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Evaluation of Below Bubble Point Viscosity Correlations & Construction of a New Neural Network Model

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Abstract

This paper, precisely, evaluates two famous below bubble point viscosity correlations and tries to create a new Neural Network model for estimating this property. The new created model outperforms the two investigated correlations namely Khan Model (1987) and Labedi Model (1992). The new technique (Artificial neural network) found to be successful in developing a model for predicting viscosity below bubble point with an outstanding correlation coefficient of 99.3%. A limited number of data points have been collected from Pakistani fields in order to construct, test, and validate the model. Viscosity from 99 sets of differential liberation data covering a wide range of pressure, temperature, and oil density were used to validate the correlations and to develop the new model. A series of statistical and graphical analysis were conducted also to show the superiority of the model that has been formulated through an Artificial Neural Network technique. A thorough literature review is also made to check the applicability of the existing correlations and their drawbacks.

Introduction

The main objective of this paper is to propose a simple procedure to predict black oil viscosity at the region below bubble point pressure as a function of easily determined physical properties. Based on thorough and critical literature survey of available technical and published papers, only two models that dealt with viscosity below bubble point were chosen; Khan *et al* model (1987) [(1)] and Labedi model (1992) [(2)].

Utilizing Matlab statistical toolbox, programs have been generated using regression analysis for both correlations. Neural Network toolbox was used for creation of a new successful model. Back propagation/feed forward scheme has been followed to generate a model. Statistical analysis was used to test the validity of the new model.

Viscosity is the measure of the resistance to flow exerted by a fluid; the lower the viscosity of a fluid, the more easily it flows. Like other fluid properties viscosity is mainly affected by temperature and pressure. An increase in temperature causes a decrease in viscosity. A decrease in pressure causes a decrease in viscosity, provided that the only effect of pressure is to compress the liquid. In addition, in the case of reservoir liquids, there is a third parameter which affects viscosity, which is the reduction in the amount of gas in solution in the liquid. It causes a decrease in viscosity; hence, the amount of gas in solution is a direct function of pressure.

However, as reservoir pressure reduces below the bubble point, the liquid undergoes a change in composition. The gas that evolves takes the smaller molecules from the liquid, leaving the remaining reservoir liquid with relatively more molecules with large complex shapes. This changing liquid composition causes large increase in viscosity of the oil in the reservoir as pressure decreases below the bubble point (as illustrated in Figure (1). Crude oil viscosity is needed in reservoir engineering as well as many petroleum applications such as calculation of two-phase flow, gas-liquid flowing pressure traverse, gas-lift and pipeline design, calculation of oil recovery either from natural depletion or from recovery techniques such as waterflooding and gas-injection processes. Besides, these correlations are also needed for the calculation of multiphase flowing pressure gradients in pipes at different temperature and pressures. Live oil viscosity is a strong function of pressure, temperature, oil gravity, gas gravity, gas solubility, molecular sizes, and composition of the oil mixture. The variation of viscosity with molecular structure is not well known due to the complexity of crude oil systems. It is not a quite trusted procedure to estimate viscosity depending on the crude oil composition.

When it is hardly to be measured in the laboratory, viscosity might need to be specified with high degree of accuracy in order to be involved in a series of highly sensitive calculations. The ordinary way to measure viscosity is definitely through laboratory equipment. The alternative way is through empirical correlations in case of lack of PVT information, which were found to be easily applied if they gained a wider range of confidence in industry.

This study was particularly conducted to provide a quick estimate of the viscosity below bubble point pressure that is needed in the case of lack of laboratory equipment. Artificial Neural Network technique is used in this study to successfully

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generate a model that predicts viscosity below bubble point pressure with high degree of confidence and precision.

Below Bubble Point Viscosity Correlations

Two viscosity-correlation methods have been proposed for the region below bubble point pressure. Unfortunately, both correlations failed to get wide popularity in industry. Crude oil has no definite and stable composition. For that reason, many viscosity estimation methods are geographically dependent. Correlation methods can be categorized either as a black-oil basis or as compositional basis. Black-oil type correlations predict viscosities from available field-measured variables by fitting of an empirical equation. Fortunately, both available correlations were black oil basis. The correlating variables are combination of reservoir pressure, bubble point pressure, oil API gravity, viscosity at the bubble point pressure. The formula of each correlation and the original and modified correlation parameters are provided in table (1& 2) at Appendix A.

Khan et al. Model (1987) was based on 75 bottomhole samples that have been collected from 62 Saudi Arabian fields. A total number of 1691 data points were used to develop his model for viscosity below bubble point pressure. An average absolute percent error was 5.175 while the standard deviation was 7.201 and finally, the correlation coefficient was 0.994.

