Romanian Journal of Petroleum & Gas Technology
Vol. V (LXXVI) • No. 1/2024

A MODEL FOR FORECASTING DEW POINT PRESSURE IN NIGER DELTA CONDENSATE RESERVOIRS USING CONSTANT VOLUME DEPLETION TESTS DATA

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DOI: 10.51865/JPGT.2024.01.02

ABSTRACT

The dew point pressure plays a critical role in developing gas condensate reservoirs. It is a crucial factor used in fluid characterisation, performance estimation of gas reservoirs, and design of production systems. However, the composition of gas condensate fluid varies from one location to another, and thus, empirical correlations have been developed to determine the dew point pressure without conducting routine tests. As a result, correlations that are solely useful in the region where they were developed and analysed are developed. This work developed an empirical correlation using data from gas condensate wells in the Niger Delta using multiple linear regression. The model was developed using the Analytical Tools and techniques in Microsoft Excel. To develop the model, we utilised 63 data sets from the Constant Volume Depletion (CVD) experiment, which involved gas condensates from resources in the Niger Delta. The model comprises an empirical correlation that estimates the dew point pressure for gas condensate reservoirs. It uses compositional information of the fluid and reservoir temperature as input parameters. The correlation is derived through multiple regression analyses. Comparing the prediction accuracy of formulas based on the developed model and other conventional methods indicated that this model is more accurate than other statistical methods in predicting DPP within the Niger Delta region. This model can produce more accurate results than other estimation methods when working under limited field information and time constraints. The correlation developed in this process has a coefficient of determination of R^2=0.869 and an Average Absolute Relative Error (AARE) of -2.0767%, along with a root mean square of 195279, indicating a high level of reliability in the proposed correlation.

Keywords: Dew Point Pressure, Reservoirs, Condensate, Constant Volume Depletion, Linear regression.

INTRODUCTION

Gas condensate (GC) reservoirs are a valuable energy source and require significant time, effort, and financial investment to be thoroughly characterised using various models. This is because they provide a greater amount of energy when compared to other fossil fuels [4], [15]. Gas condensation reservoirs are typically found at greater depths and have pressure and temperatures exceeding oil reservoirs [10]. The nature of gas condensate is derived from the behaviour of hydrocarbons, which yields two phases with specific pressure and temperature values. This phenomenon is known as phase change. When a reservoir is initially produced, it contains a single phase. However, as the pressure decreases, a second phase is generated isothermally [11], causing gas condensation (or liquid dropout) in the pore spaces of the reservoir. This phenomenon primarily occurs near the wellbore and then spreads cylindrically throughout the drainage area of the Well [12].

Gas-condensate fluids containing heavy hydrocarbons reach a dew point at reduced pressure, forming a liquid. When liquid condenses, it can reduce gas permeability and affect production. If the pressure drops below *Pd*, liquid can accumulate near the wellbore, reducing gas productivity [9]. Determining the dew point pressure (DPP) of a gas condensate reservoir is crucial for fluid characterisation, gas reservoir calculations, and production system design. DPP is one of the most significant properties for the characterisation and successful prediction of the future performance of these reservoirs [6].

DPP is the pressure at which a small amount of hydrocarbon liquid is balanced with a large amount of gas. It is the pressure below which the hydrocarbon liquid condenses out of the gaseous phase. When the pressure is above the DPP, the gas condensate fluid maintains a constant composition, and the composition of the produced gas and condensate remains the same. However, if production occurs below the dew point pressure, the gas and condensate change in composition. When the initial pressure lies above or on the dew point curve, the pressure in the reservoir decreases (at the temperature of the reservoir) with its depletion. This decrease causes some condensation from the reservoir's gas phase. As the reservoir pressure drops further, the saturation of the condensate (liquid) in the reservoir increases until it reaches a certain pressure point, which varies based on the gas condensate fluid. After this point, the liquid saturation decreases. This phenomenon is known as "retrograde condensation." [8]. Figure 1 represents the phase diagram condition for retrograde condensation in a gas condensate reservoir. Once the pressure in the reservoir drops below the DPP, the produced gas-to-liquid ratio remains constant before increasing. This decrease in reservoir pressure below the DPP has two negative effects: Once the pressure reaches values less than the DPP, the produced gas-to-liquid ratio remains constant and then increases. The reduced reservoir pressure below DPP has two negative effects:

i. Decrease in gas production and gas condensate due to blockage near the Well.
ii. The producing gas has fewer valuable components due to liquid separation in the reservoir [10].

