

Artificial Neural Network Approach to Predictive Modeling of Cuttings Transport Ratio in an Inclined and Horizontal Wells

Sahmi E. Mohammed^{1,2}, Faleh H. M. Almahdawi¹

¹Petroleum Engineering Department/ College of Engineering/University of Baghdad/ Baghdad, Iraq

²Petroleum Engineering Department/ College of Engineering/University of Kirkuk/ Kirkuk, Iraq

Email: engpetro.king@gmail.com

Article Info

Volume 82

Page Number: 14419 - 14429

Publication Issue:

January-February 2020

Abstract:

In recent times several drilling problems related to poor hole cleaning have been reported. Problem such as a high torque and drag, poor hydraulics and pipe sticking have resulted into an increase in operational costs. To therefore achieve and successful drilling operation in horizontal and inclined wells; a good cutting transport ratio and higher hole cleaning efficiency are required in this is largely dependent on factors such as are fluid properties and rheology, size and density of cutting, pipe eccentricity, flow rate, rate of penetration, drill pipe rotation, average fluid velocity, and hole geometry and inclination. In this study, a new empirical correlation was established for the prediction of cuttings transport ratio from wellbore to the surface. The artificial neural network (ANN) coupled with the back-propagation (BPNN) learning algorithm technique was employed to develop the empirical correlation based on 405 experimental data. The input variables are made up of the mud density and mud rheological properties hole inclination angle, flow rate (GPM), drill pipe rotary speed (RPM) and size and density of cutting. The result obtained showed that the developed correlation using ANN technique could be applied in predicting the cuttings transport ratio with a high accuracy for average absolute errors (AAE) less than 0.5%. Moreover, the correlation coefficients (R) was higher than 0.9 for both number of neurons but six number of neurons gave the higher correlation coefficient especially in testing stage as compared with three neurons. The application of this method is cost effective with zero use of auxiliary equipment, which will undoubtedly help in accurate estimation of hole cleaning operation; an important function in drilling operation.

Keywords: Cutting transport ratio, Hole cleaning, Artificial neural network, Inclined wells.

Article History

Article Received: 18 May 2019

Revised: 14 July 2019

Accepted: 22 December 2019

Publication: 28 February 2020

I INTRODUCTION

The cost effectiveness of any drilling operation is generally a function of clean and efficient hole. This partly because an accumulation of cuttings or formation of cuttings bed in the well often leads to decreased rate of penetration, increased cost of drilling, fractured formation, increased plastic viscosity of mud as a result of grinding of cuttings and stucked pipe. The hole cleaning operation is usually affected primarily with a drilling fluid. The function of a drilling fluid is chiefly the transportation of cuttings out of a drilled hole.

Other major functions of a drilling fluid in a drilling program include: lubrication, removal of cuttings from mud at the surface, minimizing the formation damage, controlling of formation pressures, hole integrity maintenance, improving of drilling rate, aiding of well logging operations, minimizing torque, drag, pipe sticking as well as corrosion of the drill string, casings and tubing's (Ekeinde et al., 2019)

There have been a number of investigations on the factor affecting the efficiency of drilling hole cleaning operation. Pigott (1941) was the first to

identify and report the different parameters affecting the mud-carrying capacity. Williams and Bruce estimated the annular velocity required in removing the hole-cuttings as reported by Mahmoud, et al., (1951). There have been series of experimental studies conducted by many researchers for the identification of different parameters affecting the efficiency of hole cleaning operation Bouyo, et al., (2019). Dehvedar et al., (2019) reported the modeling and correlation of drilling operations using CFD models. Other investigations employed a computer aided modeling and simulation for monitoring the transportation of the cuttings.

Clark (1994) and Kamp (1999) assumed the annulus condition with stationary cutting bed layers, the suspended layer and that of the 3-bed model. Cho (2000) on the other hand made assumption on the cutting bed in stationary layer, moving bed and also in the liquid phase layer. Not many studies have been conducted in this area of research when compared to the cutting concentration models and qualitative experimental tests as buttressed by Bizanti (2003) and Larsen (1997). However, Nazari et al. (2010) gave a comprehensive accounts on the transportation of drilling cuttings [1-14].

Several parameters have been reported to affect the efficiency of hole cleaning operations viz: inclination of wellbore, the eccentricity of pipe or hole, the rheology characteristics of the drilling mud, pipe rotation, penetration rate and the flow rate of the bed cuttings Pandya, et al. 2019; Al-Azani et al., 2018). Tomren et al. (1986), investigated the effect of well borne inclination on the efficiency of hole cleaning. They later reported insignificant changes in the concentration with an inclination angle at 10° when compared with the one carried out in vertical direction. They later concluded that at a wellbore inclination angle between the range of 10° and 30° the bed cutting is usually operated under a decreased flow rate. The pipe eccentricity is another factor affecting

the cleaning efficiency as supported by Tomren et al. (1986). It has been reported that at different eccentricities in a vertical pipe, the cutting characteristics features is usually the same. On the other hand, for a drill section inclined at an angle, there is a characteristics build-up of cuttings when the eccentricity is zero [15-20].

