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Full Length Research Paper

Determination of petroleum property using artificial intelligence tools

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Viscosity is one of the most important governing parameters of the fluid flow, either in the porous media or in pipelines. So it is important to use an accurate method to calculate the oil viscosity at various operating conditions. In the literature, several empirical correlations have been proposed for predicting crude oil viscosity. However these correlations are not able to predict the oil viscosity adequately for a wide range of conditions. In present work, an extensive experimental data of oil viscosities from different samples of Iranian oil reservoirs was applied to develop an artificial neural network (ANN) model to predict and calculate the oil viscosity. Validity and accuracy of these models has been confirmed by comparing the obtained results of these correlations and with experimental data for Iranian oil samples. It was observed that there is an acceptable agreement between ANN model results with the experimental data.

Key words: Property, artificial neural network, petroleum.

INTRODUCTION

Crude oil viscosity is an important physical property that controls and influences the flow of oil through porous media and pipes (Abdini and Abedini, 2011). The viscosity, in general, is defined as the internal resistance of the fluid to flow. Oil viscosity is a strong function of many thermodynamic and physical properties such as pressure, temperature, solution gas-oil ratio, bubble point pressure, gas gravity and oil gravity (Abedini and Abedini, 2011).

Numerous correlations have been proposed to calculate the oil viscosity. These correlations are categorized into two types. The first type which refers to black oil type correlations predict viscosities from available field-measured variables include reservoir temperature, oil API gravity, solution gas- oil ratio, saturation pressure and pressure (Beal, 1946; Chew and Connally, 1959; Beggs and Robinson, 1975; Glaso, 1980; Vasquez and Beggs, 1980; Labedi, 1992; Kartoatmodjo and Schmidt, 1994; Elsharkawy and Alikhan, 1999).

The second type which refers to compositional models derives mostly from the principle of corresponding states and its extensions. In these correlations beside previous properties, other properties such as reservoir fluid composition, pour point temperature, molar mass, normal boiling point, critical temperature and acentric factor of components are used (Lohrenz et al., 1964; Little and Kennedy, 1968; Ahrabi et al., 1987; Sutton and Farshad, 1990).

MATERIALS AND METHODS

Experimental data

In this study, PVT experimental data of five sample oils from Iranian oil reservoirs have been used. These data include oil reservoir temperature, saturation pressure, API gravity and solution gas-oil ratio at reservoir temperature. Reservoir oil viscosities have been measured at various pressures above and below the bubble point pressure for different temperatures. Statistical experimental data are shown in Table 1.

Crude oil viscosity correlations

Undersaturated oil viscosity correlations, which usually use saturated crude oil viscosity and pressure above the bubble point to

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Table 1. Statistical experimental data of sample oils.

Oil properties	Oil 1	Oil 2	Oil 3	Oil 4	Oil 5
API	15.4	24.2	30.3	36.7	41.6
Temperature (ºF)	134 - 272	134 - 272	134 - 272	134 - 272	134 - 272
Solution gas-oil ratio(SCF/STB)	647	823	954	1167	1542
Saturation pressure (psia)	2490 - 3500	2520 - 3328	1340 - 2040	1585 - 2914	1638 - 4513
Undersaturated viscosity (cp)	0.394 - 2.211	0.374 - 0.726	0.683 -18.435	0.316 - 8.253	0.341 - 1.146

Table 2. Summary of undersaturated oil viscosity correlations.

Author (year)	Correlation
Beal (1946)	$\mu_o = \mu_{ob} + 0.001\left(P - P_b\right)\left(0.024\mu_{ob}^{1.6} + 0.038\mu_{ob}^{0.56}\right)$
Vasquez and Beggs (1980)	$\mu_o = \mu_{ob}\left(P / P_b\right)^m, a = \left[-3.9\left(10^{-5}\right)P\right] - 5, m = 2.6\left(P^{1.187}\right)\left(10^a\right)$
Khan (1987)	$\mu_o = \mu_{ob}\exp(9.6\times10^{-5}(P - P_b))$
Kartoatmodjo and Schmidt (1994)	$\mu_o = 1.00081\mu_{ob} + 0.001127\left(P - P_b\right)\left(-0.006517\mu_{ob}^{1.8148} + 0.038\mu_{ob}^{1.59}\right)$

