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Optimizing Drilling Fluid Properties Using Deep Learning Algorithms to Reduce Drilling Problems in a Middle Eastern Oil Field

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ABSTRACT

Drilling fluid is among the most important requirements for drilling oil, gas, and geothermal wells. Many drilling challenges are directly or indirectly related to the drilling fluids; therefore, optimizing the drilling fluid has a significant effect on the quality of drilled wellbore, and the risk of drilling operations. In this paper, it is tried to develop deep learning algorithms to optimize drilling fluid properties to minimize the possibility of occurrence of possible problems in one target field in the Middle East. This paper deals with the method of artificial intelligence for the first time to investigate the possibility of estimating optimum drilling fluid parameters using drilling and geological parameters to minimize problems- without considering the location of the target wells. Two artificial intelligence algorithms ''LSSVM'' and ''MLP-FFBP'' were used to train the machine to optimize drilling fluids (such as mud density, yield point, plastic viscosity, etc.) to minimize drilling fluid challenges such as stuck pipe, tight hole, formation influx, and even loss circulation. Results showed that for optimizing drilling fluid parameters in a newly drilled well, the developed AI networks have good capability to estimate parameters for some drilling fluid parameters such as mud density, plastic viscosity, water percentage, and API filtration properties with the accuracy of more than 95% for train and more than 85% for test data. Moreover, results showed that drilling fluids have a direct effect on the tight holes and stuck incidents.

KEYWORDS

Drilling fluid design, drilling optimization, artificial intelligence, deep learning algorithms, drilling problems

I. INTRODUCTION

Drilling fluid is one of the most important parts of any drilling operation in the oil and gas industry. Most drilling challenges are related to the used drilling fluids such as pipe stuck, wellbore collapse, etc. Therefore, designing a proper drilling fluid based on the well type and condition is critical (API, 2021). Therefore, many researchers have tried to improve the drilling fluid properties using different experimental and mathematical studies. Nowadays, by improving Artificial Intelligence and Machine Learning sciences, drilling fluid optimization can be advanced to the next generation level.

In this study, one of the most significant onshore fields in the Middle East is selected and studied. All the drilling and drilling fluids data of several drilled 17 ½'' hole sections in 10 wells in target field were gathered. Then, it is tried to optimize drilling fluid using machine learning in order to minimizing drilling problems such as the tight hole, stuck pipe, gain and formation kicks and loss of circulation.

An artificial neural network (ANN) consists of a set of neurons and unidirectional connections between them, which enables the imitation of the human brain's ability to detect patterns and learn relationships within data. Associated with each neuron is an activation function and each connection between two neurons has a weight assigned that controls the influence of the first neuron on the second one. While the neurons represent the basic computation units of an ANN, the weighted connections between them allow the modeling of complex relationships (Yang and Yang, 2014).

Thus far, articles on estimating drilling fluid parameters from fluid-dependent parameters have been conducted using artificial intelligence techniques. For instance, with ANFIS (adaptive neuro-fuzzy inference system), PSO-ANFIS (particle swarm optimization-adaptive neuro-fuzzy inference system), LSSVM-GA (least square support vector machine-genetics algorithm), and RBF (radial basis function) algorithms have been utilized to estimate the density of drilling fluid at high-pressure high-temperature wells, which have also achieved high accuracy results (Karimian et al., 2022). In another

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paper, Ahmadi developed an artificial intelligence-based method for the determination of the density of drilling fluids in good conditions when essential experimental data are unavailable (Ahmadi, 2016). In this paper, all the geological and drilling parameters, such as mud loss rate, rate of penetration, Wash and Ream Time criteria time, and quality of drilling, Stuck, affecting the wellbore stability and drilling challenges, including depth, weight on bit, Drill pipe rotating speed, Standpipe pressure, drilling torque, mud flow rate, bit type, drilling motor type, bottom hole assembly type, bit nozzles, lithology, flow line temperature, in 10 wells have been used to find the algorithms to estimate drilling fluid parameters.

Many researchers have studied drilling optimization and reduction in drilling problems using drilling fluid properties in recent years. Some of the mentioned researches are summarized in Table 1.

Table 1. Researches for drilling optimization and reduction in drilling problems using drilling fluid properties

Authors	Type of study	Kernel Function	Output Parameters	Input Parameters
Siruvuri et al., (2006)	Prediction of differential pipe sticking	GFFN	Differentially stuck or no stuck	Water based sticking model: differential pressure, hole depth, API fluid loss, MBT, chlorides, total hardness, PV, YP, gels, inhibitor concentration, pH, Oil based sticking model: PV, YP, gels, emulsion ability, HPHT fluid loss, lime, chlorides, oil water ratio, hole depth
Miri et al., (2007)	Prediction of differential pipe sticking	MLP RBF	Stuck index	Differential pressure, hole depth, API fluid loss, solid percent, mud filtrate viscosity, plastic viscosity, yield point, 10 sec and 10 min gel strength
Murillo et al., (2009)	Prediction of pipe sticking mechanism	-	Stuck pipe condition	Measured depth, TVD, bit flow rate, 10 sec and 10 min gels, mud weight, PV, YP, calcium filtrate, chloride filtrate, torque, circulating pressure, WOB, drag, bit size, BHA, ROP, RPM
Shadizadeh et al., (2010)	Predicting stuck pipe	FFBPN	probability Stuck pipe	Differential pressure, geometric factor, pH, YP, PV gel strength.
Alireza et al., (2011)	Loss circulation	FFBPN	Amount of lost circulation	Well depth from ground surface and from sea level, drilled depth, drilling time, length of open hole section, asmari formation top from ground surface, northing, easting of well, bit size, average output of pump, average pump pressure, mud weight, solid percent of mud, mud fluid loss, amount of loss circulation, amount of loss of circulation in two days
Al-Baiyat and Heinze (2012)	Predicting stuck pipe before its occurrence	FFBPN	Stuck index	Well direction characteristics, mud properties and drilling parameters
Jahanbakhshi et al., (2012)	Predicting stuck pipe before its occurrence	FFBPN	Stuck index	Differential pressure, hole depth, mud filtrate viscosity, fluid loss, solid content, BHA length, still pipe time, hole size, 10 sec and 10 mins gels, PV, YP
Chamkalani et al., (2013)	Stuck pipe predicting	RBF	Differential, mechanical, non-stuck	TVD, fluid loss, differential pressure, formation loss, cross section of annulus, ROP, RPM, measured depth, angle of well, calcium concentration, solid percent, water oil ratio, oil water ratio, open hole, formation pressure, drill collar (OD), drill collar length, 10 sec/ 10 mins gels, PV, YP, flow rate, pH
Razi et al., (2013)	Rheological properties of WBM	FFMLP	Plastic viscosity and yield point	Temperature and concentration
Zhu et al., (2013)	Model of pipe sticking prewarning	BPNN	Stuck index	Sticking point depth, WOB, revolution, displacement, pump pressure, mud density, funnel viscosity, sand content, thickness of mud cake, water loss
Jahanbakhshi and Keshavarzi (2015)	Prediction of the amount of loss circulation	Gaussian Kernel and Polynomial Kernel functions	Amount of loss circulation	Hole depth, porosity, formation permeability, differential pressure, ROP, ECD, pump pressure (avg), temperature in loss interval, PV, YP, 10 sec/10 min gels, Solid percent, Mud filtrate viscosity, API fluid loss, Minimum horizontal stress, Tensile & Uniaxial compressive strength, Natural fracture orientation, Young modulus
Shadravan et al., (2015)	Mud design	BP	Rheological Properties (RPMs of 600, 300, 200, 100, 6 & 3)	Fluid density, ingredient A content, temperature
Behnoud far,and Hosseini, (2016)	Prediction of loss circulation	FFBPN	Amount of loss circulation	Pump pressure, depth, mud flow rate, mud weight
Manshad, et al., (2017)	Prediction of loss circulation	RBF	Amount of loss	Present driller depth of well in the day of study, level in the day of study, Well trajectory, Drilling time, Length of open hole Present depth of well from sea

