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Constructing a unique two-phase compressibility factor model for lean gas condensates

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Abstract−Generating a reliable experimental model for two-phase compressibility factor in lean gas condensate reservoirs has always been demanding, but it was neglected due to lack of required experimental data. This study presents the main results of constructing the first two-phase compressibility factor model that is completely valid for Iranian lean gas condensate reservoirs. Based on a wide range of experimental data bank for Iranian lean gas condensate reservoirs, a unique two-phase compressibility factor model was generated using design of experiments (DOE) method and neural network technique (ANN). Using DOE, a swift cubic response surface model was generated for two-phase compressibility factor as a function of some selected fluid parameters for lean gas condensate fluids. The proposed DOE and ANN models were finally validated using four new independent data series. The results showed that there is a good agreement between experimental data and the proposed models. In the end, a detailed comparison was made between the results of proposed models.

Keywords: Gas Condensate, Compressibility Factor, Correlation, Design of Experiment, Neural Network

INTRODUCTION

The compressibility factor (Z), also known as the compression factor, is a useful thermodynamic property for modifying the ideal gas law to account for the real gas behavior. In general, deviation from ideal behavior becomes more significant. A gas condensate is a single phase fluid at original reservoir condition, but exhibits complex multi-phase behaviors due to condensate build up below dew point pressure condition, especially near the wellbore region. The gas compressibility factor is valid only for dry gas systems which have single phase composition. This practice also can be acceptable for highly lean and maybe lean gas condensate reservoirs. When the gas is intermediate or rich, different calculations may be seriously erroneous, and that is why the necessity of applying two-phase compressibility factor is sensed severely. In this condition, the two phase compressibility factor accounts for the formation of liquid phase in porous media.

Typically, the compressibility factor is determined experimentally as a part of any standard PVT report. Obtaining the compressibility factor for gas condensates is necessary in petroleum engineering calculations. Compressibility factors are used in material-balance equations to estimate initial gas in place [1]. They are also used in calculations of gas flow through porous media, gas pressure gradient in tubing and pipe lines (i.e., tubing performance flow equation [2], gas metering, and gas compression. Also this parameter can be used to back-calculate the average reservoir pressure from material balance equations. The expansion of the condensate part can be incorporated in the gas phase expansion by using the two phase gas deviation factor in place of the gas compressibility factor below the dew-point pressure [3]. Prediction of gas condensate properties such as two-phase z-factor can be obtained from experimentally measured data on constant volume depletion (CVD) test. In cases where CVD data is not available, equations of state and empirical correlations are used to predict the depletion performance of gas condensate reservoirs [4].

Generally, a two-phase compressibility factor is measured experimentally for each gas condensate sample, but sometimes creating a reliable correlation helps to estimate fluid parameters efficiently. Generating reliable correlation for two phase compressibility factor is already been done for rich gas condensates, but this paper seeks to generate a swift correlation for predicting two-phase compressibility factor for intermediate and lean gas condensates. Using a wide range of Iranian gas condensate experimental data along with design of experiments technique (DOE), a cubic response surface model for two-phase Z-factor was generated successfully. After that, the artificial neural network (ANN) was used to train a simulation network and then it was validated for CVD tests.

LITERATURE REVIEW

Compressibility factor values are usually obtained by calculations from equations of state (EOS), such as the virial equation which takes compound specific empirical constants as input. For a gas that is a mixture of two or more pure gases, a gas composition is required before compressibility can be calculated [1].

Reyes presented the first correlations to determine two phase compressibility factor from field data [5]. The correlation was based on the pseudo pressure and pseudo temperature of well-stream produced gas composition. The pseudo properties were calculated with the methods presented by Sutton [6]. This correlation was based on 67 fluid depletion studies for North Sea rich gas condensate systems.

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Although the maximum relative error of this correlation for lean fluid is about 20%, the order of change in compressibility factor is between low values (for example between 0.3 up to 1.1) and therefore, the low value errors could conclude in misleading results.