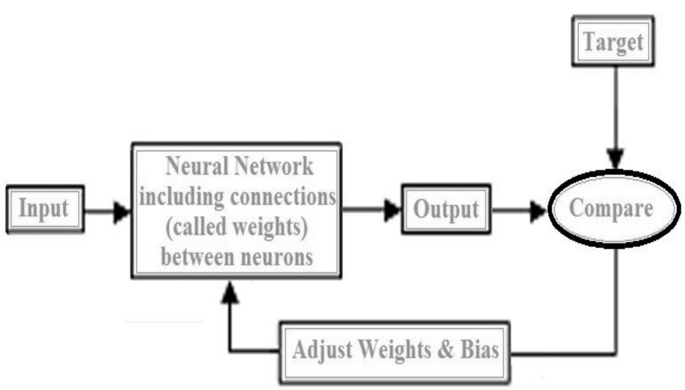

Figure 1. Schematic of network in an artificial neural network model.

predict viscosity of undersaturated oil reservoirs. These correlations are Beal (1946), Vasquez and Beggs (1980), Khan Correlation (1987) and Kartoatmodjo and Schmidt (1994). These correlations are shown in Table 2.

Artificial neural network

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems (Abedini et al., 2011). As in nature, the network function is determined largely by the connections between elements. One can train a neural network to perform a particular function by adjusting the values of the connections (weights) between elements (Ashoori et al., 2010, Abedini et al., 2011). Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is depicted in Figure 1.

There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. There are multitudes of different types of ANNs and some of them include the multilayer perceptron (MLP), which is more popular and generally trained with the back-propagation of error algorithm, Radial Basis Function (RBF), Adaptive Linear Neuron (ADALINE) and Adaptive Network Based Fuzzy Inference System (ANFIS). Some ANNs are classified as feed forward, while others are recurrent, depending on how data is processed through the network. Another way of classifying ANN types is by their method of learning, as some ANNs employ supervised training, while others are referred to as unsupervised or self organizing (Koolivand Salooki et al., 2011).

Back-propagation-type neural networks have an input, an output and in most of the applications, have one hidden layer. The number of inputs and outputs of the neural networks are determined by considering the characteristics of the application. In most of the cases, one hidden layer is satisfactory. Each neuron of a layer is generally connected to the neurons in the proceeding layer. Repeating forward propagating and backward-propagating steps performs the required learning. When a pattern is given to the input pattern, the forward propagation step begins. The activation levels are calculated and the results are propagated forward through the following hidden layers until they reach the output layer. Every processing unit sums its respective inputs and then applies a function to compute its output. Sigmoid is the most commonly used function (Abedini et al., 2011).

The output of the network is created at the output layer. The bias

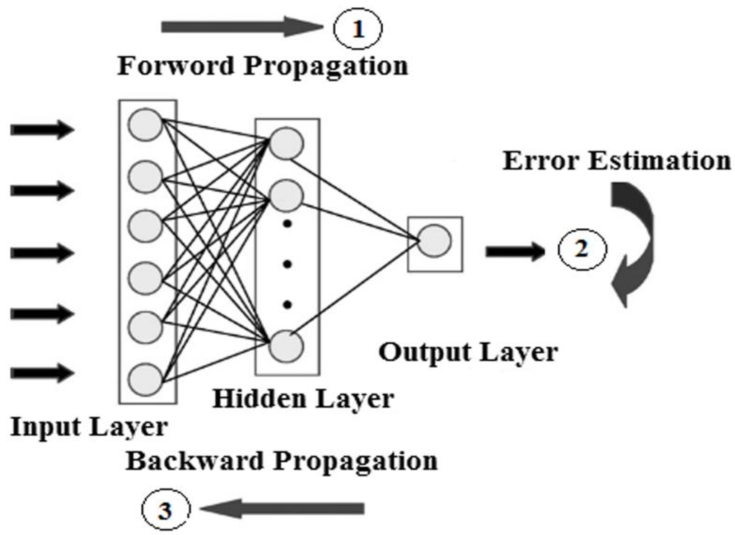

Figure 2. Back-propagation multilayer ANN with one hidden layer.