The backpropagation algorithm is a machine learning algorithm that is specifically used to train feedforward neural networks. There are backpropagation generalizations for other artificial neural networks and their function in general. In an artificial neural network, this algorithm calculates the cost slope according to the network weight for a single input-output example, it provids a simple direct calculation of the slope for each weight it performs (Wythoff, 1993).

The Multi-Layer perceptron is the most known and most frequently used type of the neural networks. On the most occasions, the signals are transmitted within the network in solely one direction: from input to output. In this type architecture which is called feedforward, there is no loop, and the output of each neuron does not affect the neuron itself. The power of the multilayer perceptron comes precisely from nonlinear activation functions (Bahri et al., 2021).

In machine learning, support vector machines -known as support-vector networks- are supervised learning models with support vector learning algorithms (kernel properties), which analyze data for classification and analysis of regression. The support vector machine training algorithm creates a model that assigns new samples to one category or another and converts it into an impermissible binary vector (Alimoradi et al., 2012).

The studied drilling fluid properties for this research are summarized in Table 2.

The drilling mud parameters that were used as artificial neural network outputs in this paper are as follows:

1. Mud Weight is the density of drilling fluid per unit volume. This is one of the most important properties of the drilling fluid as it controls the formation pressure and also contributes to the stability of the wellbore (Hughes, 2006).
2. Yield Point or chemical resistance to the initial flow of the fluid is the required stress for fluid movement. It is highly related to the capability of the drilling fluid to carrying the cuttings to the surface and efficiency of hole cleaning (Hughes, 2006).
3. Plastic Viscosity is fluid physical resistance to flow. Plastic viscosity is highly related to the solids in the drilling fluid. In addition, the loss of frictional pressure, known as Standpipe pressure, is directly related to this parameter. In order to reduce the plastic viscosity of the fluid, the solid content must be decreased using solid control equipment or diluting practices while drilling (Hughes, 2006).

Shear Stress is part of the surface tension with a cross-section of fluids. On the other hand, natural stress is caused by the force vector component perpendicular to the cross-section of the fluid on which it operates (Cristianini and Taylor, 2000). Shear stress at 6 round per minute is called R6 and shear stress at 3 round per minute is called R3. These mentioned parameters are crucially important in hole cleaning specially in low flow rates.

API Fluid Loss parameter is a result of standard fluid filtration test at low pressure (100 psi) and ambient temperature as per API13-B1 standard (API, 2021).

4. KCl Percentage: Potassium chloride salt is one of the most common and effective shale inhibitors which are used widely in drilling fluids. It may have strong relationship with wellbore quality.
5. The Methylene Blue Test is an experiment to determine the quantitative clay contents in a drilling fluid (Hughes, 2006).

All the mentioned drilling fluid properties will be measured and reported at rig site as daily routine testing. Therefore, all the data for 10 wells were gathered and used in this study. The lithology of drilled rocks in the mentioned hole section were mainly anhydrite, marl and carbonate rocks. It is worth mentioning that some other parameters such as bit type, rig type, stabilizer selection, etc. were not considered in this research.

II. METHODOLOGY

In this section, the input and output data of drilling and drilling fluids parameters were first investigated regarding the dependence of output parameters on input parameters for learning data series to remove the input parameters unaffected by machine learning using Principal Component Analysis (PCA). Then, two series of artificial neural networks were used, and their function was investigated to estimate the output parameters. The outputs are compared to actual outputs and error values were investigated.

Table 2. Description of drilling fluid properties for the research (Hughes, 2006)

Row	Drilling Fluid Parameter	Parameter Type	The Drilling Challenges Related to the studied parameters
1	Mud Density	Physical	Loss of circulation, Kick and Gain from formations, Wellbore Stability Condition
2	Yield Point	Physical (Rheological)	Hole Cleaning, Stuck pipe
3	Plastic Viscosity	Physical (Rheological)	Hole Cleaning, Torque, and Drag, Stuck pipe
4	R6 and R3 Dial Readings	Physical (Rheological)	Hole Cleaning, Stuck pipe
5	API Filtration (API FL)	Physical	Wellbore Stability Condition, Stuck pipe, Tight Hole Condition
6	KCl percentage	Chemical	Wellbore Stability Condition, Stuck pipe
7	CLAY Content (MBT[1])	Chemical	Wellbore Stability Condition, Hole Cleaning

[1] Methylene Blue Test

A. Data Preparation

The first part of which included 466 data from 34 wells at depths of 40 to 2204 meters, which reached 300 data after clearing unused data belonging to cementing days (which ROP[1], speed of drilling pipe movement (RPM[2]), and WOB[3] were zero). Table 3 lists the output parameters and the range of their changes in this dataset.

B. Principal Component Analysis for data

To properly understand the interaction between each input parameter and output parameters and to remove the input parameters unaffected by the outputs, it is required to investigate the numerical and statistical relationships of the parameters in the data. Principal Component Analysis (PCA) was used to investigate these relationships. In the first step, to remove the interdependent input parameters, this analysis is applied to the input parameters, which are inserted in Table 3 of the interaction between each input parameter for all observation data sets. In this analysis method, the obtained number range is between -1 and 1, with 1 indicating the complete correlation between the two variables and the number -1 indicating a completely inverse correlation. Interstitial numbers show these two ratios relatively (positive numbers between 0 and 1 have a direct correlation, and negative numbers between 0 and -1 have an inverse correlation).

In table 4, having stuck is considered as 1, and not facing stuck is equal to 0.

In the artificial neural network, the input parameters should not have a correlation square above 0.9 (i.e, 90%,). With the results obtained from the Table 3, it is obvious that none of the parameters have a correlation coefficient of 0.9 or more. Therefore, the parameters are independent, and none are required to be emitted.

In the next step, to remove input parameters unaffiliated with output parameters, analysis was performed on input and output parameters, in Table 5, the interaction between input and output parameters for data is observed.

