Experimental Investigation and Estimation of Light Hydrocarbons Gas-Liquid Equilibrium Ratio in Gas Condensate Reservoirs through Artificial Neural Networks

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ABSTRACT: *Equilibrium ratios for the mixture of different components are very important for many engineering application processes. Different numerical methods were explored and applied to ensure efficient estimation of gas-liquid equilibrium ratio. In this paper, the Artificial Neural Network (ANN) approach along with data of experiments performed on 25 gas condensate reservoirs has been utilized to obtain a relationship of gas-liquid equilibrium ratios in gas condensate reservoirs. The relationship between the gas-liquid equilibrium ratio and parameters of components of a mixture (critical temperature, critical pressure, and acentric factor) has been derived. Finally, the results of ANN have been compared to the proposed correlations in the literature and results of the equation of state. This investigation demonstrated that the result of ANN is more precise than the equation of state and existing empirical correlations. Whereas comparison between experimental data of 3 gas condensate samples by ANN, EOS, and existing empirical correlation show that the average absolute error for ANN was between 7.82 to 13.74% and for others was between 29.99 to 94.99%.*

KEYWORDS: *Gas condensate reservoirs; Experimental; Equilibrium ratio; Artificial neural networks; EOS.*

INTRODUCTION

Design of different parts of production system (e.g., distillation column, flow lines, separators) requires fluid phase behavior calculations at equilibrium conditions which is mainly addressed by equilibrium ratio concept. The equilibrium ratio of the *ith* component (K_i) in a mixture is defined as the ratio of the fraction of the *ith* component in the vapor phase to that in the liquid phase, at vapor-liquid equilibrium (E. (1)) [1].

$$K_i = \frac{y_i}{x_i} \quad (1)$$

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Where y_i and x_i are the mole fractions of component i in the phases vapor and liquid respectively.

The equilibrium ratio of a real solution is a function of temperature (T), pressure (P), and composition of the system (Z_i). Many methods have been proposed to predict the equilibrium ratios of hydrocarbon mixtures, the limits of these methods, is variable from a simple mathematical formula, to complex formulations, each of which has several associated dependent variables. In 1968, Wilson proposed an equation for predicting an equilibrium ratio at low pressures [2]. Equilibrium ratios calculated with Wilson equation are more accurate at lower pressures.

$$K_i = \frac{P_{ci}}{P_t} exp\left[5.37(1+\omega_i)\left(1-\frac{T_{ci}}{T}\right)\right] \quad (2)$$

Where P_t is absolute total pressure, T is absolute system temperature, ω is the acentric factor, and T_c and P_c are the absolute critical temperature and pressure respectively.

Standing [3] obtained a set of equations related to equilibrium ratio data of *Katz* and *Hachmuth* [4] at pressures less than 1000 psia and temperatures below 200 °F. Other researchers have been worked on equilibrium ratio of vapor-liquid equilibrium [5-8]. In the SRK equation [9], *Giorgio Soave* modified Redlich-Kwong equation of state applied for multi-component vapor-liquid equilibrium calculations. The Peng-Robinson equation [10] improved the ability of the SRK state equation for predicting the specific fluid mass, and other fluid properties, especially around the critical zone.

The field of neural network has, like any other field of science, a long history of development with many ups and downs. *Waren Mcculloch* and *Walter Pitts* (1943), introduced models of neurological networks, based on neurons and showed that even simple networks of this kind are able to calculate nearly any logic or arithmetic function. [11]. *Donald O. Hebb* formulated the classical hebbian rule which represents in its more generalized form the basis of nearly all neural learning procedures. [12]. Artificial Neural Networks (ANNs), have been utilized in many studies for estimation of rock uniaxial compressive strength for an Iranian carbonate oil reservoir [13], modeling the effect of oxygenate additives on the performance of Pt-Sn/.-Al_2O_3 catalyst in propane dehydrogenation [14], Kinetic modeling of Oxidative DeHydrogenation of Propane (ODHP) over a vanadium-graphene catalyst: Application of the DOE and ANN methodologies [15] as well as Investigation of the Oxidative Dehydrogenation of Propane Kinetics over a Vanadium-Graphene Catalyst Aiming at Minimizing of the COx Species [16], also due to their high ability of non-linear mapping, generalization, self-learning and self-organization, have been proved to be of widespread utility in engineering and are steadily advancing into new areas [17–26]. In petroleum engineering, neural networks have been used to predict porosity, permeability, determine facies, and zones identification [27-30], and to predict the water saturation [31 and 32]. Currently, neural network has been widely used in fields of reservoir and geotechnical engineering [33-58].

