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Research paper

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Development of a new model to predict gas viscosity using artificial neural networks

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A b s t r a c t

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Reduced temperature,
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Gas density.

Prediction of viscosity of natural gas is an important parameter in the oil and gas industry as it has a major effect on gas engineering calculations including reservoir recovery, fluid flow, deliverability, and storage. Gas viscosity is determined directly by experiment, but if unavailable, predicted by empirical correlations. An accurate prediction of natural gas viscosity is needed in the appropriate design and operation of equipment in industrials and processing.
In this work, by means of an artificial neural network which is a branch of Artificial Intelligence and a powerful tool for prediction, gas viscosity of hydrocarbon mixtures is predicted in a wide range of pressure and temperature. Therefore, different networks with variable layers and neurons in each layer are trained and tested by different training algorithms. Then, the network with minimum error values and maximum rate of convergence is chosen as the best network for gas viscosity prediction. Results showed that the network with two hidden layers trained by the Levenberg-Marquardt training algorithm has an average absolute error of 0.001 for the training and validation data set. This network is chosen as the best network for prediction of gas viscosity using reduced temperature, reduced pressure and gas density as input parameters.

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1. Introduction

Gas properties are considerably different than those of liquids. They are usually pressure and temperature dependent. Thus, any changes in the state of temperature and/or pressure will result in a major effect on gas properties [1]. The physical properties of natural gas and especially their variations with pressure, temperature, and molecular weight are very important in gas engineering

calculations in reservoirs, wellbores, pipelines and facilities. These properties are usually measured by experiments. However, experiments are expensive and time consuming. Thus, they are approximated using equations of state (EOS) or empirical correlations.

Viscosity is an essential property for the study of the dynamics of fluid flow in pipelines, porous media, and etc. Gas viscosity is a measure of the resistance to flow exerted by the gas[2]. Gas viscosity measurement by experiments is a difficult task. Thus, it is estimated using empirical correlations. Typically, the correlations are a function of temperature, pressure and gas composition, and they are corrected for non-hydrocarbon components[3]. Carr et al.'s[4] is considered to be the main correlation in the petroleum industry which was improved later by Dempsey [5], standing [6]and Dranchuk et. al. [7]. Also, Lohrenz–Bray–Clark[8], Dean and Stiel [9], Lee et al. [10], Sutton [11] , Lucas and Londono et al. [12] developed other correlations for gas viscosity prediction. Each equation has its own advantages and limitations that should be considered before using the equation. Some of these limitations include pressure and temperature conditions, gas density and non-hydrocarbon gas components [13, 14].

Besides empirical correlations; recently, by developments in computer technologies, artificial neural networks (ANN) are used to calculate gas viscosity. The main work done for gas viscosity using ANN is by AlQuraishi et al.[14]. In their study, a total of 4445 experimental measurements were used constituting 1853 pure gases and 2592 gas mixtures. In their model, viscosity was predicted as a function of gas density, pseudo reduced pressure, and pseudo reduced temperature. The networks prediction was validated and their efficiencies were tested against some other correlations. The comparison indicated a better performance for the developed neural networks compared to the conventional tested correlations [14]. Thus, ANN is an easy and efficient tool for modeling gas viscosity in a large domain of pressure and temperature.

In this work, hydrocarbon gas viscosity is predicted by AANs using a large database of gas properties. Thus, different networks with various structures are trained and tested by different training algorithms. Then, the network with minimum error values and maximum rate of convergence is chosen as the best network for gas viscosity prediction. Then, the efficiency of the selected network is tested against some empirical correlations.

2. Artificial neural networks

Artificial neural networks are powerful tools for the approximation of unknown nonlinear functions and have gained wide applications in a variety of fields. They have been used to solve complex problems that are difficult or even impossible to be solved by the conventional approaches[15].

Petroleum engineering applications of ANNs include areas such as well-test analysis, well-log interpretation, field development, reservoir characterization, formation damage, production, and drilling [16, 17].

