptian Journal of Petroleum*, vol. 29, no. 2, pp. 121-126, Egyptian Petroleum Research Institute, Dec 2019.
The definitive version is available at https://doi.org/10.1016/j.ejpe.2019.12.003

Egyptian Journal of Petroleum 29 (2020) 121–126

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Contents lists available at ScienceDirect

Egyptian Journal of Petroleum

journal homepage: www.sciencedirect.com

Full Length Article

Application of artificial neural networks in the drilling processes: Can equivalent circulation density be estimated prior to drilling?

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ARTICLE INFO

Article history:
Received 30 July 2019
Revised 25 November 2019
Accepted 8 December 2019
Available online 19 December 2019

Keywords:
Artificial neural networks
Machine learning
ECD estimation

ABSTRACT

As the drilling environment became more challenging nowadays, managing equivalent circulating density (ECD) is a key factor to minimize non-productive time (NPT) due to many drilling obstacles such as stuck pipe, formation fracturing, and lost circulation. The goal of this work was to predict ECD prior to drilling by using artificial neural network (ANN). Once ECD is recognized, the crucial drilling variables impact ECD can be modified to control ECD within the acceptable ranges. Data from over 2000 wells collected worldwide were used in this study to create an ANN to predict ECD prior to drilling. Into training, validation, and testing sets, the data were splitted. 70% of the data utilized for training, the other part used for validation and testing to avoid overfitting and create a generalized network that can perform well on new data. Based on the mean square of error (MSE), a decision was made to have one hidden layer with twelve neurons, this scenario was selected since it gave the lowest MSE among other scenarios. Multiple training functions were tested to train the network, Bayesian regularization (BR) algorithm was chosen from the other algorithms since it had the lowest MSE and the highest R-squared. After optimizing the weights and biases, the results revealed that the created network has the ability to estimate ECD with an overall R-squared of 0.982, which is very high. This result gives an indication that the created network can predict ECD prior to drilling globally within a very small margin of error. Due to the availability of large historical data sets in the petroleum industry, the ANN can be used to make better future decisions to minimize NPT and the cost of drilling.

1. Introduction

ECD management is one of the most important parameters for having successful drilling, especially for drilling ultra-deep wells which have a very narrow safe mud weight between the resevoir pressure and the leak-off pressure. The pressure exerted by the hydrostatic column resulting from the mud density, drilling fluid rheological properties, and pump flow rates which will contribute to the frictional pressure losses are the factors that affect ECD. It is essential to comprehend the effect of each parameter affecting ECD which will result in better management of ECD. Inadequate management of ECD can cause to many undisered issues like mud losses, formation influx, sticking pipe, etc. which in turn will rasie the total cost of the drilling processes.

A major challenge in the petroluem industry is the trouble of losing the drilling mud in the thief zones, billions of dollars are spent every year to stop and reduce this problem [1–7]. As the drilling environment became more challenging nowadays, managing equivalent circulation density (ECD) is a key factor to reduce non-productive time (NPT) due to many drilling problems such as pipe sticking, formation fracturing, and lost circulation. ECD can be estimated while drilling using hydraulics; however, there is no direct method to find ECD prior to drilling besides using correlations.

As managing ECD is important, different methods on how to manage ECD by means of predicting it based on different parameters on simulation and with the experimental approaches. Different scholars have been trying to navigate controllable parameters on ECD. Using computational fluid dynamics (CFD), Vajargah et al. [8] evaluated the effect of tool joints on ECD. Ahmed et al. [9] did a study on mud type, mud density and pump flow with the relationship with ECD. They created a semi-empirical model to predict ECD that is applicable in narrow mud weight windows. Vajargah et al. [10] developed an automated real-time ECD management system. In addition, an advanced ECD management

Peer review under responsibility of Egyptian Petroleum Research Institute.

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https://doi.org/10.1016/j.ejpe.2019.12.003
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system was introduced by Rommetveit et al. [11] that utilized real-time data. More recently, Elzenary et al. [12] created a model to predict ECD while drilling by utilizing artificial neural network. Their findings illustrated a decent matching among the predicted and the actual data.