Labedi Model (1992) was based on a PVT data contain about 80 oil samples data. In his study, an average absolute percent error was 3.5 while the standard deviation was 28.78. Multiple-regression also used to develop the equation.

Artificial Neural Network Model

This new computing technique can be defined as massively and highly parallel distributed information processing system that has the ability for recognizing nonlinear relationships within the available data. Neural network resembles the human brain in its function where knowledge is acquired through a learning process; and interneuron connection strengths known as synaptic weights are used to store the knowledge [3]. Feed forward/back-propagation paradigm (One of the most commonly used supervised training algorithm) has been followed to train the network. In this scheme, the Neural Network model is provided with the desired or target response vector in order to allow for mapping the relationship between available variable. It is a gradient based optimization procedure. In this scheme, the network learns a predefined set of input-output sample pairs by using a two-phase propagate-adapt cycle. The scheme starts by assuming initial random weights for each neuron. In the feed forward stage, the input values are transformed to the output values through an activation function. Output is compared with the desired output, and the error is propagated backward (back-propagation stage) through the network.

During this process, weights of the connections between neurons are adjusted. . However, each unit in the hidden layer receives only a portion of the total error signal, based roughly on the relative contribution the unit made to the original output. This process repeats layer by layer, until each node in the network has received an error signal that describes its relative contribution to the total error. Process is then continued in an iterative, parallel manner. The network converges when its output is within acceptable proximity of the desired output. After the weights are adjusted perfectly for training, they will be fixed for testing and feed forward scheme will be followed. Many complex petroleum engineering problems have been solved successfully through this technique. Numerous authors discussed the applications of neural network in petroleum engineering [4-10]. None of them has tried to model the relationship between viscosity below bubble point pressure and the properties involved in.

The developed model used two hidden layers neural network to model this property. Figure (2) shows that the viscosity below bubble point pressure model had eight neurons in the first layer and another eight neurons in the second. A total number of 99 data sets from the Pakistani fields were collected for this purpose. Almost, half of this data set was used to train the model. One quarter was used to cross validate it and another one quarter for testing the performance of the network. The data ranges for each set are presented in table (1) at Appendix A. The data used for testing the model have never seen by the network. The results showed significant improvement over the conventional correlation methods with reduction in the average absolute error for the viscosity below bubble point pressure.

Error Analysis

Error analysis was performed to check for studied correlations plus the new developed model in order to evaluate the suitability, accuracy and for comparison studies. Both graphical and statistical error analysis were utilized simultaneously.

Statistical Error Analysis. This error analysis is utilized to check mathematically for how far and good models are. The statistical parameters used for comparison are: average percent relative error, average absolute percent relative error, minimum and maximum absolute percent error, root mean square error, standard deviation of error, and the correlation coefficient. Equations for those parameters are given below.

1. Average Percent Relative Error (APE). It measures of relative deviation from the experimental data, defined by:

$$E_r = \frac{1}{n}\sum_{i=1}^{N}\left|E_i\right|$$

Where E_i is the relative deviation of an estimated value from an experimental value

$$E_i = \left[\frac{(\mu)_{\exp} - (\mu)_{est}}{(\mu)_{\exp}}\right]\times 100, \quad \mathrm{i} = 1,2,3,...,\mathrm{n}$$

2. Average Absolute Percent Relative Error (AAPE). It measures the relative absolute deviation from the experimental values, defined by:

$$E_a = \frac{1}{n}\sum_{i=1}^{n}|E_i|$$

(This will be considered as the main criterion in statistical error analysis throughout this study).

3. Minimum Absolute Percent Relative Error.

$$E_{\min} = \min_{i+1}^{n}|E_i|$$

4. Maximum Absolute Percent Relative Error.

$$E_{\max} = \max_{i+1}^{n}|E_i|$$

5. Root Mean Square Error. It measures the data dispersion around zero deviation, defined by:

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n}E_i^{\ 2}\right]^{0.5}$$

6. Standard Deviation. It is a measure of dispersion and is expressed as:

$$S = \sqrt{\left[\left(1\Big/(m-n-1)\right)\right]\sum_{i=1}^{m}\left[\left\{\left(\mu_{\exp}-\mu_{est}\right)\Big/\mu_{\exp}\right\}100\right]^2}$$

Where (m-n-1) are the degrees of freedom in multiple-regression. A lower value of standard deviation indicates a smaller degree of scatter.