The rheological properties and density of the mud is other parameters affecting the hole cleaning efficiency as buttressed by Azar (1983). There is a rise in the mudability when the plastic viscosity and the yield point were increased. However, as the plastic viscosity decreases, the hole cleaning efficiency increases correspondingly (Ford et al., 1990). Cho et al., (2001) and Ravi & Hemphill (2006) showed a direct correlation between the cutting bed and the flow rate; increasing the flow rate and annular velocity triggers a reduction in the cutting bed. Sanchez et al., (1999) also reported that the pipe rotation speed (rpm) becomes more effective when the well angle is high than when it is in a vertical well. At this point, the effective hole cleaning efficiency and penetration rate (ROP) increases accordingly (Tomren et al., 1986).

II MATERIALS AND METHOD

2.1. Implemented Artificial Neural Network (ANN)

The implementation of the artificial intelligence involved the processing of data to mimic the neural system of human being and their performance features. This is usually applicable by adapting a computer modeling techniques which maps object or data together. The use of artificial intelligence is more applicable in situation where there are large or complex inputs pattern. In this method, the outputs and the inputs were correlated using an important neural network element called neurons. The outputs from the predictive problems were obtained from the nonlinear equations.

In this study the implementation was conducted using the feed-forward neural networks with the

back-propagation (BPNN) learning algorithm and the radial basis functional networks (RBFN). The former the input and output variables are employed for the training of the network to approximated functions. A particular output is thus correlated to a specific input variable in accordance with the selection made by the user.

The BPNN method is largely dependent on the categorization of the problem being solved using different functions for activation. For this investigation the hyperbolic tangent (HTTF) was employed as activation function as presented in Figure 1. The HTTF method required higher number of neurons than the BPNN technique.

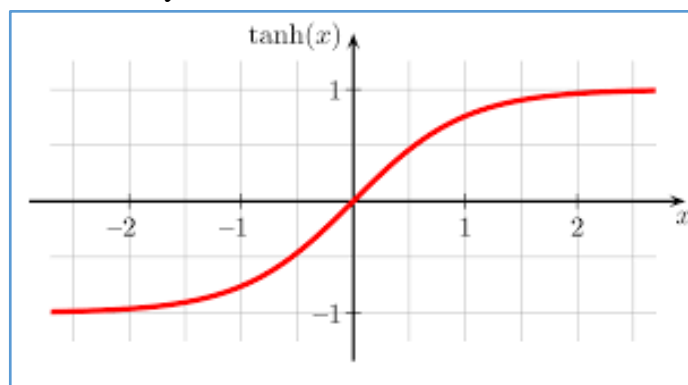


Fig. 1. Plot of the hyperbolic tangent transfer function.

2.2. Description and Analysis of Data

The work was conducted using the cuttings transport ratio in relation to the condition of the simulated down hole conditions.. In this study

nine parameters were varied to determine their corresponding impact on the cutting transport ratio (CTR) and this was achieved using a total of 405 experimental tests (Table 1).

Table 1
Test matrix for cutting transport ratio prediction.

Testing factor	Values
Annular size	4" casing ID × 2" drill string OD
Inclination Angle (θ) degree	55°-90°
Pipe Rotation (rpm)	0,60
Mud Weight (ρ _m),ppg	8.75, 8.8, 9
Plastic viscosity (P _v)cp	7.6, 13.5, 13.7
Yield point (Y _p)lb/100ft ²	11.3, 19.7, 30.2
Flow rate (Q)gpm	48.43, 70.44, 92.46
Cutting size (d _p), mm	1.7, 2.36, 4
Cutting density (ρ _p)ppg	22.57, 24.47

The above data was separated into two different sections with training and testing that group into 70 % and 30 % data, respectively. He is categorization of data into training and testing was conducted in a random manner with the aid of MATLAB algorithm. Using the BPNN method, the data training, testing and validation input data were rangely normalized at [-1,1] using the Eq.

$$x_n = \frac{x - x_{min}}{x_{max} - x_{min}} - 1 \tag{1}$$

Where, x_n : is the normalized parameter; x : is the actual parameter; x_{min} and x_{max} are the

minimum and the maximum values of the actual parameters respectively. Moreover, the correlation coefficient (R) and the average absolute error (AAPE) were employed to estimate the performance of the function as presented in Eqs. (2) and (3).

$$R = \sqrt{1 - \frac{\sum_i^N (y_{iact} - y_{ipred})^2}{\sum_i^N (y_{iact})^2 - \frac{(\sum_i^N y_{ipred})^2}{N}}}$$

$$AAPE = \frac{1}{N} \sum_i^N \left| \frac{y_{iact} - y_{ipred}}{y_{iact}} \right| \quad (3)$$

where, y_{iact} : represents the measured (actual) value; y_{ipred} : represents the predicted (estimated) value; N: denotes the number of samples.

It is worthy of note that the performance of the

predictive model increases at a reduced R and AAE values.

