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Predicting the Onset of Asphaltene Precipitation in Heavy Crude Oil Using Artificial Neural Network

Olugbenga Falode * and Sunday Oghenerume
Department of Petroleum Engineering, University of Ibadan, Nigeria
* E-mail of the corresponding author: falodelias@yahoo.com

Abstract

In flow assurance issues, asphaltene precipitation in crude oil tends to block the wellbore, the production tubing, the flowlines and as well as surface facilities, thereby reducing the quantity of crude oil that could be recovered during recovery, hence there is need to predict the onset conditions under which asphaltene would precipitate. Previous models (thermodynamic/colloidal) attempt to predict the onset of asphaltene precipitation using the solubility parameter, crude oil/n-alkane mixture and the refractive index of asphaltene. However, due to the constraint in handling numerous and complex data set, this work attempts to predict the onset of asphaltene precipitation (onset solvent to bitumen/asphaltene ratio as a function of temperature and pressure) using artificial neural network (**Neurosolution 6**).

The results obtained show that the onset solvent bitumen ratio obtained using the neural network was close to the experimental (desired) onset solvent bitumen ratio (MSE of **0**, Err% **0.0553** for the training set and MSE of **0.006581**, Err% of **3.343** for the testing set) with an average absolute deviation of **3.56**.

Artificial neural network is a robust predictive tool for predicting the onset of asphaltene precipitation in heavy crude oil.

Keywords: Asphaltene, Precipitation, Structure of asphaltene, Neural Network, Onset and amount

1. Introduction

Crude oils have complex composition; hence characterization by the individual molecular types is not possible. Instead, hydrocarbon group type analysis is commonly employed. In the oil field, asphaltenes are best known for clogging wells, flowlines, surface facilities and subsurface formations. Asphaltenes are high-molecular weights solids which are soluble in aromatic solvents such as benzene and toluene and insoluble in paraffinic solvents. Its precipitation is one of the most common problems in both oil recovery and refinery process. Asphaltene precipitation depends on the composition of the solvent, temperature and pressure. In oil recovery, especially in gas injection, formation of asphaltene aggregation following their deposition causes blocking in the reservoir. This makes the remedial process costly and sometimes uneconomical. Unfortunately, there is no predictive model for asphaltene problem treatment. Hence it is necessary to predict the amount of asphaltene precipitation as pre-emptive measure. The major questions in facing such problems are "how" and "how much" heavy organic compounds will precipitate in operational conditions. Over the years, many researchers have tried to find the answer. They introduced experimental procedures or even analytical models, but a fully satisfactory interpretation is still lacking. The problem is very difficult mainly because of the fuzzy nature of asphaltene and the large number of parameters affecting precipitation.

Predicting the onset condition of asphaltene precipitation helps in decision making pertaining to purchasing of chemicals to combat the problem of asphaltene precipitation.

The existing models used in asphaltene precipitation fall into three categories: firstly, Molecular thermodynamic models in which asphaltenes are dissolved in crude oil and crude oil forms a real solution. The validity of such models depends on the reversibility of asphaltene precipitation. Reversibility experiments strongly support this type of models. Secondly, colloidal models in which, asphaltene is suspended in crude oil and peptized by resins. The asphaltene precipitation is irreversible in such models. Reversibility experiments are strongly against this type of models. Thirdly, Models based on scaling equation, in which the properties of complex asphaltenes are not involved.

However, artificial neural network, an information processing paradigm that is inspired by the way the biological nervous system such as the brain process information can be used to predict the solvent bitumen ratio as a function of temperature and pressure.

The objective of this study is to predict the onset of asphaltene precipitation (onset solvent to bitumen (asphaltene) ratio) using artificial neural network.

