Prediction of Natural Gas Viscosity using Artificial Neural Network Approach

E. Nemati Lay[*], M. Peymani, E. Sanjari

Abstract—Prediction of viscosity of natural gas is an important parameter in the energy industries such as natural gas storage and transportation. In this study viscosity of different compositions of natural gas is modeled by using an artificial neural network (ANN) based on back-propagation method. A reliable database including more than 3841 experimental data of viscosity for testing and training of ANN is used. The designed neural network can predict the natural gas viscosity using pseudo-reduced pressure and pseudo-reduced temperature with AARD% of 0.221. The accuracy of designed ANN has been compared to other published empirical models. The comparison indicates that the proposed method can provide accurate results.

Keywords—Artificial neural network, Empirical correlation, Natural gas, Viscosity

I. INTRODUCTION

THE increasing demand for natural gas has led to the need to develop a more reliable reservoir characterization and simulation. The upstream gas industry, through the gas suppliers, is also being faced with increasing demand for precision in the monitoring of gas supplies. For the exploitation and usage to be optimal, an accurate and reliable knowledge of the viscosity, along with other thermophysical properties, of natural gas is a prerequisite [1].

Viscosity is an important property in the calculations related to fluid flow and estimation of other physical properties in liquid systems [2].

The gas viscosity generally increases with pressure. The increase of temperature increases the gas viscosity at low and moderate pressure. At high pressures, the gas viscosity behavior approaches like that liquid decrease with increase the temperature [3].

In principle, the viscosity of a fluid can be related to molecular motion and intermolecular forces acting among molecules. In practice, there is no rigorous theory that allows the complete evaluation of viscosity as a function of temperature and pressure [4]. An accurate prediction of natural gas viscosity is needed in the appropriate design and operation of equipment in industrials and processing.

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Several attempts have been made to improve the accuracy of natural gas viscosity prediction. Carr et al. [5] and Dean et al. [6] proposed a correlation for calculation of natural gas as a function of reduced pressure, reduced temperature, and reduced density of gas and molecular weight. Lee et al. [7] proposed a correlation that is the most reliable for determining the viscosity of natural gas. Guo et al. [8] presented two viscosity models based on Peng-Robinson EOS and Patel-Teja EOS and found that their model is capable of satisfactorily describing pure component hydrocarbon viscosity. Huber et al. [9] presented new correlations for the viscosity of the pure fluids n-octane, n-nonane, and n-decane that are valid over a wide range of fluid states. Xuan et al. [10] was proposed a new model to calculate the viscosity of fluids under the pressure ranging from 0.1 to110 MPa. Heydarian et al. [11] presented a new and reliable correlation for methane gas viscosity, and another method [12] for viscosity accounts for the presence of heptane plus and non-hydrocarbon components. Also Sanjari et al. [13] reported an accurate method for estimation of natural gas viscosity. At the aim of developing models for gas viscosity implementing artificial neural network (ANN) techniques, AlQuraishi et al. [14] proposed an ANN structure for prediction of hydrocarbon viscosity using 800 experimental data and accuracy of 3.65%.

The main focus of this study is designing an appropriate ANN with high accuracy to predict the viscosity in desired temperature and pressure using a reliable experimental data that measured by many of researchers from 1976 to 2010 [15]-[21]. Finally results of the ANN model is compared to the empirical models.

II. NATURAL GAS VISCOSITY

Because of the difficulties of viscosity measurements in laboratory, this parameter can be estimated from empirical correlations with low deviation. Like all intensive properties, viscosity of a natural gas is completely described by the following function [22]:

$$\mu_g = f(P, T, y_i) \qquad (1)$$

Where μ_g is the viscosity of gas phase. The above relationship simply states that the viscosity is a function of pressure, temperature, and composition. There are numerous correlations exist to predict natural gas viscosity, such as empirical correlations. It is applicable to highlight and contrast the four empirical correlations chosen in this study. For briefness only, essential elements of these four methods are presented here, and the reader is referred, in each case, to the original publications for more details.

