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Artificial Neural Network (ANN) for Prediction of Viscosity Reduction of Heavy Crude Oil using Different Organic Solvents

Dr. Firas K. Al-Zuhairi*
Lecturer
Petroleum Technology Department ,
University of Technology, Iraq
Baghdad - Iraq
Email:150009@uotechnology.edu.iq

Rana Abbas Azeez
Lecturer
Petroleum Technology Department ,
University of Technology, Iraq
Baghdad - Iraq
Email:150011@uotechnology.edu.iq

Muna Kheder Jassim
Ass. Lecturer
Petroleum Technology Department ,
University of Technology, Iraq
Baghdad - Iraq
Email:150007@uotechnology.edu.iq

ABSTRACT

The increase globally fossil fuel consumption as it represents the main source of energy around the world, and the sources of heavy oil more than light, different techniques were used to reduce the viscosity and increase mobility of heavy crude oil. this study focusing on the experimental tests and modeling with Back Feed Forward Artificial Neural Network (BFF-ANN) of the dilution technique to reduce a heavy oil viscosity that was collected from the south- Iraq oil fields using organic solvents, organic diluents with different weight percentage (5, 10 and 20 wt.%) of (n-heptane, toluene, and a mixture of different ratio toluene / n-Heptane) at constant temperature. Experimentally the higher viscosity reduction was about from 135.6 to 26.33 cP when the mixture of toluene/heptane (75/25 vol. %) was added.

The input parameters for the model were solvent type, wt. % of solvent, RPM and shear rate, the results have been demonstrated that the proposed model has superior performance, where the obtained value of R was greater than 0.99 which confirms a good agreement between the correlation and experimental data, the predicate for reduced viscosity and DVR was with accuracy 98.7%, on the other hand, the μ and DVR% factors were closer to unity for the ANN model.

Keywords: viscosity reduction, DVR, dilution technique, modeling, ANN.

الشبكة العصبية الاصطناعية (ANN) للتنبؤ بتخفيض اللزوجة من النفط الخام الثقيل باستخدام مذيبات عضوية مختلفة

د. فراس خليل الزهيري*
مدرس
قسم تكنولوجيا النفط /الجامعة التكنولوجية, العراق

رنا عباس عزيز
مدرس
قسم تكنولوجيا النفط /الجامعة التكنولوجية, العراق

منى خضر جاسم
مدرس مساعد
قسم تكنولوجيا النفط /الجامعة التكنولوجية, العراق

الخلاصة

الزيادة في استهلاك الوقود الأحفوري على مستوى العالم وذلك لأنه تقريبا يمثل المصدر الرئيسي للطاقة ،وان مصادر النفط الثقيل هي أكثر من النفط الخفيف ، لذلك تم استخدام العديد من التقنيات لتقليل لزوجة النفط الثقيل وزيادة لتسهيل جريانة اثناء

*Corresponding author
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الاستخراج والنقل. ركزت هذه الدراسة على الاختبارات التجريبية لتقنية التخفيف لتقليل لزوجة الزيت الثقيل التي تم جمعة من جنوب العراق باستخدام المذيبات العضوية ومن ثم نمذجة البيانات التي تم الحصول عليها باستخدام شبكة التغذية العصبية الاصطناعية للخلف الأمامي (BFF-ANN)، واستنادا إلى مختلف المخففات العضوية وبنسب وزنية مختلفة (5 ، 10 و 20٪ بالوزن) من (هيبتان ، تولوين ، ومزيج من نسبة مختلفة من التولوين / الهيبتان) عند درجة حرارة ثابتة. من الناحية التجريبية ، كان الحد الأدنى من اللزوجة يتراوح من 135.6 إلى 26.33 سنتي بواز عند إضافة خليط التولوين / الهيبتان (25/75 ٪ بالحجم). ان المتغيرات التي تم ادخالها للنموذج الذي تم انشاءه هي نوع المذيبات, النسب الوزنية المضافة من المذيبات ، دورة في الدقيقة ومعدل القص ، وقد أثبتت النتائج أن النموذج المقترح لديه أداء متفوق ، حيث كانت القيمة التي تم الحصول عليها من R أكبر من 0.99 مما يؤكد وجود توافق جيد بين نتائج النوذج الرياضي البيانات التي تم الحصول عليها مختبرياً ، كان الانخفاض المخمن للزوجة ونسبة درجة انخفاض الزوجة بدقة 98.7 ٪ من النتائج المختبرية ، وكانت عوامل الزوجة ونسبة درجة انخفاض الزوجة أقرب إلى واحد.
الكلمات الرئيسية:تقليل اللزوجة, درجة تقليل اللزوجة,تقنية التخفيف,نمذجة, ANN.

1. INTRODUCTION

The oil is the main nerve of the energy in the world, oil prices are changed depending on supply and demand, the heavy crude oil (HO) price is half the price of light oil attributed to contains high quantities of sulfur and heavy metals like nickel and vanadium, which is difficulties through production, transportation in the pipeline, **(Hasan, et al., 2010)**. One of the major difficulties with the production of heavy oils is transporting through the pipeline has attributed to high viscosity, particularly when there is no pre-viscosity reduction to ensure oil flow through pipelines**, (Alomair and Almusallam, 2013; Ali, et al., 2019a)**. Crude oil has various compounds, among them, asphaltenes are responsible for high viscosity and are the most polar active fraction of oil that is insoluble in saturated components like n-C_5 and n-C_7 while in aromatics are soluble such as toluene and benzene**, (Aristizábal, et al., 2017;Ali, et al.,2019b)**. Heteroatoms (O, S, and N) are located inside the asphalt molecule give high polarity which leads to the formation of large aggregates and causes a significant increase in viscosity, (**Franco, et al., 2015)**. Viscosity is an important characteristic in determining the quality of crude oil, so the production of oil from the reservoir or transporting in pipelines has become one of the most important challenges today due economically and environmentally expensive**, (Taborda, et al., 2017)**.