1.1 Flow Assurance Issues with Asphaltene Precipitation

Flow assurance issues such as asphaltene deposition are one of the important areas being studied today due to the high cost of deep-water E&P (Exploration and Production). Thus, effective measurements to understand asphaltene phase behavior in the reservoir fluid are required. The flow assurance issues in deep-water are primarily due to the deposition of solids in the production path. The tentative areas of solids deposition, amongst others can be as follows (Figure1.0): near wellbore region, production, subsea wellhead, subsea flowlines and separators. The combination of an integrated production model (IPM) with asphaltene and wax thermodynamic models (Gonzalez et al, 2007) improves means to estimate solid formation due to variations in pressure, temperature and composition during the life of the project.

1.2 Asphaltene Precipitation Onsets and Amount

At atmospheric conditions, the most common method to determine the precipitation onset is the titration of oil against the precipitating solvents (Andersen, 1999). Microscopic examination of an oil-solvent mixture is also adapted by some authors (Buckley, 1996). The most common methods for oils under high pressure and temperature are light scattering technique with a near-infrared light source and high pressure microscope (HPM) systems (Hammami and Ratulowski, 2007). HPM allows direct visual observation of multiple phases present at elevated pressure and temperature. Overall, optical methods are usually limited to light oils with low asphaltene content because of the limitation on the opacity of oils. Other methods with physical property measurements are used when the low light transmittance is encountered.

Amount of precipitation is usually measured using filtration (Leontaritis et al., 1994) and centrifugation (Akbarazadeh et al., 2005; Tharanivasan et al., 2009) techniques for oils at atmospheric conditions. In these techniques, the oil is mixed with an appropriate solvent and filtered or centrifuged. However, various filtration techniques are adapted for oils at elevated pressures and temperatures to measure the precipitation amounts (Peramanu et al., 1999; Edmonds et al., 1999; Fahim et al., 2004; Negahban et al., 2005). HPM system (Figure2.6) coupled with post-filtration technique is adapted widely for such amount measurements (Hammami and Ratulowski, 2007). Jamaluddin et al (2002) predicted the onset of asphaltene precipitation using gravimetric technique.

2.0 Methodology

2.1 Description of The Neural Model

The Artificial neural network (Neurosolution 6) consists of different networks such as the multilayer perceptron, generalized feed forward, modular neural network, Jordan/Elman network, Principal component analysis (PCA), recurrent network, the Time-lag recurrent network etc. The Multilayer perceptron and the generalized feedforward model are used in predicting the onset solvent-bitumen (asphaltene) ratio. The amount of asphaltene precipitate in heavy crude oil is a function of several parameters such as temperature, the pressure, the API gravity, the PH value of the crude oil solvent mixture, the viscosity of the crude oil and the amount of aromatic compounds present in the formation.

Knowledge of the onset solvent ratio at which precipitation of asphaltene will occur is crucial in understanding the fluid property and in remedial work carried out to ensure there is improved oil recovery from the subsurface to the surface facilities.

The onset solvent to bitumen ratio is taken as a function of the temperature and the pressure in the reservoir.

Mathematically;

$$\text{Onset Solvent/Bitumen} = F(T, P) \qquad 3.1$$

Where T is the temperature in Kelvin, P is the pressure in Bar and S/B is the ratio between the solvent and the bitumen.

2.2 BACK PROPAGATION CONCEPT

In order to train a neural network to perform some task, we must adjust the weights of each unit such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other words, it must calculate how the error changes s each weight is increased or decreased slightly. The back propagation algorithm is the most widely used method for determining the EW. The algorithm computes each EW by first computing the EA, the rate at which the error changes as the activity level of a unit is changed. For output unit, the EA is simply the difference between the actual and the desired output. To compute the EA for a hidden unit in the layer just before the output layer, we first identify all the weights between that hidden unit and the output unit to which it is connected.

2.3 INPUTING TRAINING DATA

Parameters such as pressure, temperature and the onset solvent to bitumen ratio (onset S/B) were inputted into the network builder. The onset solvent to bitumen ratio (S/B) was taken as the output parameter while the pressure (Bar) and the temperature (K) were taken as input parameters. The mixture number was skipped because they are not affecting the output (24 data was used for training) (Table1).