Despite the existence of different methods for prediction of equilibrium ratio, including empirical correlations, Equation of State (EOS), and combination of equation of state and fluid theory, application of each method depends on the conditions of system under consideration. Although experimental measurements are desirable, they are expensive and time-consuming. In this paper, the artificial neural networks and experimental data of gas-liquid equilibrium ratios for 1000 spots in gas condensate reservoirs have been used to estimate the equilibrium ratios of unknown reservoirs.

EXPERIMENTAL SECTION

In gas condensate reservoirs, with pressure reduction below dew point, the liquid and Gas phases are simultaneously in equilibrium. Here, the material balance calculations have been conducted on the fluid components, in order to obtain the composition of the liquid and gas phases at various stages of Constant Volume Depletion (CVD) test, and the equilibrium ratio values are obtained experimentally by using Eq. (1), for pressure stages under dew point pressure and at reservoir temperature. Experimental data of 25 Iranian gas condensate reservoirs (totally 1000 experimental data point from the CVD test) have been used in the neural network procedure. The CVD tests have been performed using the visual PVT cell (Vinci Technologies, Nanterre, FRANCE). Figs. 1 and 2 show the actual photo and Schematic diagram of visual PVT cell which is used for all experimental tests. The volume of this cell is one liter and has a maximum pressure of 20,000 psi and a maximum temperature of 392 ^{0}F. The range of *GOR* for these reservoirs changes from 1,150 vol/vol to29,814 vol/vol.

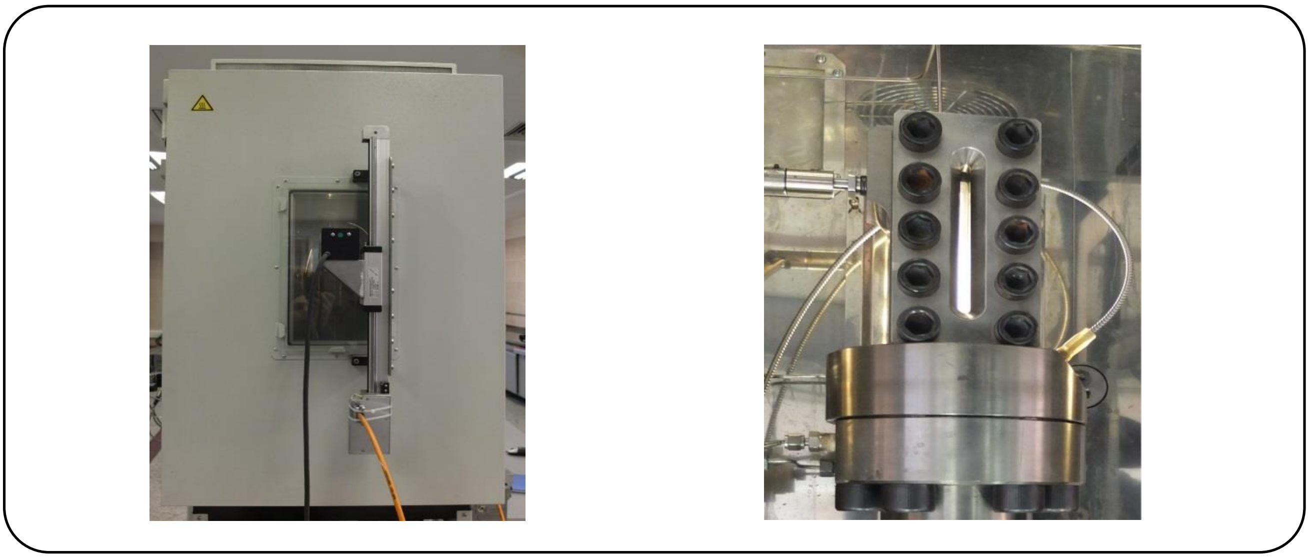

Fig. 1: Actual photo of experimental Setup.