Having an accurate understanding of DPP is crucial when it comes to managing GC reservoirs. In these types of reservoirs, productivity can drop significantly when the pressure near the wellbore falls below the DPP. To investigate this decrease in productivity, radial compositional reservoir simulation models are utilised, demonstrating that liquid dropout around the wellbore is the root cause of the productivity decline. Furthermore, increased condensation saturation around the wellbore reduces the effective permeability of gas, resulting in a rapid decline in well productivity [7]. Accurately describing phase changes and behaviour can be achieved by correctly assessing dew point pressure [5]. Numerous studies have reported the significance of dew point pressure in the productivity of gas condensate reservoirs. It has been concluded that the gas productivity, relative permeability, and recovery decline below the dew point pressure as the accumulation of condensate increases around the wellbore. Thus, it is crucial to determine the dew point pressure for fluid characterisation and effective management of gas condensate reservoirs [1].

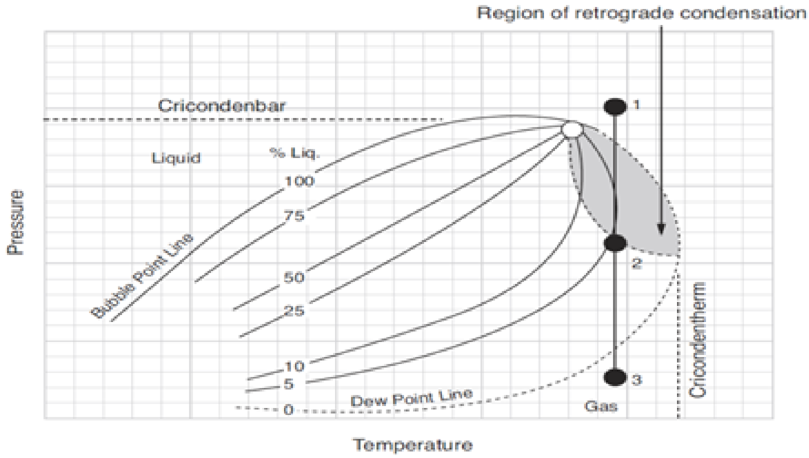

Figure 1. *Gas condensate reservoir's Phase Diagram displays Retrograde Condensation conditions* [2]

There are various methods to calculate DPP for gas condensate reservoirs. The first method is an experimental measurement of DPP from collected laboratory samples. The commonly used experimental techniques for measuring DPP are constant composition expansion (CCE) and constant volume depletion (CVD) tests. However, these methods are expensive and time-consuming, especially for lean gas condensate reservoirs where accurate measurements are crucial [3]. Moreover, the result generated might adversely be affected by some inherent technical and monetary constraints such as restricted experimental budgets, the insufficient ability to acquire enough representative samples, incomplete analysis due to the limited number of samples, and natural errors of each test.

The second approach is an iterative estimation of DPP using any equation of state (EOS). Studies show that the application of different EOS to characterise fluid behaviour in condensate gas reservoirs has been conducted. However, this approach has convergence problems because matching parameters of selected EOS should be tuned with some experimental data by the least-squared method. In addition, the EOS approach does not generalise to unseen data and usually memorises the data used to develop it [12].

The third method of dew point pressure calculation applies empirical correlations. Empirical correlations for DPP predictions have been studied by several investigators Nemeth and Kennedy [13], Elsharkawy [7], Shokir [14], and more). Empirical correlations are often created for specific geographic regions with a particular chemical composition of reservoir fluid and within a certain range of data. As a result, it is uncommon to find accurate PVT relations that are generally applicable. Most empirical PVT relations are developed using multiple linear or non-linear regression techniques and graphical techniques. It is important to note that an empirical correlation is limited to the range of data used in its development [7]. DPP can be calculated using gas-specific gravity or fluid compositions.

Improved empirical correlations are needed to predict dew point pressure for gas condensate systems in the Niger Delta to optimise reservoir development strategies. This study developed a correlation exclusively for the Niger Delta region, which will compete favourably with some other existing correlations developed for other regions.

METHODOLOGY

A set of 63 experimental data points of CVD tests have been utilized in developing and testing the new model. Table 1 summarizes the statistical analysis of experimental PVT data from the CVD test used to develop the mathematical model.