There are many different neural network types, differing by their network structure and/or learning algorithm. ANNs are composed of many simple elements called neurons that are interconnected by links to determine an empirical relationship between the inputs and outputs of a given system. The neurons in each layer are usually fully interconnected with neurons from neighboring layers[15].

Consider a neural network with M layers, where the first layer is named input layer, the last layer named output layer, and the others named hidden layers. The number of hidden layers and neurons in each layer is determined iteratively. Basic components of a neuron are presented in figure 1. As shown, a neuron has two components: (1) a weighted summer which performs a weighted summation of its inputs, i.e., s =∑WiXi + b, where X1, X2,. . ., Xn are input parameters, W1, W2, …, Wn are weighting parameters and b is the bias of the neuron; and (2) a linear, nonlinear or logic function which gives an output corresponding to s, i.e. a=f(s). The weights and biases of the network are iteratively adjusted by training the network to minimize the network error function. The training process is done by different algorithms such as quick propagation, back propagation, Conjugate Gradient, etc. The trained network can be used to predict the unknown output of some input[15].

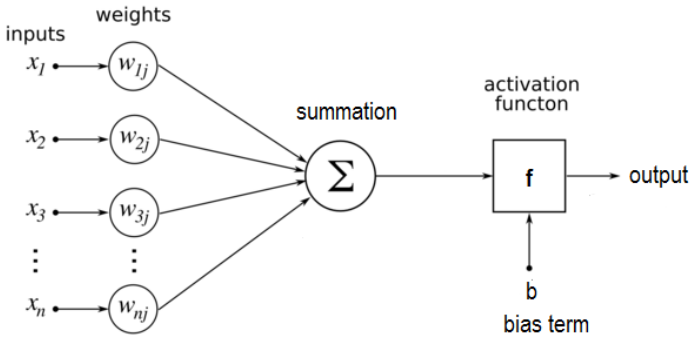

Fig.1: Basic components of a neuron

3. Model construction

3.1. Data preparation

In this work, a large database of measured gas properties consisting of 2083 set of data is used for training and validation of the proposed model. The data is for hydrocarbon gas mixtures containing methane and heavier components with various mole fractions. The database includes gas composition, viscosity, density, temperature, pressure, pseudo reduced properties of pressure and temperature, and the compressibility factor. Since the main parameters contributing to gas viscosity

include temperature, pressure, gas composition and specific gravity, a sensitivity analysis was carried out to define the important parameters in the gas viscosity model. This sensitivity analysis showed that reduced temperature, reduced pressure and gas density are the main parameters that should be considered as the input parameters of the neural network. Table 1 shows the range of input and output parameters of the model. To build the model, the dataset was normalized between 0 and 1. Then, 68 % of the dataset was selected randomly for training, 16% for validation and the rest of the data was selected for testing the model.

Table1: Ranges of data base fed into ANN

Property	min	max
Pseudo Reduced Temperature	0.774	**2.682**
Pseudo Reduced Pressure	0.022	**17.788**
Density (g/cc)	0.00038	**0.758**
Viscosity (cp)	0.0075	**0.228**

3.2. Building and training the network

After data preparation, these data were used to build the neural network model. Multiple layer perceptron neural networks with one, two and three layers and variable neurons in hidden layers were trained by the data bank; and the network with least Average Absolute Error was chosen as the best network. Table 2 shows the best network structures with different hidden layers. In these networks, the transfer function is logistic function1 for all layers. The networks are trained by different training algorithms and the best ones are chosen. Figure 2 is a schematic of the chosen networks.