Recently, applications of artificial neural networks in petroleum engineering have increased. Few examples of the application of neural networks are permeability prediction [7,8], identification of lithology [9], drill bit diagnosis [10], and improvement in gas well production [11]. Neural network techniques have also been used in studying reservoir fluid phase behavior [12-14], interpretation of well testing data [15-18], and determination of pore pressure [19].

The design of experiment (DOE) is another method to study and correlate the PVT properties. DOE considers all the variables simultaneously and predicts a response over a wide range of values. DOE provides information about the interaction of factors and the way the total system works, something not obtainable through testing one factor at a time (OFAT) while holding other factors constant. Another advantage of DOE is that it shows how interconnected factors respond over a wide range of values, without requiring the testing of all possible values directly [20].

DATA GATHERING

To propose a new correlation for two-phase compressibility factor, 39 data sets of CVD test (229 data points) were used. There are four different parameters selected to develop new two-phase Z-factor named: reduced stepwise pressures from CVD test, reduced reservoir temperature, gas specific gravity and the value of natural logarithm of GOR. The maximum, minimum, average and the median of these properties are presented in Table 1.

Finally 24 data point were used (4 CVD data set) to check validity of the new correlation. The statistical values of these data points are as below.

MODEL DEVELOPMENT

Assuming that only gas phase is produced in the surface, a liquid phase condenses in the reservoir as pressure depletes below the dew point pressure, and this results in leaving remaining volume of gas and liquid in reservoir:

$$n_r = n_i - n_p = \frac{PV_i}{Z_{2p}RT} \qquad (1)$$

In which n_r, n_i and n_p are remaining, initial and produced moles of fluid. Laboratory experiments can be used to determine the two-phase compressibility factor. Constant volume depletion (CVD) test yields the compressibility factor of the two phases present at each pressure decrease. Although CVD forms the cornerstone for determining fluid properties of gas condensate reservoir, the CVD test cannot be performed for all conditions and also it is expensive and time-consuming. Therefore, EOS models, empirical correlation and artificial neural network models can be used to predict the performance of gas condensate reservoirs.

1. Design of Experiments

Design of experiments is a much more improved procedure for planning experiments so that data can be analyzed to give valid conclusions. DOE introduces different techniques to monitor the simultaneous changes of input parameters in a systematic way. The technique is applied to choose a moderate number of simulation runs and analyze them to estimate the sensitivity of output function to various input parameters. In other words, well-chosen experimental designs can maximize the amount of information that can be obtained for a given amount of experimental design. Generally, the true relation between the different parameters of a system is really unknown. Therefore, finding an approximate solution as an empirical equation is a good way to predict the effect of input independent parameters on output dependent function. Response surface models are functions that are fitted to the observed data of experiments or simulation runs by regression. Historical data option is the best way to import existing data into Design-Expert software for analysis.

2. Artificial Neural Network

Artificial neural networks (ANN) are convenient models for linear and nonlinear function approximation. This is particularly useful in applications where the complexity of the data or task makes the design of such a function impractical. Neural networks can provide differentiable closed-analytic-form solutions that have very good generalization properties and are widely applicable [21].

An ANN is typically defined by three types of parameters:

1. The interconnection pattern between different layers of neurons.
2. The learning process for updating the weights of the interconnections.
3. The activation function that converts a neuron's weighted input to its output activation.

Two common methods of using ANN are feed-forward network and radial basis network models.

3. Feed-forward Networks

Feed-forward networks cannot perform temporal computation.

