Hole cleaning assessment in horizontal foam drilling using artificial neural network and multiple linear regression

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Abstract

Foam drilling is increasingly used to develop low pressure reservoir or highly depleted mature reservoirs because of minimizing the formation damage and potential hazardous drilling problems. Prediction of the cuttings concentration in the wellbore annulus as a function of operational drilling parameters such as wellbore geometry, pumping rate, drilling fluid rheology and density, and maximum drilling rate is very important for optimizing these parameters. This paper describes a simple and more reliable artificial neural network (ANN) method and multiple linear regression (MLR) to predict cuttings concentration during foam drilling operation. This model is applicable for various borehole conditions using some critical parameters associated with foam velocity, foam quality, hole geometry, subsurface condition (pressure and temperature), and pipe rotation. The average absolute percent relative error (AAPE) between the experimental cuttings concentration and ANN model is less than 6%, and using MLR, AAPE is less than 9%. A comparison of the ANN and mechanistic model was done. The AAPE values for all datasets in this study were 3.2 % and 10.3 % for ANN model and mechanistic model respectively.

Keywords: Hole cleaning, Foam drilling, ANN, MLR

1. Introduction

Underbalanced drilling (UBD) is increasingly used in the development of oil and gas fields because of minimizing the damage caused by invasion of drilling fluids into the formation, minimizing lost circulation, decreasing pressure differential sticking, increasing penetration rate, increasing production and extending bit life. UBD techniques are classified into gas, foam, gasified-liquid and liquid underbalanced drilling. The choice of drilling fluid type is determined by the formation pressure and formation properties. Foam is gaining increasing applications in the petroleum industry including drilling, cementing, fracturing and oil displacement. In drilling operations, foam can be used for both UBD and Managed Pressure Drilling (MPD). Foam fluids generally include 5-25% liquid phase and 75-95% gaseous phase. The liquid phase could be fresh water or brines. The gaseous phase is usually an inert gas. A surfactant is often used as a stabilizer and it comprises about 5% of the fluid system. The fluid system can be weighted up using heavy brines or barites. It has higher cuttings transport ability compared to air drilling fluids. With the ever increasing gas prices, foam will be an excellent candidate for drilling unconventional gas wells, for example, coal-bed methane drilling. Foam is a compressible and homogeneous mixture in comparison with the conventional and aerated drilling fluids. This makes foam a unique fluid for drilling through formations with continuously changing pressure gradients [1-4]. Hole cleaning (cuttings transport) is one of the main factors influencing cost, time, and quality of directional, horizontal, extended reach, and multilateral oil/gas wells. Inadequate hole cleaning can result in costly drilling problems such as pipe sticking, premature bit wear, slow drilling, formation fracturing, and high torque and drag. Cuttings transport is mainly controlled by many variables, such as the well inclination angle, hole and drillpipe diameters, drillpipe rotation, drillpipe eccentricity, rate of penetration, cuttings characteristics (size, porosity of bed), flow rate, fluid velocity, flow regime, mud type, and complex non-Newtonian mud rheology. An outstanding review of the cuttings transport discussion was given by Nazari et al. [5]. Many researchers have been carried out on cuttings transport with conventional drilling fluids in horizontal and directional wells [6-8]. Foams can have extremely high viscosity, in all instances in which their viscosity is greater than that of both the liquid and the gas that they contain. At the same time, their densities are usually less than one-half that of water. They are stable at high temperatures and pressures. Hence, if foam is applied as a drilling fluid, high viscosity of the foam permits efficient cuttings transport. In addition, its low density allows underbalanced conditions to be established, and formation damage to be minimized. Furthermore, compression requirement is decreased. For wells are drilled with foams, efficient cuttings removal is of critical significance according to multiphase flow and foam drilling hydraulic. The majority of publications of cuttings transport with foam describe operators' experiences, field practices, 1D numerical simulation of cutting transport and equipment used [2-4, 9-19]. Artificial neural network (ANN) is a simple and more reliable predictive tool that can be used to model and investigate various highly complex and nonlinear phenomena. The ANN method is an alternative statistical prediction method inspired by studies on the human nerve and brain system [20]. ANN has been applied in the multiphase flow fields and acceptable results were achieved compared with the conventional methods incorporating correlations and mechanistic models [21-28]. The aim of this study is to determine hole cleaning efficiency of foam fluid flow through a horizontal annuli using ANN. The ANN model was verified by experimental data obtained from the literature. The results show that adequate accuracy was obtained by the model to predict hole clean-up efficiency.

2. Parameters affecting cuttings transport process

It is not possible to consider all the parameters that govern the phenomenon of the cuttings transport from the bottom of hole to the ground surface. These factors include annular velocity, drilling fluid properties, hole geometry, pipe rotation, rate of penetration (ROP) and bottom hole conditions such as temperature and pressure. However, evaluating the critical factors on cuttings transport is an essential task. In addition, different forces including gravitational force, buoyancy force, drag force and lift force affect the cuttings transport [5, 7]. In this study, the effect of some important parameters on cuttings transport with foam drilling are analysed according to the literature review. Other parameters such as well geometry, cuttings properties and ROP were maintained constant in all tests.

2.1. Foam velocity effect

As expected, cuttings concentration decreased with an increase in the foam velocity. For aqueous foams (polymer concentration=0) having low qualities (70% and 80%), the improvement of hole cleaning is negligible or slight noticeable by increasing foam velocity. With high foam qualities (Γ = 90%), cuttings concentration decreases considerably by increasing foam velocity (Fig. 1). For polymer-based foam, the change in cuttings concentration versus flow velocity is more pronounced; when velocity is increased from 3 ft/s to 5 ft/s, cuttings concentration decreased from 18.8% to 3.1% [9, 10, 18, 19].

