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Application of Deep Neural Network-Artificial Neural Network Model for Prediction Of Dew Point Pressure in Gas Condensate Reservoirs from Field-X in the Niger Delta Region Nigeria

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ABSTRACT: Reservoirs of natural gas and gas condensate have been proposed as a potential for providing affordable and cleaner energy sources to the global population growth and industrialization expansion simultaneously. This work evaluates reservoir simulation for production optimization using Deep Neural network - artificial neural network (DNN-ANN) model to predict the dew point pressure in gas condensate reservoirs from Field-X in the Niger Delta Region of Nigeria. The dew-point pressure (DPP) of gas condensate reservoirs was estimated as a function of gas composition, reservoir temperature, molecular weight and specific gravity of heptane plus percentage. Results obtained show that the mean relative error (MRE) and R-squared (R^2) are 0.99965 and 3.35%, respectively, indicating that the model is excellent in predicting DPP values. The Deep Neural Network - Artificial Neural Network (DNN-ANN) model is also evaluated in comparison to earlier models created by previous authors. It was recommended that the DNN - ANN model developed in this study could be applied to reservoir simulation and modeling well performance analysis, reservoir engineering problems and production optimization.

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The search for more affordable and cleaner energy sources to suit people's needs is gradually growing as the world's population and industrialization simultaneously advance (Ejelonu and Emegha, 2022; Emegha *et al.*, 2022). Reservoirs of natural gas and gas condensate have been proposed as a potential way of decreasing this need. The increased usage of natural gas on a global scale is a development in the energy sector that is improving the economy and the environment (Faraji, 2021). Classes of hydrocarbon reservoirs known as gas-condensate reservoirs are distinguished by the production of surface gas and varied amounts of stock-tank oil (STO) (Faraji, 2021). Gas-condensate reservoirs are crucial when it comes to the sizeable global energy market. Gas condensates are present in approximately 68% of the world's gas reservoirs (Zhang *et al.*, 2019). Gas-condensate fluid has API gravity between 40^0 and 60^0, which is a measurement of weight or density (Whitson and Brulé, 2000). The majority of well-known gas-condensate reservoirs are located between 5000 and 10,000 feet below the surface, at pressures between 3000 and 8000

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psi and temperatures between 200^0 and 400 °F (Elsharkawy, 2001; Moses and Donohoe, 1987). When developing a gas condensate field, reservoir engineers must consider a number of key parameters, one of which is the dew point pressure (DPP). Gas reservoir engineers must precisely calculate the DPP for gas condensate reservoirs in order to conduct proper field development activities for gas condensate (Ahmed, 2006). In general, three main techniques have been found and used to forecast the dew point pressure of gas condensate: (i) laboratory measurement; (ii) equations of state (EOS); and (iii) empirical correlations (Skylogianni *et al.*, 2015; Louli *et al.*, 2012). For gas condensate reservoirs, determining DPP experimentally at reservoir temperature can be costly, time-consuming, and occasionally rife with inaccuracies (Hosein and Dawe, 2012). The cost and amount of time needed to execute the test constitute a significant limitation even though all tests produce satisfactory outcomes. Several additional types of error can also be introduced during experimental measurements, ranging from inaccurate measurements occurring during the test to the collection of gas sample errors (Arabloo and Rafiee - Taghanaki, 2014; Hosein and Dawe, 2012). The search for a more accurate, as well as faster model has been sparked by an understanding of these shortcomings of the current approaches. Recently, there has been a lot of interest in the artificial neural network concept. Artificial neural networks have demonstrated its usefulness in a number of industries, including the world of social media, machine learning, drilling technology, space flight, face and speech recognition, etc. The neural network is a highly parallel, distributive, flexible, and biologically inspired system (Ahmadi *et al.*, 2014). Also, neural networks are powerful tools that can learn complex patterns and relationships in data, even when the data is incomplete or inaccurate (Ali, 1994). Generally, artificial neural networks (ANNs) have been used as prediction tools that are based on simple mathematics. Each algorithm has its own distinct advantages and disadvantages. For example, the accuracy of neural network algorithms depends on their architecture (Kubat, 1999), whereas the accuracy of support vector machine (SVM) algorithms depends on the quantity of trustworthy data supplied into the algorithm (Zhang *et al.*, 2019). There is a significant variance between the dew- point forecasts produced by various algorithms. The overall accuracy of their final forecasts is impacted by the fact that some algorithms are more susceptible to data bias than others. Numerous models have been developed in the past by various researchers, but they often lack the transparency and reproducibility required for scientific rigor (Aghamiri *et al.*, 2017; Al- Shammasi, 2001). The purpose of this study is to predict the dew point pressure in gas condensate reservoirs utilizing artificial neural networks algorithm by employing Tensor Flow, Keras, Python, and Jupyter Notebooks. By utilizing experimental data collected from the Niger-delta region, it will aid in developing a model that is more accurate than others in testing, training, and validating the data collected for the artificial neural network model. Although research on the use of artificial neural networks for gas-condensate reservoirs has been done, there are still unresolved problems and shortcomings in choosing the most accurate model for prediction. Therefore, this study evaluates reservoir simulation for production optimization using Deep Neural network - artificial neural network (DNN-ANN) model to predict the dew point pressure in gas condensate reservoirs from Field-X in the Niger Delta Region of Nigeria.