An artificial neural network (ANN) is a simulation of the biological neural system. The biological neuron has a cell body, an axon, and dendrites. The information enters into the cell body through dendrites, then an output provides by the cell body goes through the axon and then to another neuron in a way that the first neuron becomes an input for the second neuron and so forth. Any ANN consists of one input layer, one or many hidden layers, and one output layer. The input and output layers are obviously for inputs and outputs. The hidden layer is responsible for the extraction of the features from the data [13].

Machine learning and data-driven solutions such as regression, support vector machine, fuzzy logic, and neural networks have been taking bigger footprints in the industry as they have the ability to solve complex problems. The application of ANNs have been used in the oil and gas industry for drill bits' selection and drill bit diagnoses [14–17]. Dashevskiy et al. [18] used ANNs to model the dynamic behavior of the non-linear, multi-inputs/outputs drilling system. ANNs have been used to predict bed heights and formation tops while drilling [19,20]. ANNs utilized to predict troubles during the drilling process using a database on drilling parameters by Lind & Kabirova [21]. Okpo et al. [22] used ANNs to predict wellbore instability with a case history from the Niger Delta oil field in Nigeria. Lost circulation prediction prior to drilling is another application of ANNs [23]. Also, ANNs used to estimate the rate of penetration based on some input data [24]. Real-time drilling fluid rheological properties have been estimated using ANNs based on historical data as well as drilling hydraulics [25–29]. The applications of ANNs in the oil and gas industry were summarized by Alkinani et al. [30].

The objective of this work is to create an ANN to estimate ECD prior to drilling using data of more than 2000 wells (over 100,000 data points) drilled worldwide. In addition, this paper will eliminate the shortcoming in the literature by using huge data sets and the model will be applicable globally since the data were collected globally.

2. Creating the network

2.1. Data Collection, data Preprocessing, and input data selection

Data collection is the most time-consuming step of this work. Key drilling parameters were collected from various sources including daily drilling reports, technical reports, mud logging reports, final drilling reports, case histories, and from the petroleum literature. Red dots in Fig. 1 show the location where data gathered. Table 1 shows the range and standard deviation of the data used in this study. Then, the data of each key drilling parameter were tested for outliers using box plots.

Fig. 1. Locations where Data Collected.

After finishing the data preprocessing step (identifying the outliers), the key drilling parameters that will be used as inputs for the model should be chosen. Inputs can be chosen based on experimental tests, modeling, simulation, sensitivity analysis, expert opinion, statistical analysis and etc. The following inputs were chosen based on two criteria which are statistical and sensitivity analyses done by Al-Hameedi et al. [4,5], and experts' opinions:

1. Mud weight (MW) in gm/cc
2. Yield point (Yp) in Ib/100ft^2
3. Plastic viscosity (PV) in cp
4. Revolutions per minute (RPM)
5. Flow rate (Q) in L/min
6. Weight on bit (WOB) in Tons
7. Nozzles total flow area (TFA) in inch^2

2.2. Data normalization

For neural networks, if the input or the output data are too small, too large or non-normally distributed; thus, data scaling should be conducted [31,32]. One method of normalizing data to have values between −1 and 1 is shown in Eq. (1) [33]:

$$X_i' = 2\left[\frac{X_i - X_{min}}{X_{max} - X_{min}}\right] - 1 \quad (1)$$

where X_i is the original value of the parameter, X_i' is the normalized value of X_i, X_{max} and X_{min} are the maximum and the minimum values of X_i, respectively.

2.3. Dividing the data and feedforward backpropagation algorithm

Typically, data are divided into three sections; training, verification, testing sets. The training data used to develop the ANN model, the desired output is utilized to help the network adjust the weights of each input. The error will backpropagate in the network and adjust the weights until calibration is reached, this method is called feedforward backpropagation algorithm. It should be noted that the network should not be overtrained since the network will lose its ability to generalize. Verification set (data not used to create the network) is used to access the network generalization, and to stop the training when generalization stops improving. Testing set (also data not used to create the network) used to test the accuracy of the network after the training and the verification steps. 70% of the data were used for training, 15% used for verification, and 15% for testing.

2.4. Choosing the transfer function

For any neural network, there are three layers; input layer that is responsible for inputs, one or multiple hidden layers to extract

Table 1
Range and standard deviation of the data.