Table 1. Statistical range of used parameters to predict two phase compressibility factor (training step)

Property	Maximum	Minimum	Average	Median
P (Psig)	8490	2270	5248	4953
T (F)	302.73	142	223.34	219
GOR (SCF/STB)	617719.7	9390.314	74902.31	88894.01
P_{Pr}	10.1077	0.449651	3.739188	3.375769
T_{Pr}	0.298698	0.198644	0.26564	0.268054
Gas specific gravity	0.8388	0.6987	0.7714	0.7724
Ln (GOR)	13.33379	9.147434	11.22394	11.3952

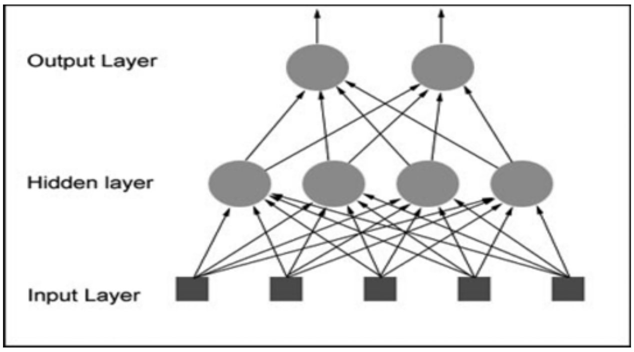

Fig. 1. Schematic structure of feed forward analytical neural network.

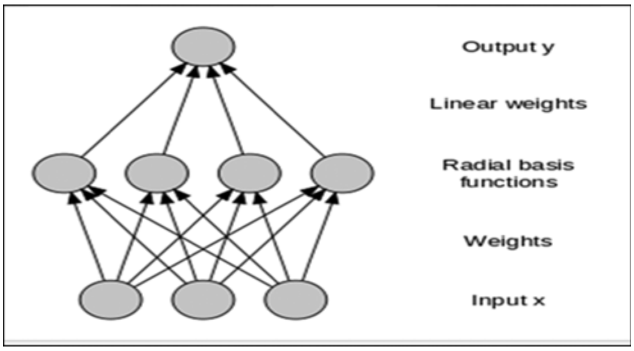

Fig. 2. Schematic structure of feed forward analytical neural network.

This study does not need temporal computation because the Z factor does not change with time. Fig. 1 shows the schematic structure of this type [22]:

4. Radial Basis Networks

A radial basis function network is an artificial neural network that uses radial basis functions as activation functions. It is a linear combination of radial basis functions. Radial basis networks may require more neurons than standard feed-forward back propagation networks, but often they can be designed in a fraction of the time to train standard feed-forward networks. They work best when many training vectors are available. This type of network uses radial basis functions for its inner transfer functions except for the last one which uses purelin function. Fig. 2 illustrates the structure of this type.

RESULT AND DISCUSSION

1. DOE

In problems which their objective is to find a mathematical relation between response and input factors, levels of factors are pre-identified and the matrix of design of experiment will be filled proportional to those levels and then the mathematical relationship between variables will be obtained. But in this study, experiments are done with different factor's level, and the purpose is to obtain a mathematical relationship between input factors and response, so historical data are used. To calculate the two-phase compressibility factor, four input factors with different factor level have been used. Since GOR has very high levels with respect to others, we use its logarithm. Due to overcomplicating problem in high-degree-models and the malfunction of lower degree models, a cubic model has been assigned according to the number of experiments and input factors. To reduce the complexity of the cubic model, unnecessary expressions have been omitted using backward selection method. This is because of unknown multicollinearity between input factors. In this study, the value of 0.001 has been allocated to uncertainty parameter named (α). Finally, a mathematical model consisting of 19 coefficients has been obtained as shown below:

$$
\begin{aligned}
Z_{two\text{-}phase} = & -167.78132 - 0.26434*P_{pr} - 311.41541*T_{pr} \\
& +17.54452*\ln(GOR) + 507.14612*\gamma_g + 0.30896*P_{pr}*\gamma_g \\
& +60.14467*T_{pr}*\ln(GOR) + 728.13333*T_{pr}*\gamma_g \\
& -22.15321*\ln(GOR)*\gamma_g + 0.022587*P_{pr}^2 - 1199.90826*T_{pr}^2 \\
& -1.46373*\ln(GOR)^2 - 622.77418*\gamma_g^2 \\
& -77.61721*T_{pr}*\ln(GOR)*\gamma_g - 0.023965*P_{pr}^2*\gamma_g \\
& +2073.10892*T_{pr}^2*\gamma_g - 575.90813*T_{pr}*\gamma_g^2 \\
& +1.86718*\ln(GOR)^2*\gamma_g - 577.26904*T_{pr}^3 + 332.00378*\gamma_g^3
\end{aligned}
$$