Table 1: *Parameters of statistics of the DPP data employed in this study*

Variables	Minimum	Maximum	Average
Dew point pressure, psia	1139	6877	3820
Temperature, °F	117	318	218
N_2, mole fraction	0.0000	0.0309	0.0034
CO_2, mole fraction	0.0000	0.1130	0.0196
H_2S, mole fraction	0.0000	0.1621	0.0027
C_1, mole fraction	0.5860	0.9610	0.8267
C_2, mole fraction	0.0180	0.1485	0.0624
C_3, mole fraction	0.0071	0.0890	0.0310
C_4, mole fraction	0.0030	0.0455	0.0161
C_5, mole fraction	0.0005	0.0254	0.0073
C_6, mole fraction	0.0007	0.0210	0.0060
C_{7+}, mole fraction	0.0030	0.0826	0.0244
Molecular weight C_{7+}	114	175	144
Specific gravity C_{7+}	0.7483	0.8211	0.7890

Correlation Development

The input parameters for this study include the compositions of hydrocarbon components, specifically C_1 to C_6 and C_{7+} (measured in mole fraction), as well as the specific gravity of the heptane-plus fraction (SGC_{7+}) and the molecular weight of the heptane-plus fraction (MWC_{7+}). In addition, non-hydrocarbon components such as CO_2,

N_2, and H_2S (measured in mole fraction) were also considered, along with the reservoir temperature (measured in Fahrenheit). In contrast, the output parameter is dew point pressure, DPP (psia). The input and output parameters were analysed to find their relationship and the possibility of grouping the parameters.

Running Multiple Linear Regression

The relationship between a dependent variable and two or more independent variables was determined using multiple linear regression.

$$y = f \tag{1}$$

The general expression gives it:

$$y = A_0 + A_1X1 + A_2X2 + A_3X3 + \cdots A_NXn \tag{2}$$

The Data Analysis Tool pack in Excel was enabled to run multiple linear regressions, and regression from all the options was selected and executed. The Dew point pressure (DPP) was added as a dependent variable Y in the input and output variables ranges. Moreover, C_1, C_2, C_3, C_4, C_5, C_6, C_{7+}, S.GC_{7+}, MWC_{7+}, N_2, CO_2, H_2S, and Tr are included in the independent variable X. To ensure correct findings, labels were enabled, and the output range was chosen before the analysis was executed.

Multiple linear regression was used to develop correlations following the process flowchart for the data analysis presented in Figure 2.

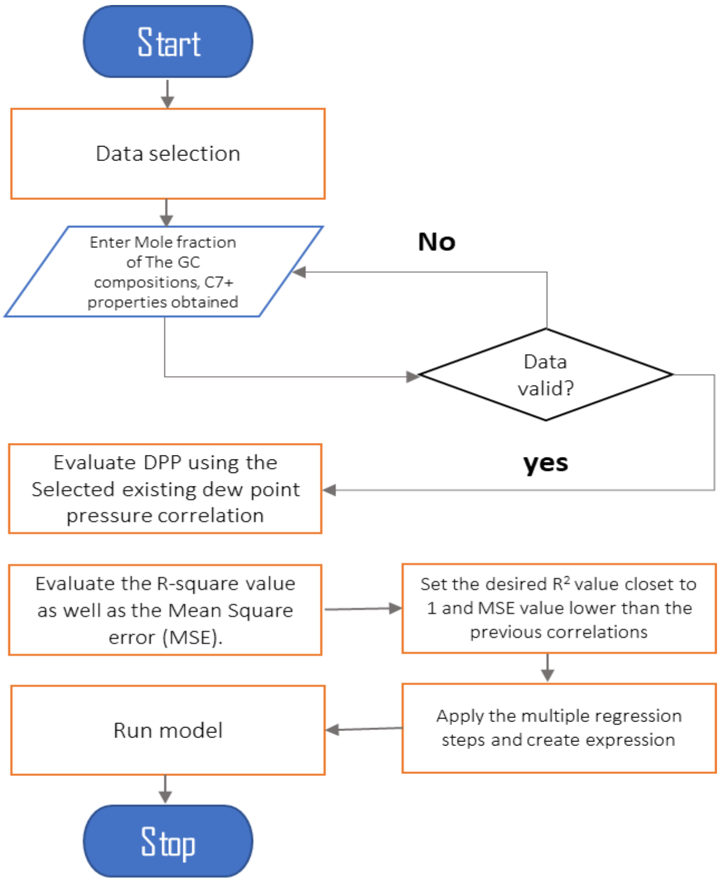

Figure 2: *Process flowchart showing the procedures for the data analysis*

The developed model was evaluated using the R-square value and the Mean Square Error (MSE) results. The correlation development aims to find one with a high R-square value as close to 1 as possible and a low MSE value. A multiple linear regression model was initially developed and then modified by grouping and adding different parameters, testing many different scenarios until a final correlation was achieved with a high R-square value, giving the lowest MSE.