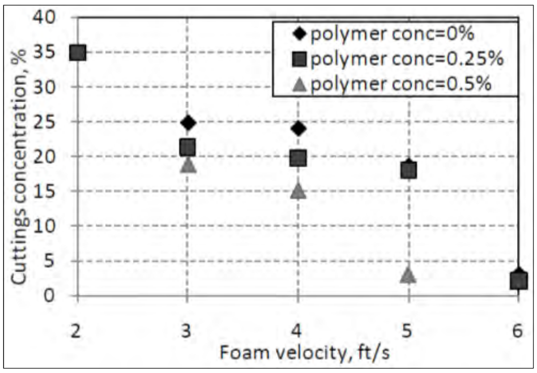

Fig. 1. Velocity effect on cuttings transport efficiency (Γ =90%, P=100psi, T =80°F) [9]

2.2. Foam quality effect

Foams are typically characterised by the quality (Γ), the ratio of the volume of gas and the total foam volume [3]:

$$\Gamma = \frac{V_g}{V_g + V_l} \times 100 \tag{1}$$

where, V_g and V_l are gas and liquid volume respectively.

Test results show that foam with higher quality is more effective in hole cleaning [9]. The reason may be clarified as follows (Fig. 2). The cuttings carrying capacity of a fluid depends on two parameters, i.e., fluid density and viscosity. A fluid with higher viscosity or a higher density normally enhances cuttings carrying capacity due to a lower cuttings slip velocity. With an increase in the foam quality, foam apparent viscosity increases, which is favourable for cuttings transport. On the other hand, foam density decreases with quality increasing, which detrimental for cutting transport. So, the improvement of cutting transport because by increasing foam viscosity, is compromised by decreasing the foam density. Therefore, hole cleaning can be improved using following three options: applying pipe rotation, increasing velocity or flow rate and increasing foam quality. Depending on other parameters, the last two options may or may not offer a great help in hole cleaning efficiency. Yet they extensively raise frictional pressure loss in most cases. By applying pipe rotation, however, both cuttings concentration and pressure loss can be reduced. Therefore, rotating the drillpipe during foam drilling, if possible, is one of the best options for hole cleaning [19].

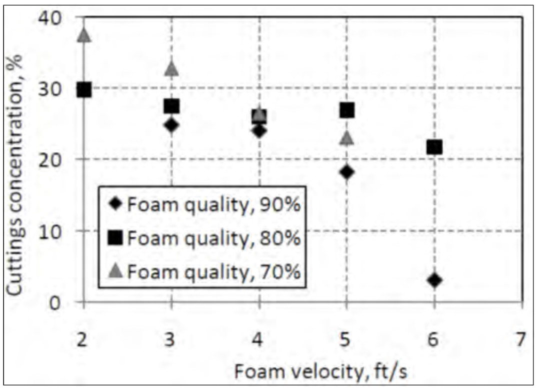

Fig. 2. Cuttings concentration versus flow velocity for 70%, 80% and 90% quality foams [9]

2.3. Downhole pressure effect

Fig. 3 shows the cuttings concentration as a function of test pressure for 80% quality foams flowing at a velocity of 3 ft/s. It appears that, as pressure increases, there is a slightly decrease in the cuttings concentration in the annulus [9, 19].

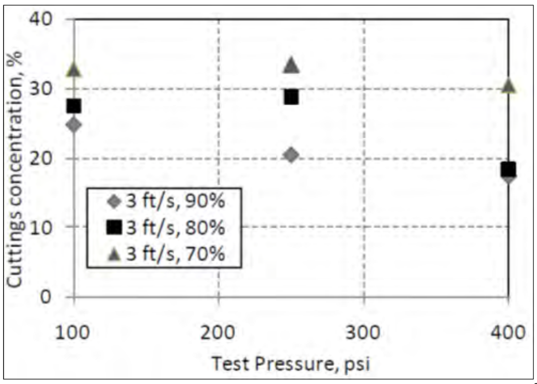

Fig. 3. Cuttings concentration versus test pressure (V = 3 ft/s, 80 ^{0}F) [9]

2.4. Temperature effect

Fig. 4 shows the cuttings concentration versus foam flow velocity at three different temperatures of 80 °F, 120 °F and 160°F for 90% quality foam in concentric horizontal annulus. Temperature slightly increased cuttings concentration.. The change in the temperature may not noticeably affect the cutting transport efficiency for practical foam drilling operation [3, 9, 10].

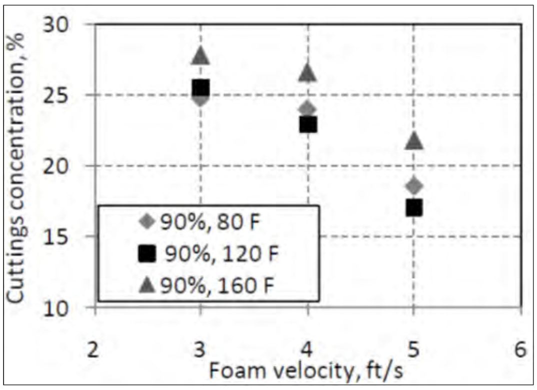

Fig. 4. Cuttings concentration versus flow velocity represented for different temperatures (Γ = 90%) [9]

2.5. Combined effect of pressure and temperature

Fig. 5 shows the cuttings concentration versus foam quality for foams tested at three different pressures (100, 250 and 400 psi) and temperatures (80 °F, 120 °F and 170°F) levels. Foam velocity is maintained at 3 ft/s. This figure shows that as both temperature and pressure increase (temperature from 80°F to 170°F, pressure from 100psi to 400 psi), cuttings concentrations slightly increase for 80% and 90% quality foams. But again, the change is still somewhat small. Based on the experimental results obtained at different combinations of pressure and temperature conditions, it can be concluded that at EPET conditions, there are slight changes in cuttings concentrations, but the changes are quite limited. Basically, foam keeps its cuttings transport property almost well under simulated downhole conditions. This is a very pleasant property for foam [3, 9, 10].