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A. Lee-Gonzalez-Eakin Method (LGE)

Lee-Gonzalez-Eakin in 1966 presented a semi empirical relationship for calculating the viscosity of natural gases [7]. The authors expressed the gas viscosity on terms of the reservoir temperature, gas density, and the molecular weight of the gas. Their proposed equation is given by:

$$\mu_g = 10^{-4} K \exp\left[X\left(\frac{\rho_g}{62.4}\right)^Y \right] \tag{2}$$

Where each of "K", "X" and "Y" are a function of temperature and molecular weight, and ρ_g is the gas density at reservoir pressure and temperature in lb/ft^3.

B. Adel Elsharkawy Method

Adel Elsharkawy in 2004 presented a modification of the Lee-Gonzalez-Eakin gas viscosity correlation to account for the presents of heptanes plus fraction and non-hydrocarbons [23]. This correlation has the following equation:

$$\mu_g = D_1 \times 10^{-4} \exp(D_2 \rho_g^{D3}) \tag{3}$$

Where ρ_g is the gas density in g/cc, and D_1, D_2, and D_3 are dependent parameter as a function of temperature and molecular weight. This proposed modification results in correcting the original correlation to account for the presence of high content of heptane plus fraction, hydrogen sulfide and carbon dioxide in natural gases. These corrections are calculated by the following equations.

$$\Delta\mu_g = y.H_2S\left[-3.2268\times10^{-3}\log\gamma_g + 2.1479\times10^{-3}\right] \tag{4}$$

$$\Delta\mu_g = y.CO_2\left[6.4366\times10^{-3}\log\gamma_g + 6.7255\times10^{-3}\right] \tag{5}$$

$$\Delta\mu_g = y.C_{7+}\left[-3.2875\times10^{-1}\log\gamma_g + 1.2885\times10^{-1}\right] \tag{6}$$

C. Carr-Kabayashi-Burrow Method (CKB)

The correlation of Carr-Kabayashi-Burrow is often used to estimate the natural gas viscosity, particularly for gases containing significant amount of no-hydrocarbon components [5]. It initially estimates the gas viscosity at the atmospheric pressure and prevailing temperature. The equation of this method is:

$$\ln\left(T_{pr}\frac{\mu_g}{\mu_1}\right) = a_0 + a_1 P_{pr} + a_2 P_{pr}^2 + a_3 P_{pr}^3 + T_{pr}(a_4 + a_5 P_{pr} + a_6 P_{pr}^2 + a_7 P_{pr}^2)$$
$$+ T_{pr}^2(a_8 + a_9 P_{pr} + a_{10}P_{pr}^2 + a_{11}P_{pr}^3) + T_{pr}^3(a_{12} + a_{13}P_{pr} + a_{14}P_{pr}^2 + a_{15}P_{pr}^3) \tag{7}$$

Where μ_g, T_{pr} and P_{pr} are natural gas viscosity, pseudo reduced temperature and pseudo reduced pressure, respectively. The calculated viscosity at the atmospheric pressure, μ_1, is then adjusted for pressure, using the gas pseudo

reduced temperature and pressure, over ranges of 1-3, and 1-20, respectively, as:

$$\mu_1 = \mu_h + (\Delta\mu)_{N2} + (\Delta\mu)_{CO2} + (\Delta\mu)_{H2S} \tag{8}$$

Where μ_h is calculated as follow:

$$\mu_h = \left[1.709\times10^{-5} - 2.062\times10^{-6}S_g\right](T-460) + 8.188\times10^{-3} - 6.15\times10^{-3}\log S_g \tag{9}$$

D. Heydarian-Moghadassi-Salarabadi method (HMS)

Heydarian et al in 2010 developed a new correlation to prediction of natural gas viscosity [12]. This method is valid in range of $6 \leq P_{pr} \leq 35$ and $1.8 \leq T_{pr} \leq 2.2$. Their proposed equation is following by:

$$\mu = \frac{A_1 + A_2 P_{pr} + A_3 P_{pr}^2 + A_4 P_{pr}^3 + A_5 T_{pr} + A_6 T_{pr}^2}{1 + A_7 P_{pr} + A_8 T_{pr} + A_9 T_{pr}^2 + A_{10}T_{pr}^3} \tag{10}$$

However the draw backs of these empirical correlations are Limited range of application, complexity of calculation, and density involving in the calculations. Hence the accuracy of viscosity calculations is dependent on the accuracy of density estimation.