2.3. Estimation of CTR

The cutting transport ratio was estimated using the BPNN learning algorithm. The sensitivity analysis was determined for the hidden layers, neuron number, and transfer function using several tests. Two cases were used in the final neural network with the first case containing a single input layer with eight variables and three neurons. The second case is the hidden layer containing six neurons, hyperbolic transfer function and one output layer. As presented in Figure (2) and (3).

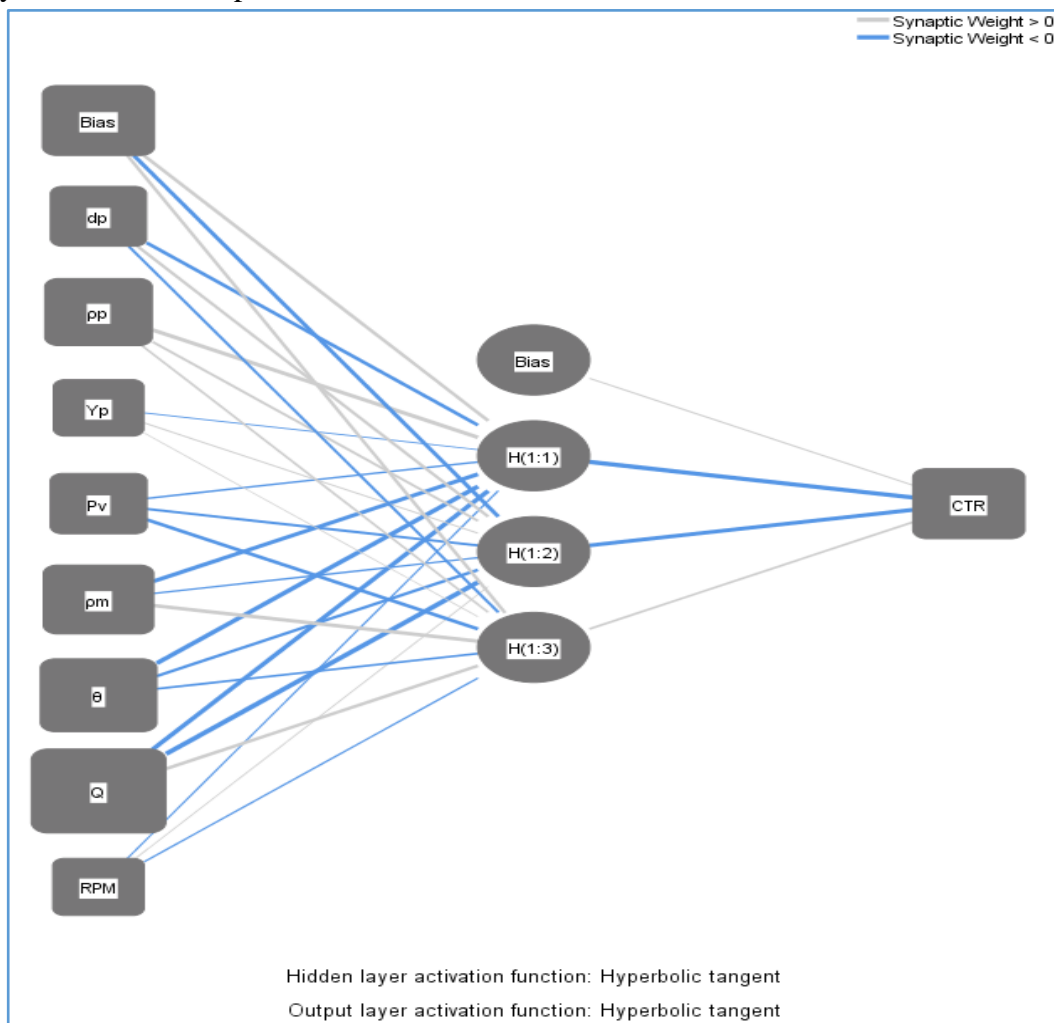


Fig.2. ANN topography for three layers with three neurons.