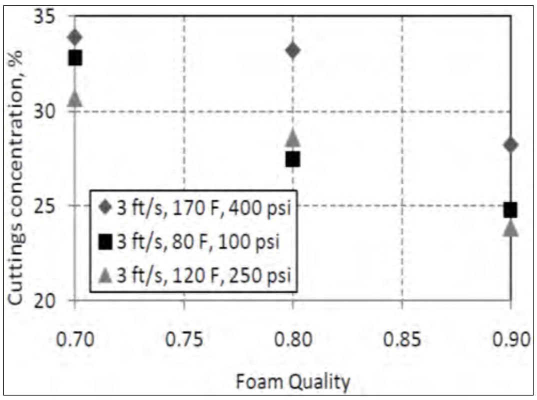

Fig. 5. Cuttings concentration versus foam quality given for a combined effect of temperature and pressure [9]

2.6. Pipe Rotation effect

Pipe rotation affects the cuttings bed erosion significantly. It has been illustrated that rotation produces a velocity profile that makes bed erosion easier. Optimizing the use of rotation can also give an improvement of drilling efficiency [29]. Pipe rotation not only reduces cuttings concentration in a horizontal annulus for foams with different qualities and at various foam velocities but also lead to a significant reduction in frictional pressure loss. This is due to a reduction in cutting concentration in the annulus [10,19]. Fig. 6 illustrates the effect of pipe rotation on cuttings transport in eccentric horizontal annulus using high quality (90%) foams.

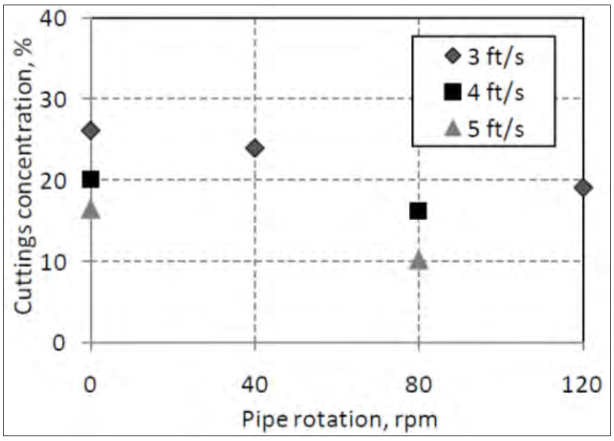

Fig. 6. The effect of pipe rotation on cuttings transport using high quality (90%) foams [19]

2.7. Eccentricity effect

Fig. 7 shows the effect of eccentricity (*$e=E/(R_o-R_i)$*, where E is offset distance between the centers of the inner tube, R_i, and the outer tube, R_o), of annulus.) on cutting concentration for 80% foam quality. The particle volume fraction increases in narrow gap with eccentricity increasing. Thus, the axial pressure drop deceases with increased eccentricity. Eccentricity of annulus is 0.78.

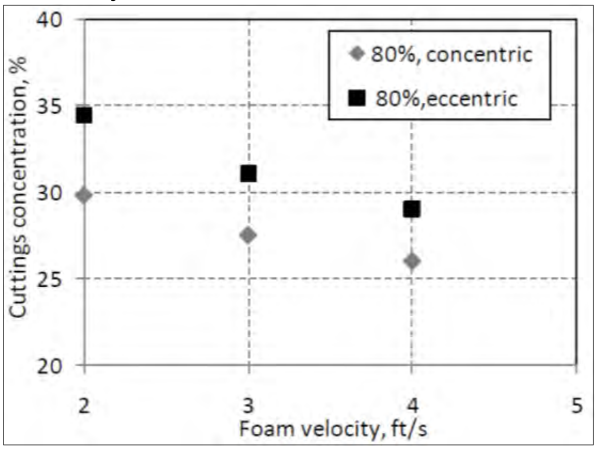

Fig. 7 The effect of pipe eccentricity on cuttings transport [9, 10]

3. Artificial neural networks (ANNs)

ANNs are generally defined as information-processing systems, which operate based on the human mind system. Neuron is the simplest unit of a neural network with a large number and connections and operates as a processing element. Fig. 8 illustrates a typical neuron structure. The mechanism of the ANNs is based on the following assumptions [20, 30]: a) Information processing occurs in neurons, b) Signals are passed between neurons over connection links, c) Each connection link has an associated weight, which, in a typical neural network, multiplies the signal being transmitted, d) Each neuron applies an activation function (Fig. 9), typically a nonlinear expression, to its net input in order to determine its output signal.