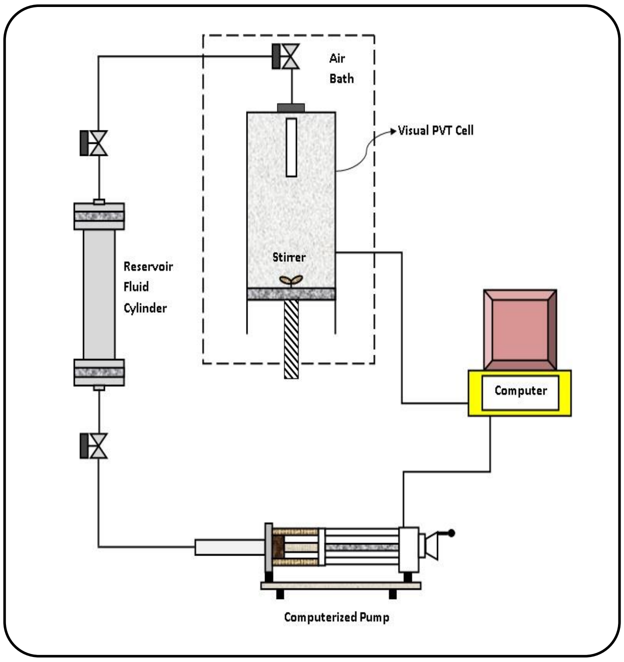

Fig. 2: Schematic Diagram of experimental Setup used for CVD experiments.

In this research, the neural networks for different components of reservoirs' fluid has been used to obtain the relationship between the gas-liquid equilibrium ratio (K_i) with reduced pressure (P_{ri}), reduced temperature (T_{ri}) and acentric factor (ω_i) for component *i* of the gas condensate reservoir fluid. Also, three gas condensate reservoirs have been used for validating the results of neural networks, and also for comparison of the results obtained through the neural networks, SRK, PR EOS, and Wilson correlation (Eq. (2)) [2]. The properties of these reservoirs are briefly summarized in Table 1.

A technical side of FeedForward Neural Network is composed of three layers, input, output & hidden layer. In this study, a feedforward neural network has been designed with Backpropagation (BP) algorithm in which each neuron in one layer, has only directed connections to the neurons of the next layer (towards the output layer). The neurons layer of a feedforward network are separated, 28 input layers, 8 output layers and 30 processing layers also called hidden layer. BP algorithm has problems associated through learning procedures, there are various solutions to this problem such as reset the weights to different random input data and try to retrain the network. Another way is to add "momentum" to the weight change. The combination of the weights which minimizes the error function which considered to be a solution to learning problem. Activation function for trained network is the Sigmoid as shown in Fig. 3. The network keeps training all the patterns repeatedly until the total error falls to some pre-determined target value and then it stops. This ANN is known for its accuracy as it allows itself to learn and improve to reach the target data.

RESULTS AND DISCUSSION

Reduced pressure (Pr), reduced temperature (Tr), and acentric factor (ω) are used as input data to develop an ANN model to predict Gas-liquid equilibrium ratios (k-value). Experimental data for a gas-liquid equilibrium ratio

Table 1: Properties of candidate gas condensate reservoirs.

Component	Unit	Case 1	Case 2	Case 3
H_2S	mole%	0.01	0.05	2.29
CO_2	mole%	0.89	2.37	6.46
N_2	mole%	0.2	0.1	0.07
CH_4	mole%	85.62	83.97	72.24
C_2H_6	mole%	6.85	5.88	4.86
C_3H_8	mole%	3.26	2.8	2.48
iC_4	mole%	0.44	0.48	0.62
nC_4	mole%	1.03	1.12	1.43
iC_5	mole%	0.32	0.43	0.54
nC_5	mole%	0.36	0.49	0.64
C_6	mole%	0.38	0.54	1.06
$C7_+$	mole%	0.64	1.77	7.31
Molecular weight of reservoir fluid	gr/mole	20.03	21.73	31.27
Molecular weight of C_{7+}	gr/mole	105.63	118.98	144.02
Density of C_{7+}	gr/cc	0.737	0.750	0.786
Dew point at reservoir temperature	psia	1900	2850	4790
Reservoir temperature	°F	110	180	239
Reservoir pressure	psia	3000	3033	5700
Gas oil ratio, GOR	SCF/STB	110402	36500	8189