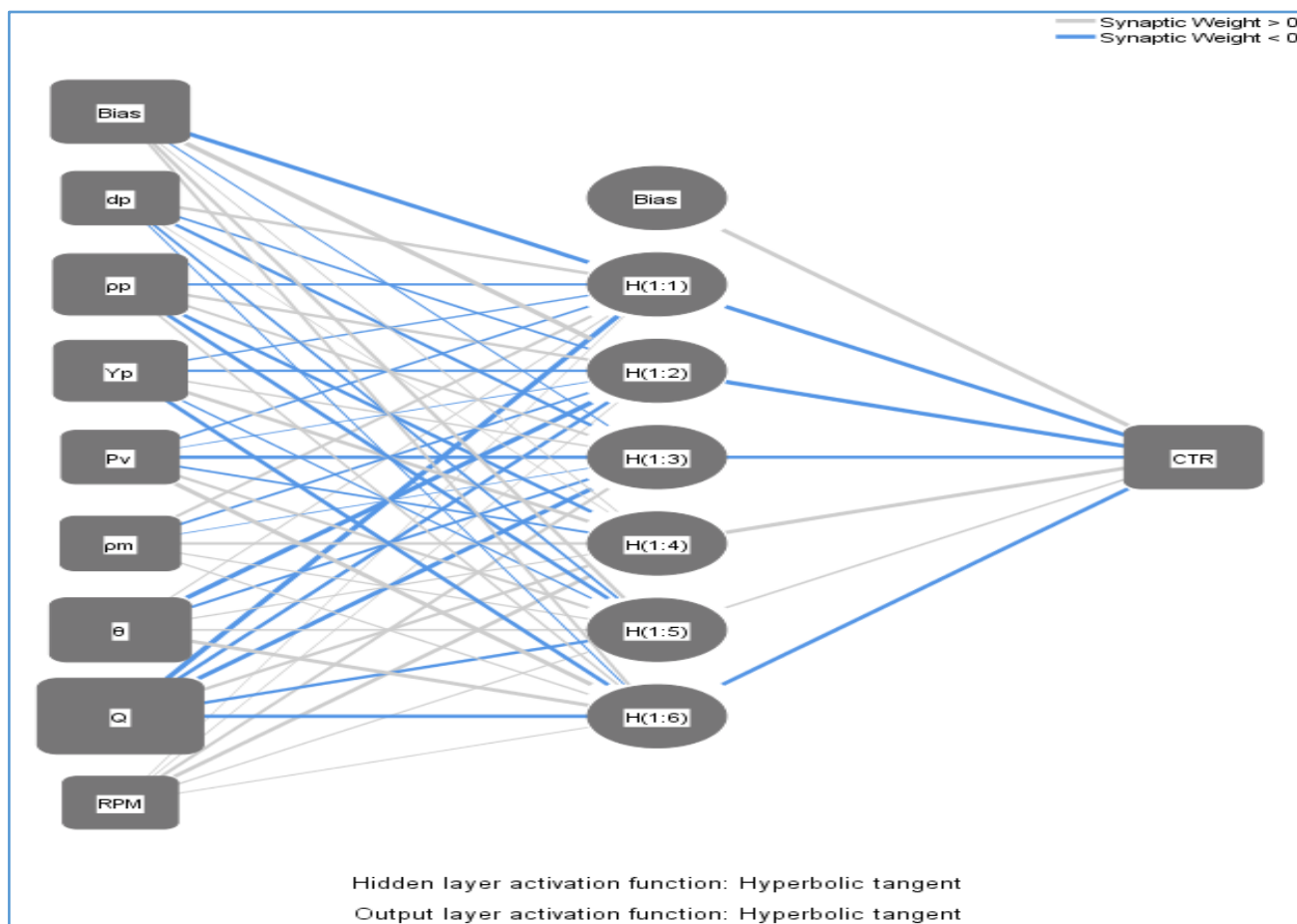


Fig. 3. ANN topography for three layers with six neurons.

III RESULTS AND DISCUSSION

The CTR was calculated using the BPNN learning algorithm. The training is presented in Figure (4) and (5) consisting of actual and predicted cutting ratio. This was plotted against the number of test ascontained in the training section with 3 and 6 number of neuron. . Moreover, Figures (6) and (7) presented the regression plots for all stages between the actual and predicted data for three and six number of neurons respectively. The figures show the closeness of the predicted CTR to the actual CTR.

Table (2) summarizes the results obtained from implementing the BPNN technique for estimating cutting transport ratio. The results show six

number of neurons gave high correlation coefficient and minimum AAE for all stages as compared with three neurons especially in testing stage. Also, results for all stages indicate that the model performance is very satisfactory. The empirical model in this study based on weights and biases shown in Tables (3) and (4) for three and six number of neurons respectively, associated with the input layer/hidden layer and hidden layer/output layer has been developed by incorporating the dataset. Before presenting the input-output data to the LM-ANN model, all the datasets were normalized between the ranges [-1, 1] using Equation (1) for hyperbolic tangent transfer function.

Table 2

Weights and biases of suggested empirical model for Eq. (4) with three neurons.

Hidden Layer	Input Layer Weight Matrix (w_{1i})	Input Layer	Hidden Layer	Output Layer
--------------	--	-------------	--------------	--------------

Neurons (i)									Bias (b ₁)	Weight Vector (w _{2_i})	Bias Vector (b ₂)
1	-0.1284	0.05203	0.26504	-0.1223	-0.32696	-1.1374	0.40868	0.09313	0.58708	2.1219	1.8577
2	-0.04305	0.17681	0.06727	-0.0861	-0.25805	0.53297	-0.34697	-0.0055	0.29755	-5.2971	
3	0.77061	-0.0396	0.62209	-1.133	0.37412	-0.03262	-2.3526	0.05491	2.3492	0.63321	

Table 3
Weights and biases of proposed empirical model for Eq. (4) with six neurons.