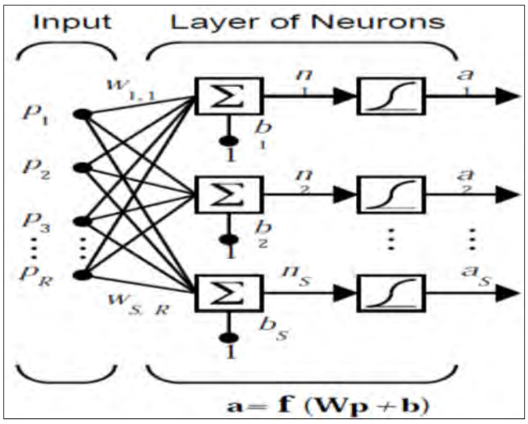

Fig. 8. A typical neuron [31]

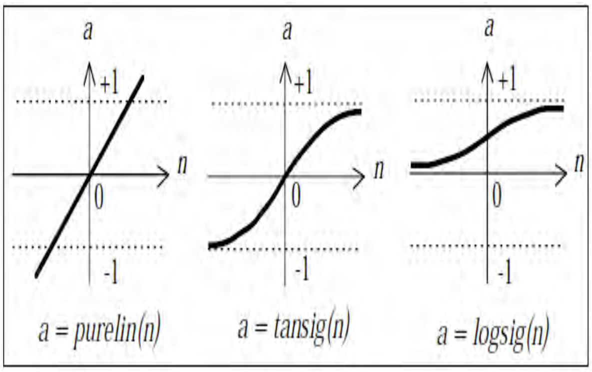

Fig. 9. Three examples of activation functions [31]

The information processing occurs as follows; inputs (p_i) coming from another neuron are multiplied by their individual weights ($w_{1,i}$), and weighted input connections are joint inside the neuron and the bias term (bi) is incorporated to the summation at the neuron in order to increase or decrease the input (nj) that goes into the activation function. The various n (i) form an S-element net input vector n. Finally, the neuron layer outputs form a column vector (n). An activation function is then applied to the summation, and the output (a) of that neuron is now calculated and ready to be transferred to another neuron. This procedure is formulated as below:

$$n_j = \sum_{i=1}^{R} (p_i w_{ij} + b_j) \quad , j = 1,2,..., S \tag{2}$$

where,

$$W = \begin{bmatrix} w_{1,1} & w_{1,2}....w_{1,R} \\ w_{2,1} & w_{2,2}....w_{2,R} \\ & \\ w_{S,1} & w_{S,2}....w_{S,R} \end{bmatrix}, P = \begin{bmatrix} p_1 \\ p_2 \\ \\ p_R \end{bmatrix}, b = \begin{bmatrix} b_1 \\ b_2 \\ \\ b_S \end{bmatrix} \tag{3}$$

Then, final output of a neural network can be calculated as follows:

$$a_S = f(n_S) \tag{4}$$

While these neurons are combined to create a neural network, the system undergoes a training stage where input and output pairs are introduced to the network and the weights in between the neurons are modified so that the network outputs reach the desired outputs as close as possible. The learning is ceased as soon as the error between the desired and the real outputs are within an reasonable range; this is performed by summing up the error terms at the output and forming a performance function in terms of network inputs and weights and minimizing this performance function with regard to the network inputs. The performance function is usually derived from mean square error (MSE) of the outputs. Due to the nature of this algorithm, these types of neural networks are also called supervised neural networks. Once the training is finished, the weights in between the neurons are stored for each layer and the network is ready to conduct a testing process. Testing is carried out by introducing an input-output sample that is not part of the training pairs. The stored weights are used to estimate the output. The difference between the desired and real output describes whether the learning was satisfactory and successful. It may also show how similar the new input-output pair is to any of the trained patterns. A typical neural network has always one input layer and one output layer, but depending on the particular network type, a different number of hidden layers may be incorporated. However, some networks even lack any hidden layer. A single hidden layer is enough to approximate any function to a desired degree of accuracy [32].

3.1. Back Propagation Neural Network (BPNN)

The feed-forward neural networks with back propagation (BP) learning algorithm are very powerful in function optimization modelling. BPNNs are recognised for their prediction capabilities and ability to generalise well on a wide variety of problems. These models are a supervised type of networks, in other words, trained with both inputs and target outputs. During training stage the network tries to match the outputs with the desired target values. Learning begins with the assignment of random weights. The output is then calculated and the error is eventually estimated. This error is used to update the weights until the stopping criterion is reached. It is noted that a stopping criterion is usually the average error or epoch. Over fitting phenomenon is the main disadvantage of the BPNN technique. This may happen when the error on the training set is driven to a very small value, but when new data is introduced to the network, the error is large. This problem occurs mostly in case of large networks with only a small number of available data sets. Early stopping and Automated Bayesian Regularization (ABR) methods can be applied to avoid over fitting problem [31]. In ABR technique, the available data is separated into two subsets. The first subset is the training set, which is used to calculate the gradient and updating the network weights and biases. The second one is the test set. This method works by modifying the performance function, which is generally selected to be the sum of squares of the network errors on the training set. The most common performance function that is used for training feed forward neural networks is the mean sum of squares of the network errors according to the following equation:

$$mse = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \tag{5}$$

where, N represents the number of samples, $\hat{y}_i$ is the predicted value, y_i denotes the measured value and e_i is the error. One may improve the generalization if the performance function is modified by adding a term that comprises the mean of the sum of squares of the network weights (msw) and biases which is expressed by:

$$mse_{reg} = \gamma\, mse + (1-\gamma)\, msw \tag{6}$$

where, mse_{reg} is the modified error, γ represents the performance ratio, and

$$msw = \frac{1}{N}\sum_{i=1}^{N} w_i^2 \tag{7}$$

Using this performance function enables the network to have slighter weights and biases. This will force the network response to be smoother and less likely to over fit [31].