Various techniques were used to reduce the viscosity of heavy oil such as heating, emulsion, electric or magnetic field, nanotechnology, and dilution with organic solvents like kerosene, light naphtha and gas condensing, **(Al-Adwani and Al-Mulla, 2019;Al-Hashmi, et al., 2017),** each of these techniques has benefits and drawbacks. Dilution is effective technique for transport HO in pipelines, it has drawn the attention of most researchers to reduce the viscosity of HO and facilitate flow oil in pipelines due to reduce the cost of pumping and avoid pressure drop **,(Mohammadi, et al., 2019)**. Another benefit including maintaining the original character of hydrocarbon in contrast to the emulsification method, in addition, it can be applied at any sites regardless of weather conditions, while heating is not effective in cold places**, (Luo, et al., 2007)**, reduce the viscosity of crude oil needs to select the best diluents to get an acceptable viscosity, to ensure the smooth flow of oil transported as considered an influencing factor economically. Recently, some researchers have used intelligent programming to find appropriate relationships between input and output data, a fast and accurate prediction model was designed to predicate the reduction in viscosity of heavy crude oil with various organic solvents to reduce the time in practical experiments, **(Daryasafar and Shahbazi, 2017)**.

Advanced technology using intelligent tools has been widely applied for finding the non-linear relationships between inputs and outputs values, like artificial neural networks and adaptive neuro-fuzzy interference systems, the fuzzy systems were used to model scientific constraints, while Artificial Neural Networks (ANNs) were used as an efficient tool of modeling, predict, solved the problems and identifies errors, the ANN a computing model is widespread and highly flexible and can be used in all application of science and engineering, **(Tatar, et al., 2016)**. Many studies have been a focus on the analysis and predictions were in the last years especially in the petroleum industries, **(Makinde, et al., 2012)**. **(Eletta, et al., 2019),** investigated the effect of binary diluents (ethanol/n-hexane) on oil yield at different conditions such as various ratio of binary diluent, temperatures and time using response surface methodology (RSM) and ANN model to predicting oil yield, they found the predicted values by ANN model was more precise than that of RSM when comparison with practical values. **(Doust, et al., 2016),** presented the ANN and ANFIS models are successfully in the application for forecasting kinematic viscosity of RFO and high viscous oil in the petroleum industry. **(Karadurmuş, et al., 2018),** prepared the various ratio of binary mixture of based oil and tested the properties of the prepared oil, these consequences modeled in ANN and RMSE, MAPE% and regression coefficient (R) values, The founded the proposed model was a succeeded in predicting the properties of oils, give a high correlation coefficient and MAPE with small value for RMSE, that means the model performs better. In addition, **(Tavakoli, et al., 2017),** predicted the density of Athabasca bitumen – tetradecane mix, at different conditions (temperature, pressure, and weight percentage of diluents) using a radial basis function neural network (RBF-NN) technique, they conclude the proposed model is a suitable model for density forecasting of bitumen – tetradecane mix. **(Eghtedaei, et al.,2017),** presented accuracy calculating for viscosity reduction by proposed a radial artificial neural network function(RBF-ANN) for relationship between heavy oil viscosity and the Athabasca bitumen mix, as a function of the temperature, pressure and weight% of tetradecane when comparing the obtained results with previous studies.

However, the literature focuses on a prediction of the effect of n-heptane, toluene, and mixture from different volume percentages of toluene/n-heptane as dilutes solvents on the viscosity reduction of heavy oil using intelligent model Back Feed Forward Artificial Neural Network (BFF-ANN) looks to be rare. As a consequence, in this study, the results obtained from practical laboratory experiments were used as input data to build a model of an artificial neural network, then proposed model was used to examine a section of laboratory results to know its accuracy for future approval in obtaining direct results without referring to the laboratory, the input parameters to ANN are solvent types, solvent addition, RPM, and shear rate, while the output parameters are viscosity and DVR.

2. EXPERIMENTAL

2.1 Materials and Experimental Methods

The crude oil from south of Iraq (Amara oil field) was used in the present study; the density, API, and viscosity of this oil are 0.979 g/cm^3, 16, and 135.6 cP respectively at 298.15 K. The solvents toluene and n-Heptane (purity = 99%), the diluents solvents n-Heptane and toluene were used as received, and the prepared mixture from different volume percentages of toluene / n-Heptane (25/75, 50/50 and 75/25) were also used as diluents in this study. The mixtures of heavy crude oil with different weight concentration of solvents (5, 10 and 20 wt. %) were done in a closed cylinder-shaped beaker size 125 ml, with working volume 100 ml under continues mixing using a magnetic stirrer for an hour to approve a homogenous blend, **(Mortazavi-Manesh and Shaw, 2016)**. The viscosities of samples were measured at temperature 298.15 K and shear rate range from 2 to 42 s^{-1} using Brookfield viscometer model DV-11.

2.2. Experimental Data Analysis using ANN

Artificial neural networks are a system inspired by the biological nervous system, in which problems or information are treated as inputs, the brain processes this information, and the problem is solved. The basis of the functioning of the biological network depends on the modifications that occur in the neural connections and thus reaching the goal, this idea was adopted in the work of artificial neural networks, the artificial neural network solves the complex problems that the brain sometimes fails to recognize, the artificial neural network consists of three layers, the input layer for input data, the output layer that represents the output data and a hidden layer through which the network is learned. In each layer there is a group of neurons that are associated with two factors, w (weights) and b (biases), whose value is random at the beginning and their values are continuously updated in each attempt until the desired result is achieved which represents the goal. Determining the number of neurons in each layer and choosing the appropriate transfer function is very important in determining the speed and accuracy of the obtained results, **(Usman and Ademola, 2013)**.

The feed-forward back propagation net is using a back propagation training algorithm. In this type of network, the results are calculated, the error rate is calculated and compared with the permitted error rate, and this process is repeated a number of times until the goal is reached. Finally, the reached network is used in predicting results from new inputs, **(Fahriye and Turgay, 2017)**.