Using the Table 4, the Azimuth parameter of wells can be removed because they have a zero correlation coefficient with the outputs, which means that they do not have a significant relationship with the outputs, and as a result, entering them into the artificial neural network does not help to estimate the output parameters.

In the next step, to find the output parameters depending on each other, the analysis was performed on the data of the output parameters, and the results of the analysis are listed in Table 5.

Using Table 6, the two parameters Mud Weight and Plastic Viscosity have a correlation coefficient of approximately 90%. Therefore, it is predicted that it is possible to estimate them with accuracy percentage. The same is true of the two parameters R6 and R3.

Table 3. List of output parameters and their range of changes in the data of this article

Row	Output's Parameter	Parameter's Unit	Parameter's range of changes
1	Mud Weight	PCF (pounds per cubic feet)	66-122
2	Yield Point	lb./100ft^2	2-39
3	Plastic Viscosity	cP (centi Poise)	1-47
4	R6 and R3	-	1-19
5	API Filtration (API FL)	cc/30min	0-130
6	KCl Content	%	0-6
7	Clay content from Methylene Blue Test (MBT)	Pound per bbl.	2.5-30

Table 4. Interaction input parameters

Parameter	Measured Depth	weight of bits	Round per Minute	STANDPIPE PRESSURE	torque	Mud Flow rate	ROP	Lithology Type	Mud Loss Rate	Wash & Ream Time	stuck	Flowline temperature
Measured Depth	1	-0.244	-0.132	0.043	-0.056	-0.205	-0.679	0.517	0.208	0.051	0.061	0.576
weight of bits	-0.244	1	0.599	0.544	0.435	0.583	0.375	-0.275	0.081	0.07	0.031	-0.105
Round per Minute	-0.132	0.599	1	0.807	0.777	0.756	0.378	0.078	0.092	0.137	0.055	-0.12
Stand pipe Pressure	0.043	0.544	0.807	1	0.641	0.742	0.174	0.153	0.111	0.171	0.017	0.063
torque	-0.056	0.435	0.777	0.641	1	0.633	0.314	0.077	0.052	0.052	0.013	-0.14
Mud Flow rate	-0.205	0.583	0.756	0.742	0.633	1	0.418	0.041	0.12	0.179	-0.027	-0.08
ROP	-0.679	0.375	0.378	0.174	0.314	0.418	1	-0.31	-0.07	0.016	-0.032	-0.475
Lithology Type	0.517	-0.275	0.078	0.153	0.077	0.041	-0.31	1	0.149	0.054	0.014	0.368
Mud Loss Rate	0.208	0.081	0.092	0.111	0.052	0.12	-0.07	0.149	1	0.029	0.048	0.116
Wash & Ream Time	0.051	0.07	0.137	0.171	0.052	0.179	0.016	0.054	0.029	1	0.12	0.087
stuck	0.061	0.031	0.055	0.017	0.013	-0.027	-0.032	0.014	0.048	0.12	1	0.051
Flowline temperature	0.576	-0.105	-0.12	0.063	-0.14	-0.08	-0.475	0.368	0.116	0.087	0.051	1

1. Rate of penetration (while drilling)
2. Round per minute
3. Weight on bit

Table 5. Interaction between input parameters and output parameters

Parameter	Mud Weight	Yield Point	Plastic Viscosity	R6	R3	API Fi	KCl	MBT
Depth	0.587	0.071	0.643	-0.354	-0.343	-0.581	0.383	-0.305
weight of bits	-0.117	-0.092	-0.198	0.157	0.144	0.006	-0.04	-0.024
Round per Minute	-0.129	-0.09	-0.165	0.027	0.018	-0.073	0.025	-0.157
Stand pipe Pressure	0.005	-0.013	-0.021	0.002	-0.01	-0.186	0.125	-0.068
torque	-0.068	-0.073	-0.129	0.025	0.003	-0.111	0.025	-0.043
Mud Flow rate	-0.24	-0.006	-0.225	0.172	0.172	0.069	0.088	0.002
ROP	-0.471	-0.057	-0.475	0.243	0.228	0.432	-0.359	0.211
Bit Type	-0.089	0.03	-0.048	0.085	0.085	-0.006	0.169	-0.134
Motor Type	-0.01	-0.021	0.027	-0.076	-0.082	-0.04	0.093	0.107
Bottom Hole Assembly Type	0.059	-0.168	-0.03	-0.02	-0.025	-0.008	-0.008	0.051
Bit Nozzle number	0.402	0.028	0.441	-0.16	-0.132	-0.203	-0.086	-0.083
Bit Nozzle size	0.321	0.128	0.388	-0.102	-0.076	-0.173	0.092	-0.094
Lithology Type	0.156	0.076	0.282	-0.226	-0.224	-0.252	0.092	-0.167
Mud Loss Rate	0.097	0.093	0.145	-0.033	-0.036	-0.087	0.052	-0.028
Wash & Ream Time	0.025	0.034	0.044	0.068	0.06	0.014	0.167	-0.045
azimuth	0	0	0	0	0	0	0	0
Time of drilling	0.014	0.004	0.02	-0.042	-0.055	-0.045	0.077	0.036
stuck	0.102	-0.002	0.081	0	0	-0.038	0.019	0.049
Flowline temperature	0.607	0.006	0.619	-0.191	-0.153	-0.320	0.066	-0.252

C. Data Normalization

For the artificial neural network to find the conceptual patterns in a large data set, the input and output parameters values of the dataset must be in an equal and defined range, for the effect of all of them on the network is the same. For this purpose, one of the common techniques of statistical studies called normalization was used. Using this method, the data falls into a new range. In the newly obtained set of numbers, the maximum value of the initial data is scored as 1 and the minimum value is scored by -1. The used normalization equation is:

$$X_{new} = (X_{old} - X_{min})/(X_{max} - X_{min}) \quad (1)$$

In the above equation, Xmin has the minimum data value, Xmax has the maximum data value, Xold and Xnew are the primary and converted values of each data, respectively. This transfer formula affects all input and output parameters of the data set to make the input and output data to normalize the inputs the artificial neural network.

2.4. Multi-Layer Perceptron (MLP) Algorithm

The multilayer perceptron consists of a system of simple interconnected neurons, or nodes, as illustrated in Fig. 1, in which a model representing a nonlinear is mapping between an input vector and an output vector. The nodes are connected by weights and output signals, which are a function of the sum of the inputs to the node modified by a simple nonlinear transfer, or activation, function. It is the superposition of many simple nonlinear transfer functions that enables the multilayer perceptron to approximate extremely non-linear functions. If the transfer function were linear then the multilayer perceptron would only be able to model linear functions. Due to its easily computed derivative, a commonly used transfer function is the logistic function. The output of a node is scaled by the connecting weight and fed forward to be an input to the nodes in the next layer of the network. This implies a direction of information processing; hence, the multilayer perceptron is a feed-forward neural network. The architecture of a multilayer perceptron is variable but, in general, will consist of several layers of neurons. The input layer plays no computational role but merely serves to pass the input vector to the network. The terms input and output vectors refer to the inputs and outputs of the multilayer perceptron and can be represented as single vectors, as shown in Fig. 1. A multilayer perceptron may have one or more hidden layers and finally an output layer (Bahri et al., 2021).