Hidden Layer Neurons (i)	Input Layer Weight Matrix (w _{1_i})								Input Layer Bias (b ₁)	Hidden Layer Weight Vector (w _{2_i})	Output Layer Bias Vector (b ₂)
1	-0.26143	-0.0753	0.1982	0.8663	-1.3496	-0.67025	-3.0182	0.0383	1.4765	0.63816	2.1068
2	-0.16054	0.1351	-0.2320	0.1750	-0.05553	-0.51849	-0.37551	-0.0238	0.43997	-5.4785	
3	0.026921	-0.0135	-0.9552	0.0807	0.74582	1.9277	-1.0367	-0.2188	1.1918	-1.2941	
4	-1.1244	0.0932	0.3546	2.7115	-0.70638	-2.6505	0.33145	-0.0156	3.1966	0.68511	
5	-0.37956	2.0728	-1.7421	-1.1678	-1.6947	-1.5817	-1.1094	0.2699	0.09369	-0.382	
6	-3.8847	-1.0264	-1.0293	-0.0543	-0.41382	1.0523	2.2407	-0.3648	0.7011	0.4379	

Also, to convert the ANN technique to a white box, the weights and the biases was extracted from empirical correlation for Matlab program. Eq. (4) has been used for prediction cutting transport ratio (CTR) in inclined and horizontal

wells based on weights and biases in Tables (3) and (4).

$$\begin{aligned}
 &= \text{TANH}\left[\sum_{i=1}^N w_{i,2} \times \text{TANH}(w_{1,1}dp + w_{1,2}pp \right. \\
 &+ w_{1,3}yp + w_{1,4}pv + w_{1,5}\rho m + w_{1,6}\theta \\
 &\left. + w_{1,7}Q + w_{1,8}RPM + b_1)\right] \\
 &+ b_2] \tag{4}
 \end{aligned}$$

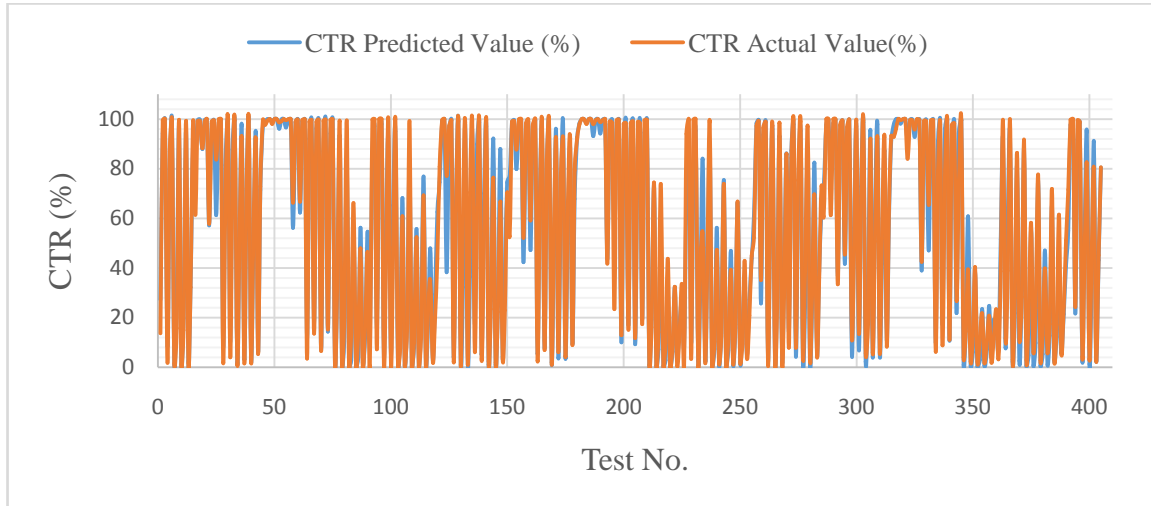


Fig. 4. Actual (experimental) And BPNN-predicted cutting concentration versus test number from network training for three neurons.

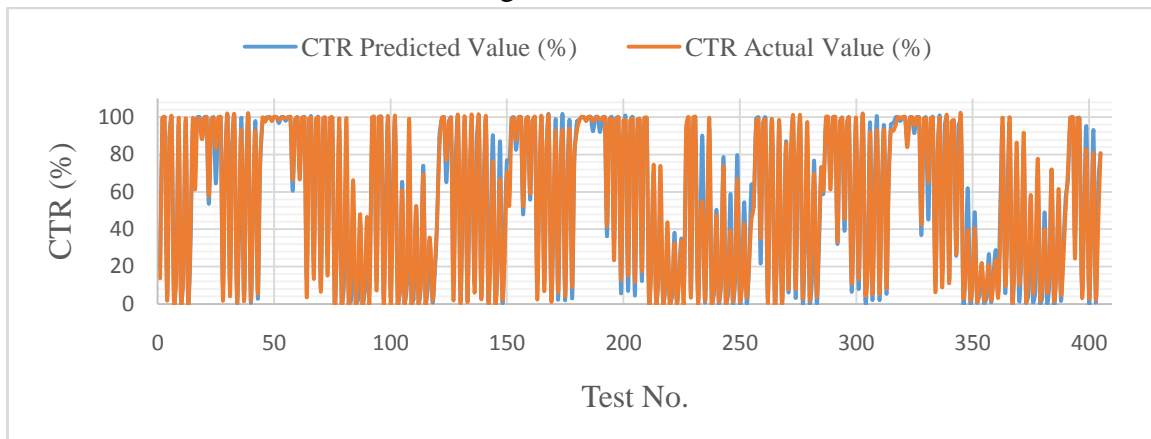


Fig.5. Actual (experimental) and BPNN-predicted cutting concentration versus test number from network training for six neurons.

