Determination of Minimum Miscibility Pressure in Gas Injection Process by Using ANN with Various Mixing Rules

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Abstract
Miscible gas injection is one of the most effective enhanced oil recovery techniques and minimum miscibility pressure (MMP) is an important parameter in miscible gas injection processes. Accurate determination of this parameter is critical for an adequate design of injection equipments project investment prospect. The purpose of this paper is to develop a new universal artificial neural network (U-ANN) model to predict the minimum miscibility pressure of CO_2 and hydrocarbon gas flooding. Different MMP correlations and models have been proposed regarding the type of injection gas and the mechanism of miscibility, respectively based on mathematical and thermodynamic calculations. Almost all the correlations proposed in the literature either represent condensing /vaporizing mechanisms or give reasonable results only in a limited range of data they are based on. A new model is introduced by taking into consideration both condensing and vaporizing mechanisms and by using a wider range of data. Experimental data from different crude oil reservoirs carried out by slim tube test have been applied in order to propose a new model. Mixing rules are used to decrease independent variables. The significance of this model is that MMP can be determined for any composition of oil and gas, no matter which mechanism is dominant in achieving miscibility. Comparing the percentage error of this model to those of the previous literature data showed that the results obtained from the new MMP model are more accurate and universal than most common correlations available.
Keywords: Minimum miscibility pressure (MMP), Gas injection, Neural network, Mixing rules, Critical property, Slim tube

1. Introduction
In recent years, much attention has been devoted to enhanced oil recovery. Enhanced oil recovery includes many techniques. Miscible gas injection is one of the most effective methods. An effective parameter in miscible gas injection process is minimum miscibility pressure (MMP). MMP is the minimum pressure at which the injected gas can attain dynamic miscibility with the reservoir oil [1-3]. The reservoir to which the process is applied ought to be operated at or above the MMP in order to develop multi contact miscibility. Reservoir pressures below the MMP are reported to cause immiscible displacements and consequently lower oil recoveries. A considerably high operating level of MMP may result in inflated process costs. On the other hand, if the predicted MMP is too low, the miscible displacement process may become useless, leading to a high possibility of the process malfunction. Thus, accurate estimation of MMP would bring significant economic benefits [4]. A number of methods have been suggested for measurement of the MMP. Slim tube displacement experiments are among the most frequently used experimental methods [5]. While experimental details are considerably various, the fundamental approach is to establish a nearly one-dimensional flow in which gas displaces oil with the outlet pressure held constant [6]. A series of displacements are performed at rising pressures, and the fraction of oil recovered (typically at 1.1 or 1.2 pore volumes of gas injection) is measured. The MMP is usually taken to be a pressure above which recovery exceeds some specified values (often 90%); however, different investigators have adopted different criteria to determine the MMP from measurements of recovery.
The rising-bubble-apparatus (RBA) approach (developed in the early 1980s) is generally recognized as a capable method to determine gas–oil MMP [7]. Zho and Orr (1997) deduced that the rising bubble experiment is mainly a scrutiny of the effects of changes in interfacial tension (IFT) on bubble shapes as the components in the bubble dissolve in the oil and components in the oil transfer to the bubble [8]. They concluded that rising bubble experiments could be used to measure the MMP for vaporizing gas drives but are less accurate for condensing gas drives, while an experiment that makes use of a drop of oil falling through gas could be used for condensing gas

drives. An experimental method which determines the density of the injection gas rich upper phase in contact with stock tank oil as a function of pressure was described for measuring gas–oil MMP at low temperatures below 50 ^{o}C [9]. An alternative approach utilizes the pressure at which the pure solvent reaches liquid-like densities [10]. This is achieved by extrapolating the vapor pressure curve of the solvent. Rao and Lee (2002), and Orr and Jessen (2007) reported that straight measuring interfacial tension of an oil–solvent mixture at reservoir conditions could provide a quick means of determining MMP [6,11].Experimental methods for MMP measurements are very costly and time consuming; therefore development of a highly accurate approach for determination of natural gas– oil MMP is usually required. To facilitate screening procedures and to gain insight into the miscible displacement process, many correlations have been proposed relating the MMP to the physical properties of the oil and displacing gas.

From the literature review, pure CO2–oil MMP correlations have been reported in Cronquist [12], Lee [13], Holm and Josendal [14], and Emera and Sarma [18]. On the other hand, impure CO2–oil MMP correlations have been reported in Kovarik [19], Alston et al. [15], Sebastian et al. [20], Eakin and Mitch [21], Dong [22], and Emera and Sarma [23]. In addition, pure or impure CO2–oil MMP correlations have been reported in Johnson and Pollin [24], Orr and Silva [25], Enick et al. [26], and Yuan et al. [27].However, the main concern with statistical techniques such as multiple linear and nonlinear regression techniques is the difficulties in satisfying many strict assumptions that are essential to justifying their applications, such as those of sample size, linearity, and continuity [17]. Therefore, nonlinear modeling techniques such as artificial neural networks are necessary for building a precise and reliable predictive model. Additionally, when artificial neural networks are used for prediction and forecasting, the underlying idea is similar to that used in traditional statistical approaches. In both cases, the unknown model parameters (i.e. the connection weights in the case of ANNs) are adjusted in order to obtain the best match between a historical set of model inputs and the corresponding outputs. Therefore, ANNs and statistical models are closely related. Consequently, the principles considered acceptable practices in the development of statistical models usually need careful attention. The main areas that should be addressed include data pre-processing, choice of adequate model inputs, choice of an appropriate network geometry, parameter estimation, and model validation.