$$P_d = f \tag{3}$$

Comparative Analysis with Existing Models

The developed model was tested on the data set. Existing models, such as Nemeth and Kennedy, El-Sharkaway, Shokir and Haji-Savameri, were tested on the same data set, and the model result was compared. The tools for comparison were:

The Average (Mean) Relative Error (Deviation), ARE, %;

$$ARE = \frac{100}{N}\sum_{i=1}^{N}\left[\frac{(P_d)_{measured}-(P_d)_{predicted}}{(P_d)_{measured}}\right] \tag{4}$$

The Average (Mean) Absolute Relative Error (Deviation), AARE, %;

$$AARE = \frac{100}{N}\sum_{i=1}^{N}\left[\left|\frac{(P_d)_{measured}-(P_d)_{predicted}}{(P_d)_{measured}}\right|\right] \tag{5}$$

Note: ARE characterises the accuracy (bias), and AARE describes the precision (scatter) of predicted values obtained from a particular correlation.

Mean Square Error (MSE)

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left[(P_d)_{measured} - (P_d)_{predicted}\right]^2 \tag{6}$$

Correlation of Coefficient (R)

$$R = \sqrt{1 - \left[\frac{\sum_{i=1}^{N}[(P_d)_{measured}-(P_d)_{predicted}]}{\sum_{i=1}^{N}(P_d)_{actual}-\overline{\Delta P_d}}\right]} \tag{7}$$

Where;

$$\overline{\Delta P_d} = \frac{1}{n}\sum_{i=1}^{N}[(P_d)_{actual}]_i \tag{8}$$

Where;

$(P_d)_{measured}$ is the experimentally measured Dew point from the laboratory

$(P_d)_{measured}$ is the Dew point pressure predicted from the newly developed correlation

N is the number of data sets used in the study

$\overline{\Delta P_d}$ is the average value of the experimentally measured Dew Point Pressure DPP

RESULTS AND DISCUSSION

The present study employs a multiple linear regression-based empirical correlation to determine the DPP in gas condensate reservoirs. Equation 8 portrays the relationship between the gas condensate properties and DPP, and Figure 3 to 6 provides the results. The result of the linear correlation between the individual hydrocarbon components, the non-hydrocarbon components, the reservoir temperature, and the observed dew point pressure is as presented in Figure 3 (“A” to “F”), Figure 4 (“A” to “B”), Figure 5 (“A” to “D”) and Figure 6 (‘”A” to “C”). Subsequently, Table 2 summarises the correlation coefficient between the DPP and GC properties.

