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Abstract

Drilling fluids are the most important materials in drilling operations, therefore improving the properties of these fluids are very essential in order to meet up with the increase in demands and required standards. In this experimental study, Solanum tuberosum formulated biopolymer was used to improve the water based mud rheological properties and artificial neural network predicted data for (PV) plastic viscosity, (AP) apparent viscosity and (YP) yield point. Artificial neural network (ANN) was used to train the rheological properties of the formulated mud and the network developed predicted the rheological properties of an untrained combination of bentonite and modified biopolymer. The main target is to regenerate or predict the rheological properties of the formulated mud; (AP) apparent viscosity, (YP) yield point and (PV) plastic viscosity generated originally from experimental procedures but this time using the ANN. The mean average error target was set to around 5-10%. As a model for choosing the best ANN architecture for predicting target value, two statistical parameters, mean squared error (MSE) and correlation coefficient (R2) were utilized. A system with the lower estimations of MSE and the higher estimations of R2 gives more precise forecasts. Three different network were created and the two statistical parameters were used to determine the best number of neurons in the hidden layer. The developed neural network with best prediction has Root Mean Square Error (MSE) of 1.25221 and overall correlation coefficient (R2) of 0.99373 for the predicted plastic viscosity, yield point and apparent viscosity

Keywords: Drilling Fluid, Water Based mud, Artificial Neural Network, Rheology, Solanum tuberosum

Introduction

Drilling fluids are materials that are exceptionally basic to drilling activities and as a result of rapid development in the petroleum industry (Afolabi et al. 2017; Fadiaro et al. 2012b), improving the properties of these fluids are very essential, so as to achieve the required standards and growing demands. The selection of drilling fluids and additives used in formulating the drilling mud is very important in determing the success of any drilling operation (Fadiaro et al. 2018). Not forgetting the ever stringent safety regulations and environmental policies that has come into effect. Additives are substances that are added to enhance the properties of the drilling fluid (Fadiaro et al. 2012a; Fadiaro et al. 2013). Many of these additives use in mud formulation have some distinct properties that helps in solving certain difficulties experienced during drilling operations. A wide variety of biopolymers are utilized in the petroleum industry for the purpose of improving the performance of drilling fluids to meet up with practical necessities, for example, suitable rheological propeties, mud density, control of filtration property etc. (Amanullah & Yu, 2004). Chesser, (2008) looked into water-soluble biopolymers performance as a fluid loss control agent and viscosity enhancer. They included starches, cellulosic, gums, derivative gums, and derivative starches. Additives such as Pre-gelatinized starches, Sodium carboxymethlcellulosics (CMC), Lignins and Tannins, Polyanionic Cellulosics (PAC), Sodium polyacrylates (SPA) and Biopolymers, which have been employed in enhancing drilling fluid properties are imported (Seteyeobot, Uma and Enaworu, 2017; Orodu et al. 2019), which has led to massive and unnecessary financial burden for the Nigerian oil and gas industry. However, recycling agricultural waste in Nigeria is rare practice (Abila and Kantola, 2013), thus leading to challenges such as; dumping heaps of refuse on roads, obstruction of drainage system that leads to flooding in rainy seasons. These aforementioned factors have led to epidemics outbreak faced by our environment today. Solanum tuberosum peelings which is one of the agricultural waste has not been explored as a source of biopolymer formulation, which is useful as an additive for drilling fluid. The Nigerian petroleum industry can adopt the use of local additives which are readily available to enhance economic development through, the reduction of cost for sourcingforeign additives and also in encourage local expertise and small business enterprise. Also on the basis of cost, Bloys et al. (1994) gave a report that drilling fluid is about 5%- 15% in total of drilling cost but can lead to 100% drilling operational challenges. However, to formulate drilling mud with a desired rheology propeties that will suit a particular formation and combat wellbore issues, a detailed analysis is necessary. Shadravan et al. (2015), opined that drilling fluids alongside all other wellbore fluids have been designed using a trial and error approach in the laboratory; with an intial guess which largely depends on mud analyst or the mud engineer experince in the laboratory. Abdollahi (2007) mentioned that the know how acquired from experience can be easily lost when the mud engineer or analyst with the required information and experience exits the company. Therefore a reliable system that will utilize all the avaliable data in understanding trends and utimately providing a better understranding of the mud design. Shadravan et al. (2015). An area of topical importance is the use of artificial nueral network, which has numerous benefits and applications in the industry. These include: predicting situations with complex relationships with output and input parameters while allowing it to obtain the best values of predicted properties with a minimized errors in calculation in a given area, etc. (Okorie et al. 2018). Artificial neural network (ANN) has demonstrated itself in having the capacity to take care of complex issues in different fields, i.e. engineering, science and therapeutic fields (Barton et al. 1998; Behnoud et al. 2016; Bektas et al. 2015; Jahanbakhshi et al. 2014; Rooki et al. 2012). ANN can take care of complex issues by utilizing basic scientific capacities and it requires short investment to play out these calculations to get required outcomes which make it more alluring for the petroleum industry (Osman et al. 2003; Bravo et al. 2012). The aim of the research constitutes developing an ANN (artificial neural network) system for the prediction of improved WBM (water-based mud) rheological properties. The study scope covers different composition of drilling mud being formulated using various amounts of biopolymer concentration and Model 800 OFITE Viscometer was used for measuring the rheological properties of the enhaced WBM (water-based mud). The simulation outputs were compared with the experimental values in order to validate prediction performance of the developed ANN system.