In the current research, 25 neurons were chosen as the ideal number after experimenting with a different number of neurons (10, 15, 20, and 25), **Fig. 1** shows the selected network. Tangent Eq.(1) and Linear Eq.(3) transfer functions for the hidden layer and output layer respectively were selected as two transfer functions, **(Andy, 2017; Yonaba, et al., 2010)**. Also, the Bayesian Regularization Back Propagation algorithm was selected to improve the values of w (weights) and b (biases) in the back propagation algorithm.

$$\Phi(x) = \frac{1}{1+ e^{-x}} \quad (1)$$

Where: x = total synaptic input defined by Eq. (2).

$$x = \sum_{i=1}^{I} w_i x_i + b_i \quad (2)$$

$$\Phi(x) = x \quad (3)$$

In this study, the ANN model was accomplished using MATLAB software to analyze and predict viscosity reduction of heavy crude oil using different solvent from the experimental data, the data used in this study consists of (177) sets of (Solvent type, wt. % of Solvent, RPM, and Shear rate) as inputs, and viscosity and DVR as outputs as shown in **Appendix (A)**. The training set is used for neural network training, depending on the number of attempts (epochs) through which the error rate is improved. The validation set is used to calculate network generalization. The testing group is used to measure the strength of network improvement in predicting results for previously untrained values. Thus give an independent measure of network performance during and after training. In the current work, the data were divided into three sets, namely, training set (80%), validation set (10%) and testing set (10%).

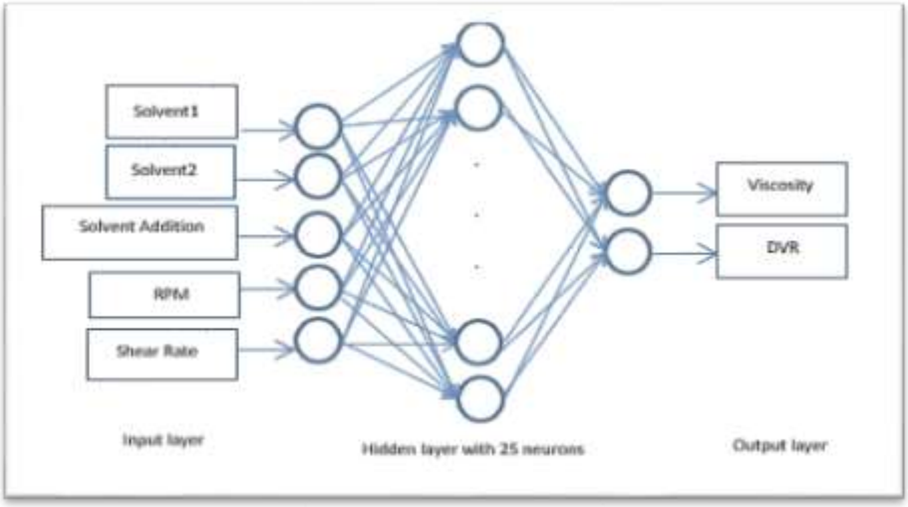

Figure 1. Selected ANN topology (5:25:2).

3. RESULTS AND DISCUSSION

3.1. Experimental Results

Reductions of heavy crude oil viscosity using different lighter hydrocarbons were considered the first and a preferred methodology**, (Martínez, et al., 2011)**. It was noted from the obtained results as shown in **Figs.2 and 3**, the little viscosity decline for pure crude oil has occurred from 135.6 to 111.5 cP during the shearing rate, whereas, the addition of different weight fractions of solvent decrease the viscosity of heavy oil, the higher reduction appeared at 20 wt. % of solvent. Moreover, the viscosity reduction with additions of the solvent mixture from toluene and n-heptane were greater than toluene and n-heptane solvent alone and the higher viscosity reduction was about from 135.6 to 26.33 cP when the mixture of toluene/heptane (75/25 vol. %) was added. These results as an aspect of the aromatic distinctive of the toluene which consents to an interfere in asphaltene aggregation attitude by aggravating asphaltene self-congregation**, (Tao, 2006)**, self-aggregation as a result of heteroatoms contained in asphaltene structures that firstly lead to colloidal aggregates then permit the growth of aggregates and subsequently increasing the viscosity of crude oil, **(Ghanavati, et al., 2013),** similar tendencies were obtained by**, (Mortazavi, 2016)**.

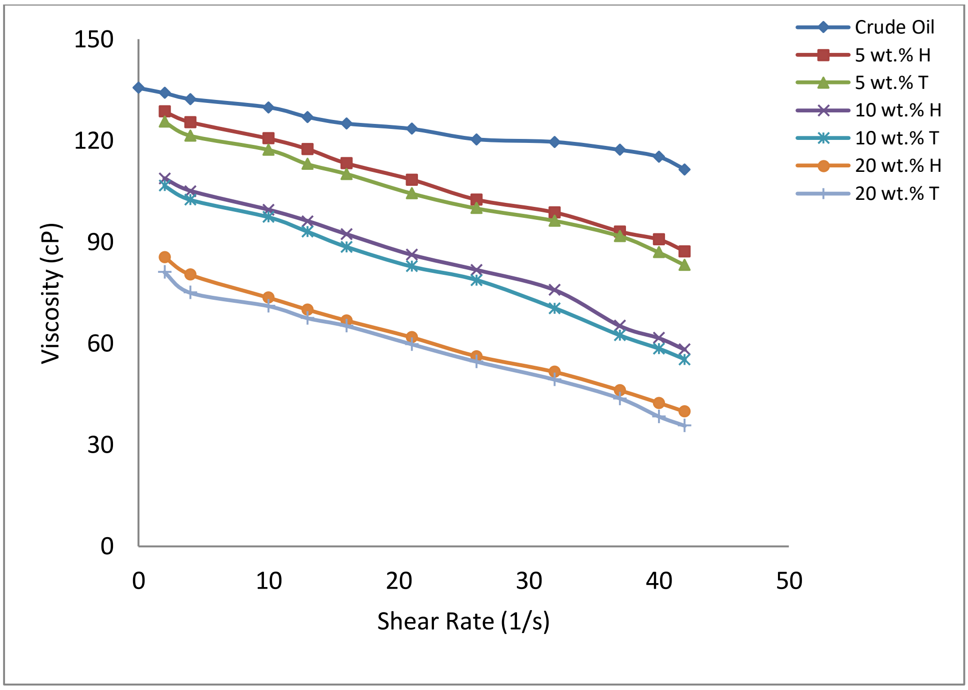

Figure2. Viscosity of heavy oil at different weight fraction of pure n-heptanes and toluene.