E. Sanjari-Nemati Lay-Peymani method (SNP)

Sanjari et al [13] in 2011 developed a new correlation to prediction of natural gas viscosity. This method can predict the viscosity of natural gas with AARD% of 2.127% in the range of $1.01 \leq T_{pr} \leq 3.0$ and $0.01 \leq P_{pr} \leq 21$. This method is presented as follow:

$$\mu = \frac{A(p_{pr}) + B(T_{pr})}{C(p_{pr}) + D(T_{pr})} \tag{11}$$

$$A = a_1 + a_2 p_r + a_3 p_r^2 + a_4 \ln(p_r) + a_5 \ln^2(p_r) \tag{12}$$

$$B = \frac{a_6}{T_r} + a_7 \ln^2(T_r) \tag{13}$$

$$C = 1 + a_8 p_r^2 \tag{14}$$

$$D = \frac{a_9}{T_r} + \frac{a_{10}}{T_r^2} + \frac{a_{11}}{T_r^3} \tag{15}$$

F. Artificial Neural Network (ANN)

In order to find relationship between the input and output data derived from experimental works, a more powerful method than the traditional ones are necessary. ANN is an especially efficient algorithm to approximate any function with finite number of discontinuities by learning the relationships between input and output vectors [24]. The structure of the information-processing system is constituted of an assemblage of several highly-interconnected elements of processing called "neurons", working together to process the information and solve the problem.

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They are the result of scientific investigations that use mathematical formulations to model nervous system operations. The resulting techniques are being successfully applied in a variety of everyday technical, business, industrial, and medical applications [25].

Fig 1 shows multiple layers arrangement of a typical interconnected neural network is consist of an input layer, an output layer, and one hidden layer with different roles. Each connecting line has an associated weight.
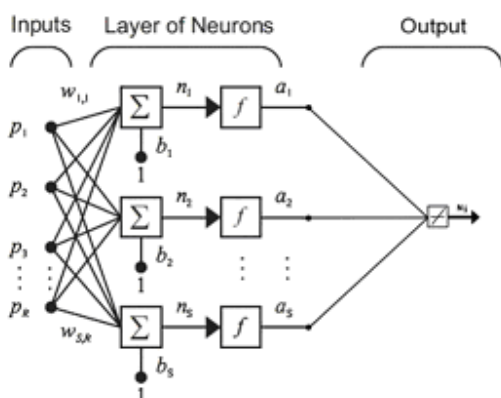

Fig 1 The Neural Network structure

Artificial neural networks are trained by adjusting the connection weights, so that the calculated outputs may be approximated by the desired values. The output from a given neuron is calculated by applying a transfer function to a weighted summation of its input to give an output, which can serve as input to other neurons, as follows [26]:

$$\alpha_{jk} = F_k \left(\sum_{i=1}^{N_{k-1}} w_{ijk} \alpha_{i(k-1)} + \beta_{jk} \right) \qquad (16)$$

Where α_{jk} are jth neuron outputs from k th layer and β_{jk} is the bias weight for neuron j in layer k. The model fitting parameters w_{ijk} are the connection weights. The nonlinear activation transfer functions F_k may have many different forms. The classical ones are threshold, sigmoid, Gaussian and linear function, etc. [27].

During training the weights and biases of the network are iteratively adjusted to minimize the network performance function. One of typical performance function, used for training feed forward neural networks, is the network Average Absolute Relative Deviation (AARD %) that presented by the following equation.

$$AARD\% = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{z_{\exp} - z_{calc}}{z_{\exp}} \right| \times 100 \qquad (17)$$

Through different types of neural networks, the back propagation learning algorithm is the most commonly used algorithm to prediction the properties of natural gas. Several back-propagations training methodologies exist, which includes the Levenberg–Marguardt Algorithm (LMA), the Scaled Conjugate Gradient (SCG), the Pola–Ribiere Conjugate Gradient (CGP) and others. A review of investigations using similar applications indicates that the LMA is sufficiently robust and produces accurate ANNs [25]. The LMA, that similar to Gauss–Newton method, is used in a back-propagation of error manner to reduce the average absolute relative deviation of the output.