Biopolymer

Biopolymers used in drilling mud formulation, are of a class of compounds called polysaccharides and made up of polymerized sugar molecules (Biduski, et al. 2018; Zhu et al. 2017). Benyounes et al., (2010) obtained results that showed latex polymer reduces fluid loss and provides excellent bridging ability at lost circulation zones.

(ANN) Artificial Neural Network

The artificial neural networks (ANN) can be described as mathematical test systems in wherein data is processed in a similar way to that of a biological neural system works in terms of its intricacy and functionality (Mohaghegh, 2000). A basic meaning of an artificial neural system is outlined input space to an out space. This definition can be more summed up by contrasting the ANN with a biological sensory system in which it will gain from past experiences (Hejazi et al.2018). That process will create another new output after understanding the qualities of the information sources. The biological neuron is the major building piece of the nerves system which comprises of soma, dendrites and axon (Jafari, et al. 2009). The data as electrical signs are recognized by the dendrites, prepared by the soma and then moved over to the axon. A similar thing is occurring in the artificial neuron networks; the artificial neuron is the fundamental building piece of the artificial neuron arrange in which data as information sources duplicated by weights alongside inclination entering the artificial neuron to a summing capacity and disregarded the summation to an exchange capacity to an output (Sun et al. 2000).

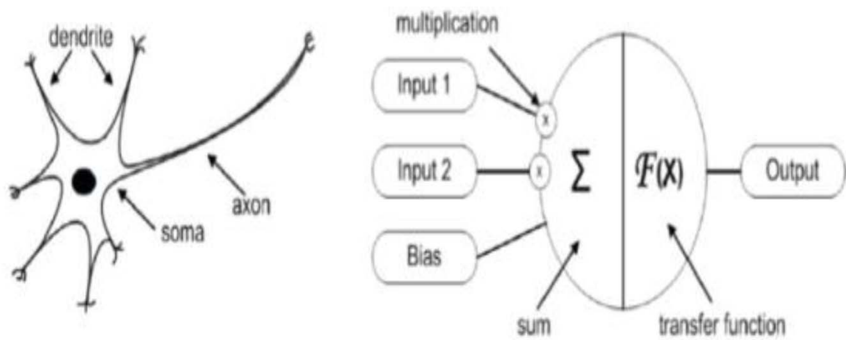

Figure 1.0—Representation for both Biological neuron on the left and artificial neuron on the right (K. Shaffer et al. 1994).

Applications of Artificial Neural Network in the Petroleum Engineering Field

The petroleum industry is one where Artificial neural system had been presented back in the 1980's in when specialists found that it had gigantic potential in taking care of numerous related issues in the business in various petroleum engineering fragments, for example, well testing, reservoir characterization, enhanced oil recovery, reservoir stimulation and drilling(K. Shaffer et al. 1994).

An examination was led that portrayed the ANN applications in the petroleum industry as a function of the problem type, for example;

i. Control Application
ii. Prediction and correlation
iii. Optimization
iv. Pattern or cluster analysis
v. Signal or image processing

An unconventional oil reservoir located in West Texas was characterized using Artificial Neural System by (Sung et al. 1995). The Artificial Expert System that was developed was able to produce a synthetic well log and identifying payzones. Moreover, high and low-resolution logs were predicted using both average and 3D seismic data. These logs then were used to locate and identify payzones. Also, for the same field production maps were generated utilizing the artificial neural system. The main goal of this expert system was to predict the production profiles for cumulative oil and gas quarterly for a total of two years. The produced result when it was compared to the actual field data it shows a close matching between both of them. These results were used then to approximate the placement of new infill drilling with the aid of the surface maps.

Methods

Rheological properties measurements

Measurement of the rheology properties of the drilling mud was carried out with model 800 OFITE Viscometer which has eight test speeds that is regulated from (RPM: 3, 6, 30, 100, 200, 300 and 600). These were used to determine the characteristics that enable flow of the formulated WBM (water based mud) when the biopolymer was introduced. The viscometer speed was controlled with a control knob and the dial readings were shown on a lighted magnified dial (Afolabi et al. 2017; Tomiwa et al. 2018; Orodu et al. 2018). The viscometer calibration was done using the API specified standard procedures (13B-1 and 13B-2), following the standard with which the equipment is calibrated, (Afolabi et al. 2017; Tomiwa et al. 2018; Orodu et al. 2018).

Artificial Neural Network Development

ANN carried out predictive studies on the the rheological properties of the formulated water based mud, using a feed- forward neural network (FFNN) with Levenberg – Marquardt training algorithm for the prediction from MATLAB.

Artificial Neural Network Structure

A total number of 65 data values were involved in the training of the ANN which constituteed both the input and output data. The data were randomly divided, using dividerand function in MATLAB, as follow: 70%, 15%, and 15% for training, validation and for testing respectively. The random division of data has the advantage of covering a wide range of input properties without repeating. Moreover, the validation and the testing were monitored as shown in figure 3.4 to ensure that the ANN will not be overtrained or memorized. Overtraining occurs when the validation and/or the testing line deviate away from the training line as shown in figure 3.5. Besides monitoring the validation and testing performance plot as shown in figure 3.6, the error difference between the ANN and experimental results were compared for both the training and testing cases to be close to the targeted error of 5-10% and the ANN structure was adjusted consequently to reduce the error to the desired target. The error, however, was calculated by comparing the results of the simulator and those predicted by the ANN (Liu et al. 2007). The absolute difference was calculated using the following equation:

$$Error\ \% = \left|\frac{Result_{Experimnet} - Result_{ANN}}{Result_{Experimnet}}\right| \times 100$$

For the blind testing mean error average calculation, the following formula was used to calculate the average error for each case:

$$Average\ Error\ \% = \frac{\sum_{i=1}^{N}\left|\frac{Result_{Experimnet} - Result_{ANN}}{Result_{Experimnet}}\right| \times 100}{N}$$

Where N represents the time-frequency each test case has been collected.