7. The Correlation Coefficient. It represents the degree of success in reducing the standard deviation by regression analysis, defined by:

$$R = \sqrt{1-\sum_{I=1}^{n}\left[(\mu)_{\exp}-(\mu)_{est}\right]^{n}{}_{i}\Big/\sum_{I=1}^{n}(\mu)_{\exp}-\overline{\Delta\mu}}$$

Where

$$\overline{\Delta\mu} = \sum_{I=1}^{n}\left[(\Delta\mu)_{\exp}\right]_i$$

'R' values range between 0 & 1. The closer value to 1 represents perfect correlation whereas 0 indicates no correlation at all among the independent variables.

Graphical Error Analysis. Graphical tools aids visualizing the performance and accuracy of a correlation. Two graphical analysis techniques are employed; those are crossplots and error distribution that presented as follows:

Error Distributions. Figures (5-9) show the error distribution around the zero line to assure that the models have an error trend or not. Fortunately, none of them show this phenomenon. Figures (5-7) show the error distribution for the new model (this study) separately (for training, validation, and testing sets). A range of -0.02 to 0.021 is achieved for validation set. Whereas a range of -0.032 to 0.018 is found out by testing set. These two ranges are shown to be minimal compared to the ones that found for both investigated Khan et al and Labedi correlations (from -0.07 to 0.15 & from -0.38 to 0.58), respectively. The relative frequency of deviations between estimated and actual values are depicted in figures 10 through 14 for training, validation, testing sets (this study), and for both Khan et al and Labedi models. Normal distribution curves are fitted to each one of them. An error range of -4% to 6% for viscosity below bubble point (testing set) while a range of -5% to 14% & -5% to 15% is used for Khan et al and Labedi models, respectively. All models show, fairly, normal error distribution with mean equal to zero. Comparisons between average absolute percent error and the correlation coefficients are provided in figures 20 & 21.

Crossplots. In this technique, all estimated values are plotted against the observed values and thus a crossplot is formed. A 45° straight line between the estimated versus actual data points is drawn on the crossplot which indicates the perfect correlation line. The closer the plotted data points to this line, the better the correlation.

Figures 15 through 19 present crossplot for oil viscosity below the bubble point. The new model gives very close values to the perfect correlation line in all data points.

Statistical comparison between the three models is presented in table (4), Appendix A.

Conclusion

This study leads to the following conclusions

- Artificial neural network was found to be successful in developing a model for predicting viscosity below bubble point with an outstanding correlation coefficient reaches 99.3%.

- The new model outperforms Khan et al and Labedi Models for predicting viscosity below bubble point.

- The few number of data points that were used may weaken the new model. More data points with wider range of variable are needed to verify this study.

- The original correlation coefficients of both correlations are shown to be less in this study because of the limited number of data and low range of variable used.

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Nomenclature

API = Oil gravity, ^{o}API
P = Pressure
P_b = Bubble point pressure, psia
Rs = Solution gas oil ratio, Scf/Stb
T = Temperature, ^{0}F
γ_g = Gas relative density at 14.7 psia & 60 ^{0}F
μ_{ob} = Oil viscosity at bubble point, cp
μ_b = Oil viscosity below bubble point, cp
B_{ob} = Bubble point formation volume factor, RB/STB

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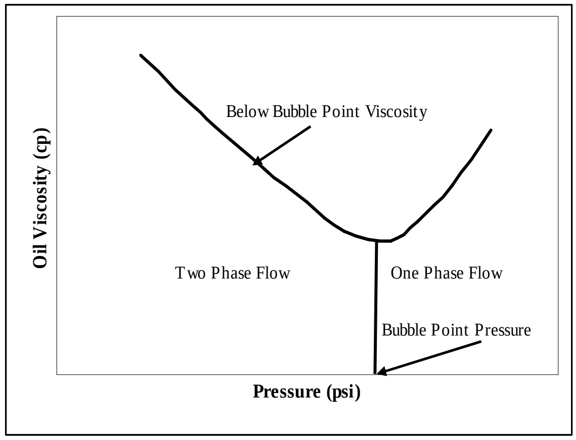