The large collection of patterns that needed to make a good quality ANN is commonly divided into three subsets, namely: training, validation, and test sets. The validation set is used to indicate the deviation produced during the training. This set is not used to alter the biases and weights, but serves to illustrate when the training should stop. Typically the deviation that obtained with the set of validation should be reduce during the training step, but should increase as the network starts to learn the specific training patterns used in the training set. The testing set is used to check the quality of the partitioning of the whole pattern set into these subsets. Thus, if the error in the testing set reaches a minimum value at a significantly various iteration number of that in which the minimum occurs with the validation set, this might indicate a poor division of the original data set .

A set of data containing pseudo-reduced pressure, pseudo-reduced temperature, Molecular weight, and viscosity was collected from experimental data. These data contain 3841 points of different natural gas mixtures reported in the literatures. The gas mixtures have different molecular weight from 16.4 to 20.8 or gas gravity from 0.566 to 0.719. The properties of gas mixtures used for training and testing the neural network have been reported in Table I.

Neural network training can be made more efficient if certain preprocessing steps are performed on the network inputs and targets. The neurons in the hidden layer perform two tasks: summing the weighted inputs connected to them and passing the result through a nonlinear activation function to the output or adjacent neurons of the corresponding hidden layer. By using LM algorithm that is more accurate than other back-propagation methods, more than 70% of data set is used to train each ANN and the rest have been used to evaluate their accuracy and trend stability using LM algorithm. Number of hidden neurons has been systematically varied to obtain a good estimate of the trained data.

III. RESULT AND DISCUSSION

To find the optimum number of nodes in the hidden layer, which provides good estimates of the output, different number of neurons was considered. The criterion for selection was AARD% between network output and training data. The results are illustrated in Fig 2.

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TABLE I
PROPERTIES OF NATURAL GASES USED IN THIS STUDY

|	Minimum	Maximum	Average
Composition (mol %)			
Methane	66.25	100	97.2421
Carbon dioxide	0	2.19	0.2941
Ethane	0	9.306	1.3825
Propane	0	4.963	0.2908
i-butane	0	0.719	0.0596
n-butane	0	1.279	0.0534
i-pentane	0	0.226	0.0436
n-pentane	0	0.249	0.0431
Hexane	0	0.179	0.0464
Heptane plus	0	0.136	0.0095
Argon	0	0.042	0.0010
Nitrogen	0	9.752	1.0634
Hydrogen	0	33.75	0.1854
Helium	0	0.052	0.0012
Pressure (Mpa)	0.1	97.3	10.96
Temperature (K)	250	570	371.45
Viscosity (μP)	95.93	586.63	165.26
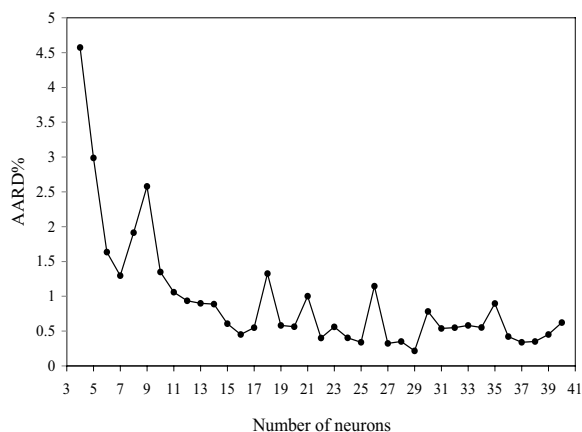
Fig. 2 Determining the optimum number of neurons

As shown in Figs 2, architecture of ANN having 29 neurons, gave the lowest average relative error for the training data set, and its AARD% value is 0.221%. Fig 3 shows the network architecture with 29 neurons in hidden layer.