3.2. Cuttings concentration prediction using BPNN

In this study, 77 cutting transport experimental datasets at Tulsa University obtained from the literature [9, 10] were used to create a BPNN model. Table 1 gives test matrix of experiments.

Table 1. Test matrix of cuttings transport using aqueous foam [9, 10]

Testing parameter	Value
Annular size	5.76" by 3.5"
Pipe rotation (rpm)	0, 40, 80, 120
Foam velocity (ft/s)	2, 3, 4, 5, 6
Foam quality (%)	60, 70, 80, 90
Eccentricity (-)	0, 0.78
Temperature (F)	80, 120, 160, 170
Pressure (psi)	100, 200, 250, 400
Cuttings size(mm)	3
Cuttings density (kg/m^3)	2610
ROP(ft/hr)	50

Input parameters of BPNN include foam velocity (V), foam quality (Γ), eccentricity of annulus (e = E /(R_o - R_i), where E is offset distance between the centers of the inner tube, R_i, and the outer tube, R_o, of annulus), subsurface condition (pressure, P, and temperature, T), and pipe rotation (RPM). The output of network is cutting concentration (CC %). Table 2 outlines the correlation matrix between cuttings concentration (CC) and independent variables. According to this table, foam quality (Γ), foam velocity (V) and pipe rotation (RPM) are more effective on cuttings transport phenomenon.

Table 2. Correlation matrix between cuttings concentration and independent variables

	P	T	V	RPM	Γ	e	CC
P	1						
T	0.071	1					
V	-0.12	0.059	1				
RPM	-0.121	-0.145	-0.223	1			
Γ	0.026	0.183	0.404	-0.115	1		
e	-0.266	-0.245	-0.298	0.613	-0.144	1	
CC	-0.046	0.14	-0.57	-0.256	-0.679	0.053	1

Considering the requirements of the ANN computation algorithm, both input and output data were normalised to an interval by a simple transformation process. In this study, normalization of data was carried out within the range of [-1, 1] using Equation (8),

$$p_n = 2\frac{p - p_{\min}}{p_{\max} - p_{\min}} - 1 \tag{8}$$

where, p_n is the normalised parameter, p denotes the actual parameter, p_{min} represents a minimum of the actual parameters and p_{max} stands for a maximum of the actual parameters. About 70% of the total data sets (60 out of

77 of the data) were selected for training and the rest for testing purposes. Several architectures comprising varied numbers of neurons in hidden layer with ABR algorithm and mean square error (MSE) performance function were tried to predict cutting concentration using BPNN. Two criteria were employed in order to assess the effectiveness of each network and its ability to make accurate predictions; they are: average absolute percent relative error (AAPE) and the correlation coefficient (R).

The AAPE concept gives an idea of absolute relative deviation of estimated from the measured data. It can be calculated from the following equation:

$$AAPE = 100 \times \frac{1}{N} \sum_{i=1}^{N} \left| \frac{(y_i - \hat{y}_i)}{y_i} \right| \quad (9)$$

where, y_i is the measured value, $\hat{y}_i$ denotes the predicted value, and N stands for the number of samples. The lowest the AAPE value, the more accurate the prediction is.

The last measure, known as the efficiency criterion, R represents the percentage of the initial uncertainty explained by the model. It is given by:

$$R = \sqrt{1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} y_i^2 - \frac{\sum_{i=1}^{N} \hat{y}_i^2}{N}}} \quad (10)$$

The best fitting between predicted and measured values, which is unlikely to occur, would have AAPE=0 or R=1. The optimal network of this study is a feed forward multilayer perceptron. This network comprises one input layer with 6 inputs (P, T, V, RPM, e, Γ) and one hidden layer with 10 neurons. Fletcher and Goss [33] suggested that the appropriate number of nodes in a hidden layer varies between ($2\sqrt{n}$ + m) and (2n + 1), where n is the number of input nodes and m represents the number of output nodes. Each neuron has a bias and is fully connected to all inputs and employs a log-sigmoid activation function. The output layer has one neuron (CC) with a linear activation function (purelin) without bias. Training function of this network is ABR algorithm (trainbr). In this study, (n=6) and (m=1) and thus the appropriate number of hidden layer neurons was chosen as 10 (6-10-1). Fig. 10 shows the BPNN architecture constructed in this work.

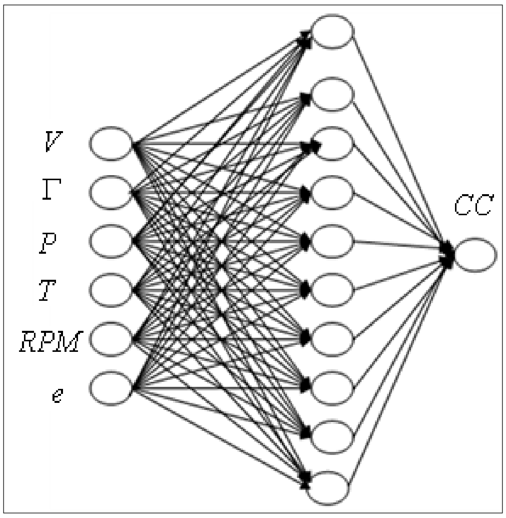

Fig. 10. BPNN architecture (6-10-1)