2. Problem definition

Miscible gas flooding is widely employed for improving or enhancing oil recovery for many oil reservoirs. A key parameter used for assessing the applicability of the process for a reservoir is the minimum miscibility pressure. Therefore, accurate prediction of minimum miscibility pressure is of utmost importance. There are many components in oil and gas-injected compositions which all of them are directly effective in MMP and are considered as independent variables in the proposed model. This data exists in PVT test reports. An attempt was made in this study to investigate the application of a neural networks concept for prediction of MMP in a gas injection process and establish a proper relation between independent and dependent variables. Of course, artificial neural network was used before while some independent variables (not all variables) were applied directly. However, the outstanding feature of this study is coupling mixing rules to benefit from all variables properties and then applying artificial neural network to simulate slim tube apparatus accurately.

3. Theoretical background

A neural network is a powerful data modeling tool that is able to capture and represent complex input/output relationships. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain. Neural networks resemble the human brain in the following two ways:

1. A neural network acquires knowledge through learning.
2. A neural network's knowledge is stored within inter-neuron connection strengths known as synaptic weights.

The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships as well as to learn such relationships directly from the data being modeled. Traditional linear models are simply inadequate when it comes to modeling data that contains nonlinear characteristics. A neural network is a system of simple processing elements, called neurons, which are connected to a network by the architecture of the network, the magnitude of the weights and the processing element’s mode of operation. The neuron is a processing element that takes a number of inputs(p), weights them(w), sums them up, adds a bias (b) and uses the results as the argument for a singular valued function (f), which results in the neurons output (a) [29].

The knowledge of the neural network is encoded in the values of its weights. The task of determining the weights is called training and is basically a conventional estimation problem. For this purpose, the back propagation strategy has become the most frequently used method that tends to reasonable answers [17].

The training function in this work updates weight and bias values according to Levenberg-Marquardt back-propagation optimization. Moreover, training occurs according to the function's training parameters.

4. Implementation

4.1 Mixing-rules method

The direct application of mixing rules to the corresponding states principle (CSP) correlations to describe mixtures assumes that the behavior of a mixture in a reduced state is the same as some pure components in it. When the reducing parameters are critical properties and are made functions of composition, they are called pseudo critical properties because the values are not generally expected to be the same as the true mixture critical properties. Thus the assumption in applying corresponding states to mixtures is that the PVT behavior will be the same as that of a pure component whose T_c and P_c are equal to the pseudo-critical temperature, T_{cm}, and pseudo-critical pressure of the mixture, P_{cm}, and other CSP parameters such as acentric factor can also be made adequately composition-dependent for reliable estimation purposes.

Thus, for the pseudo-critical temperature, T_{cm}, the simplest mixing rule is a mole fraction average method (Equation 1). This rule, often called one of the Kay's rules (Kay, 1936), can be satisfactory.

$$T_{cm} = \sum_{i=1}^{n} y_i T_{ci} \tag{1}$$

For the pseudo-critical pressure, P_{cm}, a mole-fraction average of pure-component critical pressures is normally unsatisfactory. This is because the critical pressure for most systems goes through a maximum or minimum with composition. The only exceptions are when all components of the mixture have quite similar critical pressures and/or critical volumes. Equation 2 shows the simplest rule which can give acceptable P_{cm} values for two-parameter or three-parameter CSP is the modified rule of Prausnitz (1958) [31].

$$P_{cm} = \frac{Z_{cm} R T_{cm}}{V_{cm}} = \frac{(\sum_{i=1}^{n} y_i Z_{ci}) R (\sum_{i=1}^{n} y_i T_{ci})}{\sum_{i=1}^{n} y_i V_{ci}} \tag{2}$$

Where all the mixture pseudo-critical Z_{cm}, T_{cm}, and V_{cm} are given by mole-fraction averages (Kay's rule) and R is the universal gas constant. For three-parameter CSP, the mixture pseudo acentric factor is commonly given by a mole fraction average (Equation 3).

$$\omega_{cm} = \sum_{i=1}^{n} y_i \omega_{ci} \tag{3}$$

While no empirical binary (or higher order) interaction parameters are included in equations (1) to (3), good results may be obtained when these simple pseudo-mixture parameters are used in corresponding-states calculations for determining mixture properties [31].

4.2. Factors affecting gas–oil MMP

The key factors affecting gas–oil MMP are reservoir temperature, reservoir fluid composition, and composition of injected gas [3,4,15,18,20,24]. The reservoir temperature has a considerable effect on gas–oil MMP; as the temperature increases, the MMP increases and vice versa [16]. Rathmell, et al., (1971) stated that the existence of volatile components, such as methane in the crude oil leads to the increase of the gas–oil MMP, while the presence of intermediates C_2 to C_6 can reduce the gas–oil MMP [32]. Metcalfe and Yarborough (1974) argued that any gas–oil MMP correlation should take into account the presence of light ends and intermediates in the crude oil [33]. Alston, et al., (1985) in their experimental slim-tube tests showed that the oil recovery decreases at gas breakthrough and the resulting gas–oil MMP increases by improving the ratio between the amounts of volatiles to intermediates in the crude oil composition. In addition, Alston, et al. stated that molecular weight of C_5^+ is better for the correlation intention than the oil API gravity [15]. Also, Cronquist (1978) used the temperature and molecular weight of C_5^+ as correlation parameters as well as the volatile mole percentage of C_1 and N_2 in the crude oil. In addition, the presence of non-CO_2 components (e.g., C_1, H_2S, N_2, or intermediate hydrocarbons components such as C_2, C_3, and C_4) in the injected gas brings about a big effect on the gas–oil MMP, either increasing or decreasing it contingent on the component type [15]. As a general rule, the presence of H_2S or intermediate hydrocarbon components in the injected gas lessens the gas–oil MMP, while the presence of C_1 or N_2 in the injected gas considerably increases the gas–oil