To compare the accuracy of presented model versus experimental data, 3841 viscosity data points of different mixtures provided from literatures [15]-[21].
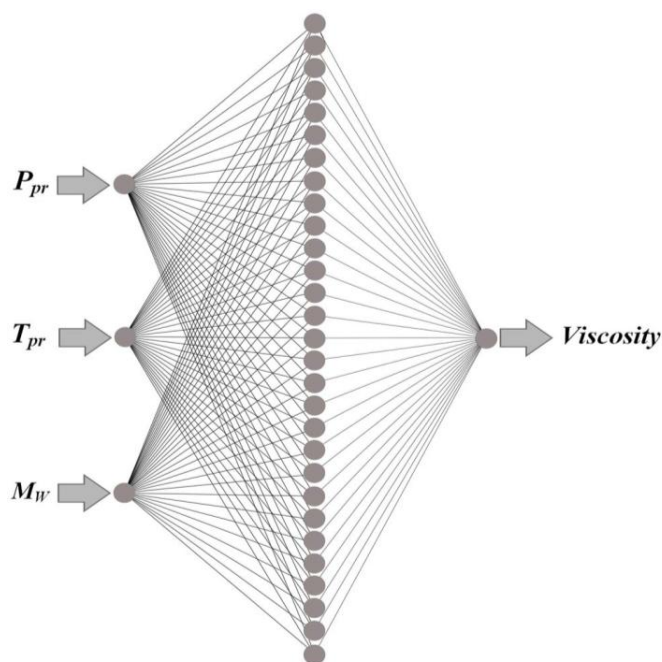

Fig. 3 Optimal back-propagation neural network paradigm

For estimation of the accuracy of computed neural network data, the calculated values from this model versus 3841 experimental data points has been showed in Fig 4.
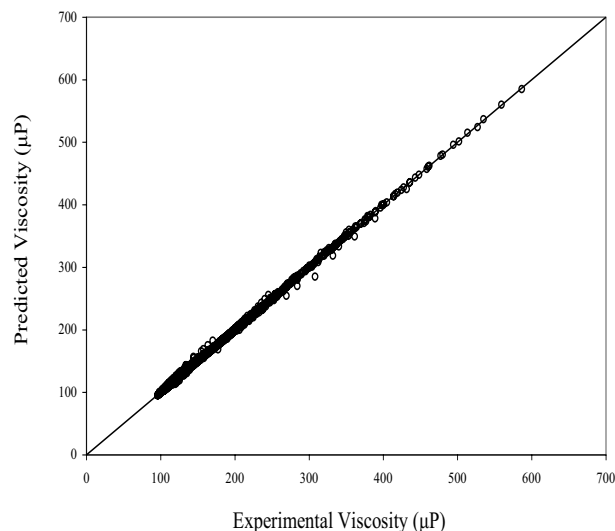

Fig. 4 A Comparison between ANN and experimental data

Also Fig 4 showed the difference between viscosity of experimental data and output of the neural network in range of $0.01 \le P_{pr} \le 21$, $1.01 \le T_{pr} \le 3.0$.

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Fig 5 showed the cumulative frequency of this study correlation versus AARD% of method compared to ADEL, LGE, HMS, CKB, and SNP models.
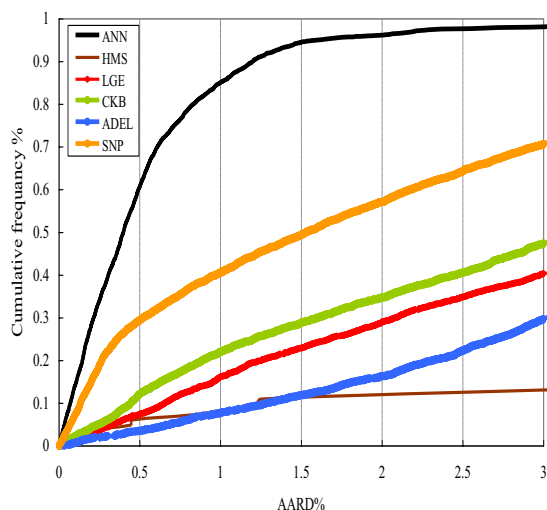

Fig. 5 cumulative frequency of various methods in calculating natural gas viscosity as function of AARD%

According to Fig 3 and by assuming an acceptable engineering error is 5%, ANN is more accurate than five common correlations. This Fig shows accuracy of presented method in prediction of viscosity of the 3841 measurements as compared to other methods discussed in this study. The new method has successfully predicted 85% of the 3841 measurements with AARD% of less than 1%, and 95% of the data with AARD% of less than 1.5%. Only 1% of the 3841 viscosity measurements were predicted with AARD% on the order of 3 to 10% by the new method. SNP, that is the second accurate method, predicted 40% of the viscosity measurements with AARD% of less than 1% and 70% of the measurements with AARD% of less than 3%. And also LGE, that is the third accurate correlation, has less than 1% of AARD to prediction only 20% of the experimental data. Hence the neural network show its priority over all the methods considered in this study.