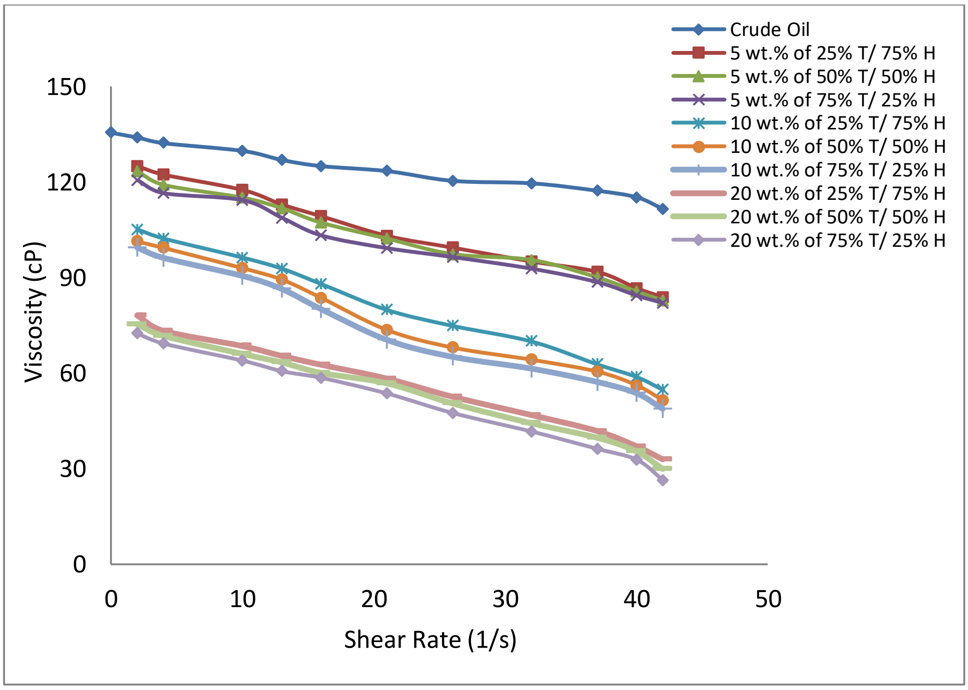

Figure 3. Viscosity reduction of heavy oil a different weight fraction of (25/75 vol. %), (50/50 vol. %) and (75/25vol. %) toluene/heptane.

The results for degree of viscosity reduction (DVR %) as a function of shear for the crude oil blended with different weight fractions of solvents were calculated by Eq. (4), **(Quan, et al., 2019),** as shown in a **Figs.4 to 8**.

$$DVR\,\% = \frac{\mu_i - \mu_f}{\mu_i} \times 100 \qquad (4)$$

μ_i and μ_f are the viscosity of crude oil before and the after dilution.

The DVR% was enhanced with increasing the solvent fractions, the results display the maximum change in viscosity were happens at 20 wt. % for all tests, as was noted the uppermost values were achieved with additions of the solvent mixture from toluene and n-heptane, moreover it increased with increasing the toluene percentage, and the higher value was about (80.58) when the mixture of toluene/heptane (75/25 vol. %) was added, these results recognized to the structure formation of crude oil within solvent under a shear rate, **(Ghannam, et al.,2012)**.

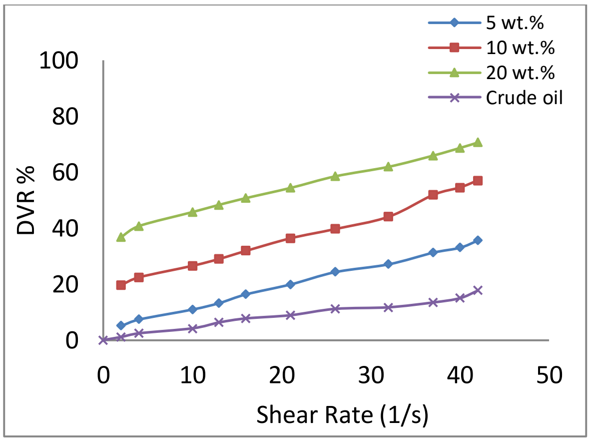

Figure 4. The degree of viscosity reduction of heavy oil at differentweight fraction of n-heptanes.

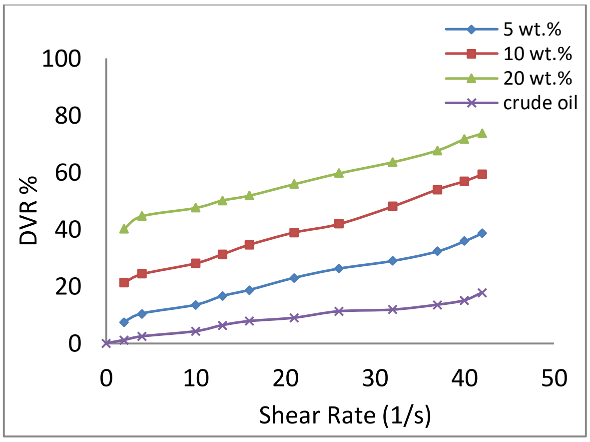

Figure 5. The degree of viscosity reduction of heavy oil at different weight fraction of pure toluene.