Training Algorithm and Transfer Function. For the training algorithms, two of the commonly used training algorithms were tested, scaled conjugate gradient training algorithm (trainscg) and resilient backpropagation training algorithm (trainrp), however, trainscg produced the least mean error for the production profiles compared to other training algorithms available in the MATLAB's tool box. Moreover, for the transfer-function, log-sigmoid (logsig) transfer function was used and found to perform better that other transfer links. In addition, the performance of the network was controlled using the mean sum of squares of the network error with regularization performance function (msereg) and gradient descent with momentum weight and bias(learngdm) was used as learning algorithm.

Results and Discussions

The results from the experiments and their discussions are presented in this section.

The bentonite and Solanum tuberosum biopolymer concentrations used in the formulation of the mud and the corresponding experimental plastic viscosity (PV), apparent viscosity (AP) and yield point (YP) data are shown in Table 3.1. The addition of Solanum tuberosum biopolymer in the mud, improved the drilling fluid properties, the changes occuring in the properties which can be seen are due to the concentration of Solanum tuberosum biopolymer in the mud.

Table 3.1—Bentonite and Solanum tuberosum biopolymer concentrations

Run Order	Bentonite content(g)	S/T Biopolymer (g)	Experimental PV(cp)	Experimental YP (Ib/100ft^2)	Experimental AP(cp)
1	20	6	15	49	39.5
2	24	10	11	22	22
3	24	6	11	23	22.5
4	22	8	11	17	19.5
5	24	6	18	45	40.5
6	24	6	11	22	22
7	26	4	9	20	19
8	26	8	9	13	15.5
9	24	6	11	34	28
10	22	4	8	28	22

ANN rheological properties prediction

The main target is to be able to regenerate or predict the apparent viscosity, plastic viscosity, yield point generated originally from laboratory procedures but this time using the ANN. The mean average error target is to be set around 5-10%. As a model for choosing the optimum nueral network architecture for simulating a target value, two statistical parameters, (MSE) mean squared error and (R^2) correlation coefficient were utilized (Shaffer, et al. 2002). A system with a lower estimation of MSE and a higher estimation of R^2 gives more precise forecasts. Three different network were created as shown in figure 3.1 –3.3 and the two statistical parameters were used to give the best neuron number in the hidden layer (Vitor Diego da et al. 2017). The ANN architecture in fig. 3.2 with two parameters, seven neurons and three output parameters in the input layer, hidden layer and output layer respectively gave a better prediction; within the layers are nodes, with special feedback system which process information in form of signals. The two input parameters used for the neural network training were the bentonite and solanum tuberosum biopolymer quantity used in the mud formulation. While the out parameters used for the training were the experimental yield point, apparent viscosity and plastic viscosity. In the ANN architecture the 2 input parameter and 3 output parameter mentioned above did not change throughout the training, but the hidden layers' number of neurons changed progressively with the prediction to get the structure with the accurate prediction. The estimated (MSE) mean square error and (R^2) correlation coefficient were the two statistical parameters used in choosing the best ANN architecture that gave the best prediction of the target values. A precise prediction was obtained from a system with a low MSE and high R^2 estimate

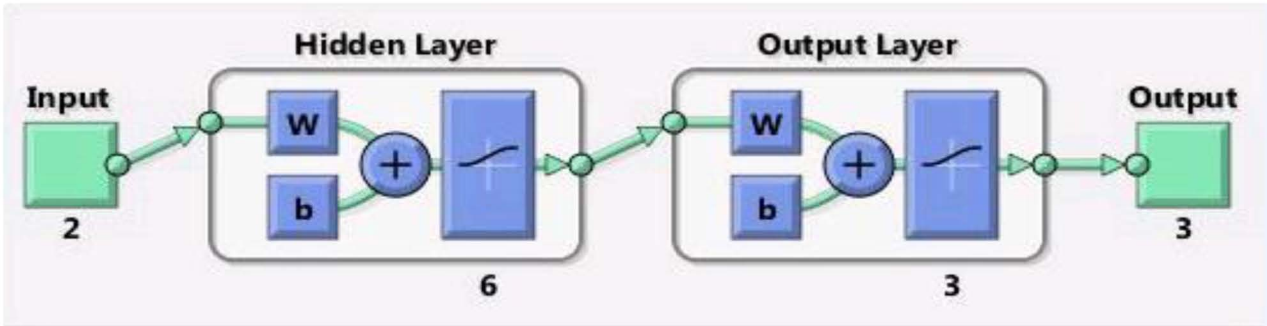

Figure 3.1—ANN Architecture for hidden layer with six neurons.