MATERIAL AND METHODS

Data Acquisition and Analysis: The artificial neural network was created using a collection of test data obtained from field X in the Niger-Delta region. Field X's recent gas condensate reservoir samples are included in these statistics.

Material and Equipment: The neural network model was implemented using the following techniques and technologies.

TensorFlow is an open-source, free machine learning software library. Although it can be applied to many different tasks, deep neural network training and inference are given special attention.

Keras is a Python-based deep learning API.

Python is a high-level, interpreted language. It is the current language for artificial intelligence and is utilized for a wide range of scientific and engineering applications. Numerous libraries, including Numpy, Pandas, Sci-kit-Learn, and Matplotlib, are included with Python.

Colab: In order to "create open-source software, open standards, and services enabling interactive computing spanning dozens of programming languages," Colab is a project and community. It is a cloud place where you may execute your programs to save time by not having to implement them locally.

Design Concept: Multivariate regression and the Deep Neural Network technique were used to create the model.

Deep Neural Network: DNNs are artificial neural networks (ANNs) with more than two layers between the input and output layers. Notwithstanding the wide range of neural network configurations, all neural networks are composed of the same constituent parts: neurons, synapses, weights, biases, and functions. These pieces behave similarly to human brains and may be trained just like any other ML algorithm. Deep neural networks are capable of modeling intricate non-linear interactions. The object is expressed as a layered composition of primitives in the compositional models generated by Deep Neural Network architectures. It is possible to model complex data using fewer units with the additional layers than with a shallow network that performs comparably because they enable the composition of characteristics from lower levels. Generally speaking, feed-forward systems—in which data flows directly from the input layer to the output layer—are what deep neural networks are. The DNN starts by creating a map of virtual neurons and assigning random numerical values, or "weights," to the connections between them. When the weights and inputs are multiplied, an output between 0 and 1 is generated. If the network was having problems accurately recognizing a particular pattern, an algorithm would adjust the weights. The method is able to determine the optimal mathematical operation to fully examine the data while simultaneously giving some factors more weight than others.