Table 4
Results of estimating CTR using BPNN.

Stage	Number of neurons					
	Three			Six		
	R	R ²	AAPE(%)	R	R ²	AAPE(%)
Training	0.98	0.96	0.358	0.982	0.964	0.33
Validation	0.982	0.964		0.981	0.962	
Testing	0.976	0.952		0.982	0.964	
All	0.98	0.96		0.982	0.964	

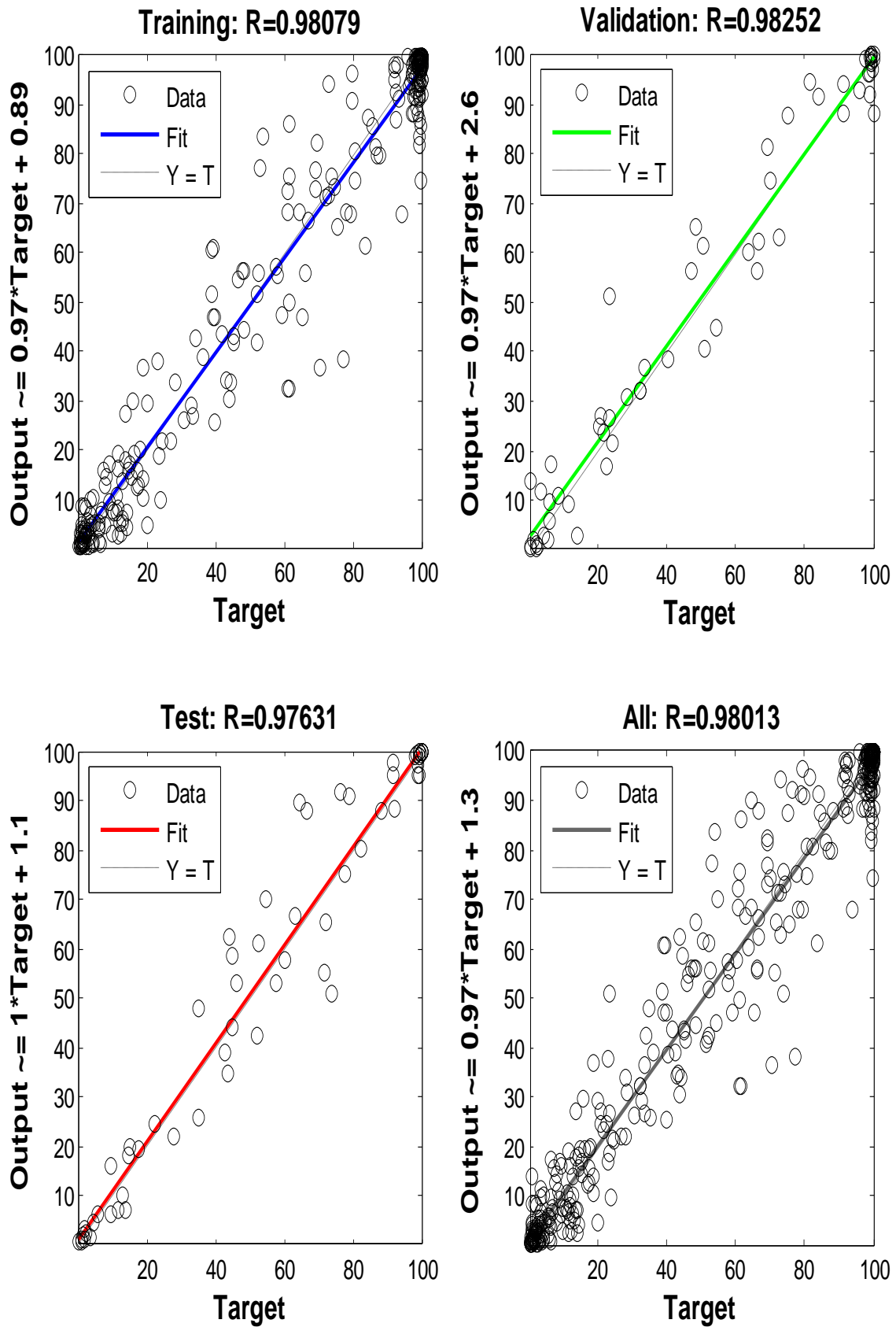


Fig.6. BPNN-predicted versus actual (experimental) cutting transport ratio for all stages with three neurons.