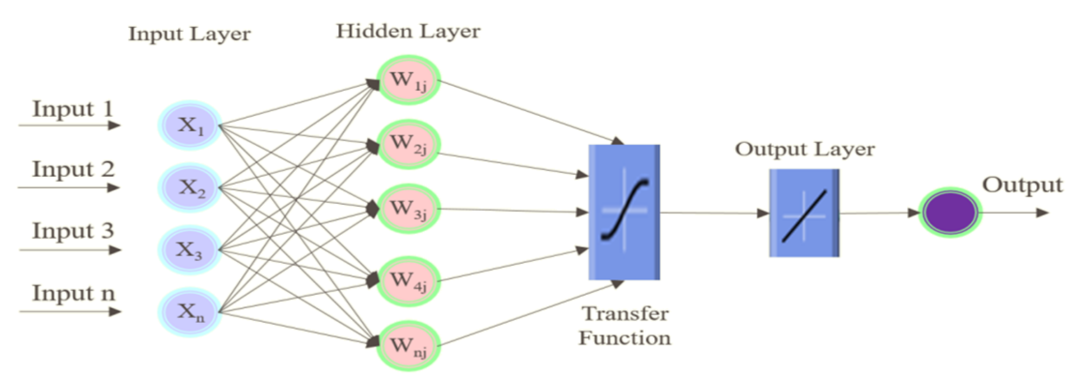

Fig. 3: Artificial Neural Network structu.

Table 2: Input and Target data for training of neural network.

Component	Input Data			Target Data
	Pr	Tr	ω	K-value
C_1	0.330~6.303	1.659~2.035	0.010	1.072~7.671
C_2	0.311~5.945	1.036~1.271	0.098	0.430~2.408
C_3	0.357~6.841	0.855~1.049	0.152	0.225~1.474
iC_4	0.417~7.956	0.776~0.951	0.165	0.152~0.792
nC4	0.400~7.636	0.744~0.912	0.200	0.156~0.683
iC_5	0.449~8.564	0.687~0.843	0.228	0.053~0.522
nC_5	0.450~8.596	0.674~0.826	0.251	0.083~0.516
C_6	0.455~8.696	0.623~0.765	0.299	0.012~0.427

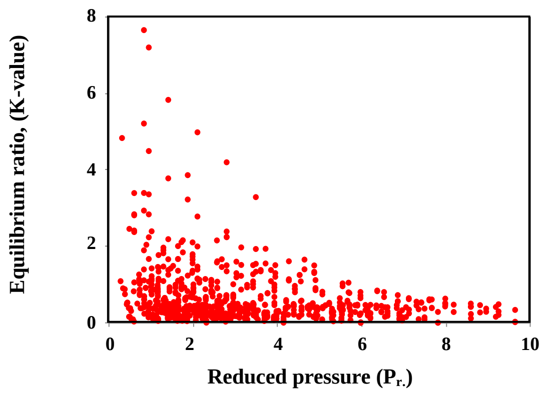

Fig. 4: Equilibrium ratio values versus reduced Pressure.

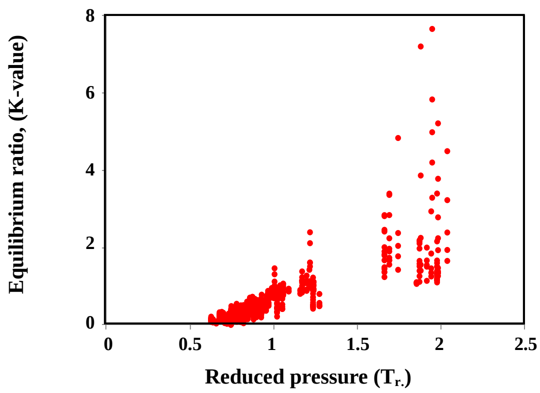

Fig. 5: Equilibrium ratio values versus reduced temperature.

from a CVD test of 25 Iranian gas condensate reservoirs (total of 1000 points) were used to design such a model (Table 2, Figs. 4 and 5).