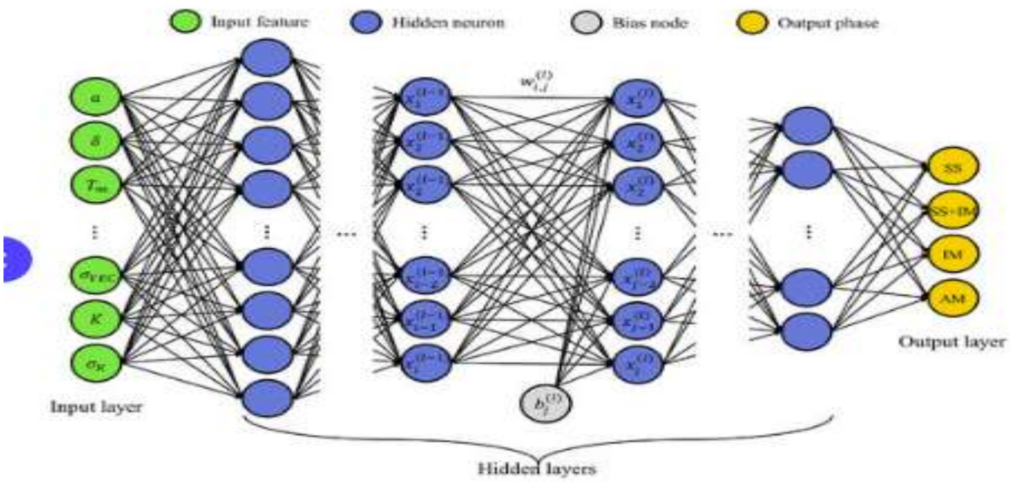

Fig 1: Schematic diagram of the deep neural network an architecture of DNN model comprised of input, hidden, and output layers (Soo *et al.*, 2020)

Multivariate Regression: Numerous data factors are analyzed using multivariate regression, a supervised machine learning technique. Multivariate regression is an extension of multiple regressions and consists of several independent variables and one dependent variable. Taking into account the quantity of independent variables, we try to predict the outcome.

Below is the generalized equation for the multivariate regression model-

$$y = \beta_0 + \beta_1 . x_1 + \beta_2 . x_2 + \ldots\ldots\ldots + \beta_n . x_n \quad (1)$$

Where; n = the number of independent variables; β_0 - β_n = the coefficients; x_1- x_n = the independent variable.

Neural Network Data Input: Selecting the input variables for the model comes next, after discovering and obtaining the data set. The foundation for dew point pressure prediction using existing correlations is the concept that dew point pressure for retrograde gas condensates is a function of the hydrocarbon and non-hydrocarbon reservoir fluid compositions, reservoir temperature and the heptane plus percentage.
The correlation between the Dew point pressures and the other variables is seen in Equation 2

$$P_d = f(T, Z_i, MWC_7, SGC_7) \quad (2)$$

Where: P_d = Dew point pressure (psia); Z_i = Composition of the system; T = Reservoir Temperature
MWC_7 = Molecular weight of Heptane plus fraction; SGC_7 = Specific gravity of Heptane plus fraction

This strategy led to the selection of temperature, non-hydrocarbon composition (H_2S , Co_2 and N_2), hydrocarbon compositions of C_1 through C_7, heptane plus specific gravity, and heptane plus fraction (MW-C_{7+}) molecular weight as the input parameters for the artificial neural network model for the prediction of dew point pressure of retrograde gas.

Neural Network Training and Testing: The artificial Deep Neural Network design must be developed after the input data has been selected; the original network structure was a seven-layer network. The number of neurons in the hidden layers and the weights applied to the input parameters were calculated using the keras library. Since the purpose of constructing a computational model is high accuracy in general analysis and prediction, it is imperative that the model be trained for predicting unknowns. After training, the final model should produce outputs with accuracy. A series is split into training and testing data to prevent over- or under-fitting and to assess how a model performs on data that has not been seen yet. Typically, the data is divided into ratios of 80% to 20% or 70% to 30%. 60% of the data used in this model went toward training, 20% went toward testing, and 20% went toward validation.