Figure (1): Viscosity Regions at Constant Temperature

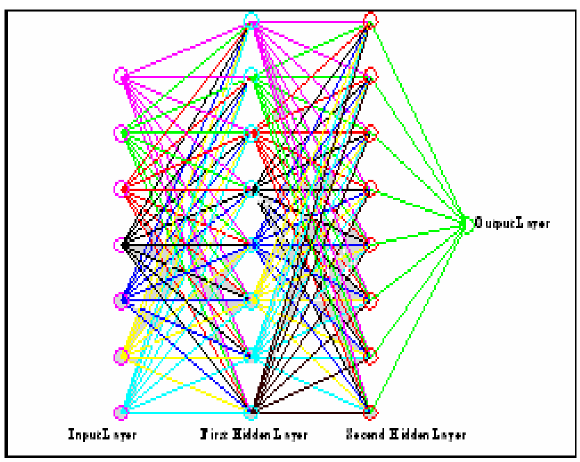

Figure (2): Below Bubble Point Viscosity Neural Network

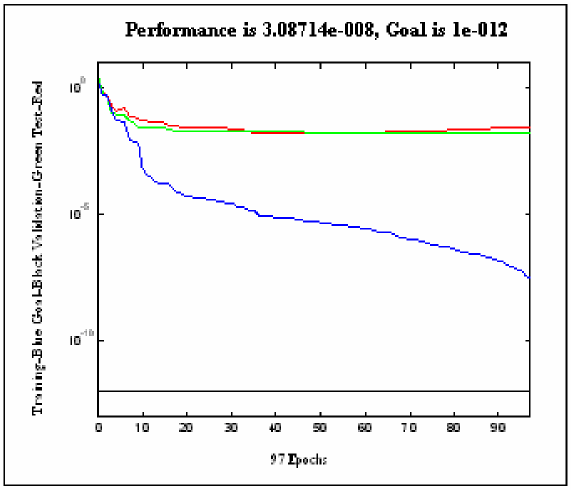

Figure (3): Training Of the Network

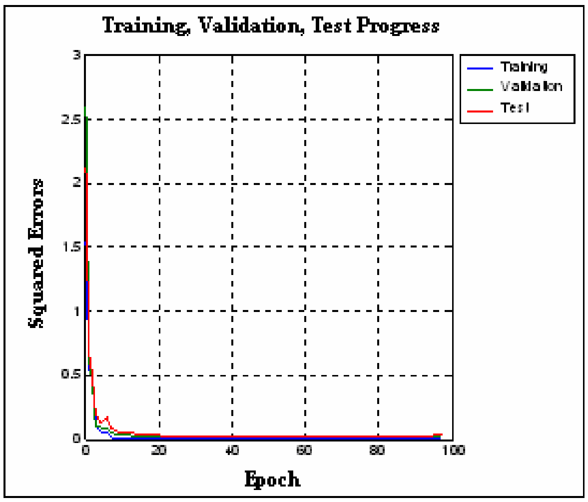

Figure (4): Errors vs. Training, Validation, and Test Progress

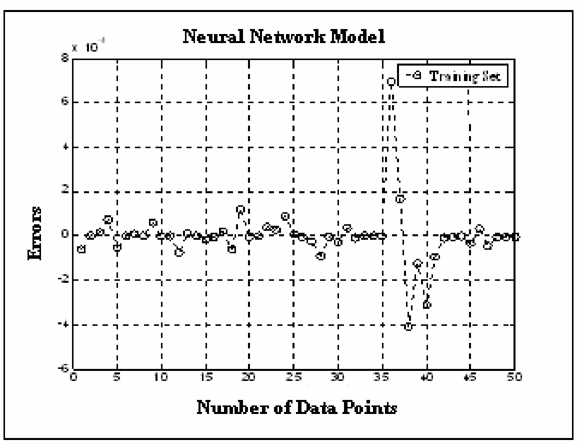

Figure (5): Errors Trend for Training Set (This Study)

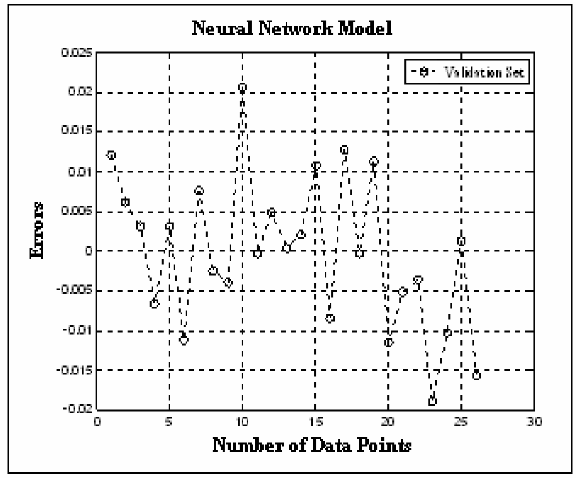

Figure (6): Errors Trend for Validation Set (This Study)

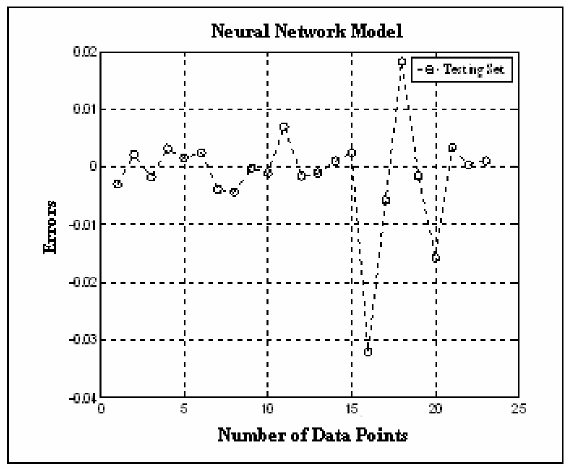

Figure (7): Errors Trend for Testing Set (This Study)