2. Feed Forward

In this study, the structure of the feed forward neural network consists of four inputs, five neurons for first hidden layer, four neurons for second hidden layer and one neuron for outputs. Transform functions from input to output layer are logsig, logsig and purelin, respectively. Obtaining a mathematical relationship is the reason for using these types of functions. The 6000 epoch used for network training with Levenberg-Marquardt algorithm and their performance are evaluated by mean square error method.

3. Radial Basis

In radial basis neural network, the learning algorithm and evaluation are similar to feed forward network. This type of network is working with radial basis transport functions that specifically are applicable for regression. This type of network requires a "spread" number to obtain smoothness of the regression curve. As the value of "spread" becomes larger, more and more neurons contribute to the average with the result that the network function becomes smoother [21]. A smaller "spread" would fit data better but is less smooth. In this study a value of 0.55 has been selected for "spread" number, which is in a common range. This value maintains the trend of two phase compressibility factor and shows a good result in fitting to data set. Therefore, it is an optimum value for the "spread" number.

The above developed models are compared with two tables, No. 4 and No. 5, for the initial and test conditions, respectively. It's expected that the errors for test data are more than training and developing data, but all three models have very high precision. Also Figs. 3, 4 and 5 compare the real values of two phase compressibility factor as test data with these values resulting from FF, DOE and

Table 2. Statistical range of used parameters to predict two phase compressibility factor (testing step)

Property	Maximum	Minimum	Average	Median
P_{Pr}	9.837771	0.913473	4.403395	4.169346
T_{Pr}	0.255722	0.232466	0.240916	0.234991
Gas specific gravity	0.772333	0.6971	0.727201	0.722385
Ln (GOR)	10.93687	9.330768	10.16152	10.28837

Table 3. The values of statistical parameters for initial data

Method	Average relative error, %	Average absolute relative error, %	RMSE	SD
ANN (feed forward)	−0.55	4.76	0.066	0.12
ANN (radial basis networks)	−0.60	4.90	0.06	0.115
DOE	−0.75	3.59	0.059	0.11

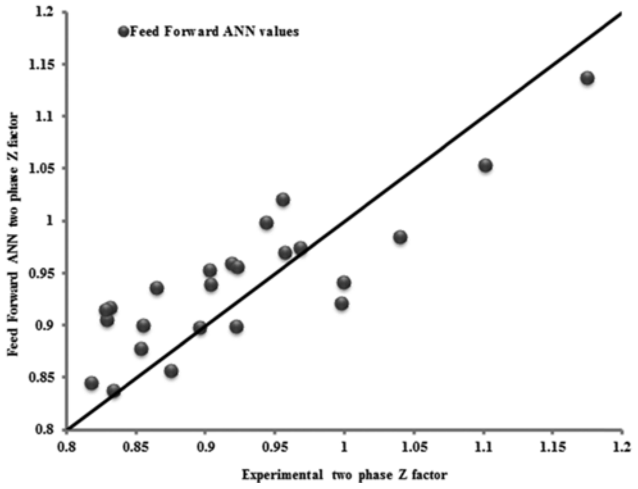

Fig. 3. Comparison of two phase compressibility factor test data with resulted values from FF model.