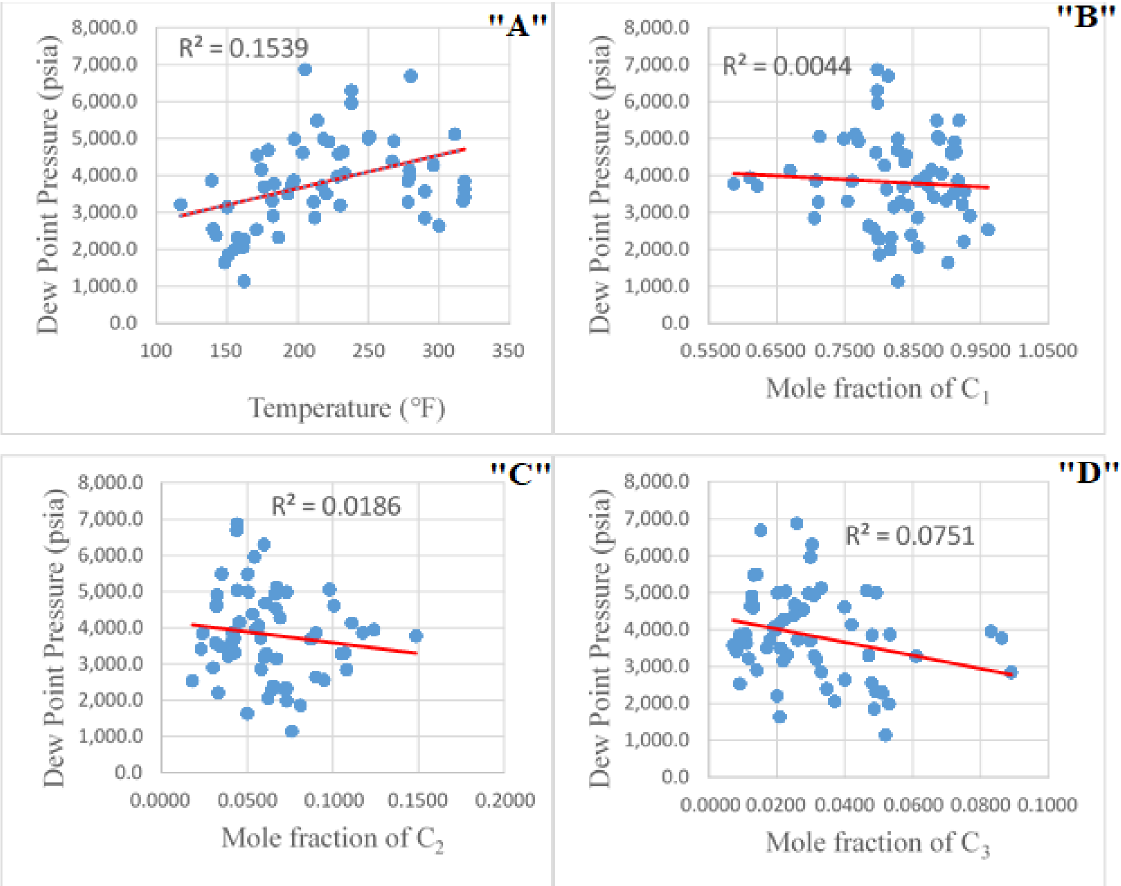

***Figure 3A, B, C & D**: Dependency of the DPP on the reservoir temperature (Figure 3A) and on the mole fractions of C_1 to C_3 (Figures 3B to 3D)*