Parameter	Minimum	Maximum	Standard Deviation
MW (gm/cc)	1.04	2.3	0.06
PV (cp)	6	23.0	3.39
Yp (Ib/100ft^2)	11	30.0	4.33
Q (L/Min)	1232	3168.0	393.07
RPM	50	120.0	16.12
WOB (Ton)	4	21.0	3.35
Nozzles, TFA (inch^2)	0.312	10.6	2.05
ECD (gm/cc)	1.06	2.5	0.06

the information from the data, and output layer for outputs. Each input will be assigned to weight (w), and each neuron will be assigned to biases (b). The sum of the biases and input weights will be an input for transfer function (f) [33].

The tan-sigmoid transfer function was chosen for the hidden layer, and a linear transfer function was used for the outputs layer. Using this combination will allow the network to capture the non-linear relationship between the inputs and the outputs. The linear transfer function was selected for the output layer since it is suitable for fitting problems (regression) [33].

2.5. Choosing the optimum number of hidden layers and number of neurons

The optimum number of hidden layers, as well as the number of neurons in the hidden layer, were chosen based on an iterative process. A various number of hidden layers and number of neurons were tested, the goal was to build a network that has the lowest mean squared error (MSE) which is the average squared error between the network estimate outputs (a) and the real output (t). MSE can be calculated using Eq. (2) [33]:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \tag{2}$$

where N is the number of data points. Fig. 2 shows MSE with the number of hidden layers in the network. The MSEs for all scenarios are very small and not significantly different. Thus, for simplicity, the decision was made to have one hidden layer in the network. Fig. 3 shows MSE with the number of neurons in the hidden layer. Once again, the MSEs for all scenarios are very small and not significantly different. Therefore, the decision was made to have 12 neurons in the hidden layer. It is important to mention that the number of hidden layers and the number of neurons in the hidden layer should be chosen carefully since having multiple numbers of hidden layers and many neurons may cause overfitting which makes the network lose its generalization.

2.6. Examination of the training function

This is a very pivotal step in creating the network. There are many algorithms available to choose from. Table 2 summarizes the algorithms examined in this study (more information about each algorithm can be found in Demuth et al. [33]). After testing all algorithms, the lowest MSE with the highest R-squared algorithm was chosen to train the network. R-squared can be calculated using the following Equation:

$$R^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{n}(\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

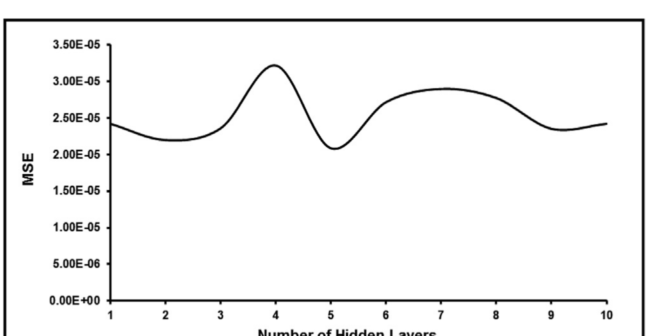

Fig. 2. MSE vs. Number of Hidden Layers.

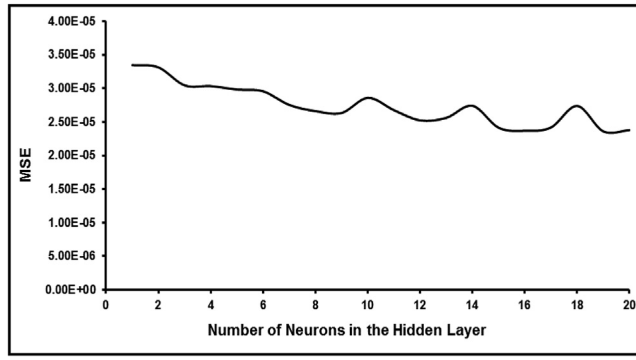

Fig. 3. MSE vs. Number of Neurons in the Hidden Layer.

Table 2
The algorithms examined in this study.