In the following, the trained neural network model has been used to estimate equilibrium ratio for three new candidate gas condensate reservoirs with various gas-oil ratio (GOR). The GOR values of candidate reservoirs are in the range of GOR values for 25 reservoirs which have been previously used for training the neural network. Fig. 6 shows experimental data of equilibrium ratio for various components of reservoir fluid, at different pressure stages of CVD test (case 1). These equilibrium ratio values were obtained by using the material balance on the Target data of CVD test. In order to distinguish the data in a better way, the axis of equilibrium ratio was converted to a logarithmic scale.

After training the neural network with 1000 experimental input data (Figs. 4,5) and obtaining the estimated results, in order to validate the results of the model, three considered gas condensate reservoirs (presented in Table 1) have been used. Equilibrium ratios calculated according to Wilson correlation (Eq. (2)) [2], SRK and PR EOS for components of hydrocarbon of these three considered gas condensate reservoirs. Figs. 7, 8, and 9 demonstrate the values of equilibrium ratio versus pressure according to experimental results, provided results of neural network method, EOSs (i.e. PR and SRK), and Wilson correlation for methane (C_1) component in case 1, 2, and 3 respectively.

According to the analysis represented in Figs. 7–9, it can be observed that the ANN model better predicts the experimental values of equilibrium ratio (K-value) in comparison with the proposed correlation by Wilson and EOSs. Also For the better analysis of the data, the error value of different methods compared to the experimental data for equilibrium ratios in cases 1-3 were calculated.

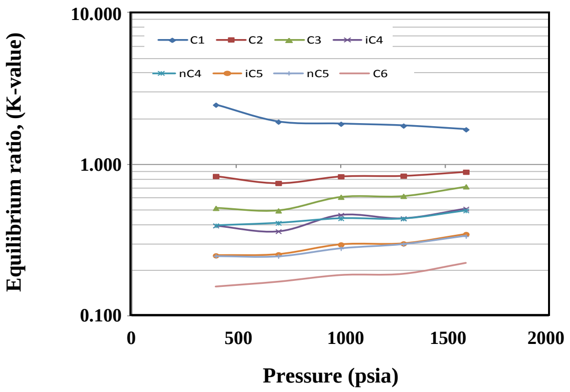

Fig. 6: Experimental equilibrium ratio values for different components of case 1 in Table 1.

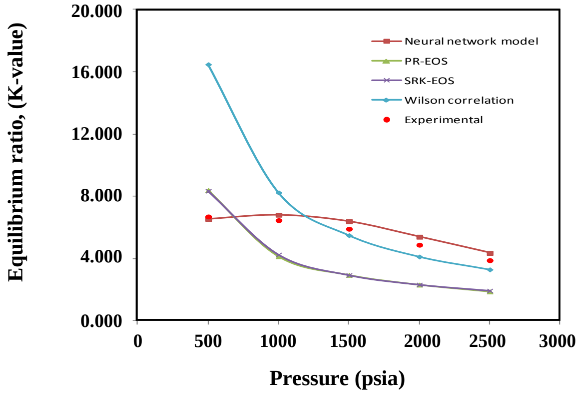

Fig. 8: The comparison of experimental values of equilibrium ratio of methane versus pressure with predicted values by neural networks method, PR and SRK EOS, and Wilson's correlation for gas condensate reservoir case 2.

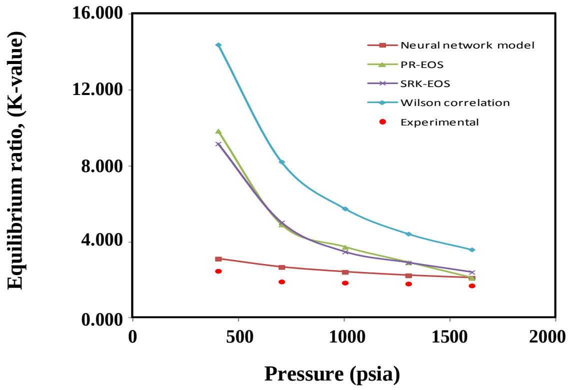

Fig. 7: The comparison of experimental values of equilibrium ratio of methane versus pressure with predicted values by neural networks method, PR and SRK EOS, and Wilson's correlation for gas condensate reservoir case 1.

