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Modeling of Two-Phase Gas Deviation Factor for Gas-Condensate Reservoir using Artificial Neural Network

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Authors' contributions

This work was carried out in collaboration between both authors. Author OOA designed the study, wrote the protocol, wrote the first draft of the manuscript and managed the analyses of the study. Author AAO performed the statistical analysis and managed the literature searches. Both authors read and approved the final manuscript.

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ABSTRACT

In petroleum engineering, reservoir fluid characterization is of great importance. Accurate determination of the two-phase gas deviation factor is essential in modeling gas-condensate and gas reservoirs, pipeline flow and reserve estimation, this is because the reservoir fluid is in a two-phase state at pressures below the dew-point pressure. Correlations are replete for predicting single-phase gas deviation factor using different Equation of State (EOS), but no correlation have been found to accurately predict the two-phase gas deviation factor.

Traditionally, the two-phase gas deviation factor for a gas-condensate fluid is determined experimentally in the laboratory, however, this laboratory experiments are quite expensive, though quite reliable. Hence, a need for simple but less expensive methods of determining the two-phase gas deviation factor. Thus, this present study modeled the two-phase gas deviation factor of a gas-condensate fluid using Artificial Neural Network (ANN), a biologically inspired non-algorithmic, non-

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digital, massively, parallel distributive and adaptive information processing system. Its ability to perform non-linear, multi-dimensional interpolations makes it unique and fit for this work.
The results obtained were compared to existing empirical and analytical correlations. Average absolute deviation (AAD), root mean square errors (RMSE) and correlation of determination (COD) between the ANN output and other correlations gave 1.343%, 1.344% and 61.6% respectively.
On the basis of the results, it was discovered that ANN approach is an improved, simple, less expensive and more accurate method of determining the two-phase gas deviation factor. ANN approach gives the closest value to the observed two-phase gas deviation factor from experimental work.

Keywords: Artificial neural network; gas-condensate reservoir; modeling; two-phase Z-factor.

ABBREVIATIONS

ANN : Artificial Neural Network
RMSE : Root Mean Square Error
AAD : Absolute Average Deviation
COD : Coefficient of Determination
Z_{2ph} *: Two-phase Gas Deviation Factor*
DAK : Dranchuk Abou-Kassem Correlation
T_{pr} *: Pseudoreduced Temperature*
P_{pr} *: Pseudoreduced Pressure*
P : Reservoir Pressure
T : Reservoir Temperature
Y_g *: Gas Specific Gravity*

1. INTRODUCTION

Gas deviation factor also known as gas compressibility factor and simply called Z-factor, is an important parameter in natural gas engineering. It is used in material balance equation for the estimation of initial gas in-place and for reserves estimation. The Z-factor is a dimensionless quantity and defined as the ratio of the actual volume of n-moles of gas at temperature (T) and pressure (P) to the ideal volume of the same number of moles at the same T and P, it accounts for the deviation of gases from ideality. For most engineering calculations, the single-phase Z-factor is mostly used [1,2,3]. However, for a gas condensate reservoir, the two-phase Z-factor has to be used. This is explained by the presence of two-phases within the reservoir at pressures below the dew-point [4,5]. Thus, there is the need to accurately determine its value.

Traditionally, the two-phase gas deviation factor is determined experimentally in the laboratory, through either a Constant Composition Experiment (CCE) test or a Constant Volume Depletion (CVD) test. However, laboratory experiments are expensive, though quite reliable. Hence, the need for simple, accurate and less expensive methods of determining the two-phase gas deviation factor. Several correlations such as Hall Yarborough, Dranchuk and Abou-Kassem, Rayes et al. [6,7] have been developed to predict the two-phase gas deviation factor using the different equations of states (EOS).