MMP [18]. Nitrogen from flue gas and C_1 from re-injected CO_2 are the large possible impurities to CO_2 and the recycled CO_2. The severance of such components from the injected gas is hard and expensive. The present tendency is to apply the flue gas stream without purification in the injected gas stream.

Indeed, the existence of non- CO_2 components (e.g., H_2S, SO_x, and C_2–C_4) with critical temperatures higher than that of CO_2 (31°C) causes an improvement in the solubility of the injected gas in reservoir oil [22]. This results in an increased injected-gas pseudo-critical temperature and a lower MMP. On the other hand, the existence of components (e.g., N_2, O_2, and C_1) with lower critical temperatures causes a reduction in the solubility of the injected gas in reservoir oil and produces the opposite effect.

Wilson (1960) stated that the pseudo-critical temperature of the injected gas affects MMP, and it could be used as a parameter in a miscibility correlation [33]. Likewise, Rutherford (1962) found, empirically, that the hydrocarbon gas/oil MMP in hydrocarbon miscible floods is a function of the injected-gas pseudo-critical temperature at a constant pressure [34]. Jacobson (1972) also suggested a similar scheme of using the pseudo-critical temperature as a correlation parameter for acid gases (CO_2 with H_2S)/oil MMP prediction. However, instead of using actual values, apparent critical temperatures were used for non-hydrocarbon components as correlation parameters [35]. Alston, et al. followed a similar approach to correlate impure CO_2/oil MMP using the injected-gas pseudo-critical temperature, where apparent critical temperatures for C_2 and H_2S components (51.67°C) were also used to determine the pseudo-critical temperature with the weight-fraction mixing rule. They found that the weight-fraction mixing rule provided better results than the mole-fraction method [15]. Similarly, Kovarik (1985) presented a correlation that is also based on the pseudo-critical temperature. In addition to the weight-fraction mixing rule, he used the mole-fraction rule to determine the pseudo-critical temperature and found that the two methods presented similar results [19].

Moreover, Sebastian, et al. (1985) also used the mole-fraction mixing rule to determine the injected-gas pseudo-critical temperature in developing their impure CO_2/oil MMP correlation. They also used an apparent critical temperature (51.67°C) for H_2S [20]. Dong (1999) presented a similar approach to that of Sebastian, et al., but instead of using apparent critical temperatures, he used a factor with non-CO_2 components (H_2S, SO_2, N_2, and C_1) in determining the injected-gas pseudo-critical temperature to represent the strength of these components in changing the apparent critical temperature of the injected impure CO_2 relative to pure CO_2 [22].

4.3. A method for decreasing the number of input variables

Due to the existence of pseudo components in oil composition and its effect on MMP, critical property of this component must be initially determined. There are several correlations for estimating the critical property of pseudo component. Most of these correlations use specific gravity and molecular weight as a correlation parameter [36]. Boozarjomehry, et al. (2005) showed Riazi - Dobert and Twu correlations are more matched with experimental data among the present correlations to estimate the pseudo component critical temperature [37].

The present study considers 27 independent variables as oil composition, pseudo component property in oil (specific gravity and molecular weight), injected gas composition and reservoir temperature. So this algorithm is used to decrease the input variables as well as to increase the neural network efficiency.

1- Weight / mole fraction mixing rules are used to decrease the input variables.

2- Critical temperature and critical acentric factor of mixture are used as pseudo component variables.

3-Riazi – Dobert and Twu correlation are applied to estimating C_7^+ critical temperature and Lee Kesler correlation are used to estimating C_7^+ critical acentric factor.

4- H_2S and C_2 Critical temperature are considered both apparent and actual.

5- Parameters T_{ro} and T_{rg} are used to dimensionless pseudo critical temperature oil and gas, and are applied instead of such variables (T_{cmix_Oil} and T_{cmix_Gas}) in some data sets generated. These parameters are defined in equations 4 & 5.

$$T_{ro} = T_{cmix\_Oil} / T_{Reservoir} \quad (4)$$

$$T_{rg} = T_{cmix\_Gas} / T_{Reservoir} \quad (5)$$

Therefore, taking the above mentioned statements into consideration helps to generate 16 data sets the details for each being showed in table 1.