TABLE II
STATISTICAL PARAMETERS OF THIS STUDY COMPARED TO OTHER METHODS
FOR EXPERIMENTAL DATA POINTS

Methods	AARD%	RMSD%
LGE	4.9428	5.9265
CKB	5.9401	8.1976
ADEL	4.5509	5.7361
HMS	18.8399	28.4532
SNP	2.1269	3.3233
ANN	0.2208	0.0171

The average absolute relative deviation percent (AARD %) and root mean square deviation percent (RMSD %) for each method have been presented in Table II.

TABLE III
AVERAGE ABSOLUTE RELATIVE DEVIATION OF ANN COMPARED TO EMPIRICAL
MODELS

Gas type	ADEL	LGE	HMS	CKB	SNP	ANN	Ref
No.2	2.0279	9.5845	17.407	3.7626	2.4761	0.2274	[14]
No.3	8.6979	3.5062	18.1899	9.2737	1.9253	0.0994	[15]
No.4	4.3753	7.2971	19.8208	9.6398	2.9619	0.1162	[15]
No.5	4.2072	7.5699	19.9511	9.4248	2.487	0.1523	[15]
No.6	2.4419	3.5954	O.R.	8.9967	2.9721	2.0496	[16]
No.7	1.5459	7.7279	O.R.	7.7456	4.7911	0.7616	[17]
No.8	1.3918	10.7704	O.R.	28.2663	4.2566	0.6745	[17]
No.9	1.0207	7.1625	O.R.	7.4375	5.2335	0.4739	[17]
No.10	1.8347	1.9373	O.R.	9.151	2.8555	0.3435	[18]
No.11	4.4431	5.9219	O.R.	12.8676	2.1231	0.139	[18]
No.12	4.9279	4.0761	14.3019	3.545	1.7427	0.1931	[19]-[20]
	4.5509	4.9428	18.8399	5.9401	2.1269	0.2208	

It can be seen from Table II that the ANN model more accurate than empirical models.

Table III reports the average absolute relative deviation (AARD %) of the new correlation compare to the most commonly used empirical models for different natural gas. The Average absolute relative deviation of ANN compared HMS correlation show very large deviations, 14.3%, and has its limitation range for both pressure and temperature that leads to set most of experimental data in out range (O.R.) of calculation. Only 87 data points are able to calculate with HMS correlation. SNP model shows superiority for pure methane substance relative to CKB, ADEL, LGE, and HSM methods. However, all the correlations showed relatively large deviations for these 3841 experimental data and finally the new method has the best accuracy among all mentioned methods for natural gas mixtures.

To estimate the applicability of artificial neural network approach for calculating viscosity of natural gas, the viscosity experimental data of the sample natural gas [15] that are not employed in structure design of ANN are considered and the results of all mentioned methods (ANN, SNP, LGE, ADEL, and CKB) are compared with experimental viscosities and presented in Figs 4 to 6. The composition of this sample mixture is presented in Table IV.

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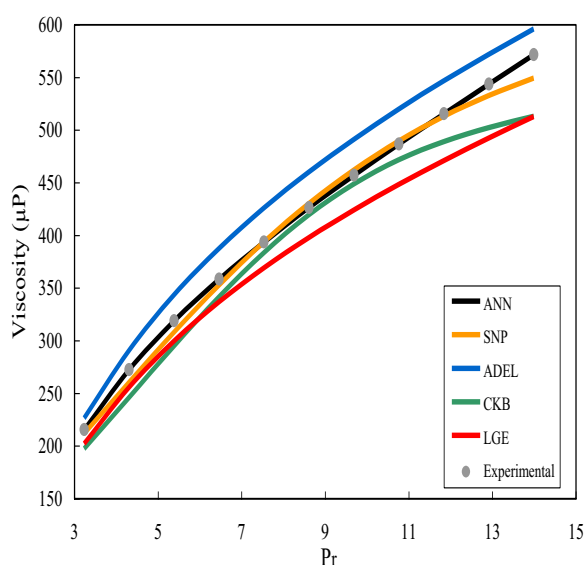International Journal of Chemical and Molecular Engineering
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Fig. 4 Experimental data and results of ANN and other method for
sample mixture in 270K

Figs 4 to 6 are showed experimental and calculated viscosity for all method at different pressures and three temperatures of 270, 300, and 330K respectively.