Numerous studies have harnessed the applicability of Artificial Neural Network (ANN) to model oil and gas reservoir rock and fluid properties [8]. In 1995, [9] used ANN in predicting permeability from porosity, while in 1996, [10] stated in their work that ANN is an especially efficient algorithm to approximate any function with finite number of discontinuities. In his study, [11] used ANN to model bubble-point pressure (P_b) and oil formation volume factor (B_o) for accuracy and flexibility. In 2002, [12] developed an alternate methodology for a better determination of relative permeability using ANN, their results showed that ANN have the potential of providing a toolbox for identifying the parameters controlling relative permeability characteristics. While in 2013, [13,14] in their work applied ANN to compensate for the weakness of conventional methods.

2. MATERIALS AND METHODS

For the purpose of this study, the two-phase gas deviation factor for a gas-condensate reservoir fluid was modelled using ANN. This was achieved by using the non-algorithmic, parallel distributive and adaptive information processing system of ANN to acquire knowledge about the relationship that exists between pressure and two-phase Z-factor for a given temperature and the error of the model is checked against experimental value and existing correlations.

According to [1] and [15], ANN is a biologically inspired non-algorithmic, non-digital, massively, parallel distributive and adaptive information processing system. It resembles the brain in acquiring knowledge through learning process, and storing knowledge in inter-neuron connection strengths. ANN's ability as a nonlinear

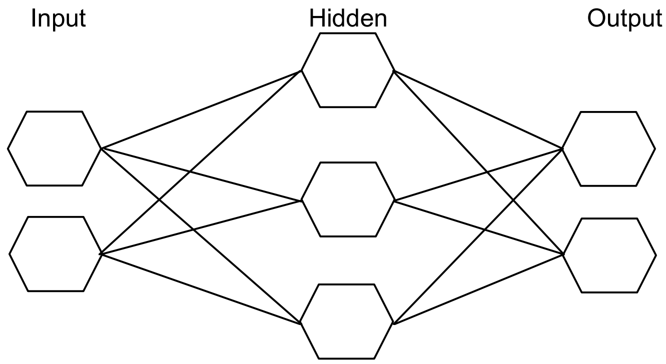

Fig. 1. Neural network flow of computation

mathematical function that transforms a set of input variables into a set of output variables (Fig. 1) makes it unique and fit for this study or work. The ANN architecture is a unique way of modeling two-phase gas deviation factor. Neural Networks is a toolbox designed to train, visualize, and validate neural network models. A neural network model is a structure that can be adjusted to produce a mapping from a given set of data to features of or relationships among the data.

According to [16], the nodes represent input and output channels and the connection between the two channels are called hidden nodes. All input and output nodes are not directly connected rather they are connected to the hidden nodes; all connections have an independent weighting factor associated with them. The transformation (of input to output) function depending on weights contain an algorithm which converts the input into a zero (0), positive one (+1), negative one (-1) or some other number. The transformation functions (e.g. sigmoid, sine, hyperbolic tangent etc) provide nonlinearity. The results of the transformed function are the output of the hidden nodes. The model is adjusted, or trained, using a collection of data from a given source as input, typically referred to as the training set. After successful training, the neural network will be able to perform estimation, prediction, or simulation on new data from the same or similar sources. The Neural Networks toolbox supports different types of training or learning algorithms. It uses numerical data to specify and evaluate artificial neural network models. Given a set of data, [xi,yi]i=1N from an unknown function, y = f(x), the toolbox uses numerical algorithms to derive reasonable estimates of the function, f(x). This involves three basic steps: First, a neural network structure is chosen that is considered suitable for the type of data and underlying process to be modeled. Secondly, the neural network is trained by using a sufficiently representative set of data. Thirdly, the trained network is tested with different data, from the same or related sources, to validate that the mapping is of acceptable quality.

2.1 Initialization

Based on the input data x and the output data y, the neural network was initialized with the number of hidden neurons specified. Special initialization algorithms exist that give well-initialized neural networks. An initialization with better performance is obtained using one of these algorithms. In this study, Levenberg-Marquart (LM) algorithm was utilized due to its stability and swift convergence [15].