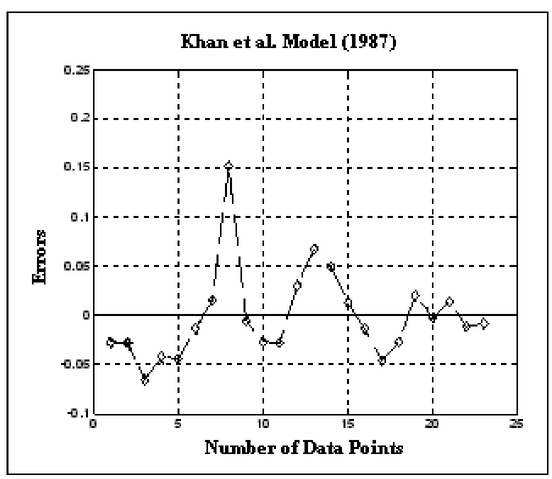

Figure (8): Errors Trend for Khan et al Model (1987)

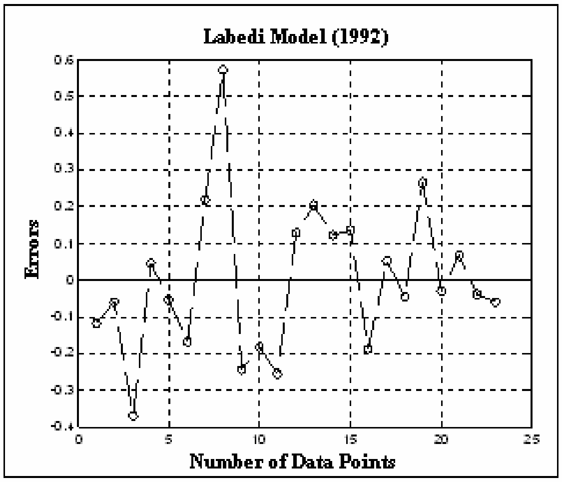

Figure (9): Errors Trend for Labedi Model (1992)

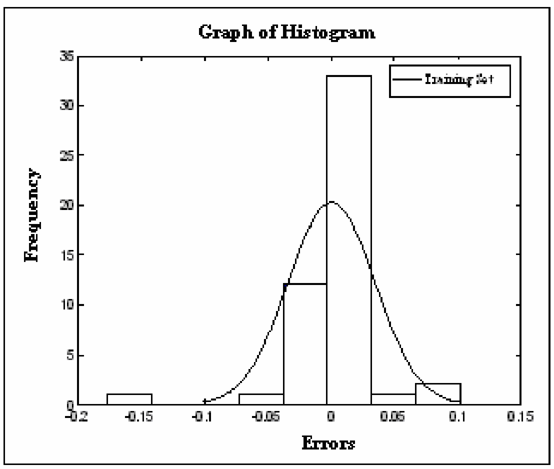

Figure (10): Histogram Errors for Training Set (This Study)

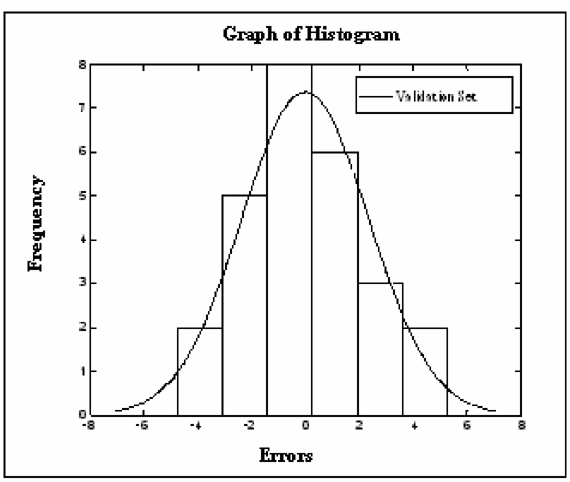

Figure (11): Histogram Errors for Validation Set (This Study)