Algorithm	Abbreviations
Resilient Backpropagation	RP
Scaled Conjugate Gradient	SCG
Fletcher-Powell Conjugate Gradient	CGF
One Step Secant	OSS
Levenberg-Marquardt	LM
Polak-Ribiére Conjugate Gradient	CGP
Quasi-Newton	BFG
Conjugate Gradient with Powell/Beale Restarts	CGB
Bayesian Regularization	BR
Variable Learning Rate Backpropagation	GDX

where SSR is the regression sum of squares, SST is the total sum of squares, $\hat{y}_i$ is the predicted data point, $\bar{y}$ is the average mean of the real data, and y_i is the real data point.

3. Results and discussion

Figs. 4 and 5 show MSE and R-squared with the training algorithms, respectively. The algorithm with the lowest MSE and the highest R-squared should be chosen since it will give the best prediction results. The LM and BR training algorithms are very close to each other; however, the BR algorithm has a higher R-squared and a lower MSE. Thus, the Bayesian regularization backpropagation (BR) algorithm was chosen to train the network. The BR algorithm is a modification of the LM algorithm that creates a good generalized network. The BR algorithm updates the weights and the biases according to the LM algorithm optimization. The BR algorithm minimizes the combination of weights and squared errors until producing a network that generalizes well [33]. More details about Bayesian regularization can be found at MacKay [34] and Foresee and Hagan [35].

Fig. 6 shows the predicted and the real ECD for training (Fig. 6a), testing (Fig. 6b), and for all data (Fig. 6c). The model has an R-squared of 0.985 for training, 0.98 for testing, and 0.982 for the overall data. This is a very high R-squared for real field data. However, the very high-quality data used in this study, good data preprocessing and preparation, and carefully choosing the key drilling parameters as inputs for the network contributed to this high R-squared. Another argument can be made about having this high R-squared is the network has been overfitted and it lost the generalization ability. This argument is not valid since overfitting can occur if multiple numbers of hidden layers and a large number of neurons in the hidden layer were used and/or the network was overtrained. Nevertheless, this network has a minimum number of hidden layers which is one, twelve neurons in the hidden layer

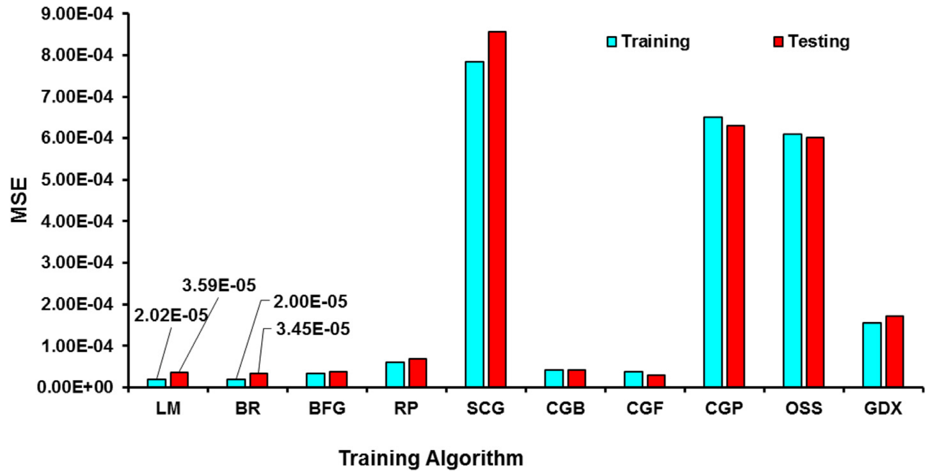

Fig. 4. Training Algorithms vs. MSE.