2.2 Training

Training the network requires a set of training data [xi,yi]i=1N containing N input-output pairs. The model was thus trained using input data x (i.e. P, T, Y_g) and output data y (i.e. Z_{2ph}-factor) with a default number of training iterations. During training, intermediate results obtained were displayed in an automatically created workbook. Once training was completed, the following information was displayed:

1. Training iteration number
2. The value of the RMSE
3. Plots of RMSE as a function of iteration

2.3 Limitations of ANN

Ignorance of neural network functionality is one of the limitations in its usage to reservoir fluid characterization. Without a comprehensive understanding of the way it works or functions, neural network are often understood of as “black box” approach instead of a beneficial technique to generate reproducible models. Another major error associated with neural networks is its susceptibility to “over fitting” just like polynomial curve fitting.

2.4 Deploy Solution

Eighty-six datasets obtained from four different gas condensate reservoirs were used to train the network. Once the data set had been trained and a training network had been established, the neural network can then be used to predict an output value given that an input value is provided which could be either same or different from the sets of training data.

The gas-condensate reservoir EXX under study was located in the Niger Delta, Nigeria. PVT study of the reservoir showed that the initial reservoir pressure and temperature were 4680 psia and 184°F respectively. From the constant mass study performed, the dew point pressure was confirmed to be 4490 psia. Fluid parameters were: specific gravity at 60°F (0.8028), molecular weight (27.31 g/mol), viscosity (0.0299 cp) and relative density (0.942) and the condensate-gas ratio (63 stb/MMscf).

2.5 Two-Phase Gas Deviation Factor

Gas deviation factor, Z, is a function of temperature and pressure:

$$Z = f\,(P, T, Y_g) \tag{1}$$

Several correlations have thus modeled the gas deviation factor to be dependent on the reduced operating conditions; reduced pressure and reduced temperature. However, for the purpose of this study, the gas deviation factor was modelled using the reservoir pressure, temperature and gas specific gravity. It is assumed that the reservoir was isothermal, thus at different reservoir operating conditions, the reservoir pressure changes due to depletion whilst temperature does not. Thus, this model was built by determining the relationship between the two-phase gas deviation factor and reservoir pressure at a given temperature. The artificial neural network, which is well suited for performing non-linear, multi-dimensional interpolations, was used to estimate the two-phase gas deviation factor.

The input data (pressure, temprature, gas specific gravity) and output data (Z_{2ph}) were loaded to the toolbox (Fig. 2). A training function was chosen, the training function used was the Bayesian Regularization. The data set was trained, and the performance of the training network was evaluated. After performance evaluation of the training network, which showed that the network passed for prediction as it was able to model the output based on the input data, the network was stored to be deployed as a solution.

The error types used by [15] in their work on gas compressibility factor prediction were employed for perfomance evaluation in this study. The three types of errors used were: Average Absolute Deviation (AAD), Root Mean Square Errors (RMSE) and Correlation (or Coefficient) of determination (COD) also known as R^2. AAD