Tables 1 and 2 show the value of some of the data after normalization. The data was normalized using the formula:

$$\frac{x-\mu}{s} \qquad (3)$$

Where: x = value of sample; μ = The mean; s = standard deviation

Table 1: Value of some Normalized data (1)

N_2	CO_2	C_1	C_2	C_3	$\mathrm{I}-C_4$	$\mathrm{n}-C_4$	$\mathrm{I}-C_5$
-0.5294	0.6959	0.0751	0.4211	-0.3208	-0.5677	-0.5422	-0.6479
1.7644	-1.2373	0.1589	-1.0563	0.6042	1.0983	1.0119	1.0966
0.4024	1.2096	-0.8033	-0.1211	0.6311	0.7045	0.8415	0.7194
0.6892	-0.2660	-1.8335	1.9771	1.5921	1.3104	1.2035	1.2852
-1.0312	-0.9478	0.7479	-0.6712	-0.3119	-0.6283	-0.3294	-0.4593
-0.4649	1.1105	0.6994	0.0266	-0.8813	-0.8464	-0.9724	-0.9261
-0.8305	-0.5649	0.9555	-0.5761	-1.3233	-1.0706	-1.2129	-1.0676

Table 2: Value of some Normalized data (2)

$\mathrm{N}-C_5$	C_6	C_{7+}	Reservoir temp.[deg]	MW of C_{7+} [g/mol]	Specific gravity of C_{7+}	dewpoint pressure [psia]
-0.6015	-0.3239	-0.2703	0.1459	-0.3247	0.8117	0.5887
1.0111	0.8436	-0.2703	-0.4290	-1.6794	0.7426	-1.1228
0.8916	0.7089	0.5916	0.8879	-0.1577	0.8194	-0.2838
1.1902	1.4274	1.8816	1.5624	0.0894	0.8302	0.3343
-0.3626	-0.4587	-0.4358	0.0206	1.0485	-1.0410	1.6427
-1.0077	-1.1952	-1.3199	-1.3862	-0.3299	-1.1348	-1.2236
-1.1211	-1.0021	-0.1767	-0.8016	1.354	-1.0281	0.0644

RESULT AND DISCUSSION

The dew point pressure (DPP) of gas condensate reservoirs was estimated using the Deep Neural Network-Artificial Neural Network (DNN-ANN) technique. The model was trained using 60% of the experimental data, validated using 20%, and tested using the remaining 20%. This method of validation, known as k-fold cross-validation, ensures that the model generalizes effectively to new data. The DNN-ANN model's MRE and R^2 values are noticeably higher than those of earlier models. This implies that compared to earlier models, the DNN-ANN model are more accurate at predicting DPP values. Also, the calculated statistical parameters shown in Tables 3 and 4 demonstrate the confidence of this algorithm. Statistical and graphical analyses were conducted to evaluate the performance of this method.

Table 3: Evaluating the performance of DNN-ANN model using statistical analysis for the training set.

R^2	MRE	MSE	RMSE
0.999861	6.363996	2903.2349	53.881676

Table 4: Evaluating the performance of DNN-ANN model using statistical analysis after testing

R^2	MRE	MSE	RMSE
0.999432	0.440941	921.067743	30.349098

Graphical Comparison: Figure 2 depicts a graphical comparison of the experimental and expected DPP levels. The data points are concentrated around the 45-degree line, demonstrating that the DNN-ANN model can predict DPP values with high accuracy. The graphical comparison demonstrates that the DNN-ANN model can predict DPP values over a wide variety of reservoir conditions. This implies that the model is robust and may be used to forecast DPP values for gas condensate reservoirs.