4. Cuttings concentration prediction using MLR

Multiple linear regression (MLR) is an extension of the regression analysis that incorporates additional independent variables in the predictive equation. Here, the model to be fitted is:

$$y = B_1 + B_2 x_2 + ... + B_n x_n + e \quad (11)$$

where, y is the dependent variable, x_is are the independent random variables and e is a random error (or residual) which is the amount of variation in y not accounted for by the linear relationship. The parameters B_is, stand for the regression coefficients, are unknown and are to be estimated. However, there is usually substantial variation of the observed points around the fitted regression line. The deviation of a particular point from the regression line (its predicted value) is called the residual value. The smaller the variability of the residual values around the regression line, the better is model prediction. In this study, regression analysis was performed using the train and test data employed in neural network data. The cuttings concentration considered as the dependent variable and V, Γ, P, T, RPM and e were considered as the independent variables. A computer-based package called SPSS (Statistical Package for the Social Sciences) was used to carry out the regression analysis.

5. Results and discussion

Using the ANN approach described above, all necessary computations were implemented by supplying extra codes in MATLAB software. The matrix of inputs in training step is a n×N vector, where n is the number of network inputs and N is the number of samples used in training step. In this paper, six input variables (V, Γ, P, T, RPM, e) and 60 samples were used to train the network and rest of samples were used for testing the network. The correlation coefficient (R) and AAPE were used for comparison of the ANN model predictions with experimental data [9 and 10] and the results of mechanistic model [10]. Fig. 11 compares the predicted cuttings volumetric concentration (%) and the experimental values for the training data set. The correlation coefficient (R) to the linear fit (y=ax) is 0.993 with the AAPE value of 2.38%; describing almost a perfect fit. This indicates the fact that the training stage was done very well. For testing stage, those data sets which were not employed by the ANN model during training process were used. A comparison of the cutting concentrations predicted by the network and the measured values for the test data set is shown in Fig. 12. A correlation coefficient (R) of 0.914 together with an AAPE of 5.93% describes a very satisfactory model performance. These results verified the success of neural networks which recognise the implicit relationships between input and output variables.

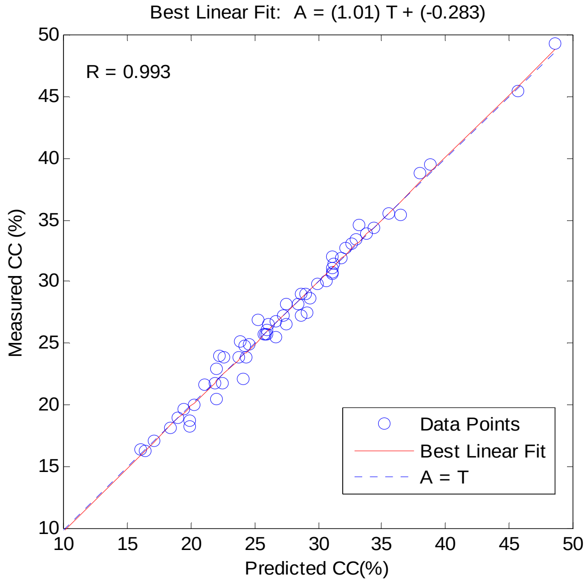

Fig. 11. ANN prediction versus measured cutting concentration [9, 10] for the training data

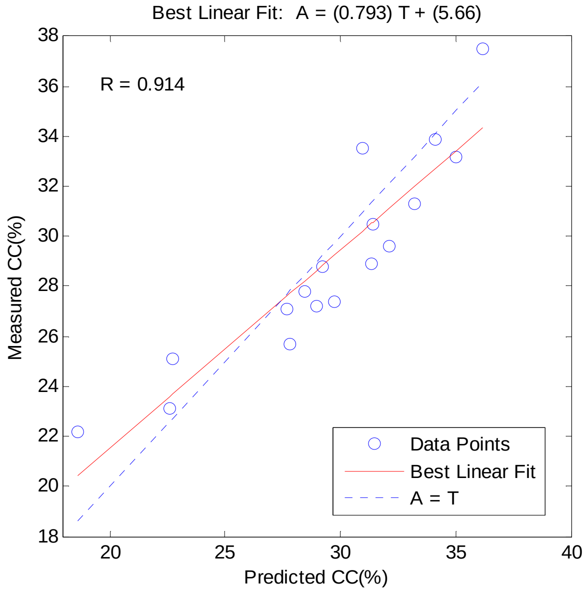

Fig. 12. ANN prediction versus measured cutting concentration [9, 10] for the test data

Using MLR approach in SPSS software, the estimated regression relationship for cuttings concentration (CC) is given as below:

$$CC(\%)=74.21-0.009*P+0.048*T-3.105*V-0.079*RPM-49.248*\Gamma \quad (13)$$

The statistical results of the model are given in Table 3. Cuttings concentration was estimated according to the Equations 13.

Table 3. Statistical characteristics of the multiple regression models

Model	Method	Independent variables	Coefficient	Standard error	Standard error of estimate	t-value	F-ratio	Sig. level	Determination coefficient (R^2)
Eq. 13	Enter	Constant	74.210	4.105	2.98	18.078	45.98	.000	0.839
		P	-.009	.004		-2.019		.049	
		T	.048	.013		3.635		.001	
		V	-3.105	.494		-6.280		.000	
		RPM	-.079	.010		-7.665		.000	
		Γ	-49.248	5.225		-9.426		.000	

Figs 17 and 18 compare the MLR cuttings concentration (%) versus the experimental values for the training and test data set respectively. The correlation coefficient (R) and AAPE for train data are 0.916 and 6.5% and for test data, they are 0.84 and 7%.