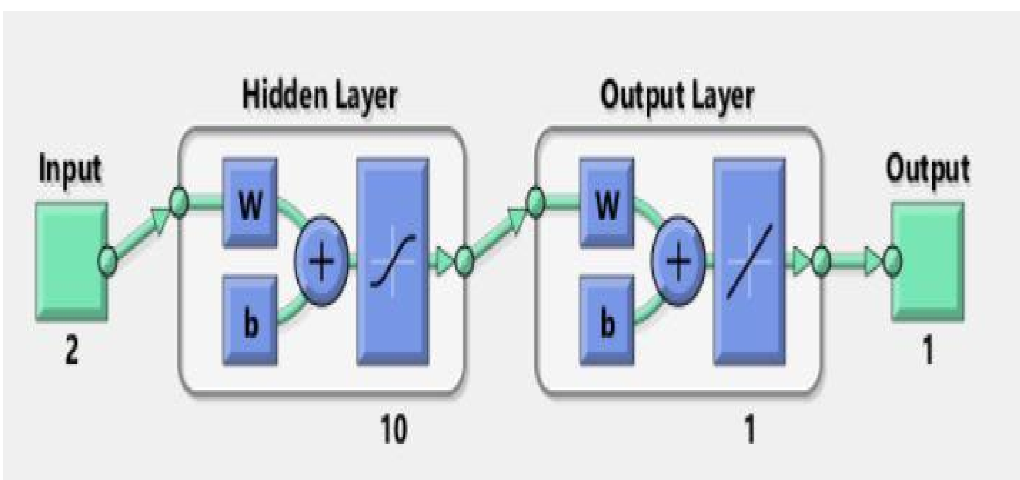

Fig. 2. ANN architecture for the model

show the amount of variation that occur around the mean as shown below:

$$AAD = \frac{1}{N}\sum\left|X - \mu\right| \tag{2}$$

RMSE is an important criterion for comparing two parameters. It was used in the work to compare observed value of Z_{2ph} with that of ANN model and other correlations. RMSE is the square root of average squared errors as shown in equation (3) below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(Z_{2phi}^{Predicted} - Z_{2phi}^{Measured}\right)^2}{N}} \tag{3}$$

Equation (4) is the COD equation, the higher the value the better the goodness of fit as shown in Fig. 5.

$$COD = 1 - \frac{\sum_{i=1}^{N}\left(Z_{2phi}^{Predicted} - Z_{2phi}^{Measured}\right)^2}{\sum_{i=1}^{N}\left(Z_{2phi}^{Predicted} - average\left(Z_{2phi}^{Measured}\right)\right)^2} \tag{4}$$

3. RESULTS AND DISCUSSION

Compositional data for gas condensate reservoir given in Table 1 was used as input. Artificial neural network was used to predict the two-phase gas deviation factor for a gas condensate reservoir at four (4) different reservoir operating conditions and the result is shown in Table 2. The neural network was able to accurately predict the two-phase gas deviation factor. In addition, the average absolute deviation between experimental values and the ANN result for the four reservoir operating conditions was determined. The average absolute deviation for the gas condensate reservoir at the reservoir operating conditions was given as 1.343% (Table 3).

The results obtained using ANN was also compared with that obtained using existing correlations for the same reservoir operating conditions. As shown in Table 2, ANN prediction gave the closest value to the observed two-phase gas deviation factor from experimental works.

Table 1. Gas-condensate composition data

Components	Mole fraction	T_{ci} (˚R)	P_{ci} (Psia)
Methane, C_1	0.7535	343	667.8
Ethane, C_2	0.085	549.8	707.8
Propane, C_3	0.0405	665.7	616.3
i-Butane, iC_4	0.0104	734.7	529.1
n-Butane, nC_4	0.0159	765	551
i-Pentane, iC_5	0.008	829	491
n-Pentane, nC_5	0.0079	845	489
Hexane, C_6	0.0108	913	437
Heptane, C_{7+}	0.0507	972	397
Hydrogen, H_2	0	60	187.05
Nitrogen, N_2	0.0156	227.4	491.55
Oxygen, O_2	0	277.8	730.8
Carbon dioxide, CO_2	0.0017	547.6	1070.6
Hydrogen sulphide, H_2S	0	672.4	1306
Dihydrogenoxide	0	1165	3199

Table 2. Comparison between ANN and other methods of calculating Z_2ph

Pseudo-reduced Pressure (P_{pr}) @ T_{pr}=1.47	Measured Z_{2ph}	Calculated Z_{2ph}				
		ANN	Rayes et al.	Hall Yarborough	Papay	DAK
4.55	0.8270	0.8158	0.7829	0.7752	0.7800	0.7765
4.99	0.8320	0.8316	0.8093	0.7950	0.7968	0.7967
5.43	0.8410	0.8538	0.8358	0.8181	0.8201	0.8180
5.71	0.8500	0.8708	0.8530	0.8349	0.8385	0.8334