Table2: Three different design types of ANN

No.	No. of hidden layers	Neurons in 1st hidden layer	Neurons in 2nd hidden layer	Neurons in 3rd hidden layer
1	1	8	-	-
2	2	8	4	-
3	3	8	5	3

[1] $F(x) = 1/(1+e^{-x})$

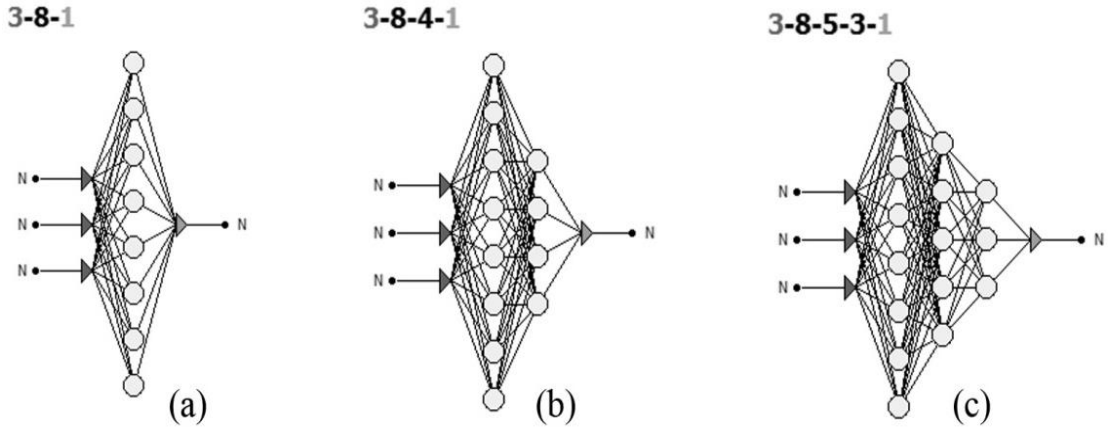

Fig.2 : Schematic of network structures: (a) one hidden layer (b) two hidden layer (c) three hidden layer

4. Results and discussion

After initial analysis of various network structures and choosing the best structures, they are trained by different training algorithms including Quick propagation (QP), Conjugate gradient descent (CGD), Quasi-Newton (QN), Levenberg-Marquardt (LM) and Back propagation (BP). Training results are presented in table 3. A comparison of the training algorithms shows that the Levenberg-Marquardt algorithm has the least training and validation error with a greater correlation coefficient. Also, the networks trained by this algorithm converged rapidly by fewer iterations. Thus, this algorithm was chosen as the best training algorithm.

Table1: Results of network structures with different training algorithms

Network structure	Training algorithm	Iterations	AAE[2] for training data	AAE for validation data	Correlation Coefficient
[3-8-4-1]	Quick Propagation	1235	0.00100	0.00128	0.99910
[3-8-4-1]	Conjugate Gradient Descent	711	0.00102	0.00123	0.99919
[3-8-4-1]	Quasi-Newton	159	0.00099	0.00115	0.99924
[3-8-4-1]	Limited Memory Quasi-Newton	504	0.00100	0.00118	0.99921
[3-8-4-1]	Levenberg-Marquardt	16	0.00099	0.00103	0.99927
[3-8-4-1]	Online Back Propagation	21109	0.00121	0.00141	0.99912
[3-8-4-1]	Batch Back Propagation	4563	0.02569	0.02540	0.89482
[3-8-5-3-1]	Quick Propagation	1808	0.00100	0.00134	0.99918
[3-8-5-3-1]	Conjugate Gradient Descent	683	0.00100	0.00122	0.99925
[3-8-5-3-1]	Quasi-Newton	390	0.00100	0.00128	0.99924
[3-8-5-3-1]	Limited Memory Quasi-Newton	691	0.00100	0.00118	0.99926
[3-8-5-3-1]	Levenberg-Marquardt	29	0.00099	0.00124	0.99931
[3-8-5-3-1]	Online Back Propagation	31356	0.00114	0.00134	0.99916
[3-8-5-3-1]	Batch Back Propagation	2035	0.02588	0.02558	0.79942
[3-8-1]	Quick Propagation	2395	0.00100	0.00124	0.99916
[3-8-1]	Conjugate Gradient Descent	194	0.00100	0.00130	0.99909
[3-8-1]	Quasi-Newton	246	0.00099	0.00135	0.99918
[3-8-1]	Limited Memory Quasi-Newton	729	0.00100	0.00122	0.99919
[3-8-1]	Levenberg-Marquardt	21	0.00100	0.00113	0.99925
[3-8-1]	Online Back Propagation	26935	0.00133	0.00160	0.99891
[3-8-1]	Batch Back Propagation	26056	0.00497	0.00518	0.97694