Table1- Considerations taken in generating different data sets

Method No.	Mixing Rule	C_7^+ Critical Temperature Correlation	Actual / Apparent Critical Temperatures for C_2 and H_2S	T_{ro} and T_{rg} as Input Variables
Data Set 1	Mole Fraction	Riazi & Daubert	Actual	No
Data Set 2	Mole Fraction	Twu	Actual	No
Data Set 3	Weight Fraction	Riazi & Daubert	Actual	No
Data Set 4	Weight Fraction	Twu	Actual	No
Data Set 5	Mole Fraction	Riazi & Daubert	Actual	Yes
Data Set 6	Mole Fraction	Twu	Actual	Yes
Data Set 7	Weight Fraction	Riazi & Daubert	Actual	Yes
Data Set 8	Weight Fraction	Twu	Actual	Yes
Data Set 9	Mole Fraction	Riazi & Daubert	Apparent	No
Data Set 10	Mole Fraction	Twu	Apparent	No
Data Set 11	Weight Fraction	Riazi & Daubert	Apparent	No
Data Set 12	Weight Fraction	Twu	Apparent	No
Data Set 13	Mole Fraction	Riazi & Daubert	Apparent	Yes
Data Set 14	Mole Fraction	Twu	Apparent	Yes
Data Set 15	Weight Fraction	Riazi & Daubert	Apparent	Yes
Data Set 16	Weight Fraction	Twu	Apparent	Yes

4.4. Neural network principles and advantages

Artificial neural network (ANN) is defined as a powerful data modeling tool that is able to capture and represent complex input/output relationships. The true power and advantage of neural networks lies in their ability to represent both linear and non-linear relationships as well as to learn such relationships directly from the data being modeled. Traditional linear models are simply inadequate when it comes to modeling data that contain nonlinear characteristics. The knowledge of the neural network is encoded in the values of its weights. The task of determining the weights is called training and is basically a conventional estimation problem. For this purpose, the back propagation strategy has become the most frequently used method that tends to yield reasonable answers. The training function updates weight and bias values according to the Levenberg-Marquardt back-propagation optimization. [29].

4.5. Developing the gas–oil MMP Model

The choice of a specific class of network for the simulation of a nonlinear system of variables depends on a variety of factors such as the accuracy desired and the prior information concerning the input-output pairs. Feed forward neural network was assumed for all the runs. Feed forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons [29].

The structure of the neural network is constructed in a way that the difference between the predicted and observed (actual) values in the output vector is as small as possible. The most successful ANN architecture is the one that has the smallest prediction error on a data set for which it was not trained or the one with the least difference between the correlation coefficients (R) of the training set and the testing set [17]. The total number of data utilized in this work is 128. In this study various neural network architectures were investigated in order to obtain desired models for predicting MMP as a function of selected input variables. Different models on the number of hidden layers as well as the number of neurons in each hidden layer were also analyzed (table 2).

Finally, the architecture of the neural network model was optimized by applying different amounts of hidden neurons. In this study, a one-hidden layer and two- hidden layer feed-forward back propagation network is created.

The first and second hidden layers have TANSIG neurons. TANSIG is the "hyperbolic tangent sigmoid transfer function". It calculates the output of a layer from its net input. The hidden layers have weights coming from the input. Each subsequent layer has a weight coming from the previous layer. Both layers have biases. The last layer is the network output.

Since the neural networks use neurons that can be trained, the universality of the model depends on the number and range of data. As the number and range of data increases, the universality of the model shall also increase. Table 3 shows the range on input data wider than other models.

Table 2 - Different neural networks models.

Model no.	No. of Layer	No. of Neurons in hidden layer 1	No. of Neurons in hidden layer 2
Model 1	1	2	-
Model 2	1	5	-
Model 3	1	10	-
Model 4	1	20	-
Model 5	1	30	-
Model 6	1	40	-
Model 7	1	50	-
Model 8	1	60	-
Model 9	2	3	2
Model 10	2	5	5
Model 11	2	10	5
Model 12	2	15	5
Model 13	2	10	10
Model 14	2	25	5
Model 15	2	20	10
Model 16	2	15	15
Model 17	2	35	5
Model 18	2	30	10
Model 19	2	20	20
Model 20	2	30	20

Table 3 - Input variables range.

Component	Oil compassion (Mole %)		Gas compassion (Mole %)	
	Lower limit	Upper Limit	Lower limit	Upper Limit
N2	0.00	1.25	0.00	19.00
H2S	0.00	2.32	0.00	50.00
CO2	0.00	15.57	0.00	100.00
C1	4.07	56.86	0.00	100.00
C2	0.75	46.83	0.00	20.00
C3	0.30	12.39	0.00	45.70
iC4	0.19	3.20	0.00	10.00
nC4	0.00	6.46	0.00	17.88
iC5	0.01	2.45	0.00	1.70
nC5	0.00	3.77	0.00	4.76
C6	0.00	7.35	0.00	3.00
C_7^+	16.59	80.75	0.00	5.09*
SpGr (C_7^+)	0.75	0.90	-	-
Mw (C_7^+)	121.91	326.91	-	-
T Reservoir (F)	90.00	350.00	-	-
Experiment MMP (Psia)	950.00	6814.7	-	-

* Mole percent of heptanes in gas composition

This study concerns data collected from Glaso [16], Kuo [30], Firoozabadi [38], Metcalfe [5], Rathmell [32], Alston [15], Sebastian [22], Pedrod [6], Emera [23], slim-tube experiment on Iranian oil reservoir α& β [28] that it includes 128 oil and gas samples.

The following procedures were used after calculating necessary parameters for network training:

1) Normalizing the inputs and targets
2) Creating the network
3) Dividing up samples for testing
4) Training the network
5) Simulating the network
6) Reversing normalized outputs
7) Plot regression

5. Results and discussion

Initially, to investigate the ability of the developed gas–oil MMP model and also in order to avoid over-training, about 20 percent of the input-output data was randomly selected for the network testing and the rest was selected for network training and validation. After utilizing the program, a minimum average absolute relative error (AARE) for different models and data sets were gained (table 4).