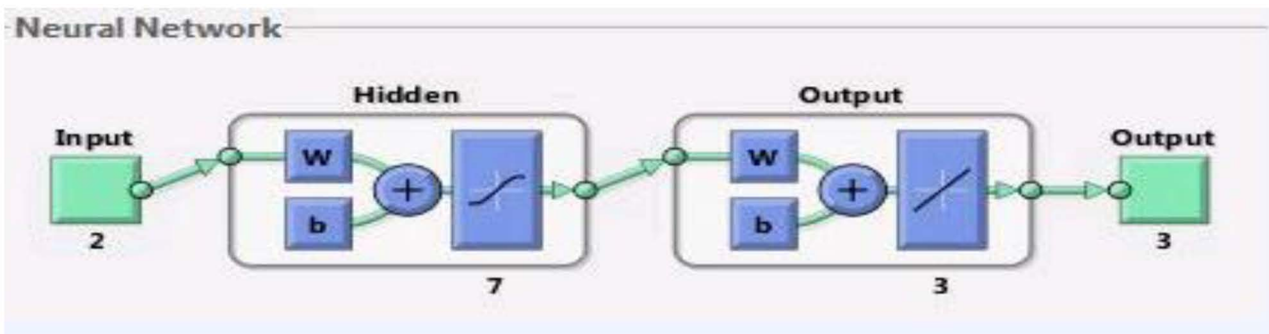

Figure 3.2—ANN Architecture for hidden layer with seven neurons.

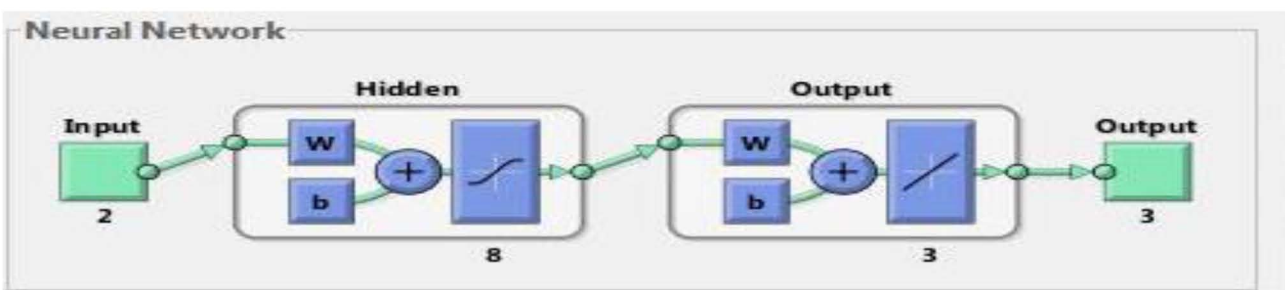

Figure 3.3—ANN Architecture for hidden layer with eight neurons.

It is worth mentioning that during the training and comparison between different ANN structures, fixed number of training, validating and testing data sets were used instead of making the neural network select random cases for the sake of comparison.

From Table 3., Having seven neurons in the hidden layer produces best performance which is in turn a satisfactory value of MSE and R^2 value. Therefore, ANN structure was fixed as 2:7:3, which explains the state of having in the input, hidden and output layers; two elements, seven neurons and three elements respectively. In figure 3.4 –3.6, the regression plot showing the training, validation, test and all R^2 from Matlab gives a better view for comparison.