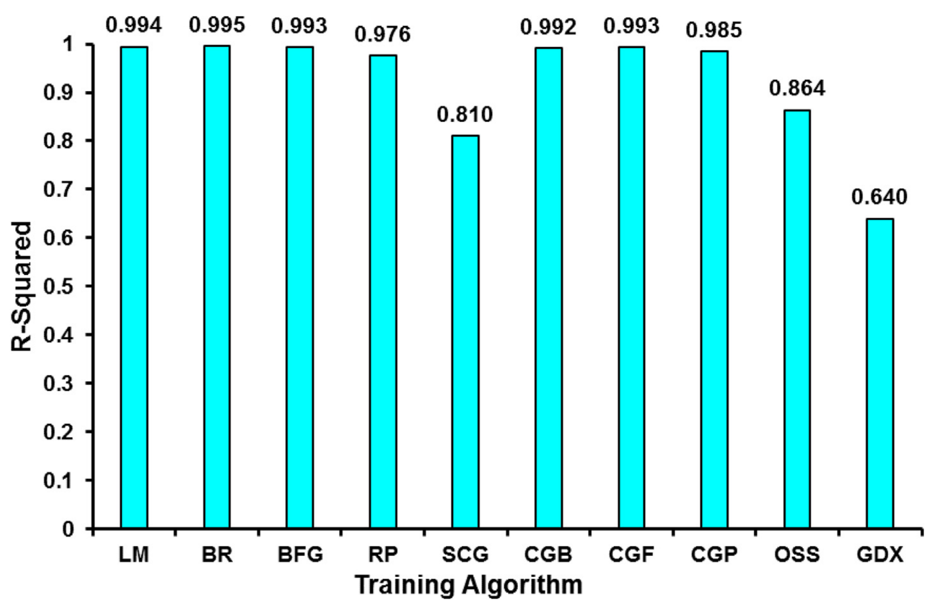

Fig. 5. Training Algorithms vs. R-Squared.

which is typical, and the BR algorithm was used to create the network which is the most powerful algorithm used for generalization and avoiding overfitting.

In order to use the network to predict ECD prior to drilling, normalized MW, PV, Yp, Q, RPM, WOB, and Nozzles TFA can be imported to Eq. (4). Table 3 shows the coefficients used for Eq. (4).

$$ECD = \left[\sum_{i=1}^{N} w_{2i}\left(\frac{2}{1+e^{-2\left(\sum_{j=1}^{J} w_{1i,j}x_j+b_{1i}\right)}}-1\right)+b_2\right] \quad (4)$$

where N is the number of neurons in the hidden layer which was optimized to be twelve, w_1 is the weight of the hidden layer, w_2 is the weight of the output layer, b_1 is the bias of the hidden layer, b_2 is the bias of the output layer, and x is the input variables. The j's are associated with the input variables such that j = 1 is MW, j = 2 is PV, j = 3 is Yp, j = 4 is Q, j = 5 is RPM, j = 6 is WOB, and j = 7 is Nozzles TFA.

The normalized values for MW, PV, Yp, Q, RPM, WOB, and Nozzles TFA can be calculated using the following Equations:

$$NormalizedMW = 1.587302 \times MW - 2.650794 \quad (5)$$

$$NormalizedPV = 0.11764706 \times PV - 1.70588235 \quad (6)$$

$$NormalizedYP = 0.10526316 \times YP - 2.15789474 \quad (7)$$

$$NormalizedQ = 0.00103306 \times Q - 2.27272727 \quad (8)$$

$$NormalizedRPM = 0.02857143 \times RPM - 2.42857143 \quad (9)$$

$$NormalizedWOB = 0.11764706 \times WOB - 1.47058824 \quad (10)$$

$$NormalizedNozzlesTFA = 0.194401 \times NozzlesTFA - 1.060653 \quad (11)$$

Eq. (4) will give the normalized ECD, Eq. (12) can be used to get the denormalized ECD:

$$DenormalizedECD = 0.72 \times (1 + NormalizedECD) + 1.06 \quad (12)$$

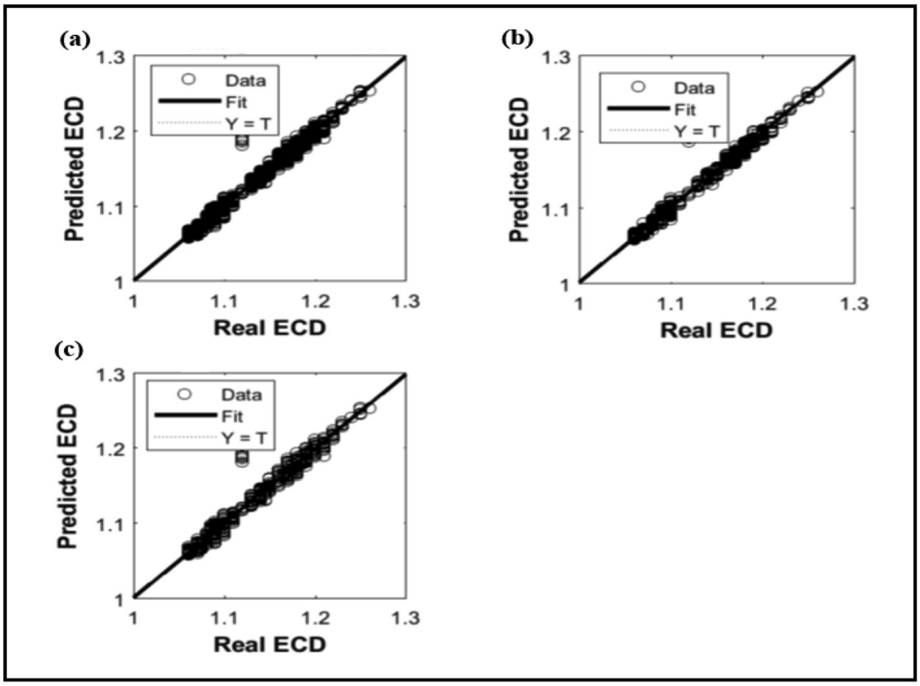

Fig. 6. Predicted and Actual ECD for Training (a), Testing (b), and All (c) Datasets.

Table 3
Coefficients for the ECD Neural Network (Eq. (4)).

Input Layer Weight Matrix							Input Layer Bias	Hidden Layer Weight Matrix	Output Layer Bias
w_{1j}									
j = 1	j = 2	j = 3	j = 4	j = 5	j = 6	j = 7	b_1	w_2	b_2
−1.2008	0.2154	0.3898	0.5579	0.4958	−0.1066	−0.7065	−0.8198	0.531816699	−0.6499
1.5459	0.1176	0.5349	−0.1862	0.5528	−0.6321	−0.0178	1.3558	−0.708647853	
1.6838	0.8050	−0.6092	−1.1859	−0.5609	0.9683	−0.4464	0.6826	−0.290876462	
1.2490	−0.2491	−1.0713	−1.1378	−0.9593	0.5552	0.3608	0.2130	0.068220247	
−1.6843	0.1302	0.6554	−0.1135	0.4651	−0.7280	−0.0497	−1.2035	−0.618595451	
−1.3056	−0.7660	0.5060	0.9014	0.4865	−0.8601	0.4180	−0.4735	−0.553128401	
0.0992	−0.3794	0.0186	0.0652	−0.0813	−0.2462	0.3758	0.1701	−1.478145582	
1.5328	0.1268	0.3090	−0.1559	0.2836	−0.3575	−0.0154	0.9347	0.835442371	
2.8776	0.6069	−0.1100	−0.5006	−0.0456	0.3047	−0.2417	2.3912	0.799337537	
−0.2927	0.1459	0.7582	−0.1243	0.5966	−0.8676	−0.0233	0.0445	0.728599715	
0.936315	−0.288	−0.18086	−0.28484	−0.29031	−0.06999	0.590354	0.758764007	1.11665311	
1.483936	0.562407	−0.16002	−0.40617	−0.09837	0.388953	−0.28098	1.088802151	−1.828425173	

4. Conclusion

The following insights have been deduced from this research:

- This study eliminated the shortcoming in the previous studies regarding ECD prediction prior to drilling. This study provided a generalized network, which can be invested to assess ECD before drilling anywhere in the world.
- The network developed in this study showed the ability to predict ECD with a very low error and a very high R-squared.
- The BR algorithm was chosen to train the network in this study since it had the lowest MSE and the highest R-squared.
- The network generated in this work can be utilized to predict ECD before drilling. In the same vein, the model can be used in reverse to obtain a target ECD by setting the key drilling parameters affecting ECD.
- Intelligent systems and machine learning have proven their potential so solve complicated problems that cannot be solved analytically. With the large data sets available in the petroluem industry, machine learning can be used to optimize the drilling operations and save time and money.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

The authors would like to thank Basra Oil Company from Iraq for providing us with various real field data.

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