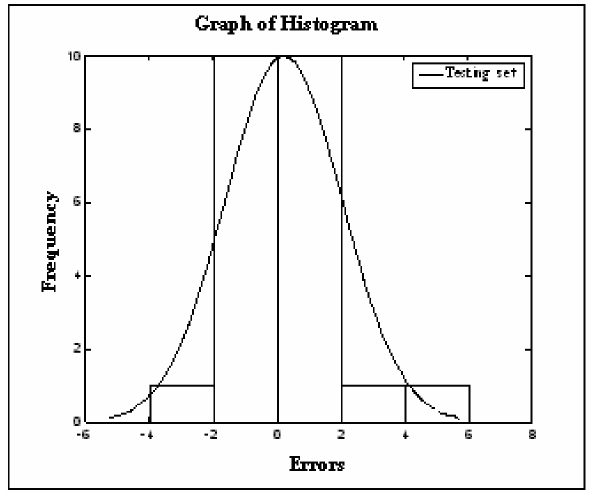

Figure (12): Histogram Errors for Testing Set (This Study)

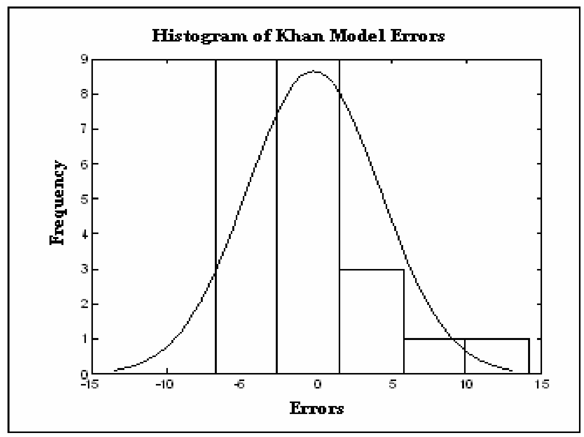

Figure (13): Histogram Errors of Khan Model Errors (1987)

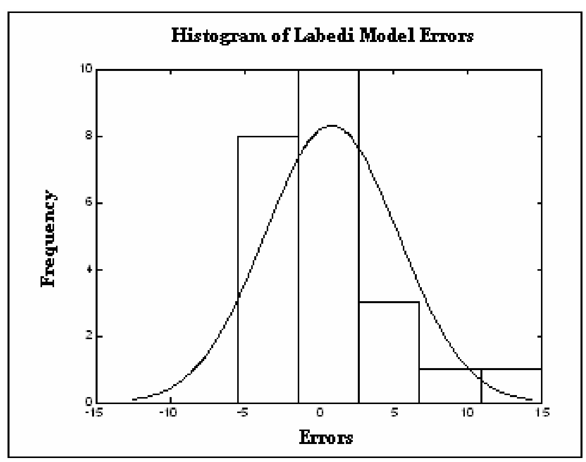

Figure (14): Histogram Errors of Labedi Model Errors (1992)

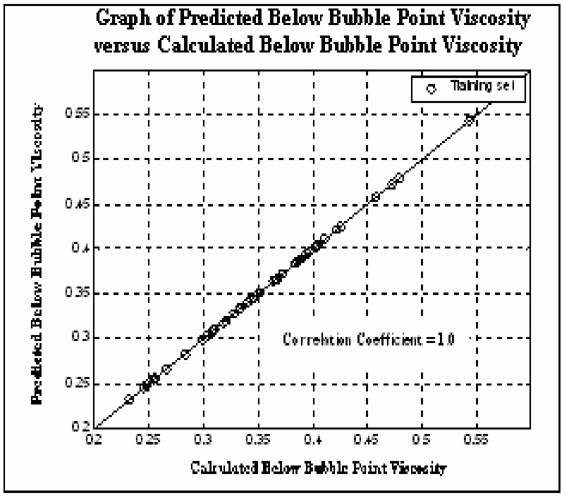

Figure (15): Crossplot between Estimated and Actual Viscosity Values for Training Set (This Study).

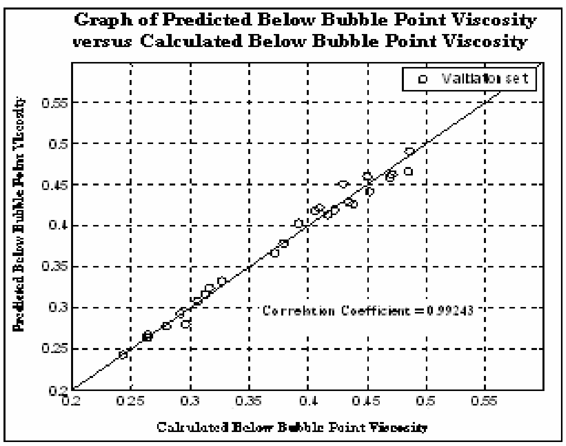

Figure (16): Crossplot between Estimated and Actual Viscosity Values for Validation Set (This Study).