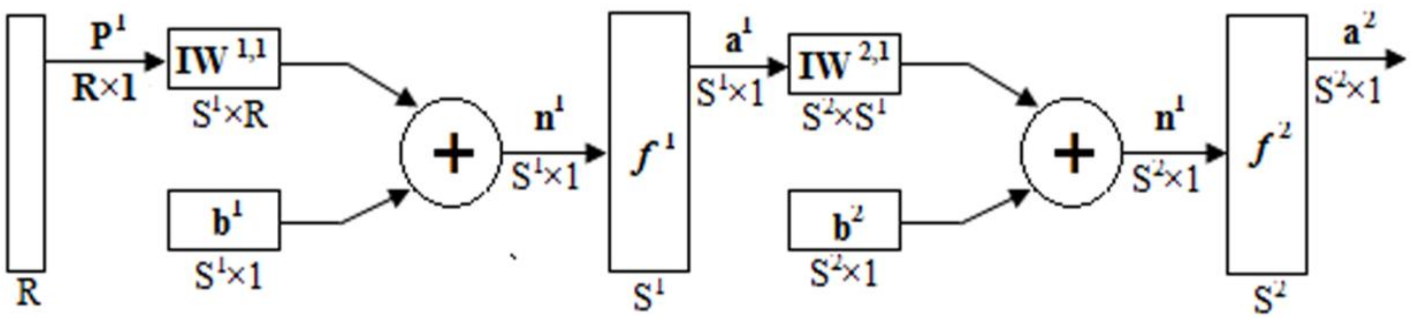

Figure 3. Multi layer perceptron

units of input and hidden layers add a constant term in the weighted sum, which improves convergence. After the network's output pattern is compared with the target vector, error values for the hidden units are calculated and their weights are changed. The backward propagation starts at the output layer and moves backward through the hidden layers until it reaches the input layer. Figure 2 shows a summary of the network topology illustration (Abedini et al., 2012).

The goal of every training algorithm is to reduce this global error by adjusting the weights and biases. An output of a three-layer MLP networks (Figure 3) is defined by:

$$a_k^2 = f^{\,2}\left(\sum_{j=1}^{S^1} w_{ij}^{2} f^{\,1}\left(\sum_{i=1}^{R} w_{ij}^{1} p_i + b_j^1\right) + b_k^2\right), k = 1 \ to \ S^2 \quad (1)$$

Where superscript 1 denotes hidden layer and superscript 2 denotes output layer. R, S^1 and S^2 illustrate the numbers of the input, hidden and output units, respectively. Also, *f*, *w* and *b* represent transfer function, synaptic weight parameter and bias, respectively.

RESULTS AND DISCUSSION

Validation of undersaturated oil viscosity correlations

The accuracy and ability of each mentioned correlation for predicting undersaturated oil viscosity was checked with experimental data and Figures 4 shows this comparison. These figures confirm the disability of correlations for accurate prediction of oil viscosities.

Development of artificial neural network (ANN) model

Inputs of a network should be selected carefully if fully satisfactory results are expected to be achieved. The input variables should reflect the underlying physics and fundamentals of the process to be analyzed. Temperature and liquid mole fraction are used as an