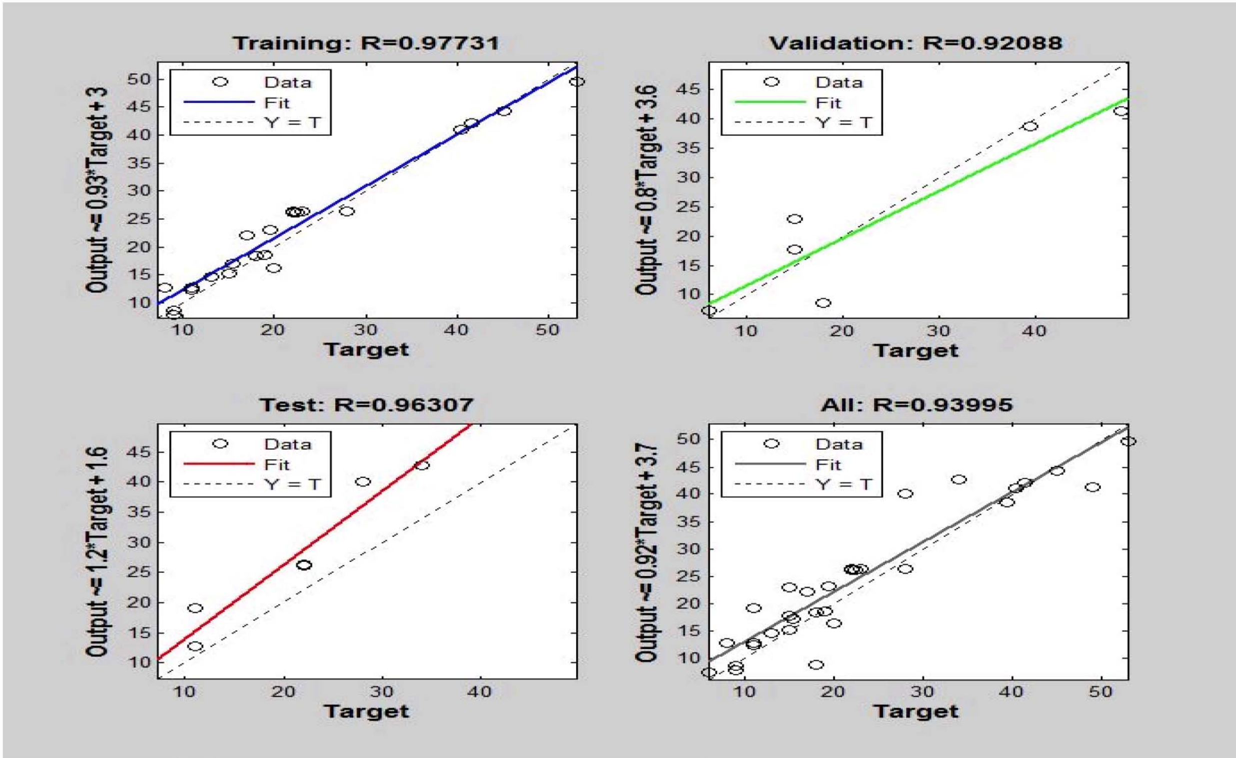

Figure 3.4—ANN regression plot for hidden layer six neurons.

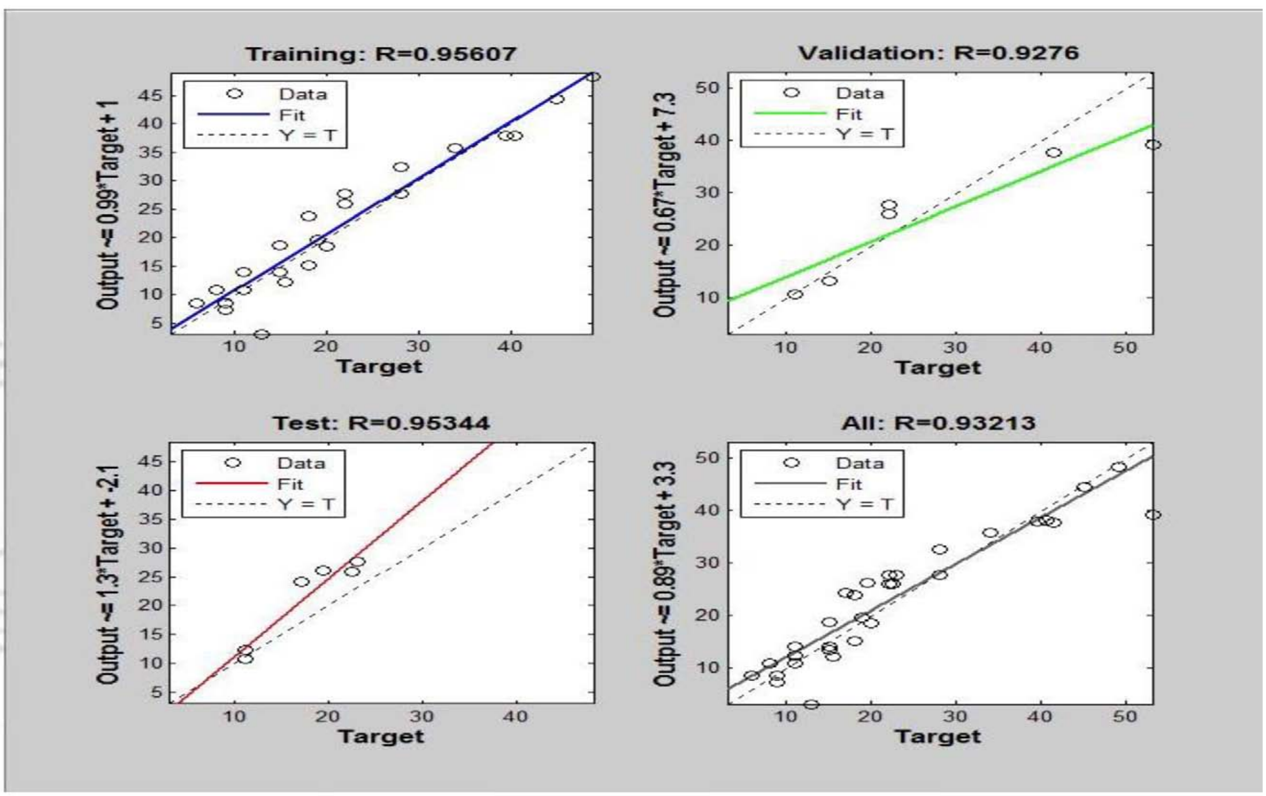

Figure 3.5—ANN regression plot for hidden layer with eight neurons.