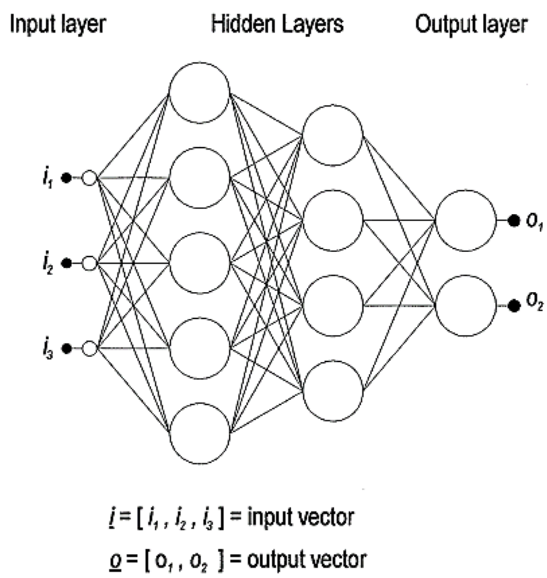

Fig. 1. A multilayer perceptron with two hidden layers (Bahri et al., 2021)

Table 6. Interaction between output parameters

Parameter	Mud Weight	Yield Point	Plastic Viscosity	R6	R3	API Fi	KCl	MBT
MUD WEIGHT	1	0.15	0.925	-0.185	-0.232	-0.334	-0.065	-0.179
Yield Point	0.15	1	0.305	0.382	0.404	0.227	-0.158	0.306
PLASTIC VISCOSITY	0.925	0.305	1	-0.156	-0.213	-0.315	-0.068	-0.147
R6	-0.232	0.404	-0.213	1	0.953	0.456	-0.232	0.346
R3	-0.185	0.382	-0.156	0.953	1	0.448	-0.247	0.345
API Fi	-0.334	0.227	-0.315	0.448	0.456	1	-0.432	0.367
KCl	-0.065	-0.158	-0.068	-0.247	-0.232	-0.432	1	-0.243
MBT	-0.179	0.306	-0.174	0.345	0.346	0.367	-0.243	1

D. Support Vector Machine (SVM) Algorithm:

SVM is one of the best-known techniques to optimize the expected solution. SVM was introduced by Vapnik as a kernel-based machine learning model for classification and regression tasks. The extraordinary generalization capability of SVM, along with its optimal solution and its discriminative power, has attracted the attention of data mining, pattern recognition, and machine learning communities in the last few years. SVM has been used as a powerful tool for solving practical binary classification problems. It has been shown that SVMs are superior to other supervised learning methods. Due to its good theoretical foundations and good generalization capacity, in recent years, SVMs have become one of the most used classification methods (Cristianini and Taylor, 2000).

The main motivation of SVM is to separate several classes in the training set with a surface that maximizes the margin between them. In other words, SVM allows for maximizing the generalization ability of a model. This is the objective of the Structural Risk Minimization principle (SRM) which allows the minimization of a bound on the generalization error of a model, instead of minimizing the mean squared error on the set of training data, which is the philosophy often used by the methods of empirical risk minimization (Syah et al., 2021).

Despite the generalization capacity and many advantages of the SVM, they have some very marked weaknesses, among which are: the selection of parameters, algorithmic complexity that affects the training time of the classifier in large data sets, development of optimal classifiers for multi-class problems, and the performance of SVMs in unbalanced data sets (Syah et al., 2021).

The support-vector network implements the following idea: it maps the input vectors into some high dimensional feature space Z through some non-linear mapping chosen a priori. In this space a linear decision surface is constructed with unique properties that ensure high generalization ability of the network. The technique of support-vector networks was first developed for the restricted case of separating training data without errors. In this article, we extend the approach of support vector networks to cover when separation without error on the training vectors is impossible. With this extension we consider the support-vector networks as a new class of learning machine, as powerful and universal as neural networks (Cortes and Vapnik, 1995).

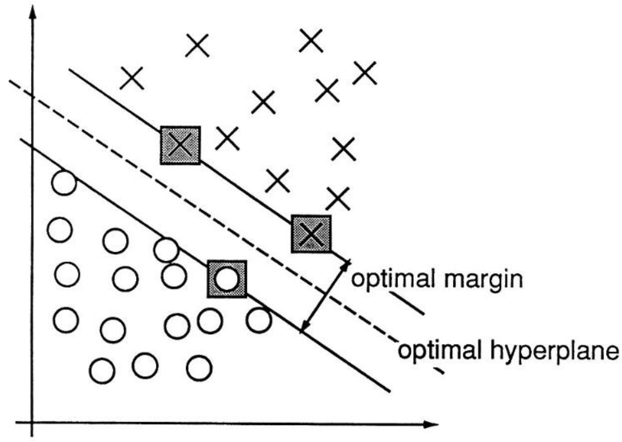

Fig. 2. An example of a separable problem in a 2-dimensional space. The support vectors, marked with grey squares, define the margin of the largest separation between the two classes (Cortes and Vapnik, 1995)

III. ESTIMATION OF DRILLING FLUID PARAMETERS BY MLP-BP & SVM ALGORITHM (TRAINING THE MACHINE)

In this article, two artificial neural networks (SVM & MLP-BP) have been used to estimate the drilling fluid parameters. Selecting the data for training and testing stages have been done entirely randomly using standard random selection operators. The mean square error (MSE), mean absolute error (MAE), and mean correlation coefficient (R) of all artificial neural networks in each stage are almost the same. In the following Fig.s (Fig.s 3 to 8), the values of the mentioned three criteria for all the output parameters of the drilling fluid once with and once without applying the related output parameters are given:

Fig.s 4 and 5 indicate that the mean correlation coefficient (R) in learning process for train data in both conditions (with and without applying the related output parameters) is near to one which is favorable. On the other hand, for test data, applying the related output parameters increases the accuracy of predictions (Fig. 4). As shown in both Fig.s 4 and 5, plastic viscosity and mud weight have the best accuracy compared to other studied parameters.