Data set 4 has lowest minimum AARE among all other data sets. Minimum AARE is 0.0609 for this data set. Data set 4 was used to generate weight fraction mixing rules and Twu correlation to estimate critical temperature C_{7+}. Also actual critical temperatures were used for C_2 and H_2S components. To determine best neural network model with minimum errors, the result for different models were investigated. Table 5 shows the best outputs of variety models for different data sets. The minimum AARE for the data set 4 with model 5 is 0.0237 which is the lowest error among all data sets with different models. Model 5 is the one – hidden layered neural network with 30 neurons. Based on neural networks theory, as the number of neurons increases, the value of errors will be decreased and with more increasing in number of neurons, the value of errors will increase due to enhance of freedom degree [29]. Fig. 1 & 2 show the minimum AARE for different models and data sets with one and two hidden layers. As can be seen in Fig. 1, the minimum error has occurred in a model with 30 neurons.

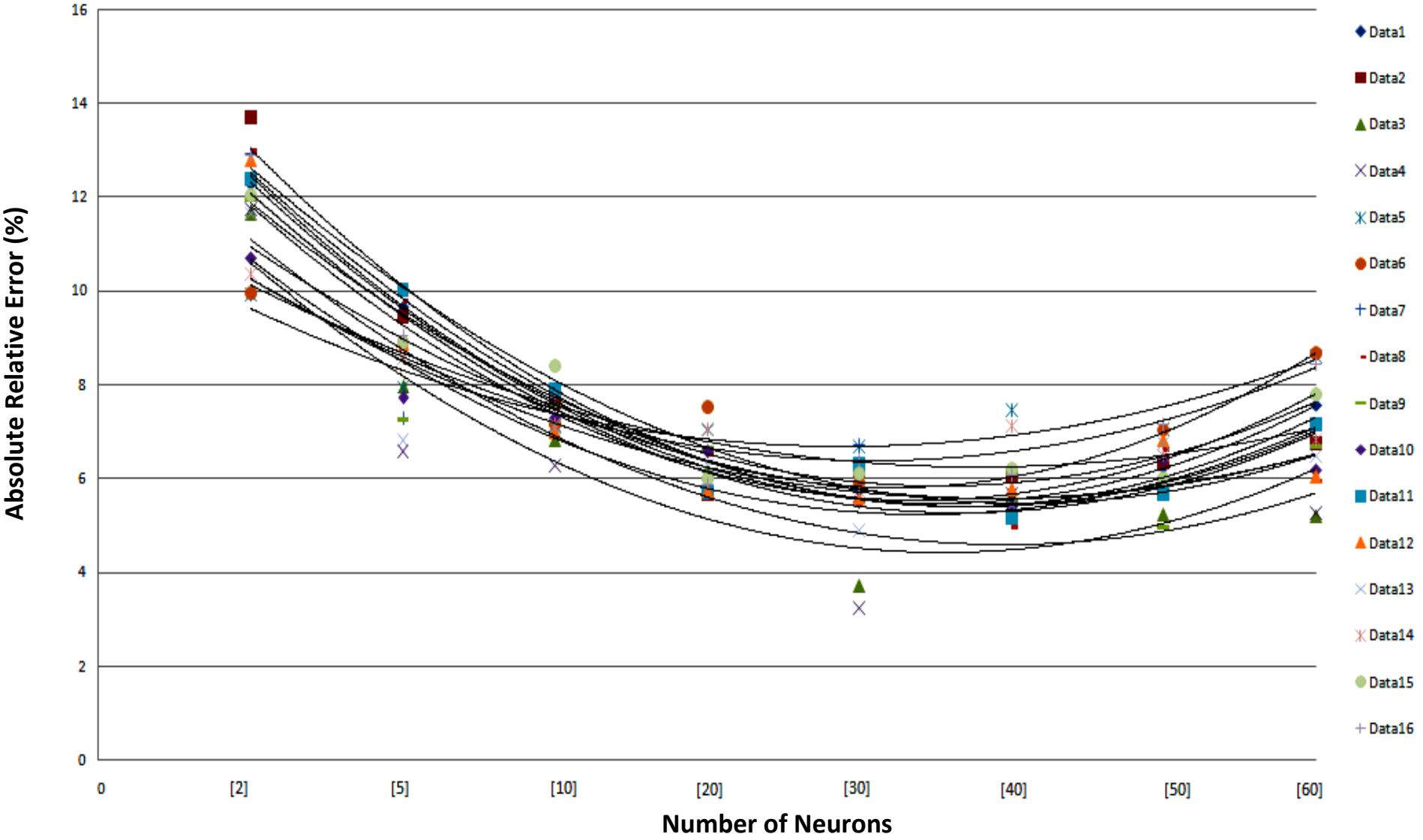


Fig. 1. Minimum average absolute relative error (AARE) versus different single hidden layer neural network.