Table 3. Accuracy of ANN compared to existing correlations

	ANN	Rayes et al.	Hall-Yarborough	Papay	DAK
AAD (%)	1.343	2.259	3.803	3.441	3.761
RMSE (%)	1.344	2.499	3.466	3.171	3.392
COD (%)	61.600	37.890	20.850	23.690	20.420

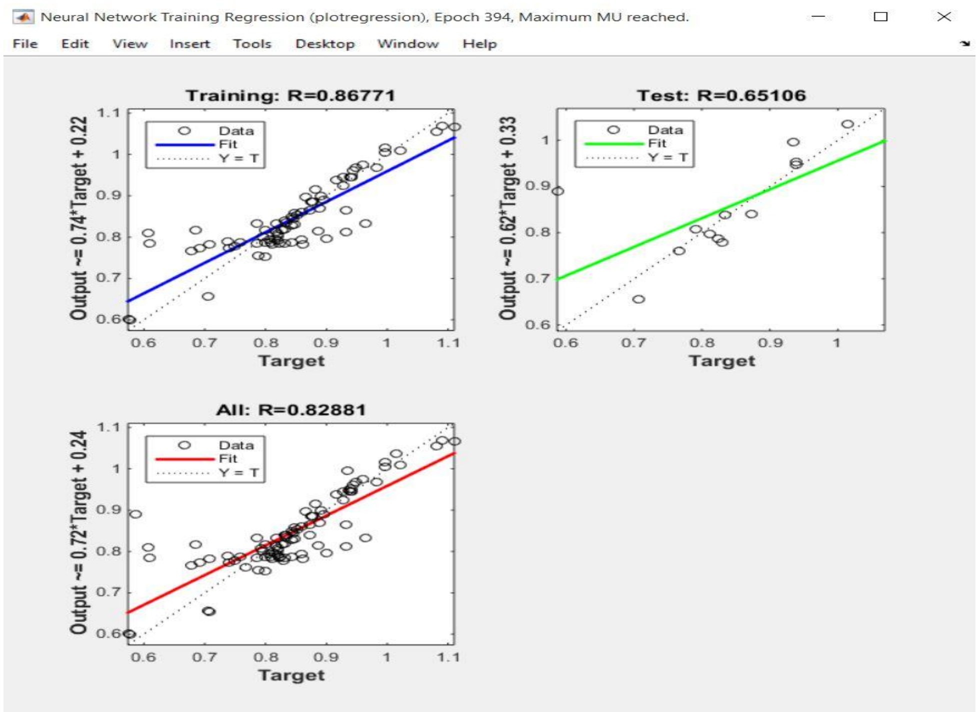

Fig. 3. Regression plot for ANN

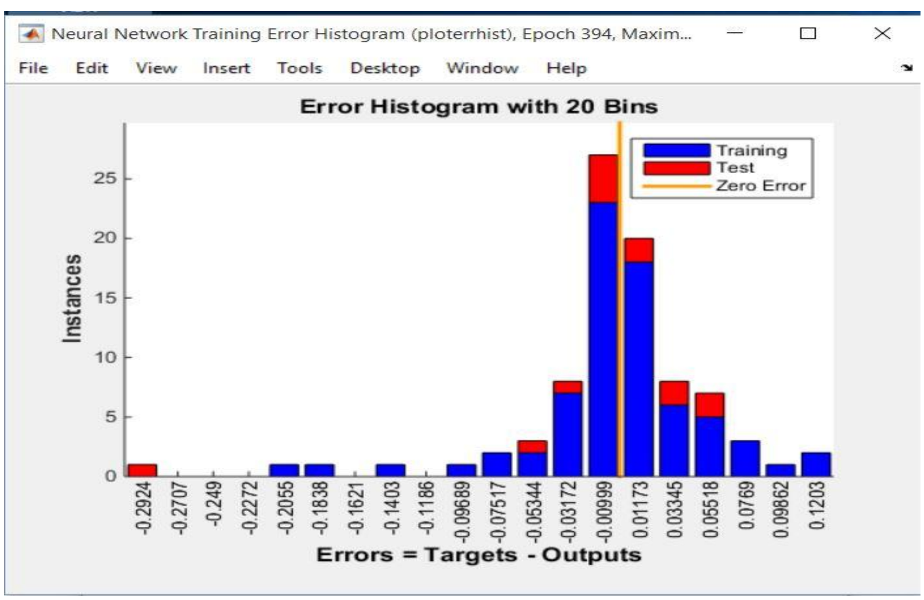

Fig. 4. Error histogram for ANN

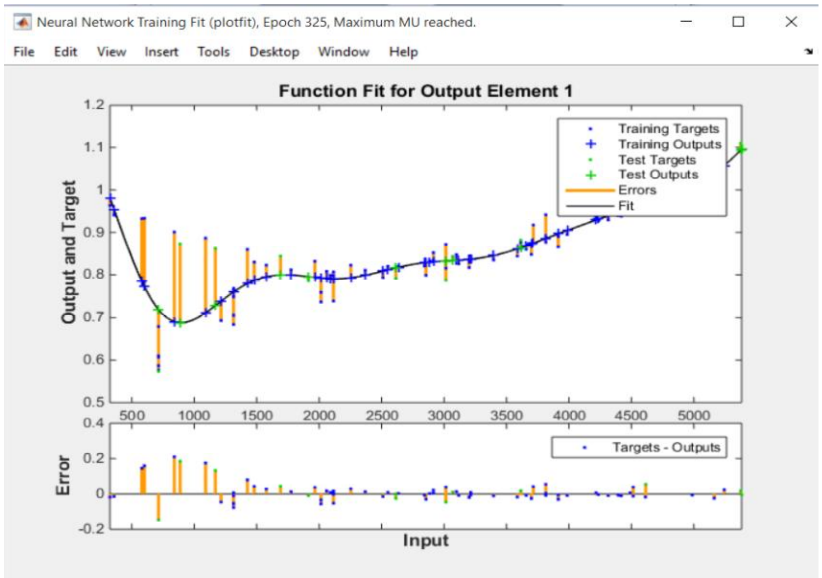

Fig. 5. Comparison of target and output values related to training, test and error

Table 3 showed the comparison of the average absolute deviation (AAD), root mean square errors (RMSE) and correlation of determination (COD) between the ANN output and other correlations, it was obvious that ANN closely matched the experimental values of the two-phase gas deviation factor having a correlation of determination value of 61.6% (the highest of the three methods), the average absolute deviation of 1.343% (the least of the three) and root mean square error of 1.344% (the least of the three methods). The accuracy of the ANN was further confirmed by the performance plots of the Artificial Training Network (Figs. 3-4). As shown in Fig. 5, the training stopped at 325 epoches.

Bearing in mind that the experimentally determined data had some forms of uncertainty as it was carried out using a visual window-type PVT cell with processes modeling that of the reservoir behavior, it can be summarized that the accuracy of the ANN in the determination of two-phase gas deviation factor is better in degree to existing correlations. Reasons for this are as follows: ANN inputs requirement are fewer than other correlations, the existing correlations are cumbersome, and have validity range of usage in the determination of z-factor. Also, according to [16], ANN used training dataset along with different training algorithms to spontaneously correct the weights and threshold to minimize error as shown in Figs. 4 and 5.

4. CONCLUSION

From the results of this study the following conclusions have been reached:

In this study, Artificial Neural Network (ANN) proved to be credible and efficient tool for modeling the two-phase gas deviation factor of a gas-condensate reservoir fluid, with high accuracy of prediction compared to experimental values and existing correlations. The accuracy of the ANN in predicting the two-phase gas deviation factor was shown by the average absolute deviation of 1.343% among existing correlations. Hence, ANN demonstrated to be a resourceful tool for solving many petroleum engineering problems such as two-phase gas deviation factor.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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