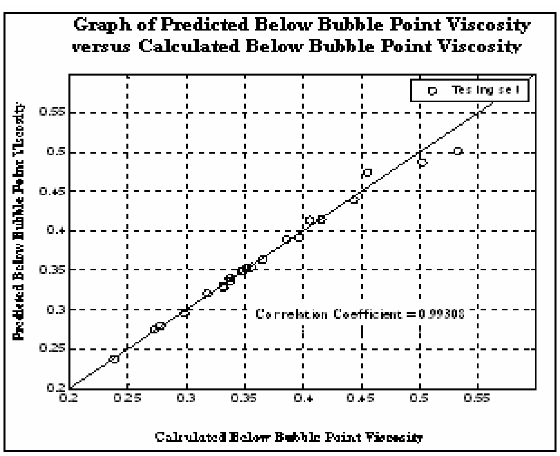

Figure (17): Crossplot between Estimated and Actual Viscosity Values for Testing Set (This Study).

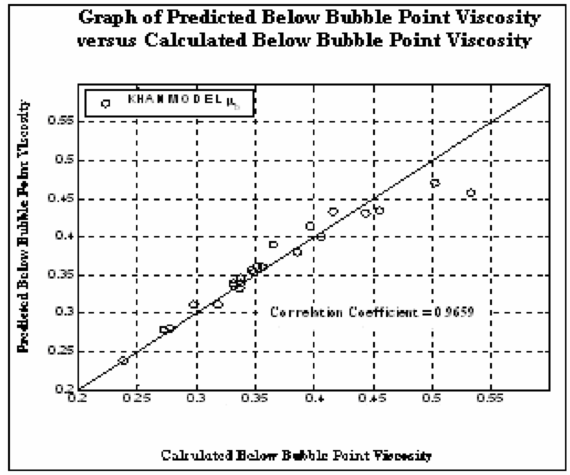

Figure (18): Crossplot between Estimated and Actual Viscosity Values for Khan et al Model (1987)

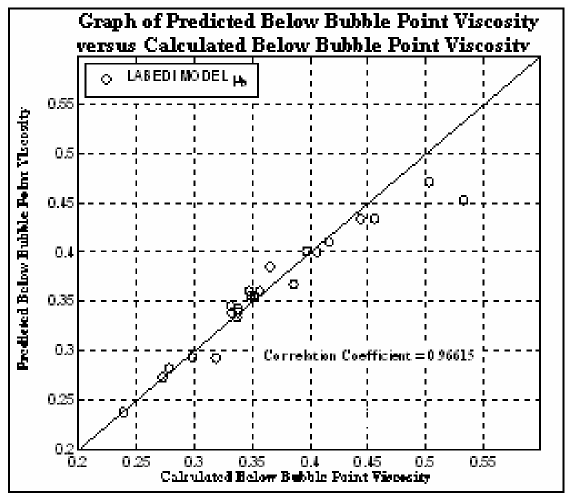

Figure (19): Crossplot between Estimated and Actual Viscosity Values for Labedi Model (1992)