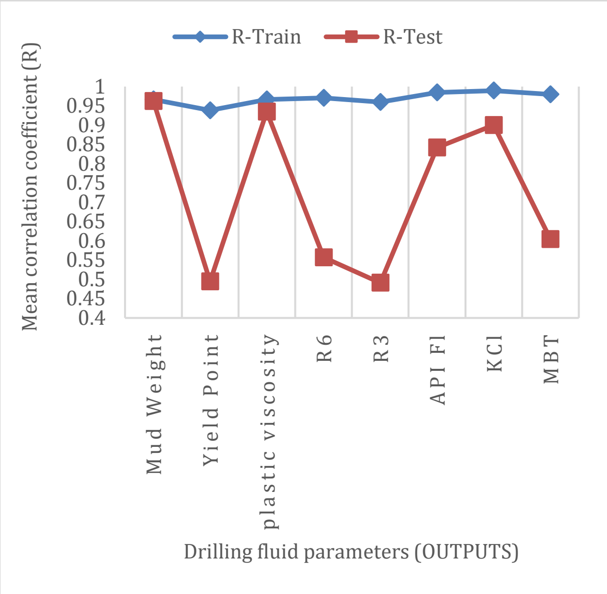

Fig. 3. Mean correlation coefficient (*R*) of the learning process for output parameters without applying other related estimated output parameters

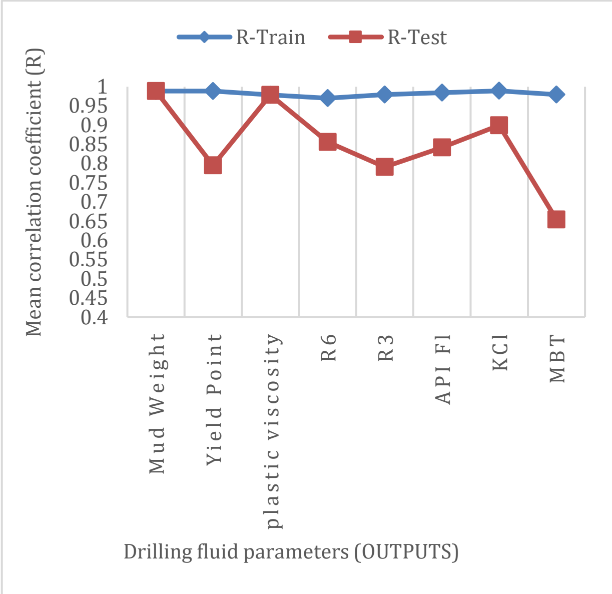

Fig. 4. Mean correlation coefficient (*R*) of the learning process for output parameters by applying other related estimated output parameters

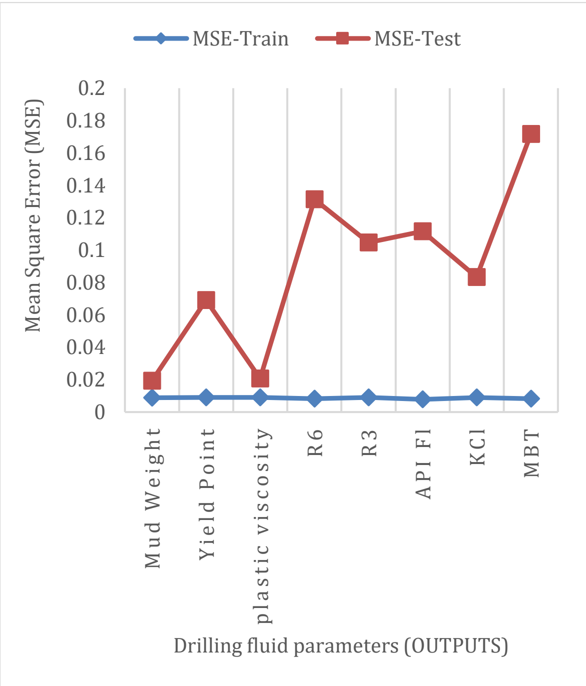

Fig. 5. Mean Square Error (MSE) of the learning process for output parameters without applying other related estimated output parameters

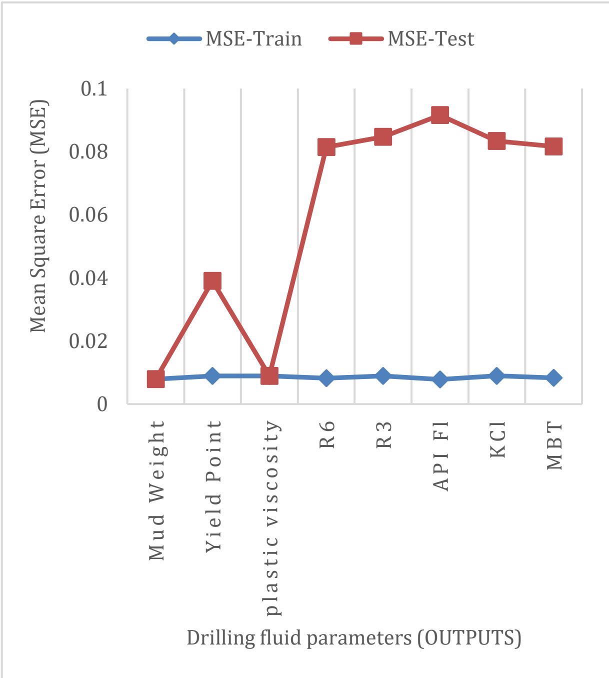

Fig. 6. Mean Square Error (MSE) of the learning process for output parameters by applying other related estimated output parameters

Figures 6 and 7 indicate that the mean square error (MSE) in the learning process for train data in both conditions (with and without applying the related output parameters) is near to zero which is favorable. In addition, for test data, applying the related output parameters decreases the error of predictions (Fig. 6). As shown in both Fig.s 6 and 7, plastic viscosity and mud weight have the best accuracy compared to other studied parameters in both train and test data sets.

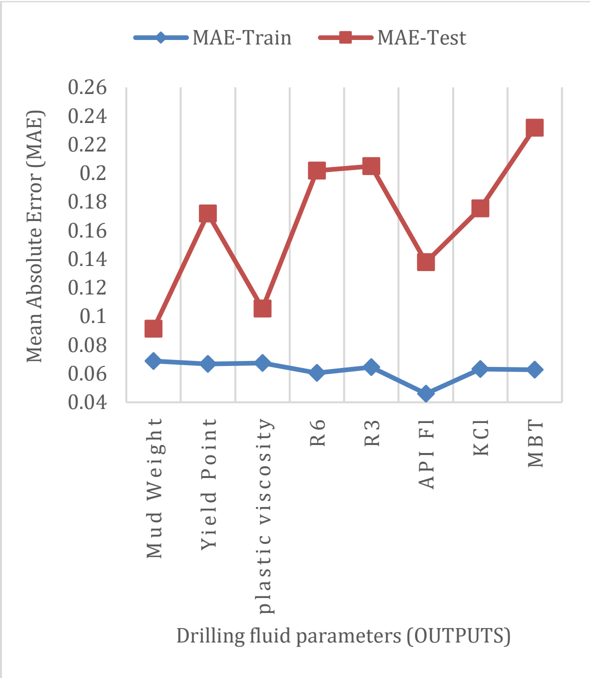

Fig. 7. Mean Absolute Error (MAE) of the learning process for output parameters without applying other related estimated output parameters