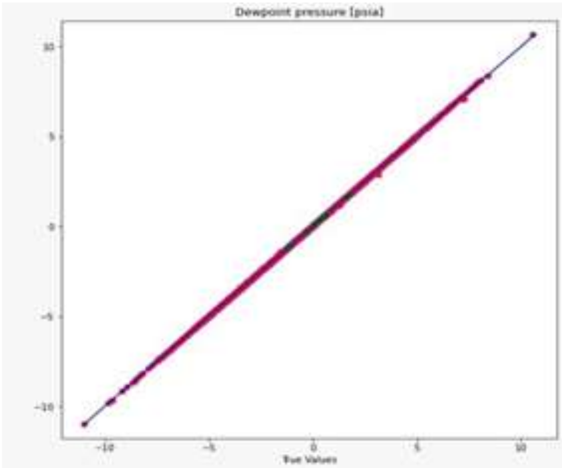

Fig 2: Plot of Predicted vs. Experimental values

The model's accuracy and loss throughout training at each epoch are displayed in Figures 3 and 4. Each epoch saw a drop in loss and an increase in accuracy, suggesting that the model was improving its ability to estimate dew point pressure. The accuracy and loss curves demonstrated how well the DNN-ANN model learned the training set while avoiding over-fitting. The model's accuracy and loss during validation at each epoch are indicated in figures 5 and 6. These imply that the model is picking up new skills and doing well when validated against data. Loss gauges the degree to which the model's predictions agree with the actual value. A better model is indicated by a lesser loss. However, a higher accuracy indicates a more accurate model. This indicates that the new model is learning from the data and improving its capacity to make exact predictions. Finally, the fact that the model performs well on the validation data indicates that it generalizes well to previously unseen data. This is significant because it indicates that the model is likely to perform well on new data sets that it has not before encountered. Overall, figures 5 and 6 indicate that the model fits the data well and can be used to estimate dew point pressure accurately.