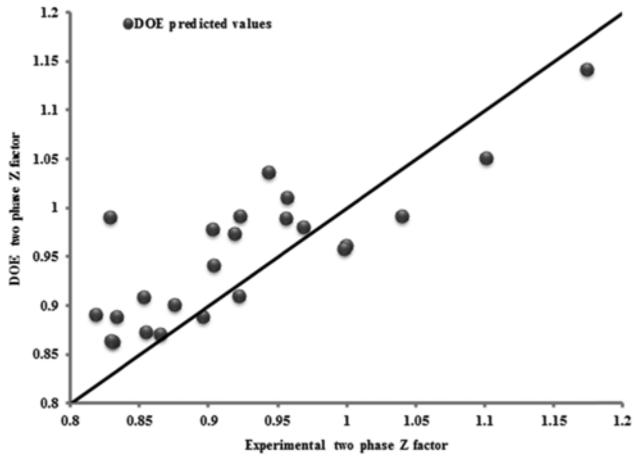

Fig. 4. Comparison of two phase compressibility factor test data with resulted values from DOE model.

Radial Base models, respectively.

As shown in the above figures, the trends of the two-phase compressibility factor for all three models are captured obviously. Radial basis model shows a little deviation of trend that can be mentioned

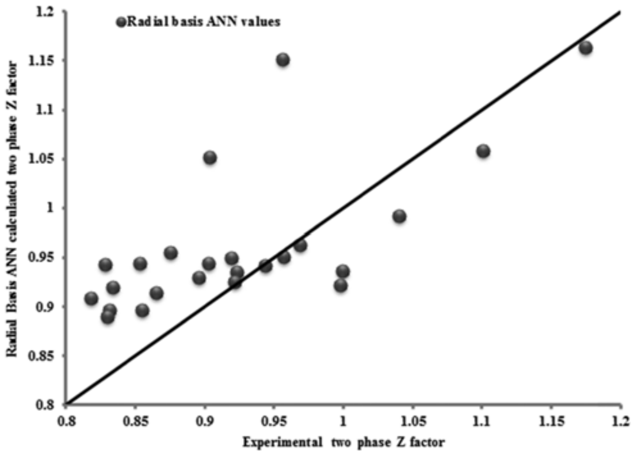

Fig. 5. Comparison of two phase compressibility factor test data with resulted values from RB model.

as failure of these types of neural networks.

According to Table 4, the values of average absolute relative errors are about 4.75, 6.49 and 5.15 percent for feed forward artificial neural network (FFANN), radial basis ANN and design of experiment, respectively, for test data. It is obvious that feed forward ANN has less error compared to the other methods; therefore, it is the best fitted model for two phase compressibility factor. Second one, with respect to preciseness, is the DOE model. Two statistical parameters, relative mean square error (RMSE) and standard deviation (SD), show acceptable values for each of the three methods. Even though the feed forward ANN has better approximation, DOE has a great privilege of obtaining an explicit mathematical relationship of fluid parameters and two phase compressibility factor, which can be used in further calculations related to reservoir simulation or other relevant fields of study.

CONCLUSIONS

A new correlation using reduced pressures, reduced temperature, gas specific gravity and natural logarithm of GOR was developed using DOE, which has good accuracy in comparison with FFANN and Radial Basis ANN. All three models capture two-phase z factor trend and are acceptable for calculation of two-phase z fac-

Table 4. The values of statistical parameters for test data

Method	Average relative error, %	Average absolute relative error, %	RMSE	SD
ANN (feed forward)	−2.12	4.75	0.05	0.02
ANN (radial basis networks)	−4.45	6.49	0.07	0.04
DOE	−3.33	5.15	0.057	0.03

tor. In spite of two types of ANN, DOE expresses the two-phase z factor with explicit mathematical relation. Generally, if the objective is to calculate the two-phase z factor alone, FFANN will be the best choice among other models, and if calculating two-phase z factor is a stage of our calculation, it is better to use DOE to model it. From a preciseness viewpoint, the accuracy of the models is identical.

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