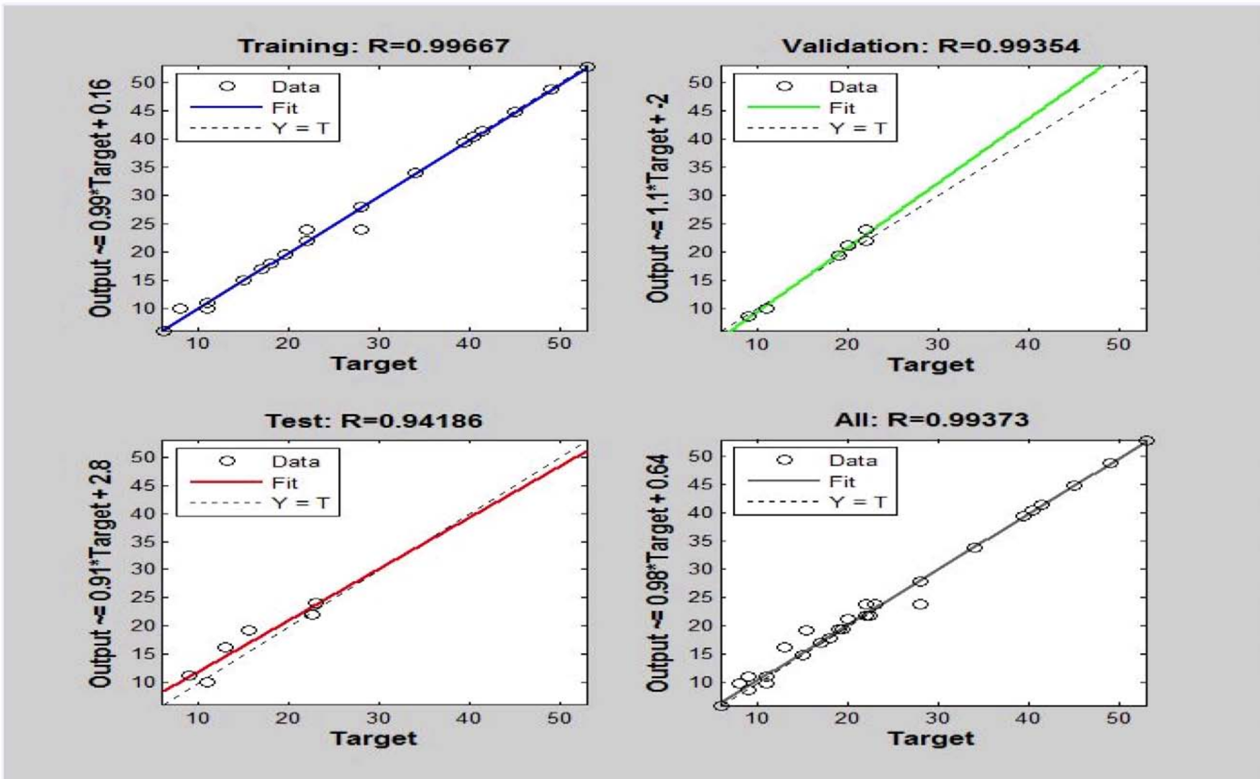

Figure 3.6—ANN regression plot for hidden layer seven neurons.

Table 3.2—Mean squared error (MSE) and Correlation coefficient (R2) for all numbers of neurons.

Numbers of neurons	R^2			MSE
	Training	Validation	All	
6	0.977731	0.92088	0.93995	9.32846
7	0.99667	0.99354	0.99373	1.25221
8	0.95607	0.9276	0.93213	7.48923

Validating the ANN network with new sets of experimental data

A new sets of experimental test were carried out in the laboratory, where different quantity of bentonite and modified biopolymer was used for the test. Ten samples with varying concentrations were produced and new data for plastic viscosity, yield point and apparent viscosity were acquired. The newly gotten data set were used to validate the new artificial neural network predictions. The quantity of bentonite and modified biopolymer used for the experiment were inputted into the developed network, which gave predicted values for plastic viscosity, apparent viscosity and yield point as shown in Table 3.3 – 3.5. The (MAD) Mean Absolute Deviation, (MSE) Mean Square Error, (RMSE) Root Mean Square Error and (MAPE) Mean Absolute Percentage Error for the prediction was calculated.

Table 3.3—Predicted values for plastic viscosity using ANN with seven neurons in the hidden layer.

Predicted PV (cp)	Experimental PV (cp)	Error	Absolute Value of Error	Square of Error	Absolute values of Errors / Experimental values
14.97587865	15	0.024121349	0.024121349	0.000581839	0.00160809
10.98968477	11	0.01031523	0.01031523	0.000106404	0.000937748

Predicted PV (cp)	Experimental PV (cp)	Error	Absolute Value of Error	Square of Error	Absolute values of Errors / Experimental values
10.98968477	11	0.01031523	0.01031523	0.000106404	0.000937748
10.99997077	11	2.92252E-05	2.92252E-05	8.54113E-10	2.65684E-06
17.97674855	18	0.023251448	0.023251448	0.00054063	0.001291747
10.98968477	11	0.01031523	0.01031523	0.000106404	0.000937748
8.663627837	9	0.336372163	0.336372163	0.113146232	0.037374685
8.150798899	9	0.849201101	0.849201101	0.72114251	0.094355678
10.9984913	11	0.001508697	0.001508697	2.27617E-06	0.000137154
7.98968477	8	0.01031523	0.01031523	0.000106404	0.001289404
Total		1.275744902	1.275744902	0.835839104	0.138872659
Number of runs	**10**				
MAD	**0.12757449**				
MSE	**0.08358391**				
RMSE	**0.289108821**				
MAPE	**1.38872659**				

Table 3.4—Predicted values for yield point using ANN with seven neurons in the hidden layer.

Predicted YP (Ib/100ft^2)	Experimental YP (Ib/100ft^2)	Error	Absolute Value of Error	Square of Error	Absolute values of Errors / Experimental values
48.95815153	49	0.04184847	0.04184847	0.001751294	0.00085405
21.99246279	22	0.007537207	0.007537207	5.68095E-05	0.0003426
22.99246279	23	0.007537207	0.007537207	5.68095E-05	0.000327705
17.00010483	17	–0.000104833	0.000104833	1.09899E-08	6.16664E-06
44.9641964	45	0.035803597	0.035803597	0.001281898	0.000795635
22.99246279	22	–0.992462793	0.992462793	0.984982395	0.045111945
21.27705986	20	–1.277059861	1.277059861	1.630881889	0.063852993
16.31472142	13	–3.314721421	3.314721421	10.9873781	0.254978571
33.96360178	34	0.036398215	0.036398215	0.00132483	0.001070536
27.99246279	28	0.007537207	0.007537207	5.68095E-05	0.000269186
Total		–5.447687005	5.721010812	13.60777085	0.367609388
N	**10**				
MAD	**0.572101081**				
MSE	**1.360777085**				
RMSE	**1.166523504**				
MAPE	**3.676093883**				

Table 3.5—Predicted values for apparent viscosity using ANN with seven neurons in the hidden layer.