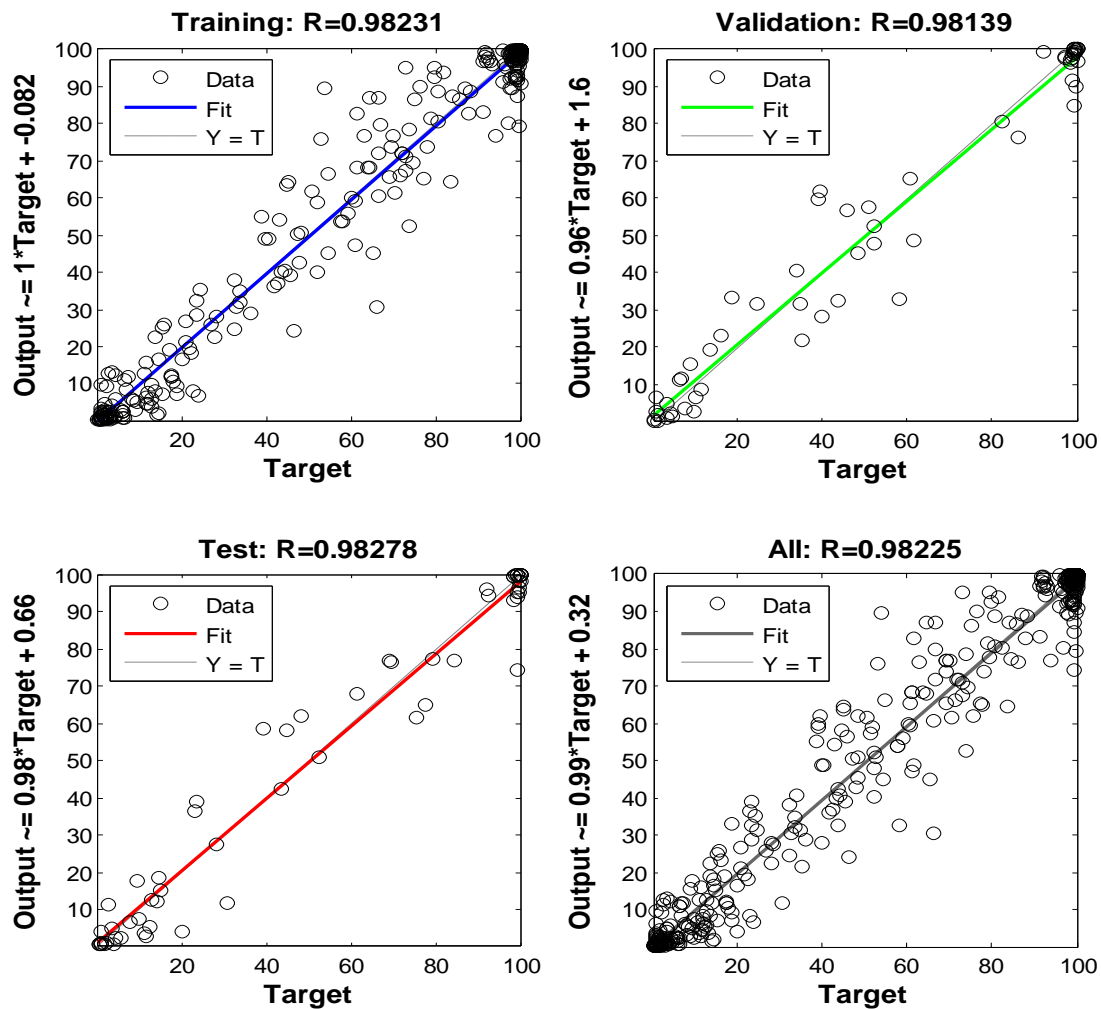


Fig.7.BPNN-predicted versus actual (experimental) cutting transport ratio for all stages with six neurons.

IV CONCLUSIONS

- The hyperbolic tangent transfer function is a good function for training network and prediction cutting transport ratio.
- Six number of neurons was gave the higher correlation coefficient and low average absolute error compared with three neurons. Meaning that increases in number of neurons gave the best results.
- The BPNN learning algorithm is a good technique for training this network and prediction cutting transport ratio.
- Artificial neural network method could be used to directly estimate CTR with good engineering accuracy and without complex procedures.

Nomenclatures and Abbreviations

<i>AAPE</i>	=	Average absolute percentage error
<i>ANN</i>	=	Artificial neural networks
<i>BPNN</i>	=	Back-propagation neural network
<i>HTTF</i>	=	Hyperbolic Tangent Transfer Function
<i>CTR</i>	=	Cuttings transport ratio (%)
<i>Q</i>	=	Flow rate (GPM)
<i>R</i>	=	Correlation coefficient (%)
<i>R²</i>	=	Coefficient of determination (%)
<i>RPM</i>	=	Pipe rotation (rpm)
<i>YP</i>	=	Yield point (lb/100ft ²)
<i>θ</i>	=	Inclination angle (degree)
<i>PV</i>	=	Plastic viscosity (cp)
<i>ρ_m</i>	=	Mud density (ppg)
<i>ρ_p</i>	=	Cutting density (ppg)
<i>dp</i>	=	Cutting size (mm)