Table 1: Input Data Set Used for Training Network (Masoudi Rahim, 2007)

PRESS(BAR)	TEM(K)	ONSETS/B
177	465	0.10
186	455	0.20
194	445	0.30
202	435	0.40
211	425	0.50
219	415	0.60
227	405	0.70
236	395	0.80
244	385	0.90
252	375	1.00
261	365	1.10
269	355	1.20
277	345	1.30
286	335	1.40
294	325	1.50
302	315	1.60
311	305	1.70
319	295	1.80
327	285	1.90
336	275	2.00
344	265	2.10
352	255	2.20
361	245	2.30
369	235	2.40

2.4 CROSS VALIDATION AND TESTING OF IMPUTED DATA

After the data were imputed, the test data sets were specified (Table 2). Cross validation is highly recommended method for stopping network training. The percentage of training data for CV and the percentage of training data for testing was read from existing files (in tab delimit format). This method monitors the error on an independent set of data and stops training when this error begins to increase (point of best generalization). Eleven (11) data was used to test the network.

Table 2: Data Used for Testing (Masoudi Rahim, 2007)

PRESS(BAR)	TEM(K)	ONSETS/B
377	225	2.50
386	215	2.60
394	205	2.70
402	195	2.80
411	185	2.90
419	175	3.00
427	165	3.10
436	155	3.20
444	145	3.30
452	135	3.40
461	125	3.50

2.5 HIDDEN LAYER

A LinearAxon transfer file and a Levenberg Marqua function as learning rule were used in each of the neural models selected with the number of processing elements specified. The number of PEs for the output layer was determined by the number of columns selected as the desired response (in this case one).

2.6 OUTPUT LAYER

A LinearAxon transfer and the Levenberg Marqua function as the learning rule with one (1) processing element. The parameters selected in this layer are dependent on the neural model, but all require a nonlinearity function to specify the behaviour of the PEs. The number of PEs is determined by the number of columns selected as desired response.

2.7 SUPERVISED LEARING CONTROL

In this control unit, the number of iterations was varied from five (5) to fifteen (15) epochs in the multilayer perceptron model and five (5) epoch in the generalized feedforward model.

2.8 PROBE CONFIGURATION

The input was configured in a bar-chart format while the desired and the output were configured in a data-writer format. General performance measures such as the mean square error (MSE), correlation factor (r), and the percentage error (%err) were used to check the performance after building the network.

2.9 TESTING

The next thing was to test the network by imputing the test data (table 2) from the existing testing file. The result was shown as the output in contrast with the desired fed into the network.

3.0 Result and Discussion

The best neural network model used in predicting the onset solvent bitumen ratio in this work is the multilayer perceptron model using linear Axon transfer function after five (5) iterations i.e epoch = 5. The multilayer perceptron models using linear Axon as transfer function were chosen by means of the mean square error (MSE), the coefficient of variation (r) and the percentage error (err%).

3.1 PERFORMANCE ANALYSIS

From the performance analysis (table 3), using five epochs with the multilayer perceptron network, the mean square error for the training data set is approximately zero, the percentage error is **0.0553** (though larger than values of higher number of runs) and the mean square error for the data used to test the model is **0.006581**, and the percentage error is **3.343** (comparing the errors of both the training and testing file, the values of the first run were relatively better and close to the desired values needed to be predicted with the artificial neural network (Neurosolution 6); invariably, this result was also better than results using the generalized feedforward network (Table 5) (which produced a mean square error of **1.308**, **0.978** for training and testing respectively and percentage error of **264.03**, **40.227** respectively). Similarly, trials of other network produced greater erroneous results, so only the multilayer perceptron network accurately yielded closed results.