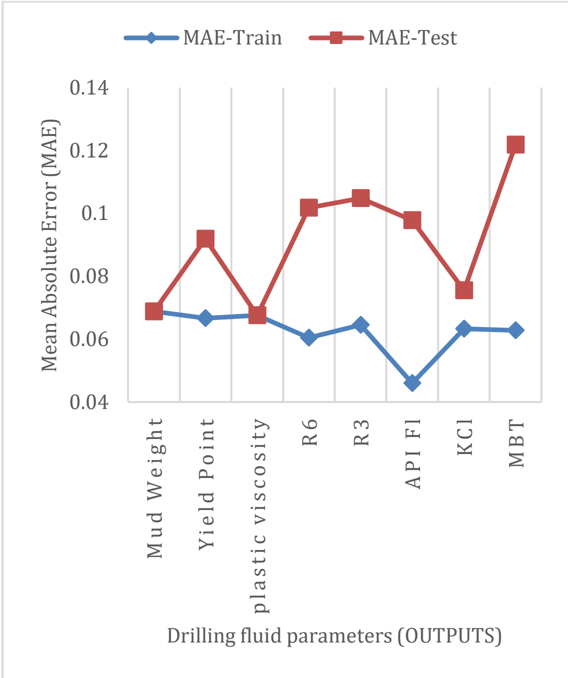

Fig. 8. Mean Absolute Error (MAE) of the learning process for output parameters by applying other related estimated output parameters

Fig.s 8 and 9 indicate that the Mean Absolute Error (MAE) in learning process for train data in both conditions (with and without applying the related output parameters) is under 0.1, which is favorable. Moreover, for test data, applying the related output parameters decreases the error of predictions (Fig. 8). As shown in both Fig.s 8 and 9, API Fl (fluid loss) have the best accuracy compared to other studied parameters in both train and test data sets.

A. Point to Point Validation (Testing the Machine)

After completing the learning process by mentioned artificial neural networks (SVM and MLP), validation or feasibility study about the capability to estimating the drilling fluid parameters by those networks were investigated. At this stage, 10% of the drilling data that were randomly separated before the artificial neural network learning process were used to validate the networks. Therefore, in Fig.s 10 to 17, the difference between the mean estimated value by the networks and the actual value for each parameter are given and discussed.

As the Fig. 10 indicates, the accuracy of prediction for mud weight parameter is high and consistent in the run tests. This accuracy can be related to the effects between plastic viscosity and mud weight, and resulting in better learning process of the machine.

As the Fig. 11 indicates, the accuracy of prediction for yield point parameter is strong and consistent. In the run tests, only two points have unreasonable errors.

As the Fig. 12 shows, the accuracy of prediction for plastic viscosity parameter is high and consistent in the run tests. This accuracy can be related to the effects between plastic viscosity and mud weight, and resulting in better learning process of the machine.

As the Fig. 12 shows, the accuracy of prediction for R3 parameter is weak in the run tests (same as R6), but trends are consistent. Further researches are required to investigate the accuracy of results.

As it is shown in the Fig. 14, the accuracy of prediction for R6 parameter is weak in the run tests (same as R3), but trends are consistent. As it was predictable, the output data for R3 and R6 are in the same trend due to their similarity. Further researches are required to investigate the accuracy of results.

As it is shown in the Fig. 16, the accuracy of prediction for KCl percentage is weak and inconsistent in the run tests. One assumption for this weak prediction for KCl percentage, can be justified for being a chemical properties and hardship to predict its effects on wellbore physical conditions.

As the Fig. 15 indicates, the accuracy of prediction for API fluid loss parameter is high and consistent in the run tests. This accuracy was predictable as lowest MAE number was gained by this parameter (Fig.s 7 and 8).

As it is shown in the Fig. 17, the accuracy of prediction for R6 parameter is fair enough but consistent in the run tests.

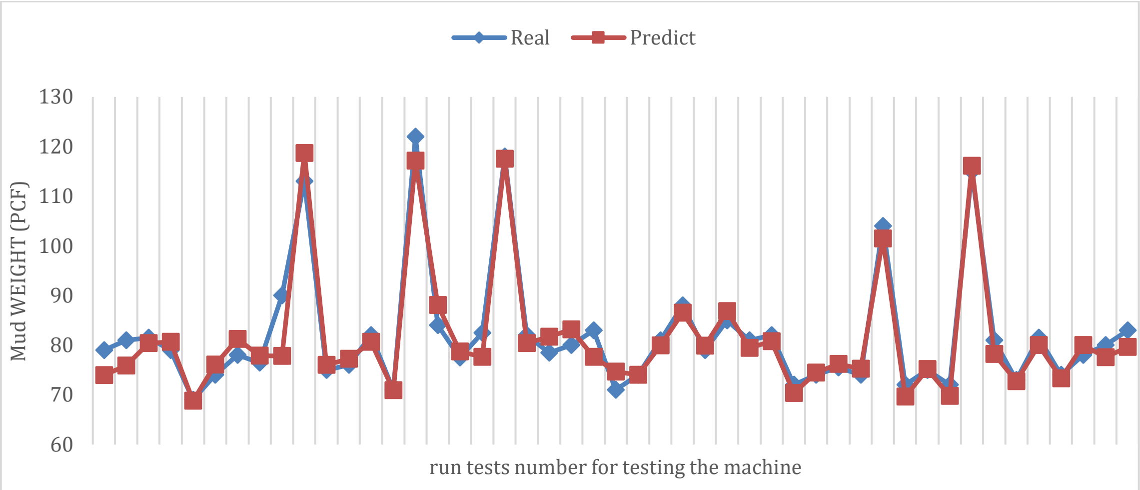

Fig. 9. Comparison of average results from two artificial neural networks compared to actual results for Mud Weight (density)

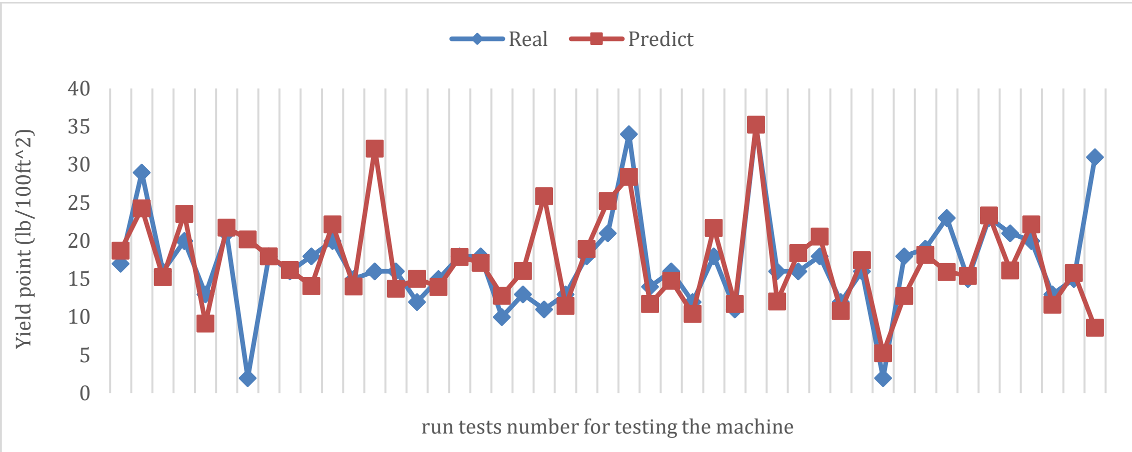

Fig. 10. Comparison of average results from two artificial neural networks compared to actual results for Yield Point