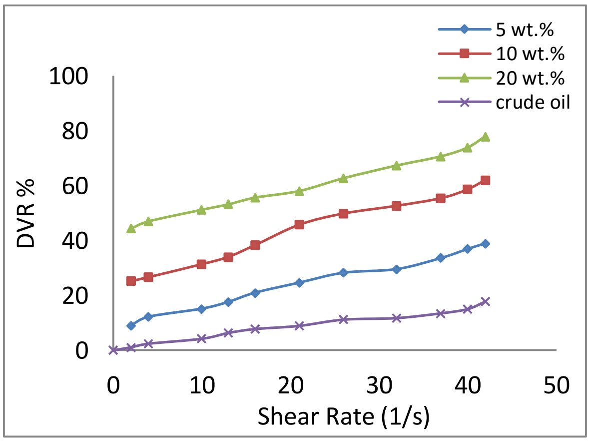

Figure 6. The degree of viscosity reduction of heavy oil at differentweight fraction of (50/50 vol. %) toluene/heptane.

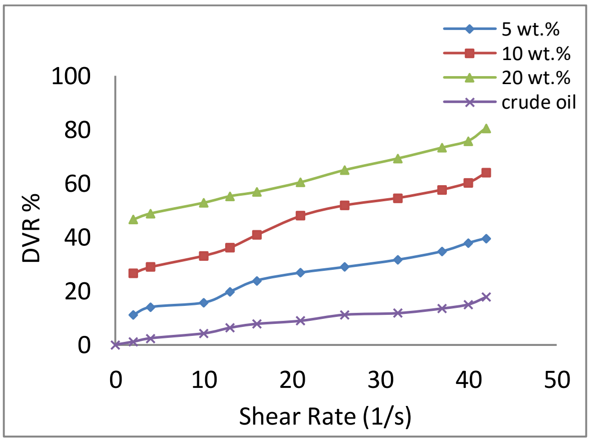

Figure 7. The degree of viscosity reduction of heavy oil at different weight fraction of (75/25vol. %) toluene/heptane.

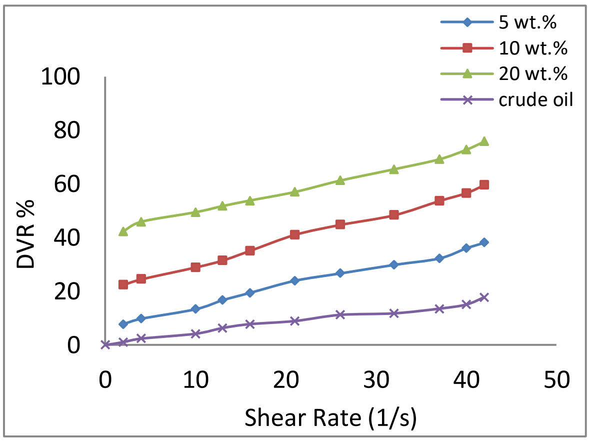

Figure 8. The degree of viscosity reduction of heavy oil at different weight fraction of (25/75 vol. %) toluene/heptane.

3.2. ANN Model Results

ANN's proposed model code was written using Matlab2018a software. The ANN topology was proposed (5: 25: 2). The input layer consists of five neurons, their names are Solvent1, Solvent2, Solvent add (wt.%), RPM, Shear Rate (1/s), 25 hidden neurons, two-output neurons are viscosity and DVR%. **Fig. 9** shows the relationship between the different layers of the developed ANN.

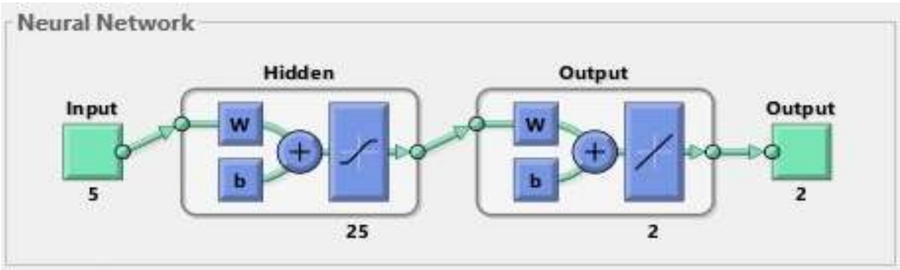

Figure 9. Design of artificial neural network.

As it was known, the ideal MSE is 0, and the R is 1. So we need to minimize the MSE and maximize R as we could, the Mean Square Error (MSE) is given in Eq. (5), while the R is calculated by Eq. (6), **(Fahriye, et al., 2017)**. These equations are used to indicate the success of the algorithms.

$$MSE = \sum_1^N \left(\frac{Q_{exp} - Q_{cal}}{n}\right)^2 \qquad (5)$$

$$R = \sqrt{\frac{1}{N}\ MSE} \qquad (6)$$

In this study, throughout the training, the best model that has MSE and coefficient of correlation equals 1.0445 and 0.99949 respectively. When it was testing, provide MSE and R about 1.6697e-1 and 0.9997 respectively.

Figs. 10 to 14 show the relevant results during the repetition for training and data testing, the solid 45 ° reveals that there is an ideal overlap between the predicted and experimental data. These results show that the suggested model is valid, because of the testing data has a value of R greater than 0.99, which is considered a good sign and correlation with the experimental data. For the ANN model, the predicate value is 98.7% and the factors of μ and DVR% are closer to unity, as a result of higher fitness and accuracy that give a good confidence between the prediction and experimental data, we can conclude that the proposed model can be applied to predict the outputs for input data that not be used in the training or testing before.