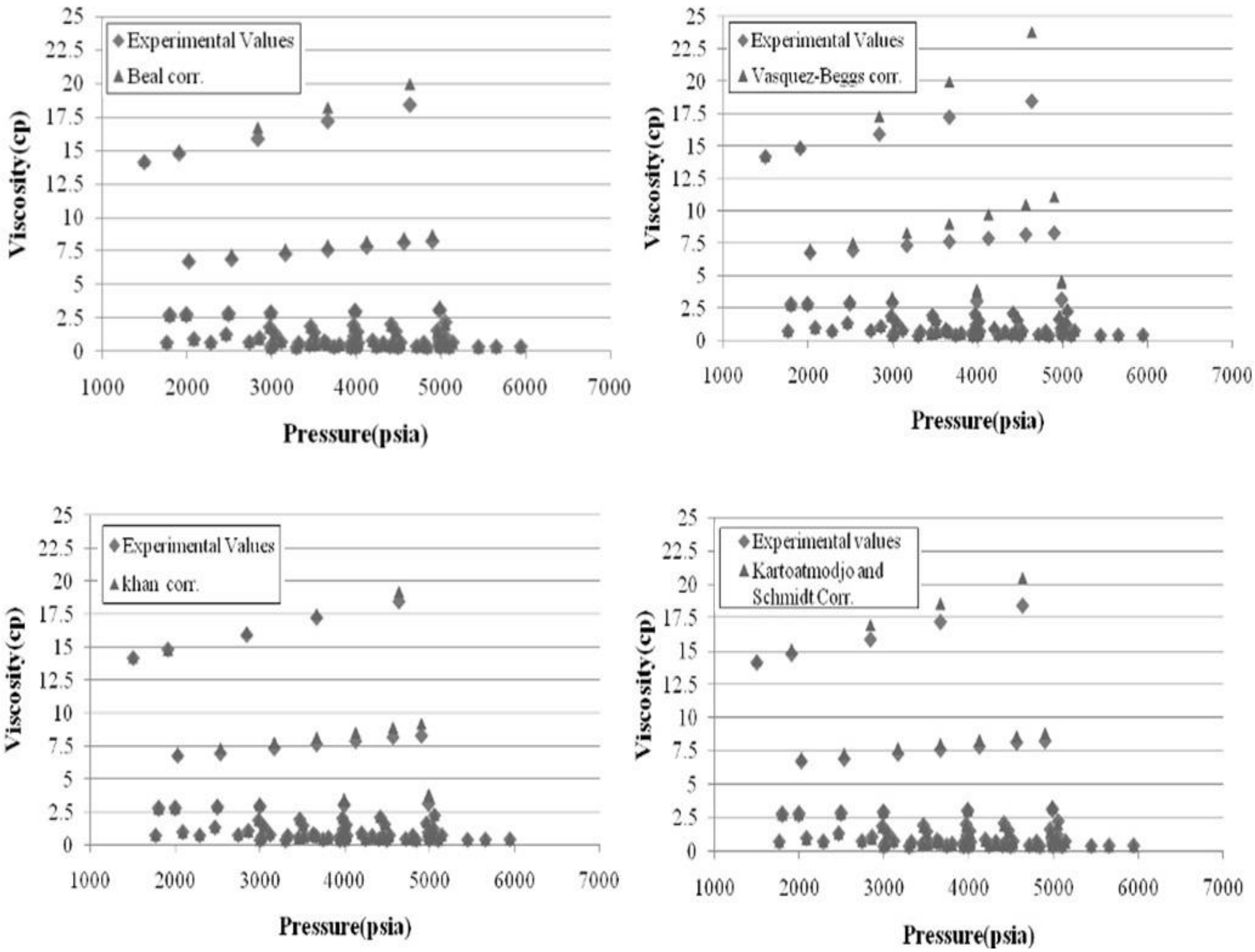

Figure 4. Experimental values compared with calculated values calculated by each correlation.

input data. The back-propagation learning with one hidden layer network has been used for each ANN set. Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM), Gradient Descent with Momentum (GDM), Resilient Back-propagation (RB) and adaptive learning rate Back propagation (GDX) has been implemented for training algorithm. As the network trained with LM gave much better results for training sets than the other algorithms, it was used for modeling of prediction of undersaturated crude oil viscosity. The developed ANN model has one input, three hidden and one output layers which has 3, 5 and 1 neuron. 65% of all experimental data was used to train the network and the rest was used to test the network.

Pressure, bubble point pressure and bubble point viscosity used as an input data and the corresponding undersaturated oil viscosity for each system was used as an input data and the corresponding undersaturated crude oil viscosity was used as a target data. Figure 5 shows the designed ANN for simulation undersayurated viscosity. Figure 6 depicts the comparison of experimental values of viscosity with predicted ones by ANN model for undersaturated oil respectively. It is obvious from the figure that the ANN provides results in good agreement with experimental values.

Accuracy of the proposed artificial neural network (ANN) models

Here, the accuracy of the proposed models in this work, as well as the correlations previously discussed, is