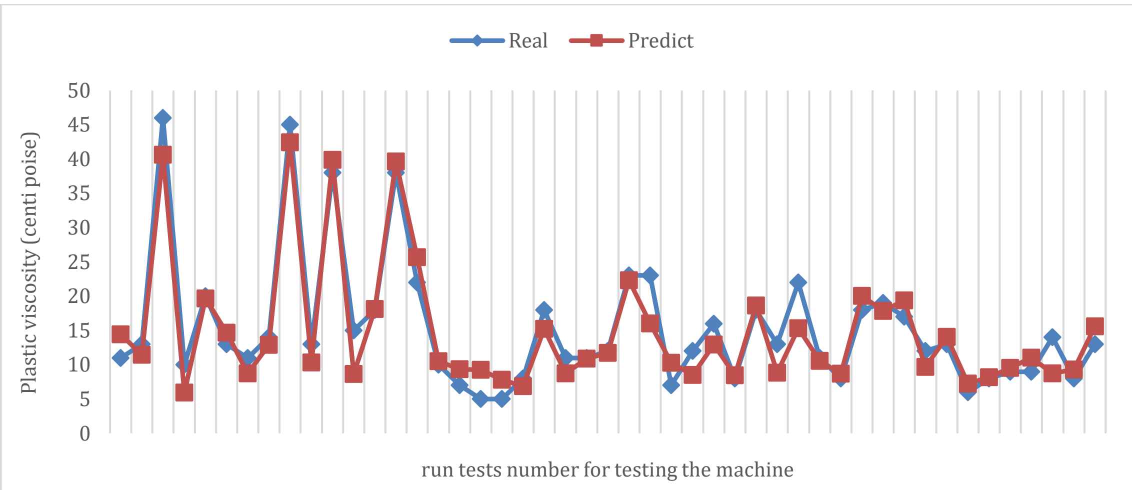

Fig. 11. Comparison of average results from two artificial neural networks compared to actual results for Plastic Viscosity

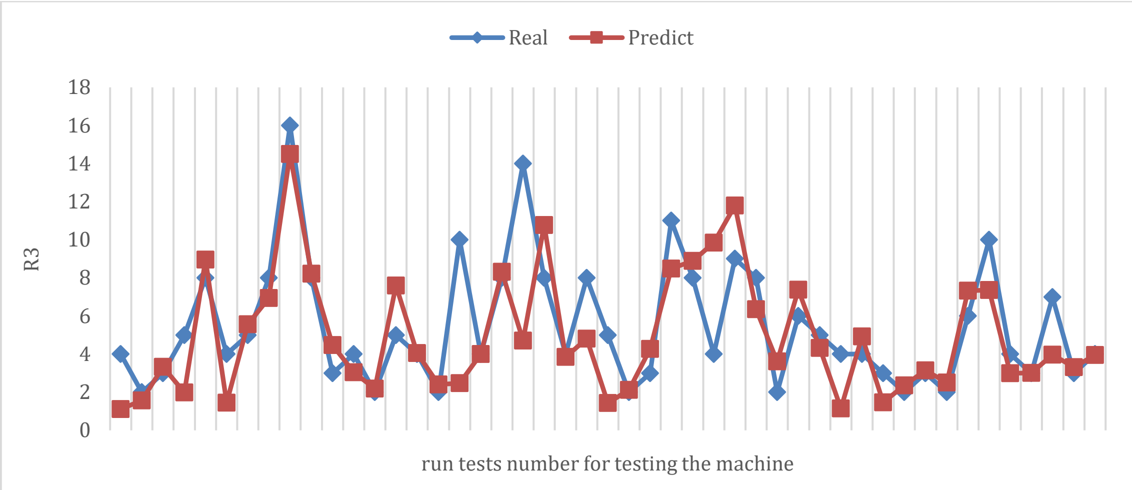

Fig. 12. Comparison of average results from two artificial neural networks compared to actual results for R3

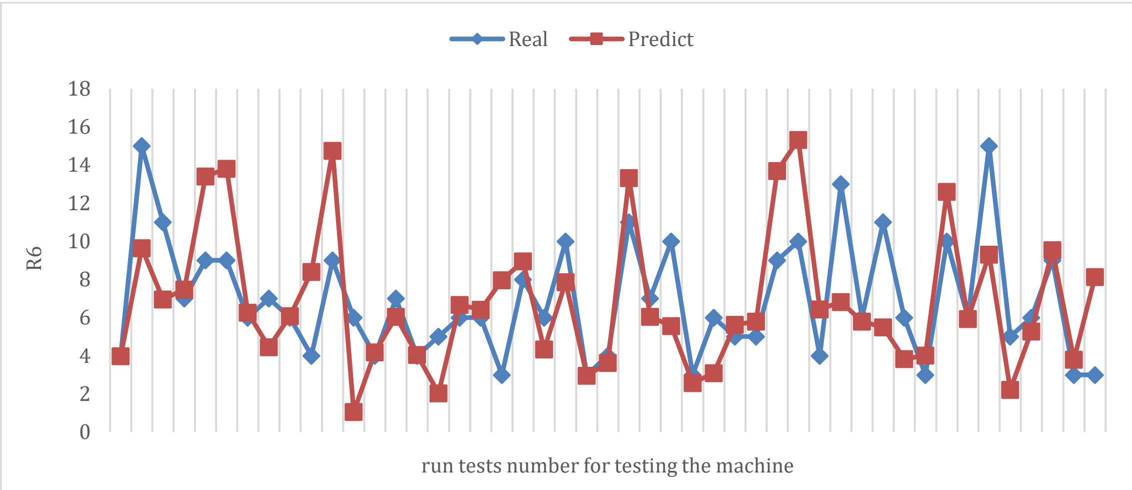

Fig. 13. Comparison of average results from two artificial neural networks compared to actual results for R6