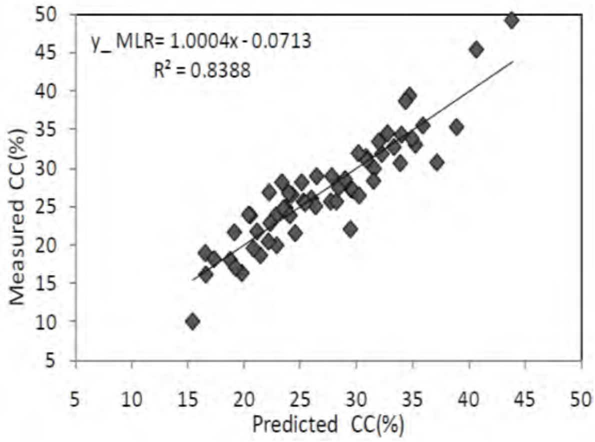

Fig. 17. MLR prediction versus measured cutting concentration [9, 10] for the train data

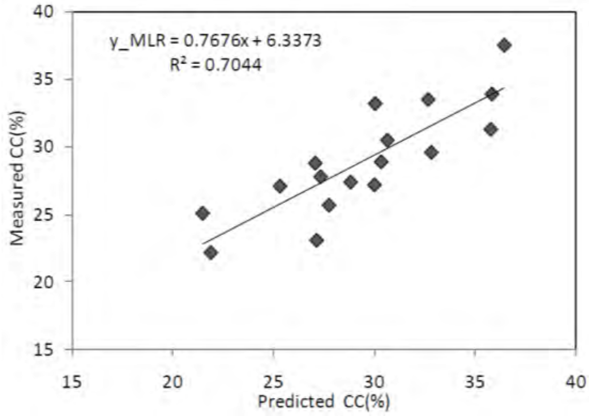

Fig. 18. MLR prediction versus measured cutting concentration [9, 10] for the test data

A comparison of the ANN, MLR and mechanistic model [10] predictions with the measured values for the all data sets used in this study with a population of 77 is shown in Fig. 14. The correlation coefficient (R) is 0.984, 0.909 and 0.8568 for ANN, MLR and mechanistic model respectively. The AAPE values are 3.2 %, 8.5% and 10.3 % for ANN, MLR and mechanistic model respectively.

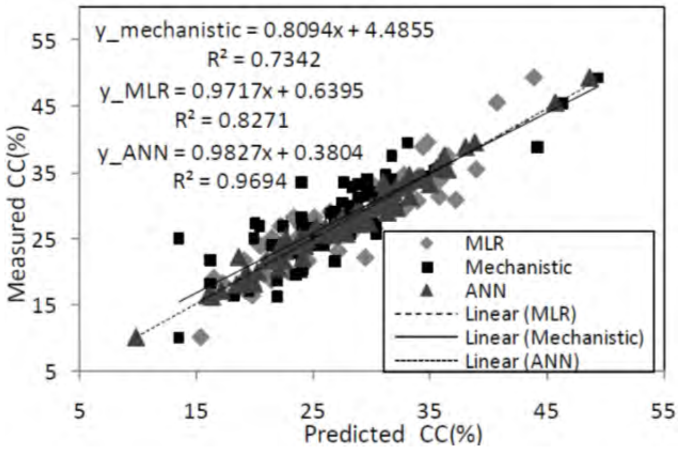

Fig. 16. Comparison of measured all datasets versus ANN, MLR and mechanistic model predictions

Table 2 compares the AAPE associated with three methods for both Duan [10] and Chen [9] data. . It is well illustrated in Table 4 that the ANN method has high capability in prediction respect to statistical and mechanistic models.

Table 4. Comparison of the AAPE associated with three methods

Method	AAPE	
	Duan data [10]	Chen data [9]
ANN model	3.1%	3.3%
MLR model	9.8%	7%
Mechanistic model	11.2%	9.4%

6. Conclusions

In this study, cutting concentration within the foam drilling in horizontal annular geometries was estimated using ANN and MLR models. The ANN presented here has three layers namely input layer, hidden layer and output layer. Input layer has six neurons including, foam velocity, foam quality, eccentricity of annulus, subsurface condition (pressure and temperature), and pipe rotation. Hidden layer has ten neurons with a log-sigmoid activation function in all neurons. Output layer has one neuron (cutting concentration, CC %) with a purelin activation function. The correlation coefficient between measured and prediction values in training and testing data is 0.994 and 0.914 respectively. The AAPE of training and testing data in ANN model are 2.38% and 5.93% respectively. A comparison of the ANN, MLR and mechanistic model was done. The results obtained from this study reveal that ANN could accurately predict the hole cleaning efficiency using foam drilling respect to MLR and mechanistic models.

References

[1] Zhu T, Volk L, Carroll H. Industry state –of-the art in underbalanced drilling. project report; USA; 1995.

[2] Li Y, Kuru E. Numerical modeling of cuttings transport with foam in vertical Wells. Journal of Canadian Petroleum Technology 2005; 44(3): 31-39.

[3] Ozbayoglu, ME. Cuttings transport with foam in horizontal and highly-inclined wellbores. PhD Dissertation; University of Tulsa; Tulsa; USA; 2002.

[4]Wang R, Cheng R, Wang H, Bu Y. Numerical simulation of transient cuttings transport with foam fluid in horizontal wellbore. Journal of Hydrodynamics 2009; 214: 437-444.