As shown in Figs 4 to 6, the designed ANN is much more accurate than other empirical methods for prediction of compressibility factors, and there is a very good agreement between experimental data and computed ANN data.
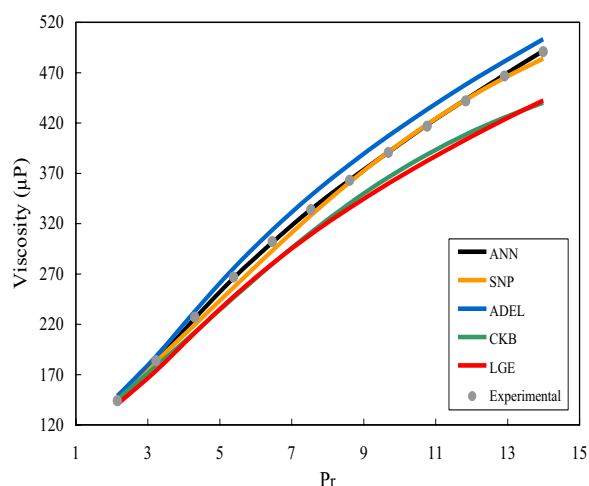

Fig. 5 Experimental data and results of ANN and other method for
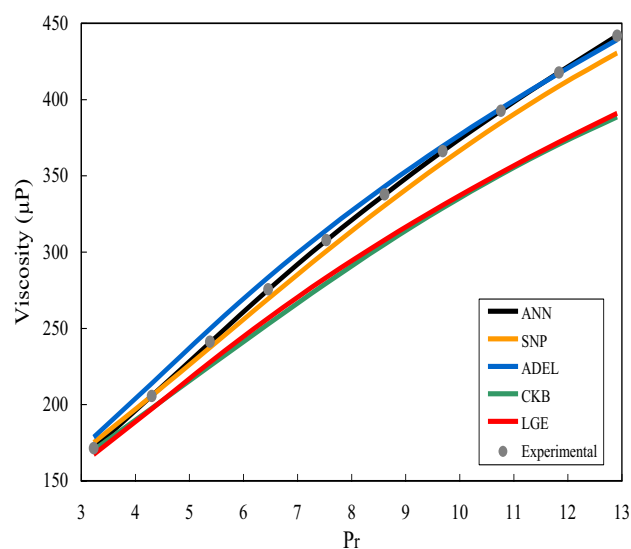sample mixture in 300K

Fig. 6 Experimental data and results of ANN and other method for
sample mixture in 330K

Figs 4 to 6 are showed experimental and calculated viscosity for all method at different pressures and three temperatures of 270, 300, and 330K respectively.

As shown in Figs 4 to 6, the designed ANN is much more accurate than other empirical methods for prediction of compressibility factors, and there is a very good agreement between experimental data and computed ANN data.

IV. CONCLUSION

In this study viscosity of different compositions of natural gas are modeled by using an artificial neural network (ANN) based on LMA algorithm back-propagation method.

TABLE IV
COMPOSITION OF SAMPLE GAS

Component	mol%
methane	0.84990
ethane	0.05529
propane	0.02008
isobutane	0.00401
n-butane	0.00585
isopentane	0.00169
n-pentane	0.00147
n-octane	0.00152
toluene	0.00090
methylcyclopentane	0.00102
nitrogen	0.03496
carbon dioxide	0.02331

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A reliable database of viscosity for testing and training of ANN has been used. The results of the ANN model are compared to the five empirical models. The comparison showed that the designed ANN model can predict viscosity of natural gas mixtures precisely.

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