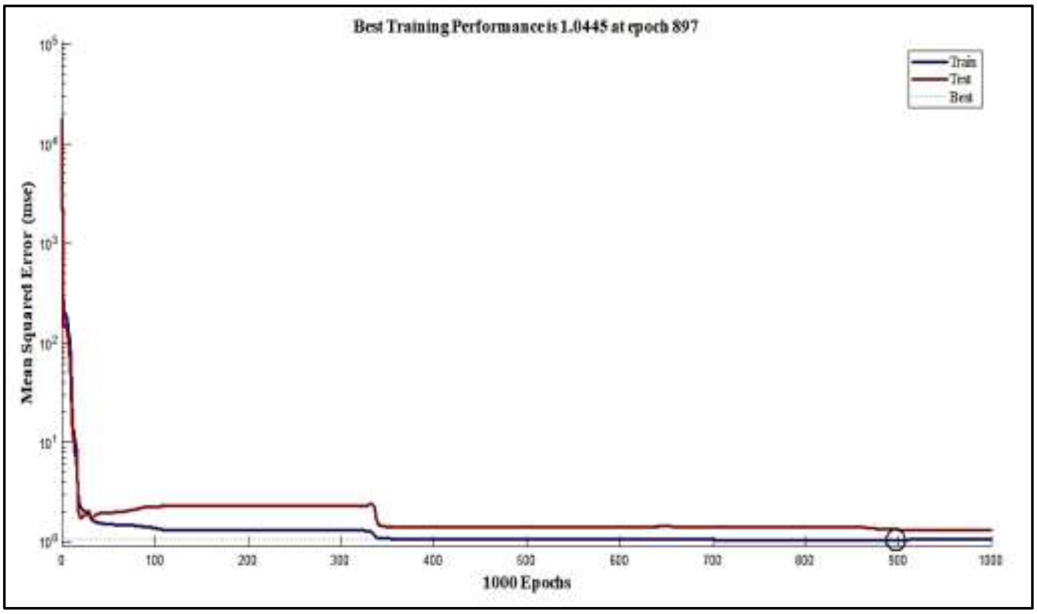

Figure 10. MSE variations for the ANN model developed.

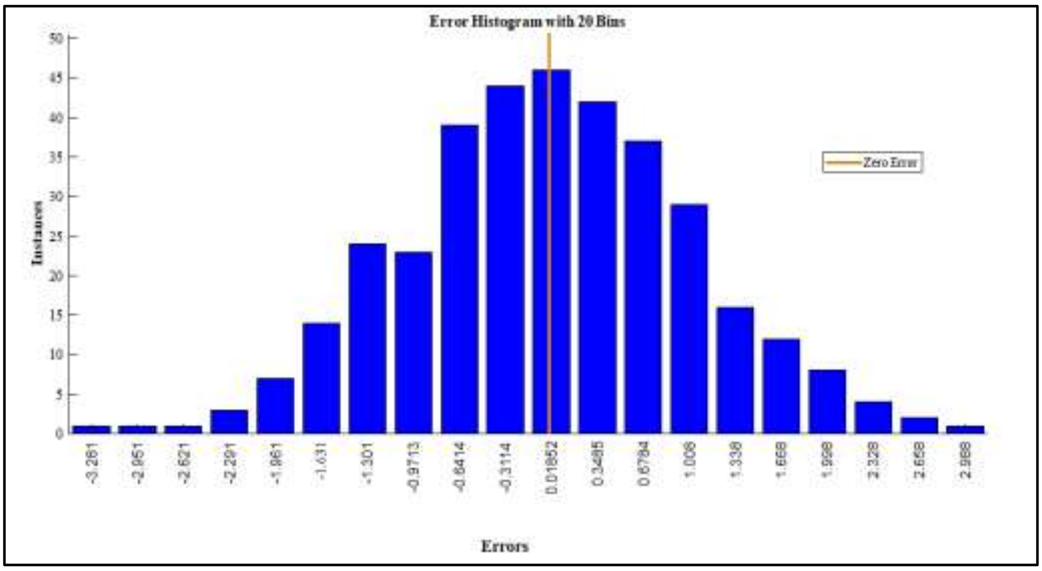

Figure11. Error histogram of the created with experimental and predicted data.

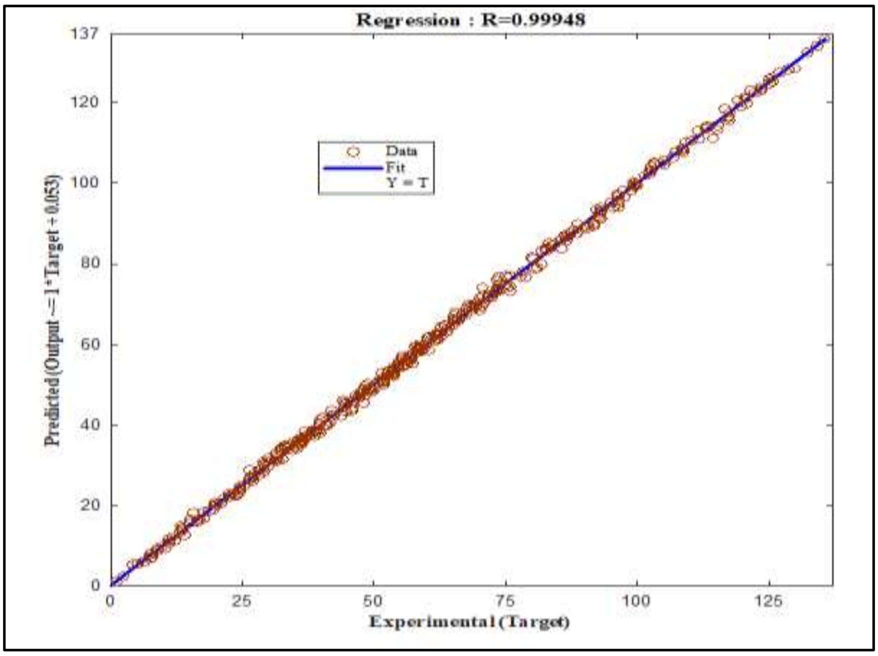

Figure12. Relationship between experimental and predicted viscosities and R values for the ANN model developed.