Table 3 : Performance Measure of the MLP

		TRAINING		
Epoch5	Run#1	Run#2	Run#3	Run#4
MSE	**0**	0	0	0
R	**1**	1	1	1
%Err	**0.0553**	0.000297	0.0000636	0.01915
		TESTING		
MSE	**0.006581**	0.0067	0.00669	0.006641
r	**1**	1	1	1
%Err	**3.343**	3.371	3.371	3.358
Epoch10		**TRAINING**		
MSE	0	0.00092	0	
r	1	1	1	
%Err	0	4.456	0	
		TESTING		
MSE	0.006694	0.1727	0.0067	
r	1	0.999	1	
%Err	337,112	17.0799	3.37112	

Table 4 Performance Measure of the GFFN

GENERALIZED NETWORK	FEEDFORWARD	
	Training	Testing
Epoch5		
MSE	1.308	0.978
R	-0.993	0.953
%Err	264.03	40.227

3.2 PREDICTED RESULTS USING THE NETWWORK

Results obtained using Neurosolution to predict the onset solvent bitumen ratio (Table 5) have an average Absolute Deviation of **3.56**.

Table 5: Absolute Deviation of the ANN values from the Desired Results

EXPERIMENTAL	ANN OUTPUT	DEV	ABS DE	AD%
2.50	2.5990	0.0990	0.0396	3.96
2.60	2.6998	0.0998	0.0384	3.84
2.70	2.7993	0.0993	0.0368	3.68
2.80	2.8988	0.0988	0.0353	3.53
2.90	2.9996	0.0996	0.0343	3.43
3.00	3.0992	0.0992	0.0331	3.31
3.10	3.1987	0.0987	0.0318	3.18
3.20	3.2995	0.0995	0.0311	3.11
3.30	3.3990	0.0990	0.0300	3.00
3.40	3.4985	0.0985	0.0290	2.90
3.50	3.5993	0.0993	0.0284	2.84

3.3 DISPLAY OF THE ANN OUTPUT AND THE TEMPERATURE

Figures 1 and Figure 5 show the distribution of the experimental (desired) onset solvent bitumen ratio (predicted by the Neuro-solution) as a function of the temperature (K) with the equation of best fit. As the temperature of the solvent bitumen mixture increases, the onset solvent bitumen ratio decreases correspondingly indicating an inverse relationship between the temperature and the onset solvent bitumen ratio.

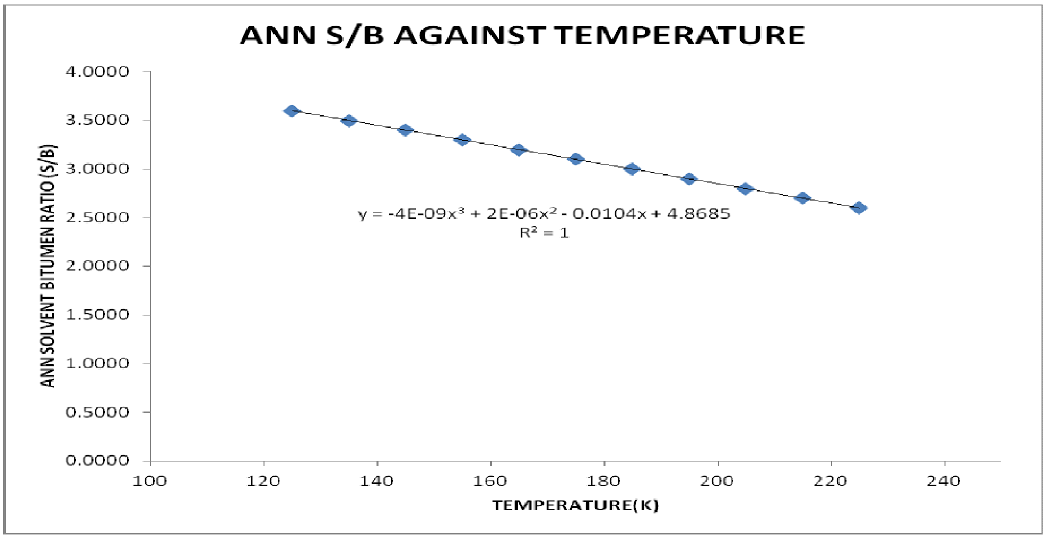

Figure 1: ANN Solvent/Bitumen (S/B) against Temperature (K)