[5] Nazari T, Hareland G, Azar JJ. Reviw of cuttings transport in directional well drilling, systematic approach. SPE 132372; California; USA; 2010.

[6] Nguyen D, Rahman SS. A three-layer hydraulic program for effective cuttings transport and hole cleaning in highly deviated and horizontal wells [J]. SPE Drilling and Completion 1998; 13(3): 182-189.

[7] Yu M, Takach NE, Nakamura DR, Shariff MM. An experimental study of hole cleaning under simulated downhole conditions. Saudi Aramco of Technology, 2007.

[8] Piroozian A, Ismail I, Yaacob Z, Babakhani P, Ismail ASI. Impact of drilling fluid viscosity, velocity and hole inclination on cuttings transport in horizontal and highly deviated wells. J Petrol Explor Prod Technol 2012: 149–156.

[9] Chen Z. Cuttings Transport with Foam in Horizontal Concentric Annulus under Elevated Pressure and Temperature Conditions. PhD Thesis; Tulsa University; USA; 2005.

[10] Duan M. Study of cuttings transport using foam with drill pipe rotation under simulated downhole conditions. PhD Dissertation; Tulsa University; USA; 2007.

[11] Machado CJ, Ikouk CV. Experimental determination of solids fraction and minimum volume requirements in air and gas drilling. JPT 1982: 2645- 2655.

[12] Okpobiri GA, Ikoku CU. Volumetric requirements for foam and mist Drilling Operations. SPE Drilling and Completion 1986; 71-86.

[13] Owayed JF. Simulation of water influx during underbalanced foam drilling. M.Sc. Thesis; University of Tulsa; 1997.

[14] Saintpere S, Marcillat Y, Bruni F, Toure A. Hole cleaning capabilities of drilling foams compared to conventional fluids, SPE 63049; 2000; Dallas-Texas.

[15] Martins AL, Luorenco AMF, de Sa CHM. Foam properties requirements for proper hole cleaning while drilling horizontal wells in underbalanced conditions. SPE Drill & Completion 2001; 16 (4): 195-200.

[16] Capo J, Yu M, Miska S. Z, Takach N.E, Ahmed R. Cuttings transport with aqueous foam at intermediate inclined wells. SPE Drilling and Completion 2006; 99-107.

[17] Li Y, Kuru E. Numerical Modeling of Cuttings Transport with Foam in Horizontal Wells. Journal of Canadian Petroleum Technology 2003; 54-61.

[18] Chen Z, Ahmed RM, Miska SZ, Takach NE, Yu M, Pickell MB, Hallman J. Experimental study on cuttings transport with foam under simulated horizontal downhole conditions. SPE Drill & Completion 2007; 22 (4): 304-312.

[19] Duan M, Miska S, Yu M, Takach N, Ahmed R, Hallma J. Experimental study and modeling of cuttings transport using foam with drillpipe rotation. SPE Drilling & Completion 2010; 25(3): 352-362.

[20] Hagan MT, Demuth HB, Beale MH. Neural network design, PWS Publishing, Boston, MA; 1996.

[21] Ternyik J, Bilgesu HI, Mohaghegh S. Virtual measurements in pipes: part—2, liquid holdup and flow pattern correlations. Eastern Regional Meeting; West Virginia, 1995.

[22] Mukherjee H. An experimental study of inclined two-phase flow. Ph.D. Dissertation, University of Tulsa (USA); 1979.

[23] Osman ESA. Artificial neural network models for identifying flow regimes and predicting liquid holdup in horizontal multiphase flow. SPE Production & Facilities 2004; 33–40.

[24] Shippen ME, Scott SL. A neural network model for prediction of liquid holdup in two-phase horizontal flow. SPE Production & Facilities 2004; 67–76.

[25] Ozbayoglu ME, Miska SZ, Reed T, Takach N. Analysis of bed height in horizontal and highly-inclined wellbores by using artificial neural networks. SPE 78939, Alberta; Canada; 2002.

[26] Ozbayoglu ME, Ozbayogl MA. Estimating flow patterns and frictional pressure losses of two-phase fluids in horizontal wellbores using artificial neural networks. Petroleum Science and Technology 2009; 27: 135–149.

[27] Ashena R, Moghadasi J. Bottom hole pressure estimation using evolved neural networks by real coded ant colony optimization and genetic algorithm. Journal of Petroleum Science and Engineering, 2011;77: 375–385.

[28] Rooki R, Doulati Ardejani F, Moradzadeh A, Kelessidis VC, Nourozi M. Prediction of terminal velocity of solid spheres falling through Newtonian and non-Newtonian power law pseudoplastic fluid using artificial neural network. International Journal of Mineral Processing 2012; 110–111: 53–61.

[29] Sanchez RA. Azar JJ. Bassal AA. Martins AL. Effect of drill pipe rotation on hole cleaning during directional-well drilling. 56406 SPE; 1999.

[30] Haykin S. Neural networks: A comprehensive foundation. 2nd edition; Upper Saddle River; NJ; Prentice Hall; 1999.

[31] Demuth H, Beale M. Neural network toolbox for use with MATLAB. User's Guide; 2002.

[32] Hornik K, Stinchcombe M, White H. Multilayer feed forward networks are universal approximates. Neural Networks 1989; 2 (5): 359-366.

[33] Fletcher D, Goss E. Forecasting with neural networks: an application using bankruptcy data. Inform; Manage 1993; 24: 159–167.