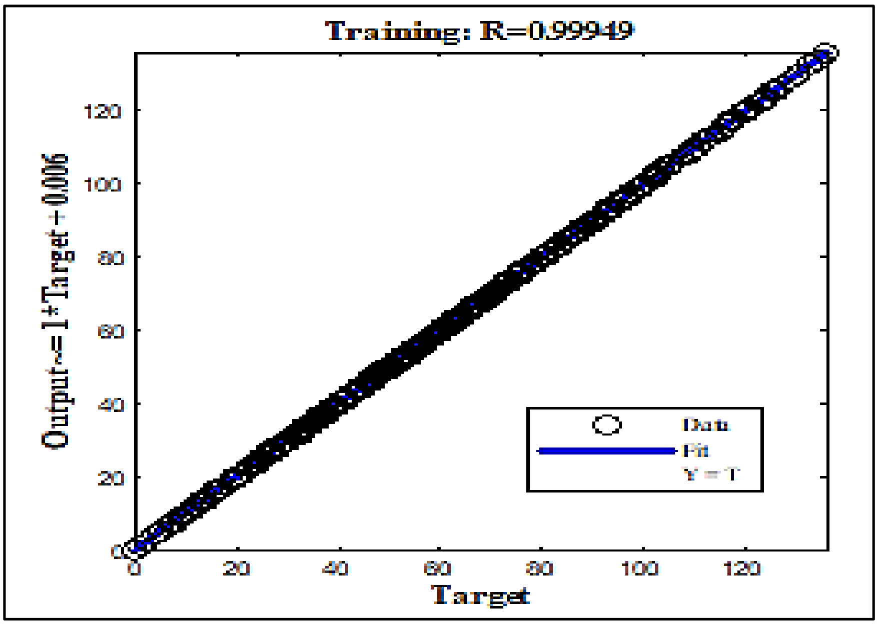

Figure 13. Relationship between experimental, predicted viscosities and R values for the training data.

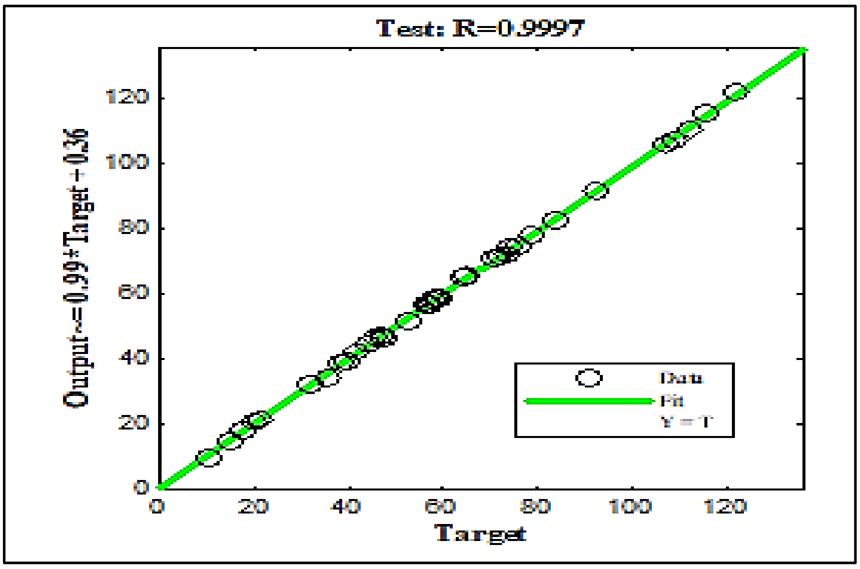

Figure14. Relationship between experimental, predicted viscosities and R values for the testing data.

Test data evaluation showed that the ANN model is able to correctly predict the viscosity and DVR% with accuracy equal to 98.7% that can be noted in **Table (1)** that represent examples for predicted results in a comparison with experimental data.

Table 1. Experimental output Vs Predicted output (examples).

Solvent	Solvent addition	RPM	Shear rate	Experimental output		Predicted output form ANN	
				Viscosity	DVR%	Viscosity	DVR%
Non	—	75	16	125.07	7.77	125.0638	7.7677
Toluene	5%	60	13	113.1	16.59	113.1827	16.5300
n-Heptane	5%	60	13	117.54	13.32	117.8003	13.1283
25% T / 75% H	20%	100	21	38.325	56.99	58.1416	57.1246
50% T / 50% H	5%	200	42	82.76	38.97	82.6513	39.0475
75% T / 25% H	10%	200	42	48.85	63.97	49.3203	63.6227

4. CONCLUSION

The obtained results have shown that the proposed (BFF-ANN) model has a superior performance, where the value of R was greater than 0.99 which confirms a good agreement between the correlation and experimental data. The higher accurate for reduced viscosity and DVR was about 98.7% and the factor for μ (cp) and DVR% were closer to unity.

NOMENCLATURE

b = biases for back propagation algorithm, dimensionless.
DVR% = degree of viscosity reduction
f = after, dimensionless.
i = before, dimensionless.
MSE = meansquare error.
n = observation number, dimensionless.
$Q_{exp.}$ = value of measurement,
$Q_{cal.}$ = calculated value
T = temperature, K.
T25% / H75% = (25% / 75 %) of Toluene/ n-Heptane, v/v%.
T50% / H50% = (50% / 50 %) of Toluene/ n-Heptane, v/v%.
T75% / H25% = (75% / 25%) of Toluene/ n-Heptane, v/v%.
w = weights for back propagation algorithm, dimensionless.
wt.% = weight Percentage
μ = viscosityof heavy oil, cP.