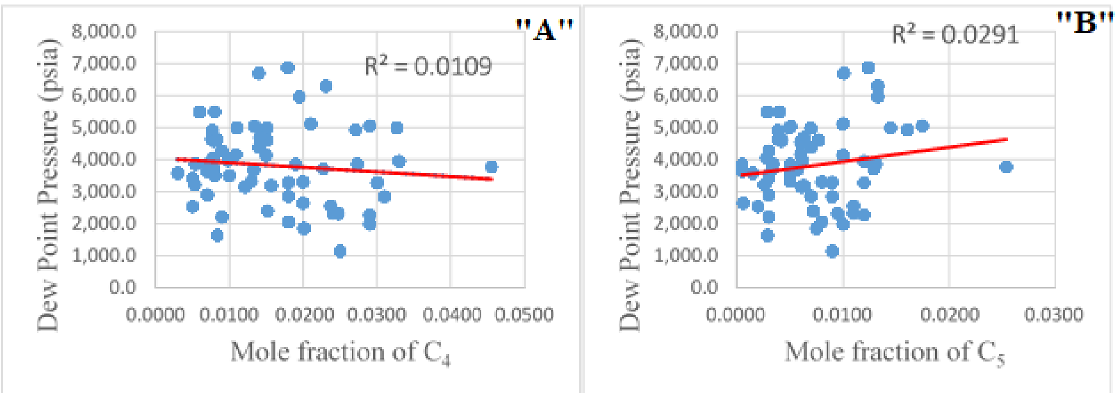

***Figure 4A & B**: Dependency of the DPP on the mole fractions of C_4 to C_5*

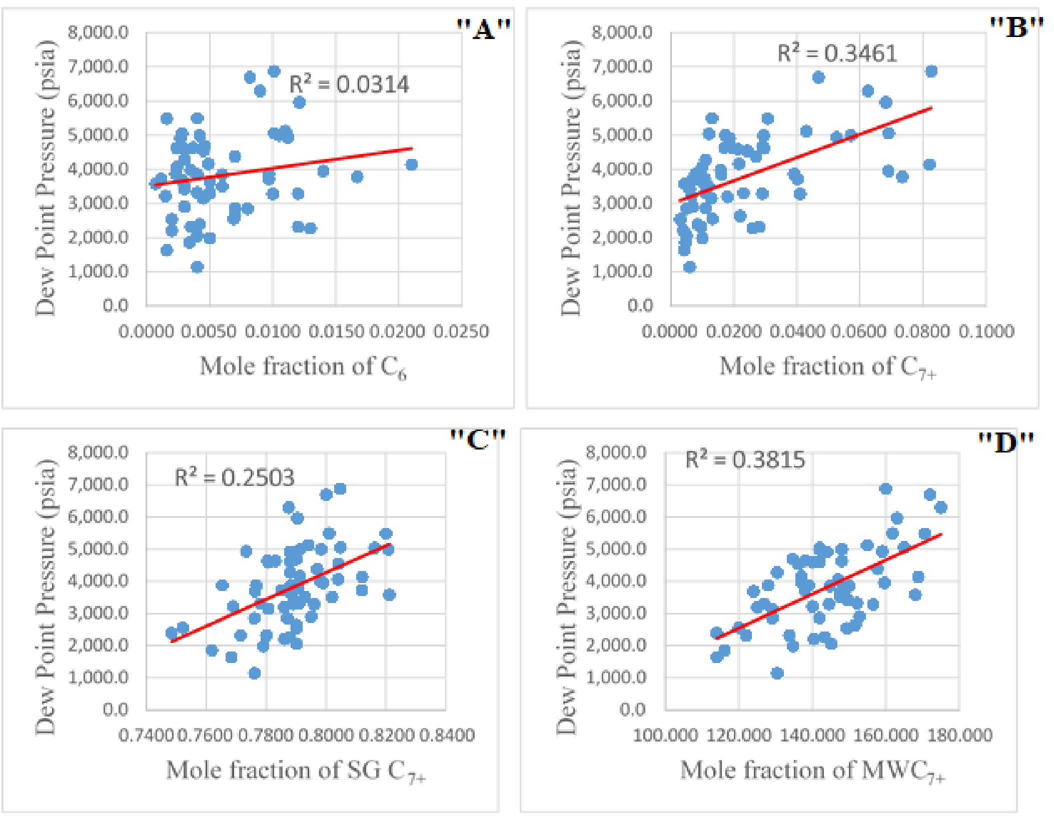

***Figure 5A, B, C & D**: Dependency of the DPP on the mole fractions of C_6 to C_{7+} and MWC_{7+}*

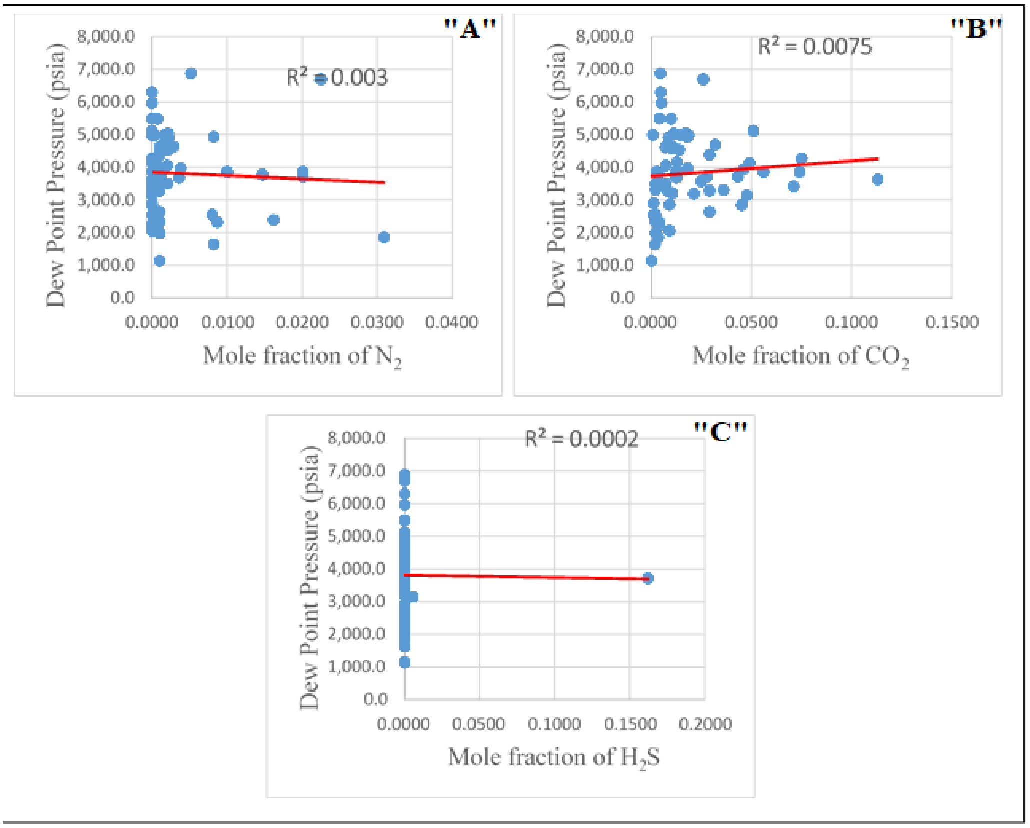

***Figure 6A, B & C**: Dependency of the DPP on the mole fractions of N_2, CO_2 and H_2S*

Table 2: Correlation coefficients between DPP and the parameters

Condensate Properties	Coefficient of Correlation with DPP
Temperature (°F)	0.1539
C_1 mole fraction	0.0044
C_2 mole fraction	0.0186
C_3 mole fraction	0.0751
C_4 mole fraction	0.0109
C_5 mole fraction	0.0291
C_6 mole fraction	0.0314
C_{7+} mole fraction	0.3461
Specific gravity C_{7+}	0.2503
Molecular weight C_{7+}	0.3815
N_2 mole fraction	0.003
CO_2 mole fraction	0.0075
H_2S mole fraction	0.0002

The comparative analysis of observed and predicted DPP is depicted graphically in Figures 7 and 8. Finally, Table 3 summarises the statistical parameters of the correlations, while Figures 9a, 9b and 9c presents a graphical representation of the same.

Developed Correlation Models

The newly developed correlation used in this study is:

$$P_d = A_1 + A_2\left(P_{N_2} + P_{CO_2} + P_{H_2S}\right) + A_3\left(P_{C_1} + P_{C_2}\right) + A_4 P_{C_3} + A_5 P_{C_4} + A_6 P_{C_5} + A_7 P_{C_6} + A_8 P_{C_{7+}+A_9 \gamma C7_{+}+A_{10} MW_{C7+}+A_{11} P_{T_r}+A_{12}} \quad (10)$$

Where;

P_i is the mole fraction of the hydrocarbon composition and the non-hydrocarbon impurities such as CO_2, H_2S and NO_2 present in the fluid

MW_{C7+} is the molecular weight of the C_{7+} composition

$\gamma C7_{+}$ is the specific gravity of the C_{7+} composition and

T_r is the reservoir temperature

The correlation coefficients are given as follows;

A_1 =-62433.481,
A_2 =-28642.95,
A_3 = -25594.395,

A_4 =-39940.196,
A_5 =-120200.05,
A_6 =95847.9948,
A_7 =-189746.42,
A_8 =212954.296,
A_9 =143695.512,
A_{10} =-806.03466,
A_{11} =4.65303818,
A_{12} =-3466.9993,
A_{13} =-9.3065629

Comparative Analysis

In this study, graphical error analysis was conducted using the cross-plot technique. The predicted data was plotted against the measured data to determine the accuracy and prediction capability of the correlation. The closer the plotted data is to the line, the higher the accuracy and prediction capability of the correlation. Cross-plots for each existing model are in Figure 7; the newly developed model is presented in Figure 8.