Predicted AP(cp)	Experimental AP(cp)	Error	Absolute Value of Error	Square of Error	Absolute values of Errors / Experimental values
39.44972459	39.5	0.050275406	0.050275406	0.002527616	0.001272795
21.98511378	22	0.014886219	0.014886219	0.0002216	0.000676646
21.98511378	22.5	0.514886219	0.514886219	0.265107818	0.022883832
19.50013516	19.5	–0.000135162	0.000135162	1.82688E-08	6.93139E-06
40.4661432	40.5	0.033856804	0.033856804	0.001146283	0.00083597
21.98511378	22	0.014886219	0.014886219	0.0002216	0.000676646
19.45699111	19	–0.456991112	0.456991112	0.208840877	0.024052164
16.3277586	15.5	–0.827758596	0.827758596	0.685184294	0.05340378
27.98391565	28	0.016084347	0.016084347	0.000258706	0.000574441
21.98511378	22	0.014886219	0.014886219	0.0002216	0.000676646
Total		–0.625123438	1.944646303	1.163730411	0.105059853
N	**10**				
MAD	**0.19446463**				
MSE	**0.116373041**				
RMSE	**0.341134931**				
MAPE	**1.05059853**				

The predicted values for plastic viscosity, yield point and apparent viscosity were plotted against the experimental data and the R^2 was determined as shown in Figure 3.7 – 3.9.

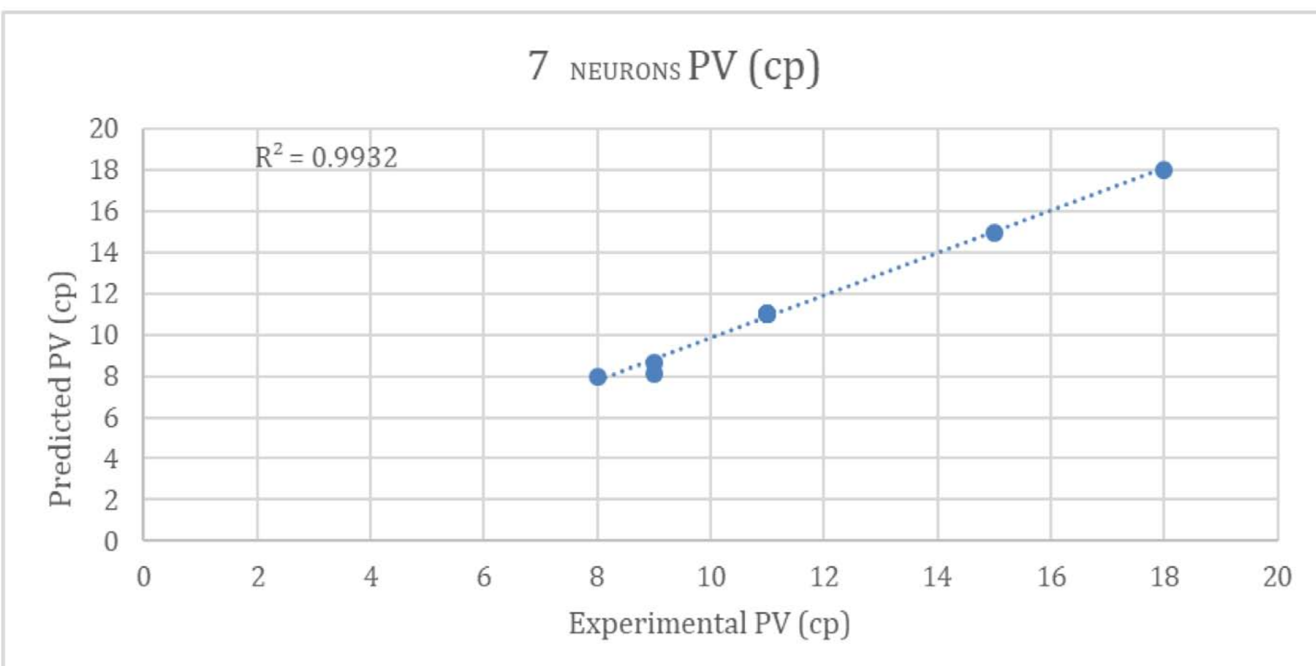

Figure 3.7—Regression plot for predicted and experimental plastic viscosity.