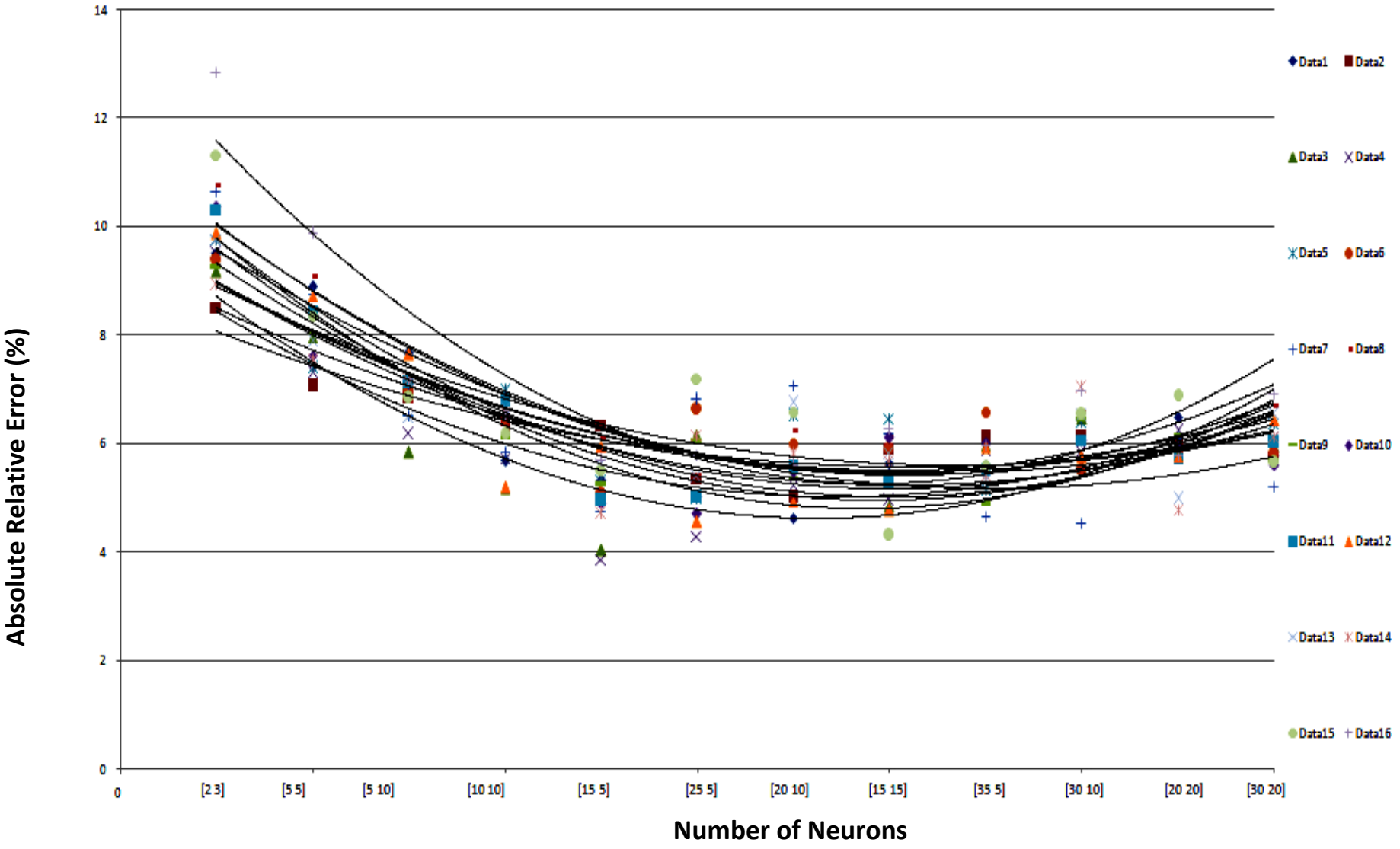
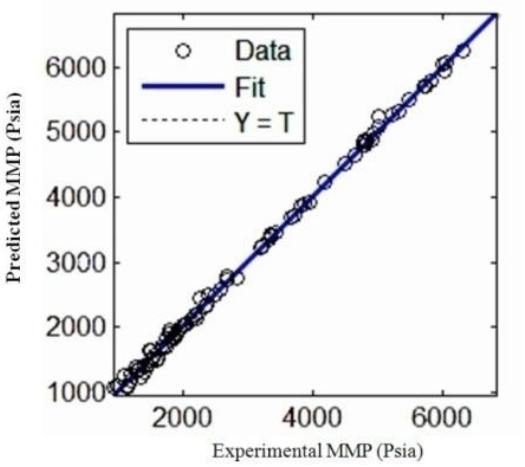


Fig. 2. Minimum average absolute relative error (AARE) versus different double hidden layers neural network.

Typically, an application of back-propagation requires both a training set and a test set. Both the two sets contain input/output pattern pairs. While the training set is used to train the network, the test set is used to assess the performance of the network after the training is complete. To provide the best test of network performance, the test set should be different from the training set. The most successful ANN architecture is the one that has the smallest prediction error on a data set for which it was not trained. For Data Set 4 with model 5, 20 percent of data select for test set and training was run with 80 percent extant. The scatter plot in Fig. 3 presents comparison of the measured gas - oil MMP values with the new ANN model derived ones after training for Data Set 4. The results of the test data are shown in Fig.4



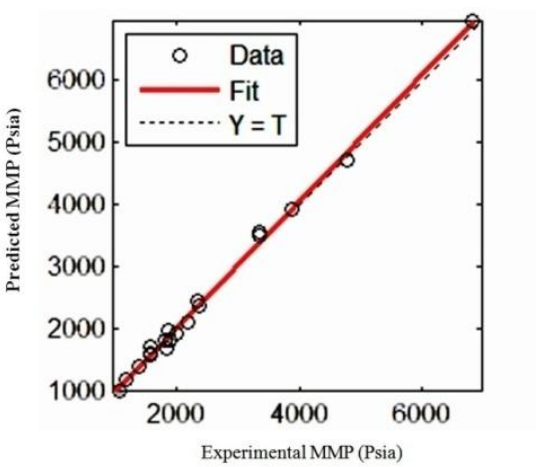


Fig. 3.The experimental versus ANN simulated gas-oil MMP (Train). Fig. 4.The experimental versus ANN simulated gas-oil MMP (Test).