3.4 DISPLAY OF ANN OUTPUT AND THE PRESSURE (BAR)

Figures 2 and Figure 4 show the relationship between the onset solvent bitumen ratio (predicted by the Neurosolution) and the corresponding pressure of the resulting mixture. The onset solvent bitumen ratio increases as the pressure increase. That is the onset solvent bitumen ratio is directly proportional to the pressure in which the mixture is subjected to. At constant temperature, the liquid density increases as pressure increases. Thus, an increase in pressure raises asphaltene solubility that in turn increases the onset dilution ratio.

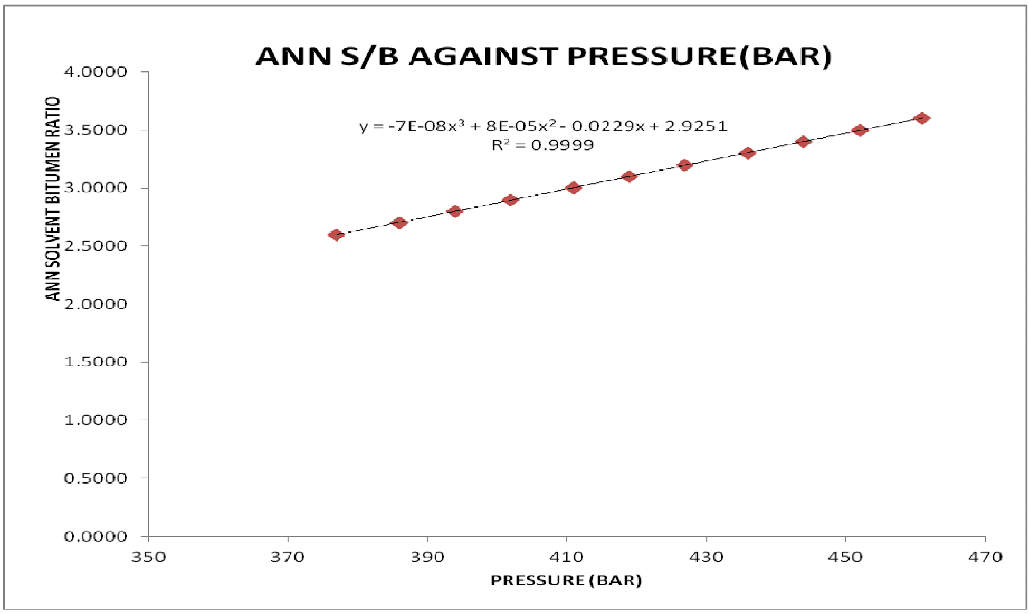

Figure.2: Ann Solvent/Bitumen(S/B) against Pressure (bar)

3.5 COLLAPSE OF THE DESIRED OUTPUT AGAINST THE ANN RESULT

The plot (Figure 3) of the results obtained using the Neurosolution against the desired output of onset solvent bitumen ratio shows a linear relationship and a perfect regression profile with the coefficient of regression as one.