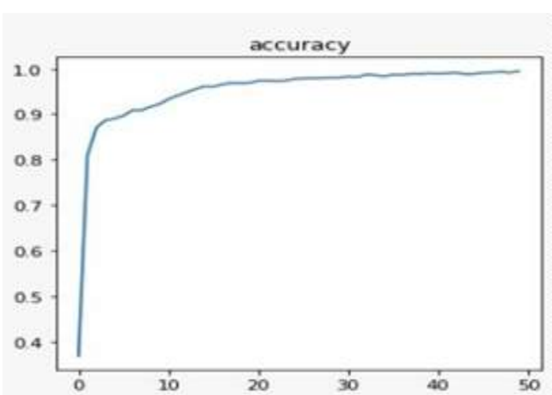

Fig 3: plot of Accuracy vs Epoches at training

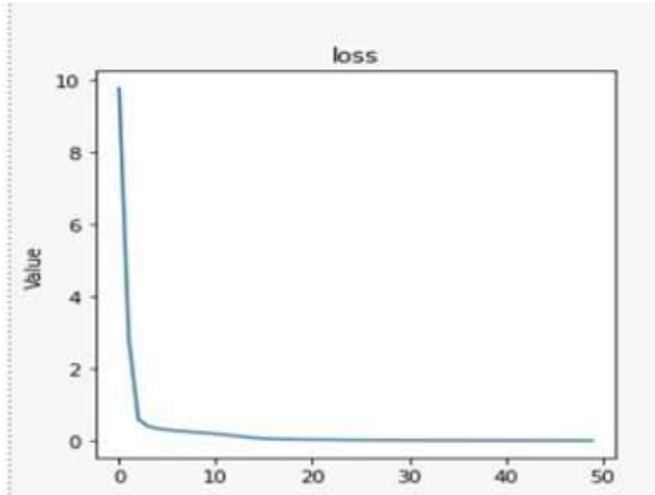

Fig 4: plot of Loss vs Epoch at Training

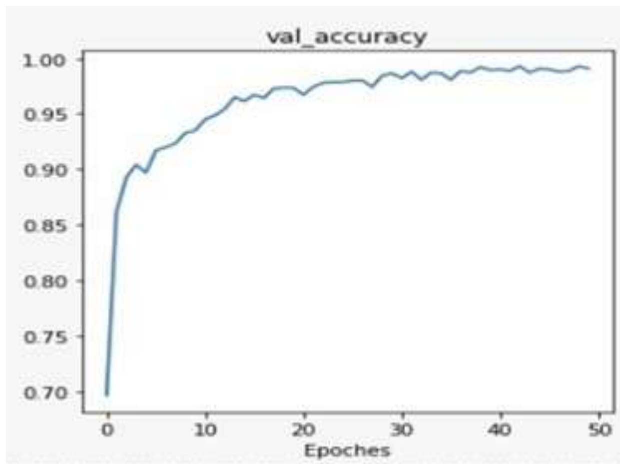

Fig 5: plot of Accuracy vs Epoch at Validation

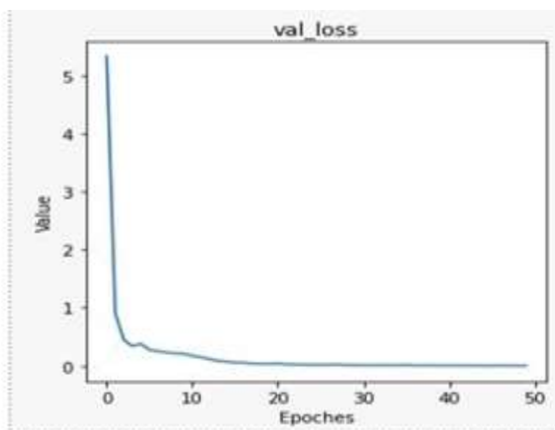

Fig 6: plot of Loss vs Epochs at Validation

*Comparison of the results of the current model with some previously published models***:** Table 5 compares the performance of our DNN-ANN model to earlier models such as NK Correlation, EA Empirical model and Gene Expression Programming (GEP) (Table 5). As can be observed, our DNN-ANN model outperforms all other previously published models in terms of accuracy. The MRE and R^2 values for the DNN-ANN model are much higher than those reported for earlier models. This implies that the DNN-ANN model can predict DPP values more accurately than earlier models. There are several reasons why the DNN-ANN model outperforms earlier models. Initially, the DNN-ANN model can figure out intricate non-linear correlations between the input variables (specific gravity of heptane plus percentage, molecular weight, reservoir temperature, and gas composition) and the output variable (DPP). Conversely, previous models were usually based on correlations that were either linear or semi-linear.

Secondly, the DNN-ANN model used a sizable collection of experimental data for training process. The model was trained on a broad range of reservoir conditions found in this data set, which helped it understand the intricate interactions between the input and output variables. In contrast, prior models were usually trained on smaller data sets that encompassed a more limited set of reservoir conditions. Based on the DNN-ANN model, some advantages over earlier models in addition to the quantitative comparison are displayed in Table 5. As an illustration, the DNN-ANN model is more adaptable and simpler to modify for different data sets and reservoir circumstances. Furthermore, the DNN-ANN model is simpler to understand and more transparent than earlier models. To sum up, the present DNN-ANN model serves as a highly effective instrument for forecasting the dew point pressure of gas condensate reservoirs. Based on the information provided above, we can draw the conclusion that the model has the ability to significantly boost the oil and gas industry's bottom line by enhancing the development and management of gas condensate reservoirs.

Table 5: Comparison to Previous Models

Models	**References**	R^2	**MRE (%)**	**RMSE**
N.K correlation	(Nemeth and Kennedy, 1967)	0.66	9.641	780.456
E.A Empirical Model	(Elsharkawy, 2001)	0.42	11.22	915.420
Gene Expression Programing (GEP)	(Ahmadi and Elsharkawy 2017)	0.9667	7.20	500.49
DNN-ANN	Current Work	0.99965	3.35	42.11

Conclusion: To forecast the dew point pressure (DPP) of gas condensate reservoirs as a function of gas composition, reservoir temperature, molecular weight, and heptane plus percentage, a DNN - ANN model was created. The model was trained and evaluated on a large data set of gas condensate reservoir parameters, and it performed admirably on the training set, with a mean relative error (MRE) of 0.99965 and an R-square value of 0.999861. The model yielded an MRE of 3.35% and an R-squared value of 0.999432, indicating strong performance on the testing set.

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