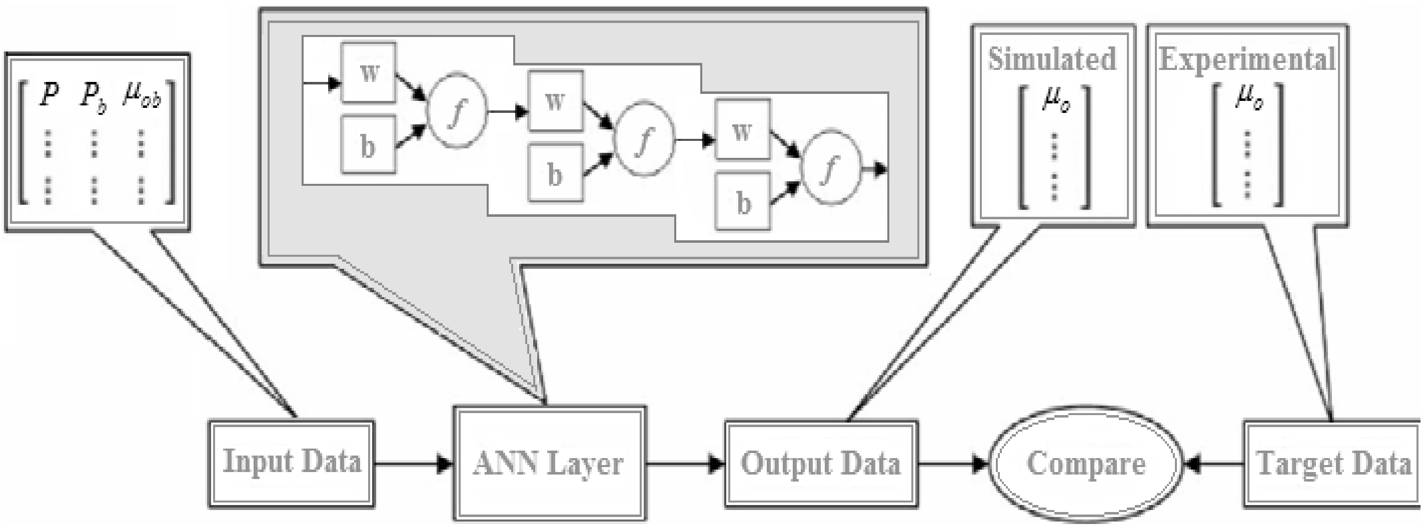

Figure 5. Schematic of the designed ANN for simulation of undersaturated viscosity.

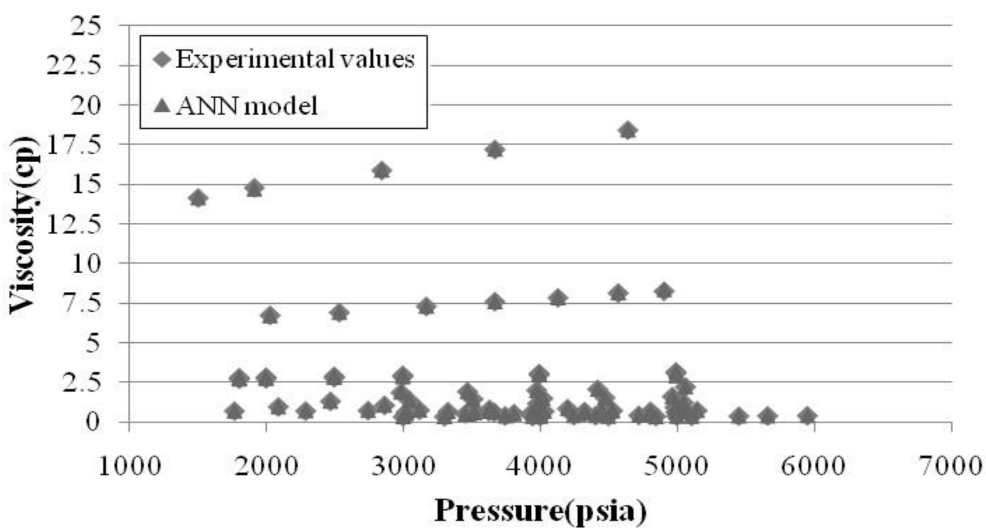

Figure 6. Experimental values compared with calculated values calculated based on the ANN model.

checked. Using the 86 real cases data series of Iranian oils, the results of this work and other ones for estimating the oil viscosity are compared. Figure 7 shows percent relative error distribution for all correlations and models (Abedini et al., 2011).