The correlation coefficient (R) test data is 0.998 which shows a high fitness with the experimental data. The correlation coefficient and the error resulted from the experimental and predicted values for this model (Data Set 4 with model 5) are presented in table 6.

Table 4 - Minimum average absolute relative error (AARE) for different models and data sets.

NN. Model	Data Set 1	Data Set 2	Data Set 3	Data Set 4	Data Set 5	Data Set 6	Data Set 7	Data Set 8	Data Set 9	Data Set 10	Data Set 11	Data Set 12	Data Set 13	Data Set 14	Data Set 15	Data Set 16
Model 1	0.0927	0.0968	0.1164	0.1272	0.0992	0.0994	0.1293	0.1299	0.0894	0.0970	0.1239	0.1279	0.1064	0.1035	0.1205	0.1288
Model 2	0.0863	0.0745	0.0796	0.0656	0.0793	0.0890	0.0729	0.0978	0.0724	0.0771	0.1003	0.0886	0.0682	0.0855	0.0889	0.0905
Model 3	0.0771	0.0761	0.0680	0.0656	0.0712	0.0714	0.0778	0.0769	0.0754	0.0727	0.0789	0.0698	0.0709	0.0716	0.0841	0.0773
Model 4	0.0601	0.0565	0.0613	0.0584	0.0703	0.0753	0.0585	0.0652	0.0656	0.0656	0.0569	0.0574	0.0627	0.0704	0.0599	0.0588
Model 5	0.0575	0.0616	0.0523	0.0237	0.0667	0.0591	0.0672	0.0632	0.0610	0.0550	0.0629	0.0558	0.0489	0.0572	0.0610	0.0639
Model 6	0.0541	0.0604	0.0562	0.0565	0.0745	0.0617	0.0568	0.0496	0.0625	0.0542	0.0517	0.0576	0.0543	0.0712	0.0620	0.0656
Model 7	0.0623	0.0635	0.0372	0.0591	0.0805	0.0703	0.0596	0.0661	0.0496	0.0641	0.0568	0.0681	0.0675	0.0649	0.0621	0.0715
Model 8	0.0557	0.0673	0.0518	0.0527	0.0761	0.0868	0.0780	0.0595	0.0669	0.0617	0.0714	0.0504	0.0747	0.0680	0.0778	0.0642
Model 9	0.0952	0.0851	0.0917	0.0950	0.0977	0.0938	0.1065	0.1078	0.0827	0.0837	0.1031	0.0958	0.0977	0.0873	0.1132	0.1256
Model 10	0.0689	0.0606	0.0796	0.0730	0.0639	0.0840	0.0875	0.0908	0.0676	0.0762	0.0541	0.0823	0.0788	0.0756	0.0836	0.0858
Model 11	0.0769	0.0704	0.0584	0.0618	0.0711	0.0638	0.0552	0.0679	0.0716	0.0711	0.0712	0.0525	0.0649	0.0715	0.0684	0.0718
Model 12	0.0558	0.0616	0.0647	0.0584	0.0640	0.0550	0.0454	0.0659	0.0657	0.0605	0.0717	0.0655	0.0551	0.0743	0.0654	0.0599
Model 13	0.0583	0.0642	0.0517	0.0573	0.0697	0.0643	0.0685	0.0697	0.0612	0.0655	0.0502	0.0420	0.0663	0.0614	0.0717	0.0651
Model 14	0.0509	0.0617	0.0615	0.0529	0.0499	0.0663	0.0681	0.0597	0.0637	0.0371	0.0620	0.0655	0.0538	0.0646	0.0720	0.0779
Model 15	0.0433	0.0502	0.0556	0.0524	0.0651	0.0600	0.0708	0.0625	0.0525	0.0547	0.0556	0.0424	0.0675	0.0581	0.0659	0.0659
Model 16	0.0564	0.0591	0.0585	0.0370	0.0646	0.0590	0.0617	0.0673	0.0534	0.0612	0.0630	0.0407	0.0580	0.0646	0.0431	0.0617
Model 17	0.0561	0.0612	0.0598	0.0587	0.0541	0.0659	0.0466	0.0553	0.0490	0.0604	0.0631	0.0563	0.0524	0.0641	0.0556	0.0767
Model 18	0.0534	0.0634	0.0503	0.0386	0.0533	0.0567	0.0476	0.0689	0.0525	0.0475	0.0495	0.0595	0.0564	0.0579	0.0552	0.0568
Model 19	0.0569	0.0598	0.0575	0.0629	0.0571	0.0585	0.0608	0.0542	0.0614	0.0593	0.0573	0.0476	0.0448	0.0471	0.0588	0.0577
Model 20	0.0549	0.0576	0.0594	0.0608	0.0637	0.0581	0.0521	0.0671	0.0568	0.0561	0.0552	0.0614	0.0644	0.0613	0.0566	0.0403
Average Minimum AARE	0.0636	0.0656	0.0636	0.0609	0.0696	0.0699	0.0685	0.0723	0.0640	0.0640	0.0679	0.0644	0.0657	0.0690	0.0713	0.0733

Table 5 - Minimum AARE different models and data sets.