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Appendix (A). The sets of input parameters and experimental results

Solvent	Solvent addition (wt.%)	RPM	Shear Rate (1/s)	μ (cp)	DVR%	Solvent addition (wt.%)	RPM	Shear Rate (1/s)	μ (cp)	DVR%	Solvent addition (wt.%)	RPM	Shear Rate (1/s)	μ (cp)	DVR%
		0	0	135.6	0.00										
		10	2	134.1	1.11										
		20	4	132.32	2.42										
		50	10	129.89	4.21										
		60	13	127.01	6.33										
Non	0	75	16	125.07	7.77										
		100	21	123.5	8.92										
		125	26	120.42	11.19										
		150	32	119.64	11.77										
		175	37	117.29	13.50										
		190	40	115.22	15.03										
		200	42	111.53	17.75										
		10	2	125.6	7.37		10	2	106.7	21.31		10	2	81.11	40.18
		20	4	121.5	10.40		20	4	102.55	24.37		20	4	75.01	44.68
		50	10	117.34	13.47		50	10	97.42	28.16		50	10	71.08	47.58
		60	13	113.1	16.59		60	13	93.11	31.33		60	13	67.51	50.21
		75	16	110.21	18.72		75	16	88.6	34.66		75	16	65.22	51.90
Toluene	5 wt.%	100	21	104.43	22.99	10 wt.%	100	21	82.77	38.96	20 wt.%	100	21	59.8	55.90
		125	26	100	26.25		125	26	78.76	41.92		125	26	54.62	59.72
		150	32	96.33	28.96		150	32	70.42	48.07		150	32	49.32	63.63
		175	37	91.81	32.29		175	37	62.37	54.00		175	37	43.76	67.73
		190	40	86.98	35.86		190	40	58.41	56.92		190	40	38.41	71.67
		200	42	83.21	38.64		200	42	55.24	59.26		200	42	35.66	73.70
		10	2	128.6	5.16		10	2	108.81	19.76		10	2	85.6	36.87
		20	4	125.5	7.45		20	4	105.11	22.49		20	4	80.32	40.77
		50	10	120.66	11.02		50	10	99.54	26.59		50	10	73.54	45.77
		60	13	117.54	13.32		60	13	96.21	29.05		60	13	70	48.38
		75	16	113.32	16.43		75	16	92.32	31.92		75	16	66.76	50.77
n-Heptane	5 wt.%	100	21	108.51	19.98	10 wt.%	100	21	86.22	36.42	20 wt.%	100	21	61.81	54.42
		125	26	102.56	24.37		125	26	81.76	39.71		125	26	56.2	58.55
		150	32	98.77	27.16		150	32	75.8	44.10		150	32	51.55	61.98
		175	37	93.13	31.32		175	37	65.21	51.91		175	37	46.11	66.00
		190	40	90.76	33.07		190	40	61.62	54.56		190	40	42.41	68.72
		200	42	87.3	35.62		200	42	58.2	57.08		200	42	39.79	70.66
		10	2	125.01	7.81		10	2	105.12	22.48		10	2	78.23	42.31
		20	4	122.31	9.80		20	4	102.27	24.58		20	4	73.385	45.88
		50	10	117.51	13.34		50	10	96.30	28.99		50	10	68.585	49.42
		60	13	112.92	16.73		60	13	92.82	31.55		60	13	65.465	51.72
		75	16	109.24	19.44		75	16	87.99	35.11		75	16	62.67	53.78
25%/75% Toluene/ n-Heptane	5 wt.%	100	21	103.08	23.98	10 wt.%	100	21	79.89	41.09	20 wt.%	100	21	58.325	56.99
		125	26	99.37	26.72		125	26	74.89	44.77		125	26	52.585	61.22
		150	32	95.02	29.93		150	32	70.00	48.38		150	32	46.815	65.48
		175	37	91.76	32.33		175	37	62.83	53.67		175	37	41.77	69.20
		190	40	86.61	36.13		190	40	58.87	56.59		190	40	36.945	72.75
		200	42	83.79	38.21		200	42	54.82	59.58		200	42	32.81	75.80
		10	2	123.43	8.97		10	2	101.43	25.20		10	2	75.35	44.43
		20	4	119.12	12.15		20	4	99.42	26.68		20	4	71.76	47.08
		50	10	115.11	15.11		50	10	93.05	31.38		50	10	66.09	51.26
		60	13	111.76	17.58		60	13	89.42	34.06		60	13	63.42	53.23
		75	16	107.21	20.94		75	16	83.66	38.30		75	16	60.12	55.66
50%/50% Toluene/ n-Heptane	5 wt.%	100	21	102.22	24.62	10 wt.%	100	21	73.55	45.76	20 wt.%	100	21	56.85	58.08
		125	26	97.32	28.23		125	26	68.02	49.84		125	26	50.55	62.72
		150	32	95.51	29.56		150	32	64.19	52.66		150	32	44.31	67.32
		175	37	90.01	33.62		175	37	60.45	55.42		175	37	39.78	70.66
		190	40	85.55	36.91		190	40	56.11	58.62		190	40	35.48	73.83
		200	42	82.76	38.97		200	42	51.43	62.07		200	42	29.96	77.91
		10	2	120.6	11.06		10	2	99.53	26.60		10	2	72.44	46.58
		20	4	116.52	14.07		20	4	96.32	28.97		20	4	69.32	48.88
		50	10	114.32	15.69		50	10	90.65	33.15		50	10	63.95	52.84
		60	13	108.76	19.79		60	13	86.54	36.18		60	13	60.62	55.29
		75	16	103.21	23.89		75	16	80.21	40.85		75	16	58.53	56.84
75%/25% Toluene/ n-Heptane	5 wt.%	100	21	99.22	26.83	10 wt.%	100	21	70.55	47.97	20 wt.%	100	21	53.61	60.46
		125	26	96.41	28.90		125	26	65.21	51.91		125	26	47.47	64.99
		150	32	92.76	31.59		150	32	61.51	54.64		150	32	41.64	69.29
		175	37	88.54	34.71		175	37	57.32	57.73		175	37	36.2	73.30
		190	40	84.31	37.82		190	40	53.76	60.35		190	40	32.76	75.84
		200	42	81.96	39.56		200	42	48.85	63.97		200	42	26.33	80.58