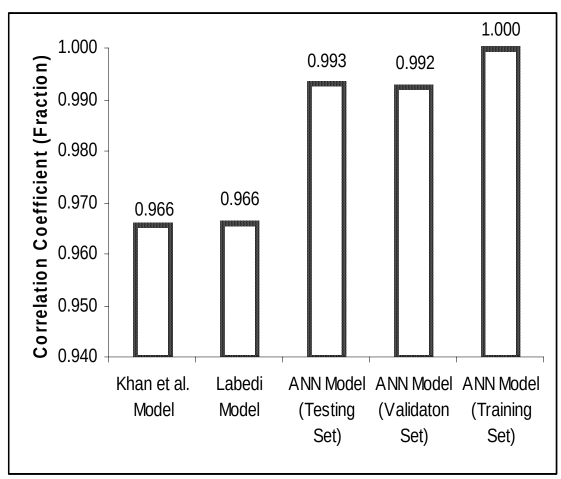

Figure (20): Comparison of Correlation Coefficients for all models

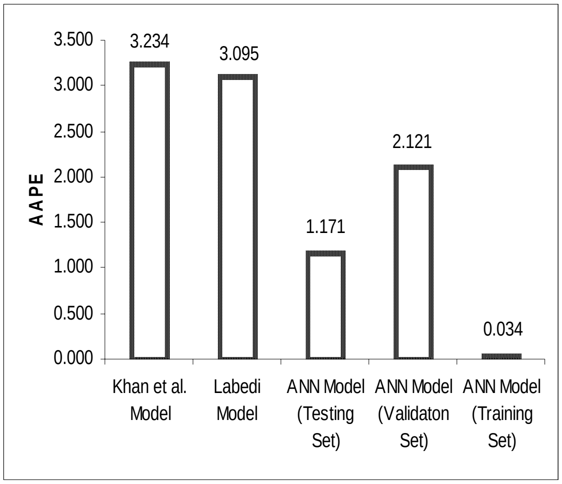

Figure (21): Comparison of AAPE for all models

Appendix A

PROPERTY	TRAINING DATA				TESTING DATA				VALIDATION DATA			
	MIN	**MAX**	**AVEG**	**STD**	**MIN**	**MAX**	**AVEG**	**STD**	**MIN**	**MAX**	**AVEG**	**STD**
Pressure	95	2615	865.57	602.40	115	3015	929.129	745.2636	152	4115	1217.71	1120.486
Temperature	188	296	240.95	27.83	188	296	243.8387	25.32337	188	296	241	31.53199
Bubble Point Pressure	1226	4975	1907.39	793.25	1226	4975	2042.097	1097.326	1226	4975	2399	1302.18
Formation Volume Factor	1.349	2.713	1.7033	0.405	1.349	2.713	1.744419	0.442845	1.349	2.713	1.857581	0.517117
Solution GOR	357	2496	884.95	570.9615	357	2496	962.2581	694.0015	357	2496	1169.484	828.4798
Gas Specific Gravity	0.825	1.643	1.367	0.1679	0.825	1.6433	1.343297	0.203474	0.8253	1.6433	1.281277	0.224333
API Gravity	29	43.8	39.14	3.4394	29	43.8	38.95161	3.270461	29	43.8	38.27419	3.714563
Below Bubble Point Viscosity	0.232	0.587	0.362	0.0764	0.243	0.486	0.364935	0.076863	0.23	0.636	0.357161	0.091215

Table (1): Neural Network Data

Khan Model (1987)

$$\mu_b = \mu_{ob}\left[\left(P/P_b\right)^{a_1}\right]\exp\left(a_2\left(P-P_b\right)\right)$$

Correlation coefficients	Original	This study
a_1	-0.14	-0.065001
a_2	-0.00025	-0.00012738

Table (2): Khan Model Parameters

Labedi model (1992)

$$\mu_{ob}/\mu_b = 1 - m\left[P - P_b\right]$$

Where

$$\ln m = a_1 + a_2 \ln API + a_3 \ln P_b$$

Correlation coefficients	Original	This study
a_1	-8.9248198	-1.6637
A_2	1.1302	-1.3485
A_3	-0.45577	-0.27628

Table (3): Labedi model Parameters

Correlation	AAPE	APE	E_{min}%	E_{max} %	STD	RMSE	R
Khan model	3.2341	-0.22251	0.2314	14.126	4.4487	4.3566	0.9660
Labedi model	3.0951	0.82386	0.077665	14.938	4.4991	4.4766	0.9662
Neural network model (testing data)	1.1709	0.23305	0.069193	6.0336	1.8357	1.8104	0.9931
Neural network model (validation data)	2.1208	-0.02206	0.075485	5.292	2.3599	2.4605	0.9924
Neural network model (training data)	0.03376	0.00076	4.695e-06	0.17667	0.03419	0.04991	1.000

Table (4): Statistical Comparisons for Below Bubble Point Viscosity Correlations and the Proposed ANN model

property	μ_b	*P*	*T*	*Pb*	B_{ob}	R_s	γ_g	*bias*	*output*
Node - 1	0.20957	0.94959	-0.5446	-1.0742	1.6821	2.2072	-0.09076	-3.2019	-2.3655
Node - 2	-0.33187	0.43809	0.030438	0.56966	-0.90794	2.6248	5.4988	-0.52393	4.484
Node - 3	-0.31451	1.6082	0.8061	1.6178	3.3735	1.4572	-2.8999	-1.5637	-1.0178
Node - 4	2.5802	0.66711	-0.84062	0.47562	-0.63571	-1.55	0.48846	0.25026	3.6956
Node - 5	-1.2724	0.56519	-0.93077	-0.54185	-0.40433	-0.65949	-0.05876	1.1771	1.1075
Node - 6	1.8247	0.015754	-0.47586	-0.21929	0.93237	1.1851	1.0166	4.401	3.873
Node - 7	-0.23554	-4.7537	-0.56959	0.47377	-0.65576	0.36129	1.7367	4.401	-1.5809
Node - 8	0.23545	-0.98501	0.89862	0.96486	1.0095	-0.3668	-0.15297	3.4172	0.09225
								Bias = 1.7228	

Table (5): Neural Network Weights for the Input/Hidden and Hidden/Output plus the Output Bias Vector