V REFERENCES

- [1] Bizanti. M. S. &Alkafeef S. F., *Simplified hole cleaning solution to deviated and horizontal wells*, 13th Middle East Oil Show & Conference held in Bahrain, April 5-8, 2003.
- [2] Bourgoyne, A. T., Millheim, K. K., Chenevert, M. E., & Young, F. S., *Applied Drilling Engineering*. Richardson, TX: Society of Petroleum Engineers, 1986.
- [3] Cho. H.H., Shah. N., &Osisanya, S.O., *A three-segment hydraulic model for cuttings transport in horizontal and deviated wells*. The 2000 SPE/Petroleum Society of CIM International Conference on Horizontal Well Technology held in Calgary, Alberta, Canada, November 6-8, 2000.
- [4] Clark. R.K. &Bickham. K.L., *Mechanistic model for cuttings transport*. SPE 69th Annual Technical Conference and Exhibition held in Now Orleans, LA, U. S.A., 25-28 September, 1995.
- [5] Kamp. A. M. & Rivero. M., *Layer modeling for cuttings transport in highly inclined wellbores*. SPE 53942 presented at SPE Latin American and Caribbean Petroleum Engineering Conference held in Caracas, Venezuela, April 21–23, 1999.
- [6] Larsen. T.I., Azar. J. J. &Pilehvari. A.A., *Development of a new cuttings transport model for high angle wellbores including horizontal wells*.SPE Drilling & Completion, 13 (2):129-135. 1997.
- [7] Nazari T., Hareland G., Azar J.J. *Review of cuttings transport in directional well drilling: systematic approach*. SPE-132372-MS presented at the SPE Western Regional Meeting, 27–29 May, Anaheim, California, USA, 2010.
- [8] Pigott R.J.S., *Mud flow in drilling*. API-41-091 presented at the Drilling and Production Practice, 1 January, New York, 1941.
- [9] Williams C.E. & Bruce G.H., *Carrying capacity of drilling muds*. Journal of Petroleum Technology **3**(4):111–120, 1952.
- [10] Ekeinde, E. B., Okoro, E. E., Dosunmu, A., &Iyuke, S., *Optimizing aqueous drilling mud system viscosity with green*

- additives*. Journal of Petroleum Exploration and Production Technology, **9**(1), 315-318, 2019.
- [11] Mahmoud, H., Hamza, A., Nasser, M. S., Hussein, I. A., Ahmed, R., & Karami, H., *Hole cleaning and drilling fluid sweeps in horizontal and deviated wells: Comprehensive review*. Journal of Petroleum Science and Engineering, 106748. 2019.
- [12] Boyou, N. V., Ismail, I., Sulaiman, W. R. W., Haddad, A. S., Husein, N., Hui, H. T., & Nadaraja, K., *Experimental investigation of hole cleaning in directional drilling by using nano-enhanced water-based drilling fluids*. Journal of Petroleum Science and Engineering, 176, 220-231, 2019.
- [13] Dehvedar, M., & Moarefvand, P. (2019). *Detecting and drilling in critical inclination window in slant wells by means of a two phase liquid-solid CFD model and experimental study*. Kuwait Journal of Science, **46**(2): 74-.
- [14] Pandya, S., Ahmed, R., & Shah, S. Effects of particle density on hole cleanout operation in horizontal and inclined wellbores. SPE/ICoTA Well Intervention Conference and Exhibition. Society of Petroleum Engineers, 2019.
- [15] Al-Azani, K., Elkatatny, S., Ali, A., Ramadan, E., & Abdurraheem, A., Cutting concentration prediction in horizontal and deviated wells using artificial intelligence techniques. Journal of Petroleum Exploration and Production Technology, 1-11, 2019.
- [16] Ritter, V.C., Nordli, H., Fekete, O.R. and Bonsaksen, T., 2017. User satisfaction and its associated factors among members of a Norwegian clubhouse for persons with mental illness. *International Journal of Psychosocial Rehabilitation*. Vol 22 (1) 5, 14.
- [17] Ferrazzi, P., 2018. From the Discipline of Law, a Frontier for Psychiatric Rehabilitation. *International Journal of Psychosocial Rehabilitation*, Vol 22(1) 16, 28.
- [18] Bornmann, B.A. and Jagatic, G., 2018. Transforming Group Treatment in Acute Psychiatry: The CPA Model. *International Journal of Psychosocial Rehabilitation*, Vol 22(1) 29, 45.
- [19] Koder, D., 2018. Recovery-Oriented Care for Older People: Staff Attitudes and Practices. *International Journal of Psychosocial Rehabilitation*, Vol 22(1) 46, 54.
- [20] Binnie, J., 2018. Teaching CBT to Pre-Registration nurses: A critical account of a teaching session to pre-registration mental health nurses on the subject of cognitive behavioural therapy and trauma. *International Journal of Psychosocial Rehabilitation*, Vol 22(1), pp.55-64.