NN. Model	Data Set 1	Data Set 2	Data Set 3	Data Set 4	Data Set 5	Data Set 6	Data Set 7	Data Set 8	Data Set 9	Data Set 10	Data Set 11	Data Set 12	Data Set 13	Data Set 14	Data Set 15	Data Set 16
Model No.	**15**	**15**	**7**	**5**	**14**	**13**	**13**	**6**	**17**	**14**	**18**	**16**	**19**	**19**	**16**	**20**
Minimum AARE	4.33	5.02	3.72	2.37	4.99	5.50	4.54	4.96	4.90	3.71	4.95	4.07	4.48	4.71	4.31	4.03

Table 6- Correlation coefficient and the error resulted for experimental MMPs and ANN predicted values.

Parameter	AARE	correlation coefficient
Training set	0.0237	0.999
Testing set	0.0325	0.998

More models present prediction of gas- oil MMP by researches that are used for pure CO2 or impure CO2. Several models are applied for determination of minimum miscibility pressure of the light hydrocarbon and flue gas. While U-ANN has more universality in comparison with the other models, it can predict minimum miscibility pressure for all types of gas in a wider range of input variable. This model is also accurate and has less error. In order to predict impure CO2 MMP, knowing the pure CO2 MMP value in all of previous models is required, while the new model directly predicts impure CO2 MMP with the effective parameters. Table 7 shows that the average relative error (ARE), average absolute relative error (AARE) and the standard deviation of error for the new proposed model are respectively 0.65 %, 2.37 %, and 3.03 % for 128 data. It should also be noted that Shokir models used 65 data in their model.

Table 7- Comparison of the gas–oil MMP obtained from the new U-ANN based model to the calculated gas–oil MMP from different literature models

	UANN	Shokir (2007)	Shokir (2007)	Emera and Sarma (2005)	Emera and Sarma (2004)	Dong (1999)	Eakin and Mitch (1988)	Alston et al. (1985)	Alston et al. (1985)	Glaso (1985)	Sebastian et al. (1985)	Kovarik (1985)
ARE (%)	0.65	0.14	0.25	−0.62	0.65	2.28	63.11	−5.05	−5.37	−0.85	1.37	−23.43
AARE (%)	2.37	3.30	2.55	5.72	4.05	10.19	70.40	6.64	7.54	9.33	5.93	39.48
Standard deviation (%)	3.03	4.67	3.11	7.15	4.25	15.17	46.83	7.51	7.26	7.18	7.55	51.69
Correlation coefficient	0.999	0.998	0.998	0.970	0.993	0.910	0.50	0.960	0.967	0.970	0.950	0.830
No. Data	128	67	30	61	20	45	52	38	30	46	60	38
Pure CO2	✓		✓		✓				✓	✓		
Impure CO2	✓	✓		✓		✓	✓	✓			✓	✓
Hydrocarbon and flue gas	✓			✓								

Ultimately, to check and confirm the precision of the new U-ANN model, MMPs were calculated for 20 systems not used in building the model for CO_2 and natural gas displacements of crude oils. The new model effectively predicted the experimental gas–oil MMP, with a high precision, for existence of different non-CO_2 components up to 70-mole%, and up to 45.7 mole% of C_1 in the injected natural gas stream (as shown in Tables 8). From Tables 8, the new model gives the precise prediction of the experimental gas–oil MMP for all the tested systems with the lowest average relative error and average absolute relative error among all tested gas–oil MMP correlations.

Table 8 - Comparison of gas–oil MMP approximated from the new U-ANN model to the experimental MMP and to the calculated MMP from different conventional correlations.

	UANN	Shokir (2007)	Emera and Sarma (2004)
ARE (%)	0.16	0.19	0.05
AARE (%)	3.75	4.47	6.69
Standard deviation (%)	4.31	6.00	9.00

6. Conclusion

An attempt was made in this study to investigate the application of a neural networks concept for prediction of MMP in a gas injection process. The interrelations of MMP with different compositions of driving gas and reservoir temperature, molecular weight of C_7^+ oil fraction and different compositions of reservoir oil have been analyzed, all of which resulting in the U-ANN model. To have a model more complete and universal than the others, 128 oil and gas samples with experimental MMP data were used. The MMP data derived from literature and slim-tube experiment of Iranian oil reservoirs were employed to train and test the models. Mixing rules were used to decrease the independent variables. The critical property of C_7^+ was estimated with existent practical correlations. 16 data sets

were generated with deferent mixing rules as well as with C_7^+ critical property estimating correlations. Various neural networks architectures were investigated to obtain desired models for predicting MMP as a function of selected input variables. Different scenarios on the number of hidden layers and the number of neurons in each hidden layer were analyzed in order to obtain the best fit to the given data.

The model was successfully applied to pure CO_2, impure CO_2, flue gas and hydrocarbon gas streams. The comparison between the prediction accuracies of the universal neural network and other methods indicated that the neural network approach was more accurate in predicting MMP. The result showed that the weight-fraction mixing rule with Twu correlation to estimating C_7+ critical property provides better results than the other methods. The model was tested with 20 different data which were not used in the network training. The testing results from the U-ANN model and empirical correlations showed that the proposed model can predict the MMP with better accuracy than other available correlations.

Thus, the results of this study suggest that the neural network model with mixing-rules methods is more reliable than other statistical methods for predicting MMP. Specially, under conditions with limited field information, the neural network approach can produce a higher accuracy than other estimating methods.

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