[2] Average Absolute Error

Table 4 presents results of training the networks by the LM algorithm. Results indicate that all the networks have a good estimate of gas viscosity. A comparison of results shows that the network with two hidden layers has the least error for training and validation data.

Table2: Error values of ANNs by LM algorithm

Network No.	Architecture	Iterations	Training Error			Validation Error		
			MSE[3](*10^{-6})	AAE	AARE[4]	MSE(*10^{-6})	AAE	AARE
1	[3-8-1]	21	1.56	0.00099	0.03292	7.55	0.00112	0.03722
2	[3-8-4-1]	16	1.53	0.00098	0.03323	1.86	0.00102	0.03217
3	[3-8-5-3-1]	29	1.44	0.00099	0.03297	21.7	0.00123	0.04339

In order to examine the accuracy of the model, the neural network efficiency was tested against two empirical correlations developed by Lee *et al.* and Sutton. Results of empirical correlations are presented in table 5. Comparison between empirical correlations and ANN results shows that the ANN model is quite efficient in gas viscosity prediction. The error values for the ANN model and Lee's correlation are almost the same and both of them have better results than Sutton's model. Thus the model developed here can be used for prediction of gas viscosity.

Table 3: Error value of empirical correlations

No.	Correlation	Error	
		AAE	AARE
1	Lee	0.00174	0.03328
2	Sutton	0.00543	0.11264

Figures 3 to 5 present the scatter diagram of the experimental gas viscosity versus computed results obtained from the ANN and from the other correlations. If all the data points fall on the 45-degree line, the calculated results are in perfect agreement with the experiments. As shown, the ANN model and Lee's correlation have acceptable results versus experimental data. Also, it is observed that predicted gas viscosity is close to the actual value in all regions. Thus, the ANN model can be used for gas viscosity prediction in the entire domain of input data.

[3] Mean Square Error
[4] Average Absolute Relative Error

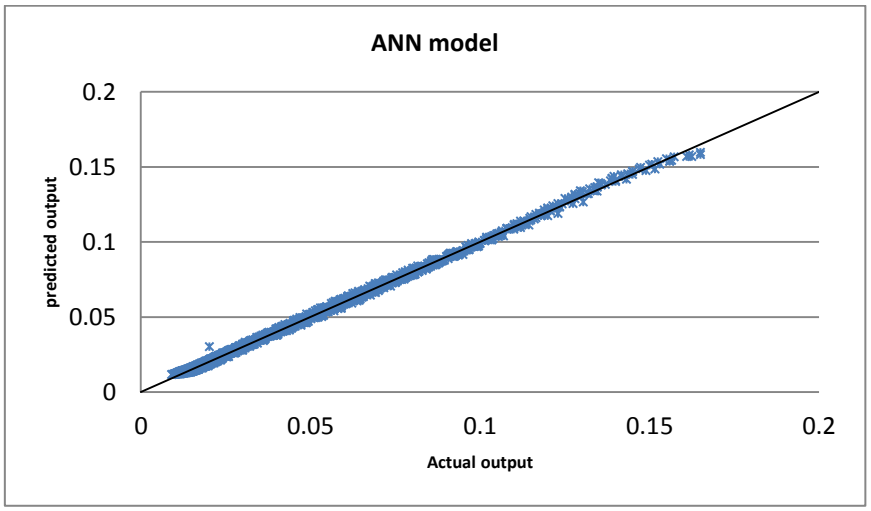

Fig.3: Comparison between estimated vs. experimental data (ANN model)