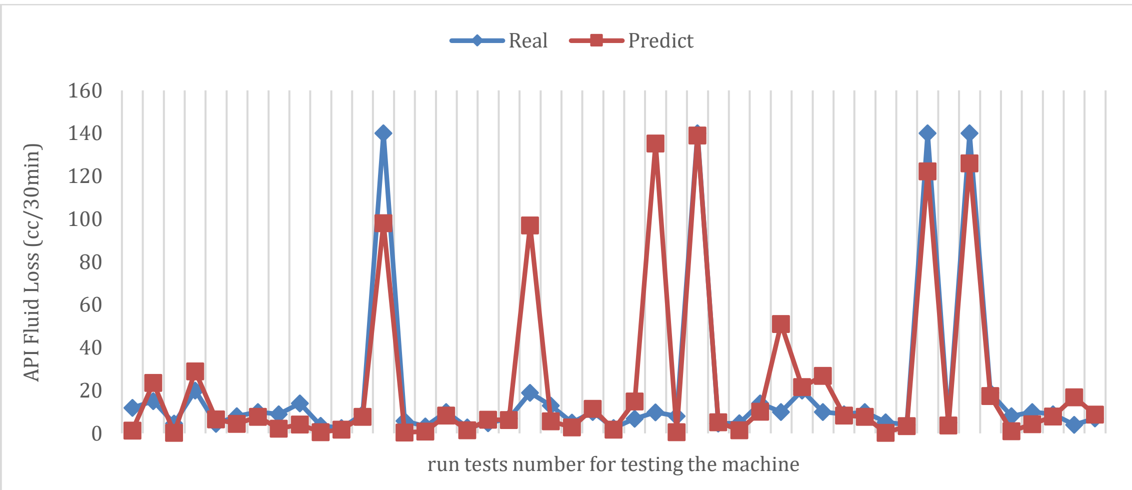

Fig. 14. Comparison of average results from two artificial neural networks compared to actual results for API Fluid Loss

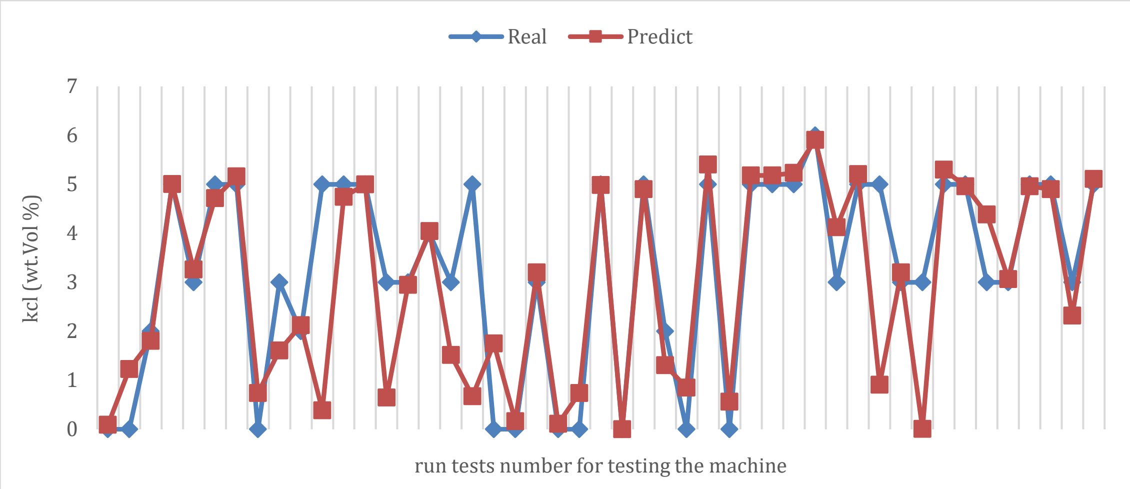

Fig. 15. Comparison of average results from two artificial neural networks compared to actual results for KCl Concentration

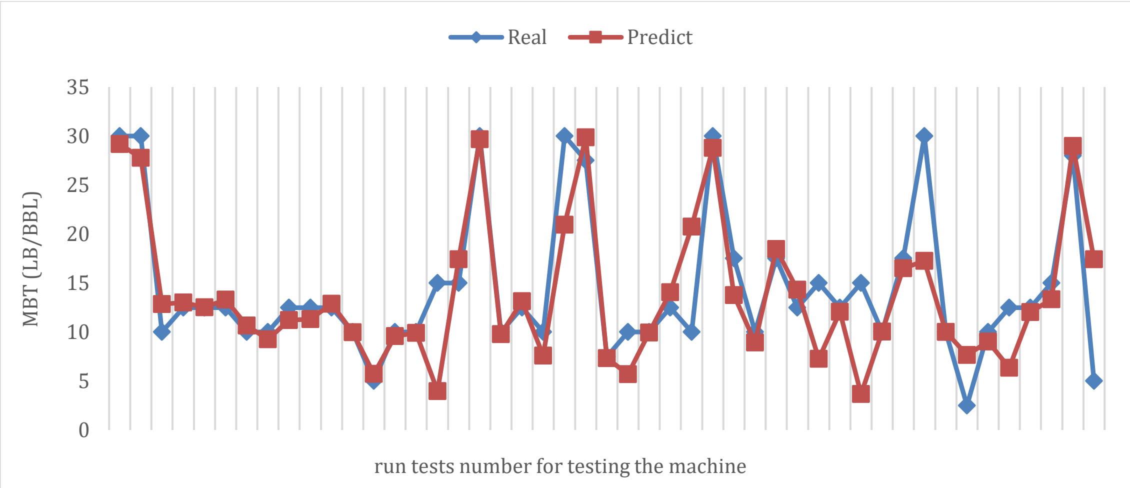

Fig. 16. Comparison of average results from two artificial neural networks compared to actual results for Clay Content (MBT)

IV. Conclusions

In this paper, we tried to implement the method of machine learning to investigate the possibility of estimating optimum drilling fluid parameters using drilling and geological parameters to minimize problems- without considering the location of the target wells. Two artificial intelligence algorithms ''LSSVM'' and ''MLP-FFBP'' were used in this study to optimize drilling fluids (such as mud density, yield point, plastic viscosity, etc. Results showed that for optimizing drilling fluid parameters in a newly drilled well, the developed AI networks have good capability to estimate parameters for some drilling fluid parameters as follows:

- Considering the quantity of used data, for most studied drilling mud parameters such as Mud Weight (Density), Plastic Viscosity, Water, and API Fluid Loss (both optimal and non-optimal), the network has a good performance and high capability to estimate parameters.
- In the field of point-to-point validation, if the previous information is available from the well, for most parameters the network has a good performance.
- Considering dependency of the two parameters Mud Weight and Plastic Viscosity have a correlation coefficient of approximately 90%, it is predicted that it is possible to estimate them with high accuracy percentage.
- Using the trained machines in this research, the drilling parameters along with favorable conditions- such as having no stuck and tight hole, loss circulation and gain- can be given to the machine as input and required drilling fluid parameters for reaching these conditions are predicted with error values of less than 5% for train and 15% for test data.

NOMENCLATURE

ANFIS = Adaptive neuro-fuzzy inference system
ANN = Artificial neural network
API = American Petroleum Institute
cP = Centi-Poise
FL = Filtration
LSSVM = Least square support vector machine
LSSVM-GA = Least square support vector machine-genetics algorithm
MBT = Methylene Blue Test
PCF = Pounds per cubic feet
PSO-ANFIS = Particle swarm optimization-adaptive neuro-fuzzy inference system
RBF = Radial basis function
ROP = Rate of penetration
MAE = Mean absolute error
MSE = Mean square error

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