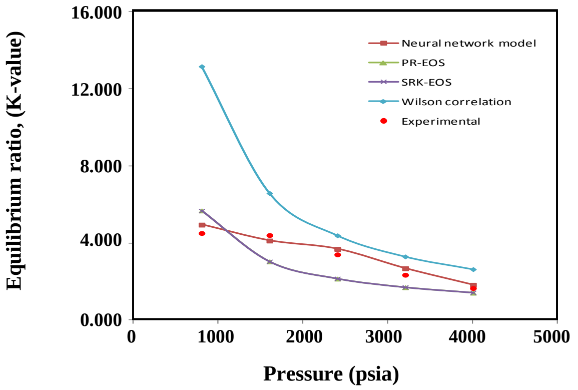

Fig. 9: The comparison of experimental values of equilibrium ratio of methane versus pressure with predicted values by neural networks method, PR and SRK EOS, and Wilson's correlation for gas condensate reservoir case 3.

Fig. 10 indicates the values of average absolute percent error and average absolute relative percent error in different methods compared to experimental data for case 1-3 (for all components of gas condensate reservoir fluids). Fig. 10 demonstrates that in Iranian gas condensate reservoirs when there is lack of experimental data for equilibrium ratio, by using ANN, we can obtain better results comparing the equations of state and empirical correlation for gas-liquid equilibrium ratio.

EOSs are based on physical phenomena and thermodynamic equilibrium concept, subsequently different parameters which attain by EOSs may affect equilibrium ratio. Instead ANN relates equilibrium ratios to dimensionless properties of fluid components (e.g., Pr, Tr, ω). Therefore ANN almost predicts equilibrium ratio more precisely from the mathematical point of view.

CONCLUSIONS

In this investigation, FeedForward neural network which is supervised learning method with BP algorithm to train the ANN is proposed. The equilibrium ratio in gas condensate reservoirs was predicted by simple empirical correlation, Equations of State (EOS), and neural network method. Experimental data of wide range of gas condensate reservoirs, with a various Gas Oil Ratio (GOR) has been used in the ANN model. The results of ANN

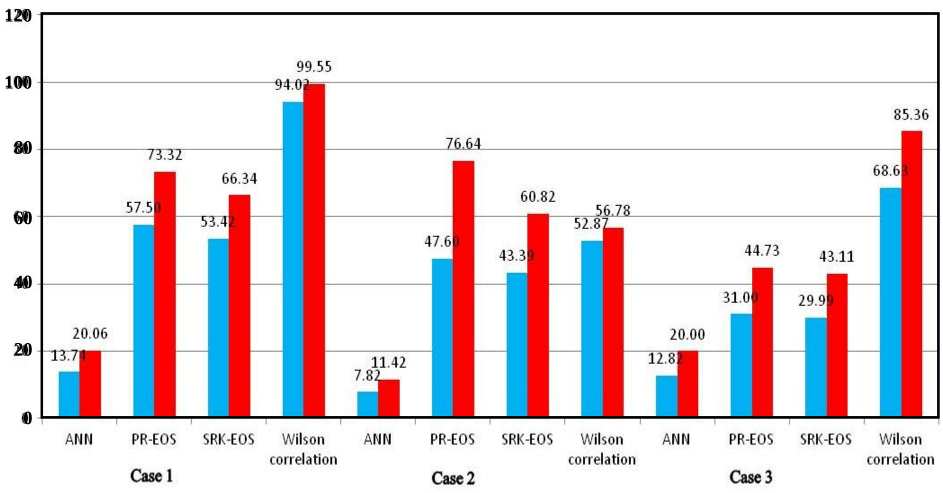

***Fig. 10:** The average absolute percent error and average absolute relative percent error of equilibrium ratio for different methods of cases 1-3.*

have predicted the equilibrium ratio for different components, more precise than the equations of state, and existing empirical correlation, and it can be presented as a new database which can predict the values of gas-liquid equilibrium ratio for similar gas condensate reservoirs better and more accurate. According to Fig. 10, quantitatively comparison between experimental data of 3 gas condensate samples by ANN, EOS, and existing empirical correlation show that the average absolute error for ANN was between 7.82 to 13.74% and the average absolute relative error was between 11.42 to 20.06%;conversely for other methods these errors are between 29.99-94.02% and 43.11-99.55% respectively.

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