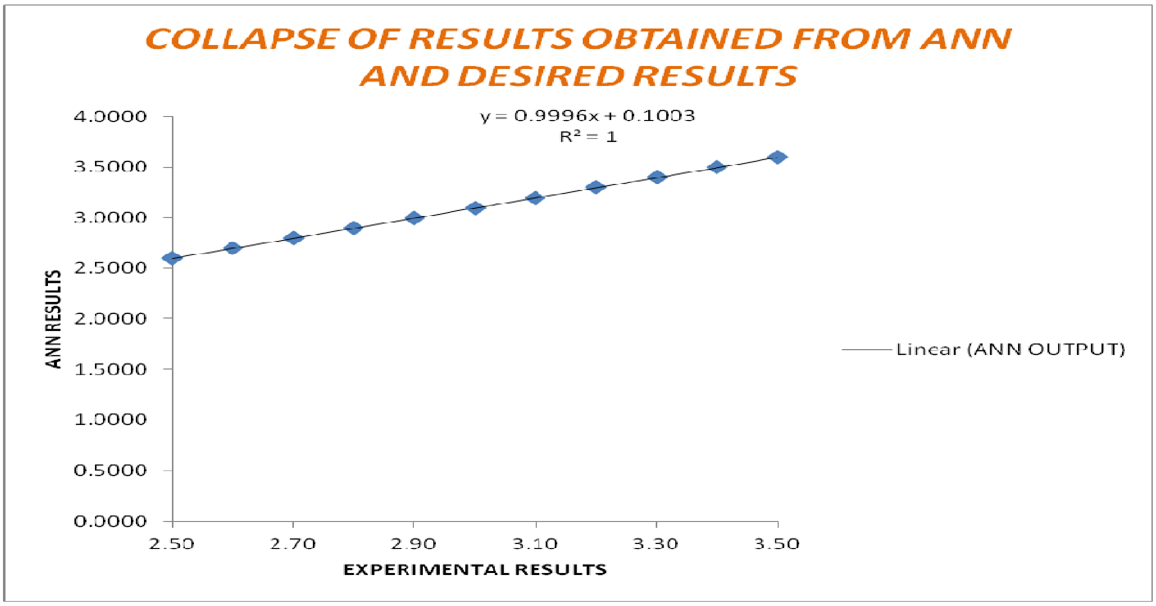

Figure.3: ANN Result versus Experimental Result

3.6 COMPARING RESULTS FROM ANN AND EXPERIMENT (DESIRED) RESULTS

The onset solvent bitumen ratio shows an inverse relationship with the temperature and a direct relationship with the pressure of the mixture (Figure 4 and Figure 5). The values obtained using artificial neural network was slightly lower than the desired values of onset solvent bitumen ratio. However, results obtained from the network gave a good match for the needed results, and as such, the network can be used to predict onset solvent bitumen ratio given the temperature and the corresponding pressure.