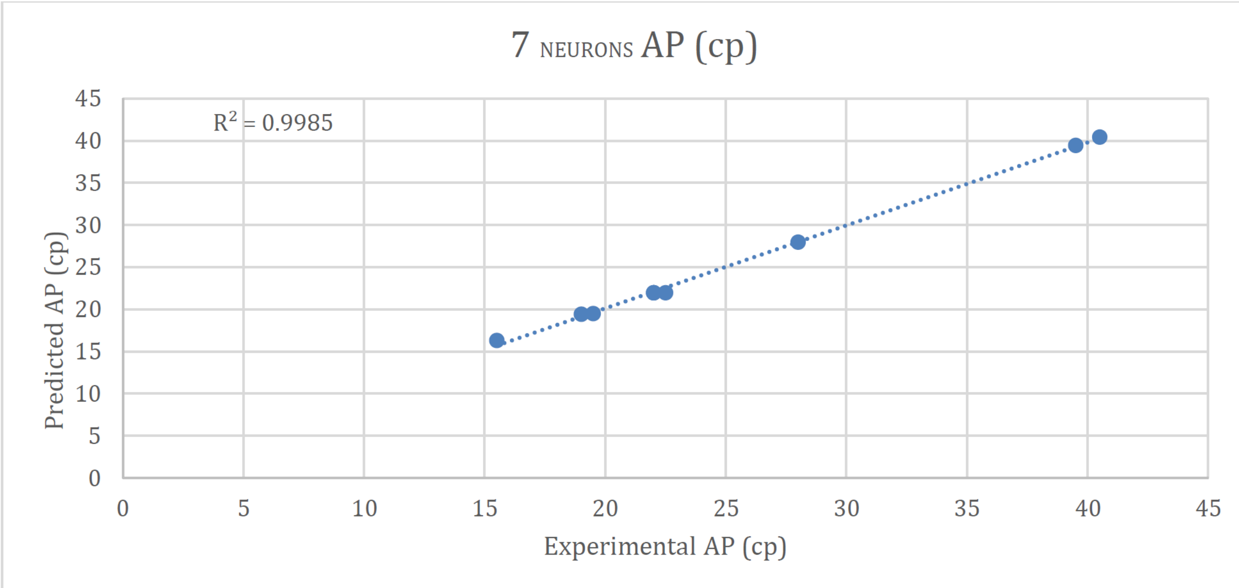

Figure 3.8—Regression plot for predicted and experimental apparent viscosity.

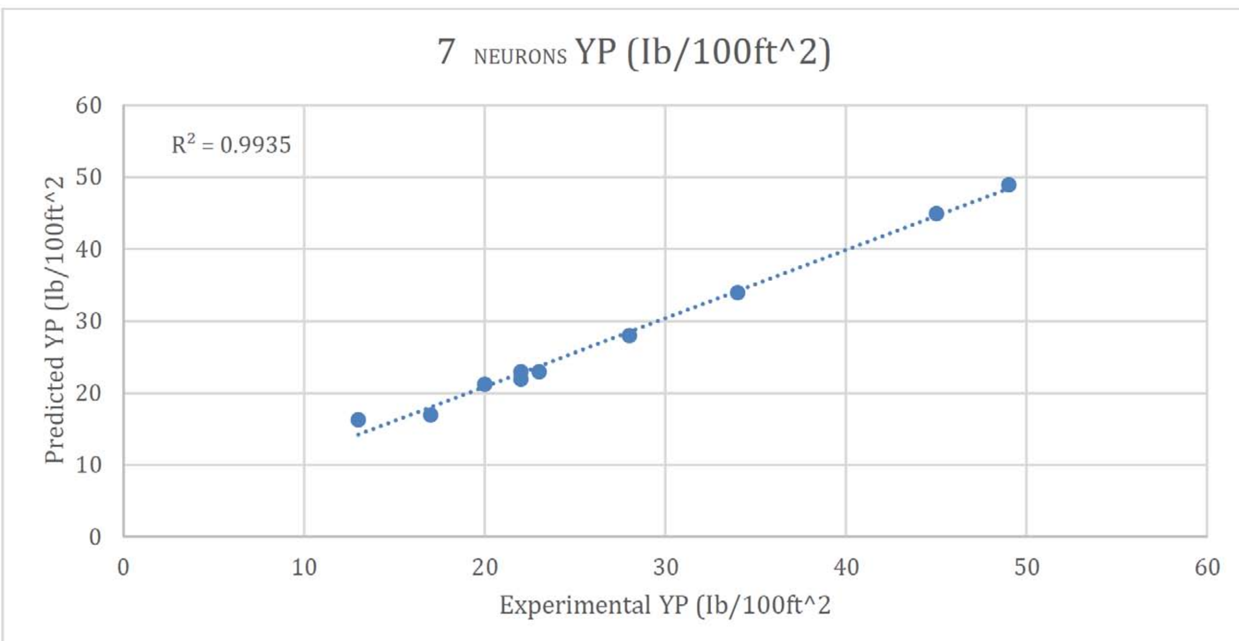

Figure 3.9—Regression plot for predicted and experimental yield point.

CONCLUSION

The rheological properties of the formulated mud were trained using artificial neural network and the developed network was used to predict new rheological properties of an untrained combination of bentonite and modified biopolymer quantity.

The results obtained from this study yielded this conclusion:

a. Training of the considered rheological properties of the modified biopolymer was done with the Artificial Intelligence network; Artificial Neural Network. The training was carried out for predictive analysis on the development of new properties of an untrained combination of bentonite and MBP quantity, with Mean Absolute Deviation (MAD) of 01275, Mean Square Error (MSE) of 0.0836, Root

Mean Square Error (RMSE) of 0.2891, Mean Absolute Percentage Error (MAPE) of 1.387 and R^2 of 0.99.

b. That ANN is efficient and reliable in the prediction of experimental and measured data, which can be applied in the petroleum industry.

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