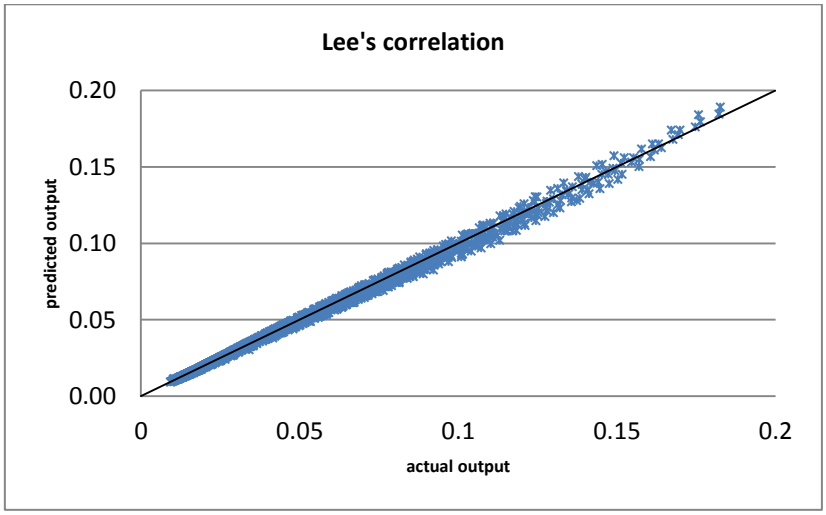

Fig. 4: Comparison between estimated vs. experimental data (Lee's correlation)

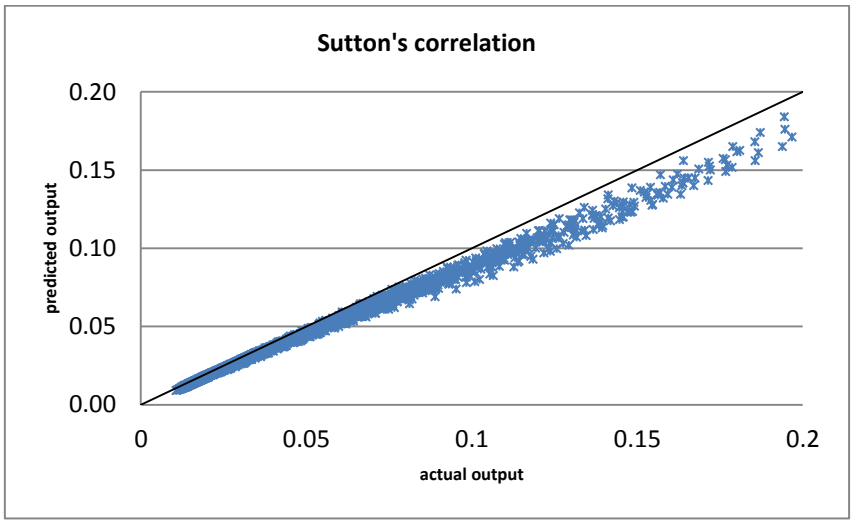

Fig.5: Comparison between estimated vs. experimental data (Sutton's correlation)

Furthermore, in order to show that the model developed here is physically correct, the ANN was subjected to intermediate data points. This was done by studying the dependence of gas viscosity on a single input parameter while maintaining the others constant. In this study, as density is a function of Ppr, Tpr and molecular weight, it could not be considered constant while changing pressure and temperature. Thus, the molecular weight is considered constant instead of density; and sensitivity analysis is done by pseudo reduced temperature and pseudo reduced pressure. Figures 6 to 8 compare the dependence of gas viscosity on reduced pressure for three different temperatures, obtained by the ANN and the two other correlations for a specific molecular weight. Figure 9 shows the effect of temperature on gas viscosity for different pressures obtained by the ANN model. These figures show that gas viscosity is an increasing function with respect to pressure and temperature which is physically correct. Hence the ANN predictions for gas viscosity are correct.