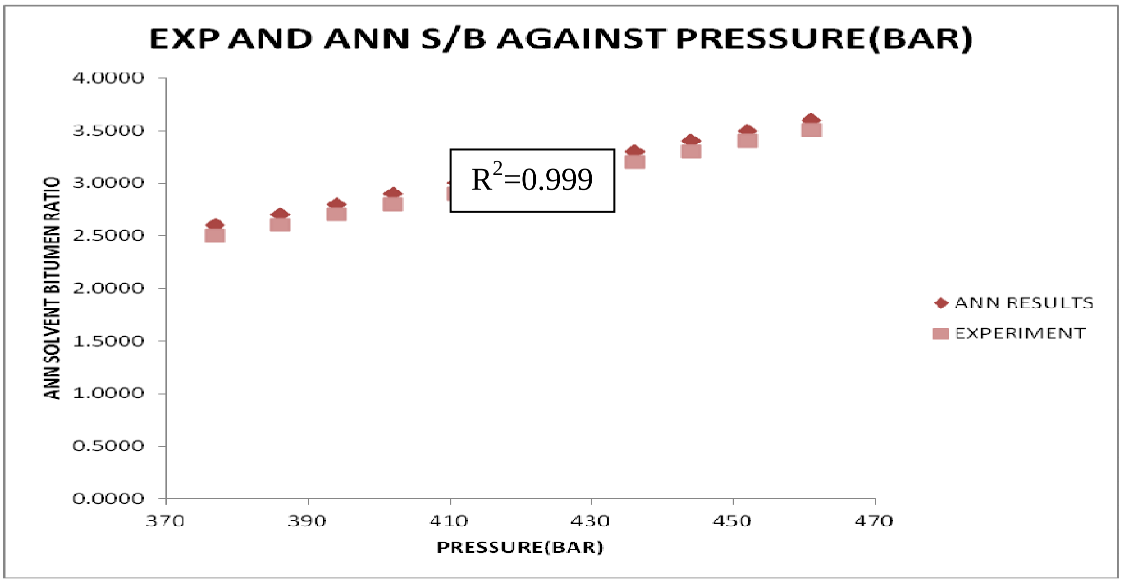

Figure 4: ANN and Experimental Results Versus Pressure

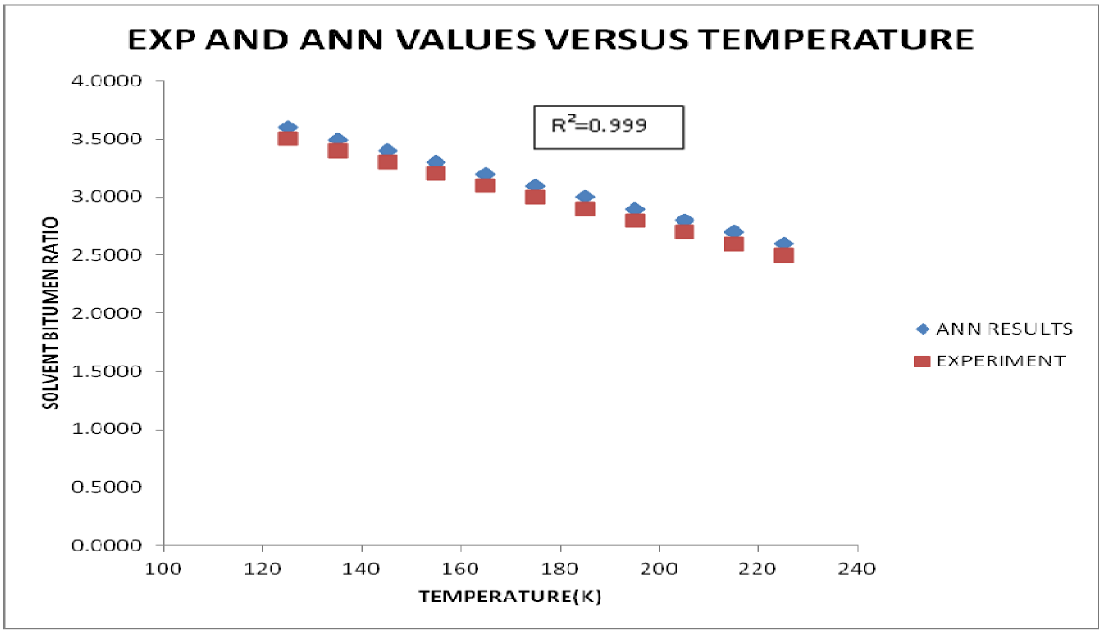

Figure.5: Comparing of Ann and Experimental Results (desired result) Versus Temperature

4.0 CONCLUSION

The onset solvent to bitumen ratio was accurately predicted in this work using the multilayer perceptron model, the LinerAxon as a transfer file and the Levenbarg marqua as transfer function with an average absolute deviation of **3.56**. Results obtained with ANN were compared with desired results from literature only, because the models used the onset solvent to bitumen (asphaltene) ratio as a function of temperature and pressure. At constant temperature and solvent to bitumen ratios, increasing pressure increases asphaltene solubility which in turn raises onset dilution ratio. Thus, the model predicts the pressure effect correctly but qualitatively.

Asphaltene precipitate can be removed using aromatic solvents but the best practice is to prevent from precipitating. As Asphaltene precipitation is predominantly due to fall in pressure, enhance oil recovery should be encouraged to increase the pressure beyond that which asphaltene will form precipitate and cause blockage in the tubing and surface facilities.

5.0 RECOMMENDATION

The following recommendation stem from the result of the study and the observations made during the study:

1. The complex relationship studied by the artificial neural network between input and output (desired) should be developed into a mathematical equation to allow subsequent use of the network whenever needed.
2. Asphaltene precipitation problem can best be solved by using suitable solvents like toluene to prevent asphaltene from forming precipitate which is a threat to oil recovery.

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