Where:

$$Ei = \left(\frac{X_{experimental(i)} - X_{calculated(i)}}{X_{experimental(i)}} \right) \times 100$$

(i= 1, 2, 3…,n_d) (3)

Conclusion

Generally the most common method for calculating viscosity of crude oils is viscosity correlations. However these correlations fail to predict oil viscosities at wide range of operating conditions such as pressure and temperature. In this work a new ANN model for estimation of undersaturated Iranian oils have been proposed. Input parameters for these models are pressure, saturation pressure and saturation viscosity, which are easily measured in oil fields. The results obtained using ANN model was compared with

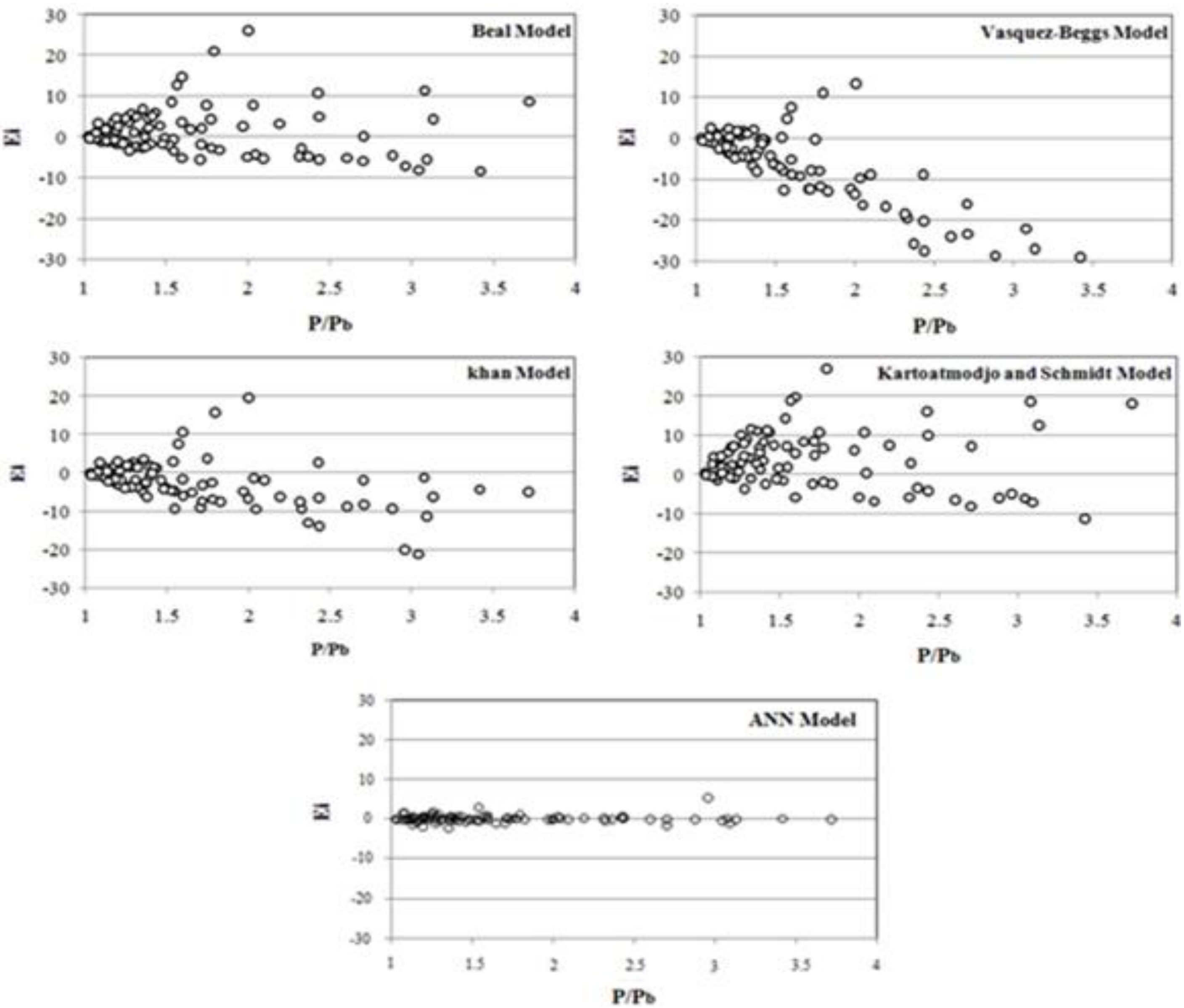

Figure 7. Percent relative error distribution for undersaturated oil viscosity correlations, ANN model.

experimental data. Finally, it was found that in comparison with correlations previously published in the literature, the ability and accuracy of new ANN model for predicting oil viscosities is better.

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