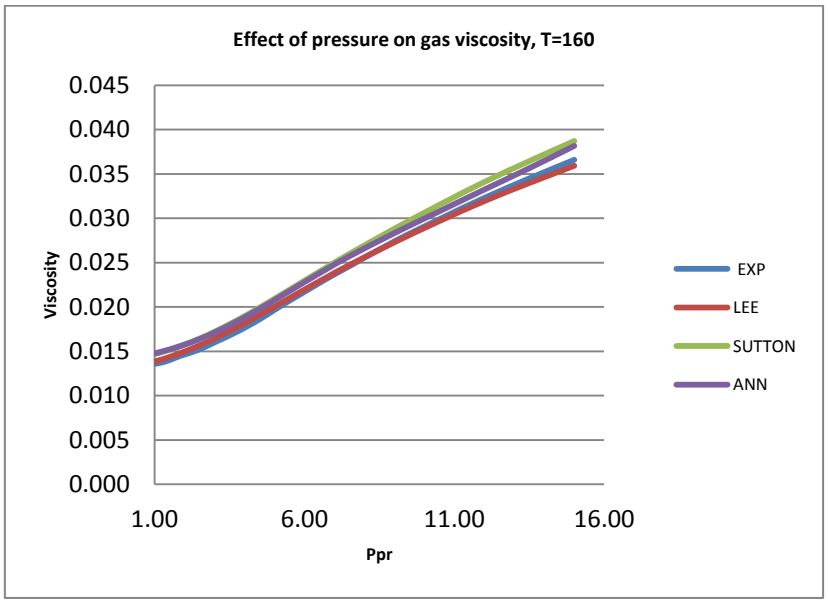

Fig.6: Effect of reservoir pressure on gas viscosity at T=160 $_{o}$ F

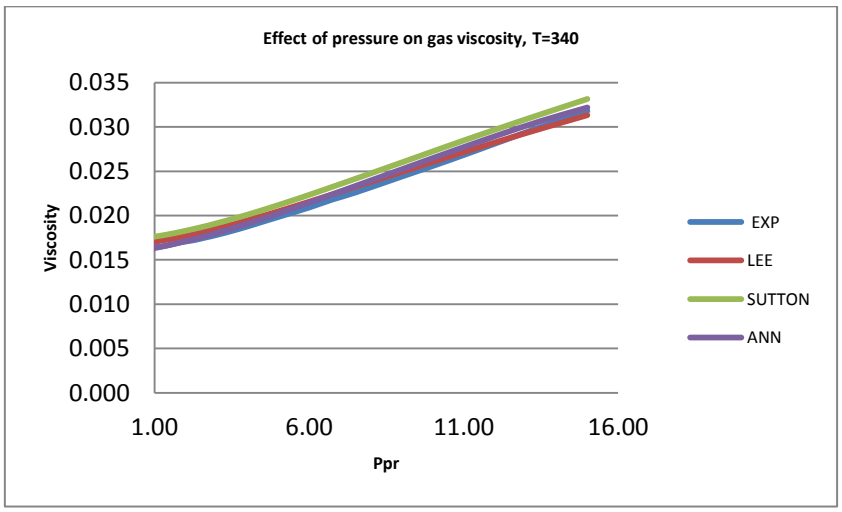

Fig.7: Effect of reservoir pressure on gas viscosity at T=340 $_{o}$ F

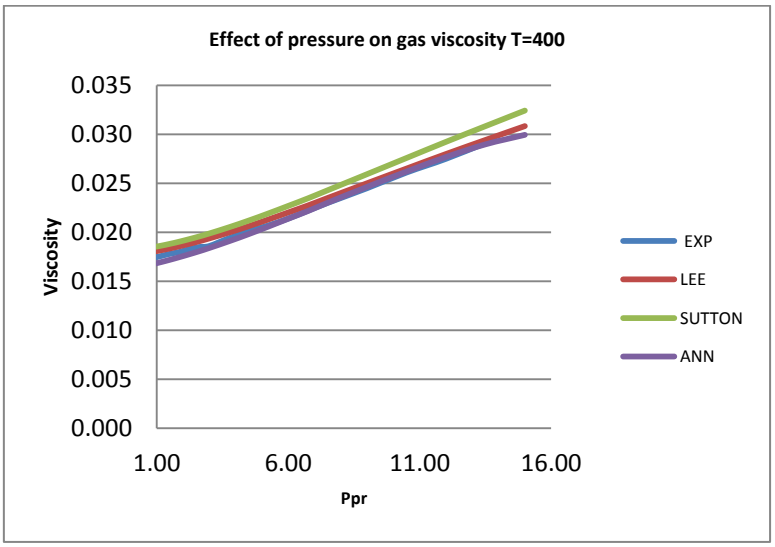

Fig.8: Effect of reservoir pressure on gas viscosity at T=400 $_{o}$ F

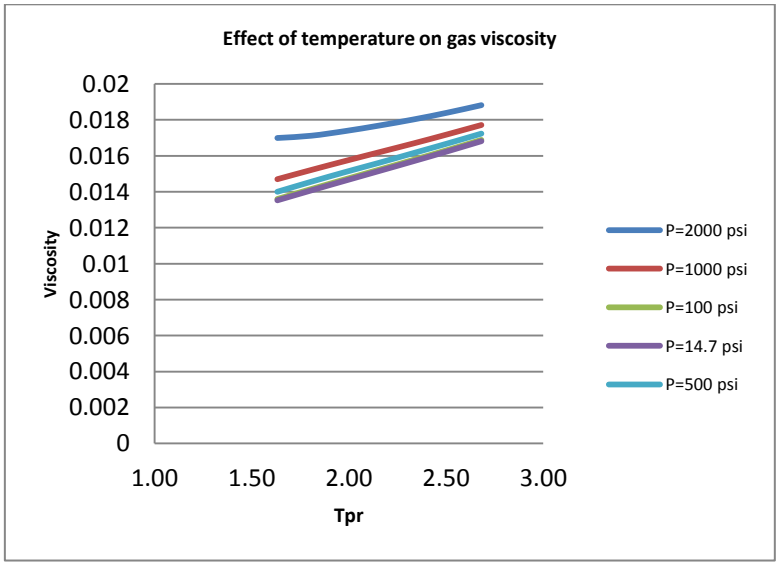

Fig.9: Effect of temperature on gas viscosity for different pressures

5. Conclusion

In this work, viscosity of hydrocarbon gas mixtures is predicted by the artificial neural network using a large data base of experimental data. Thus, the multilayer perceptron neural network with different layers and variable neurons in each layer and different training algorithms are investigated and the best network is chosen:

i- Sensitivity analysis of input parameters showed that gas viscosity of hydrocarbon mixtures can be predicted using reduced temperature, reduced pressure and gas density.

ii- A comparison of the training algorithms indicated that the Levenberg-Marquardt algorithm has the least error value with a greater convergence rate. Thus, the networks converged with less iteration.

iii- The neural network with two hidden layers and 3-8-4-1 structure trained by the Levenberg-Marquardt training algorithm has an average absolute error of 0.001 for the training and validation data set and was chosen as the best network for hydrocarbon gas viscosity prediction.

iv- Results of the ANN method are compared with two empirical correlations and it is shown that proposed method can predict gas viscosity better than those empirical correlations.

v- The scatter plot of predicted values vs. actual values shows that this model can be used for prediction of gas viscosity in the entire domain of input parameters.

vi- Sensitivity analysis of the input parameters on the output showed that the model's predictions are physically correct and reliable.

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Abbreviations

The abbreviations used in the manuscript are as follow:

EOS: Equation of state

ANN: Artificial Neural Network

AAE: Average Absolute Error

AARE: Average Absolute Relative Error

BP: Back propagation algorithm

CGD: Conjugate gradient descent algorithm

LM: Levenberg-Marquardt algorithm

MSE: Mean Square Error

QP: Quick propagation algorithm

QN: Quasi-Newton algorithm

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