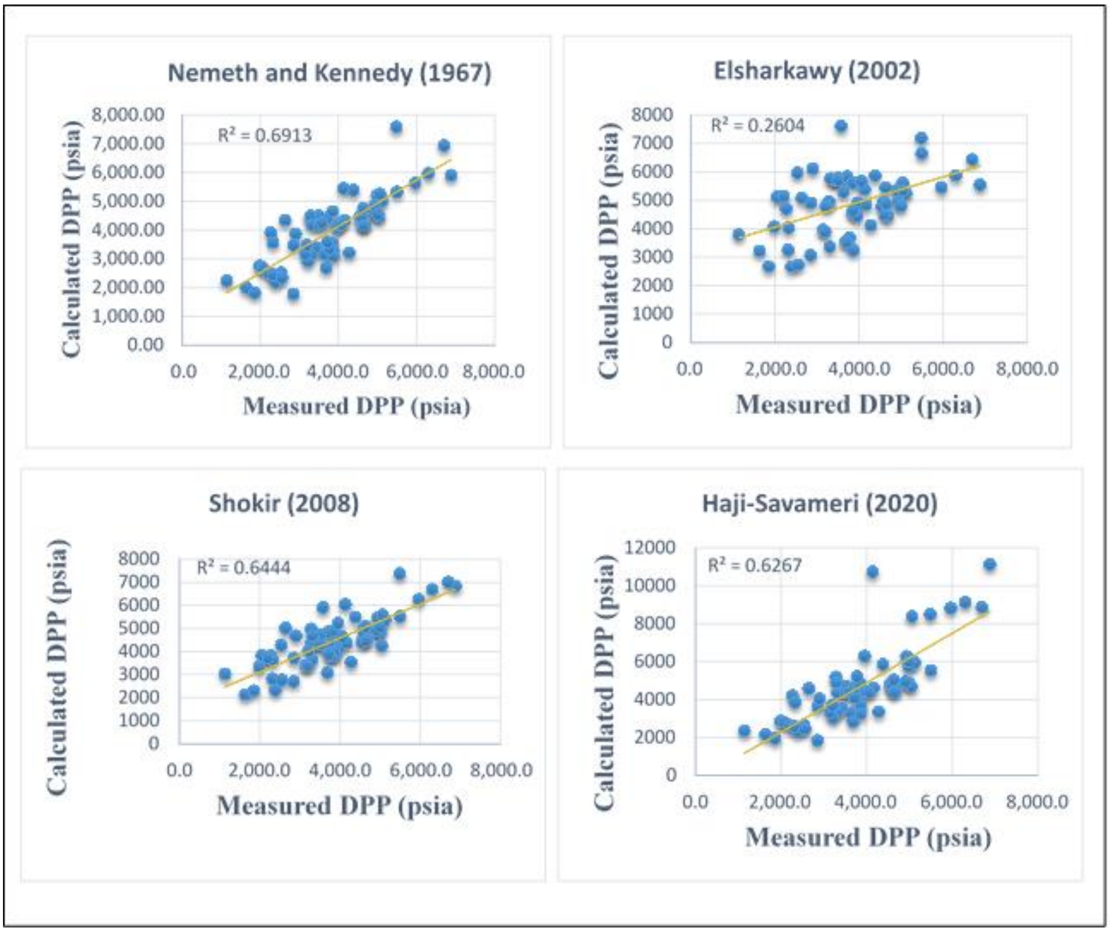

Figure 7: *Cross plot of the existing models employed*

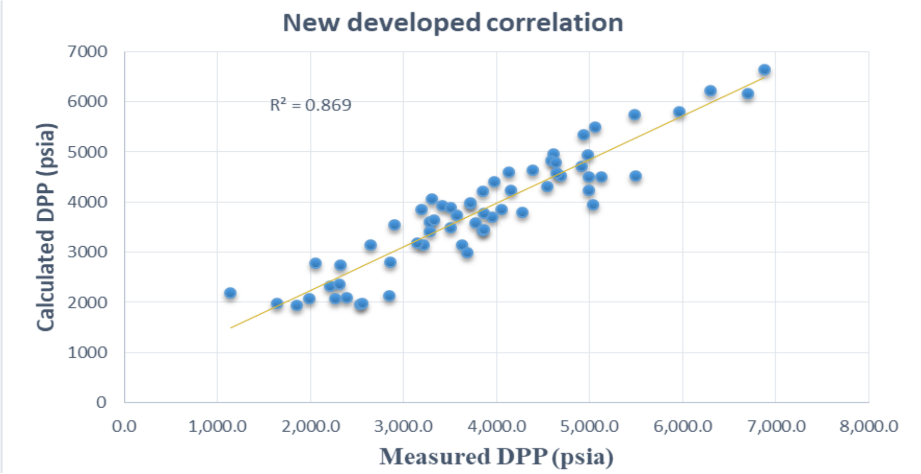

Figure 8: *Cross plot of newly developed correlation*

Table 3: *Summary of the Statistical parameters of the correlations*

Correlations	**AARE (%)**	**MAP**	R^2
Nemeth & Kennedy	-7.9108	517525.665	0.6913
A.M. Elshakarwy	-38.059	2378039.342	0.2604
Shokir	-22.639	2359238.144	0.64
Haji Savemeri	-22.996	952103.181	0.6267
New Correlation	-2.0767	195279	0.869

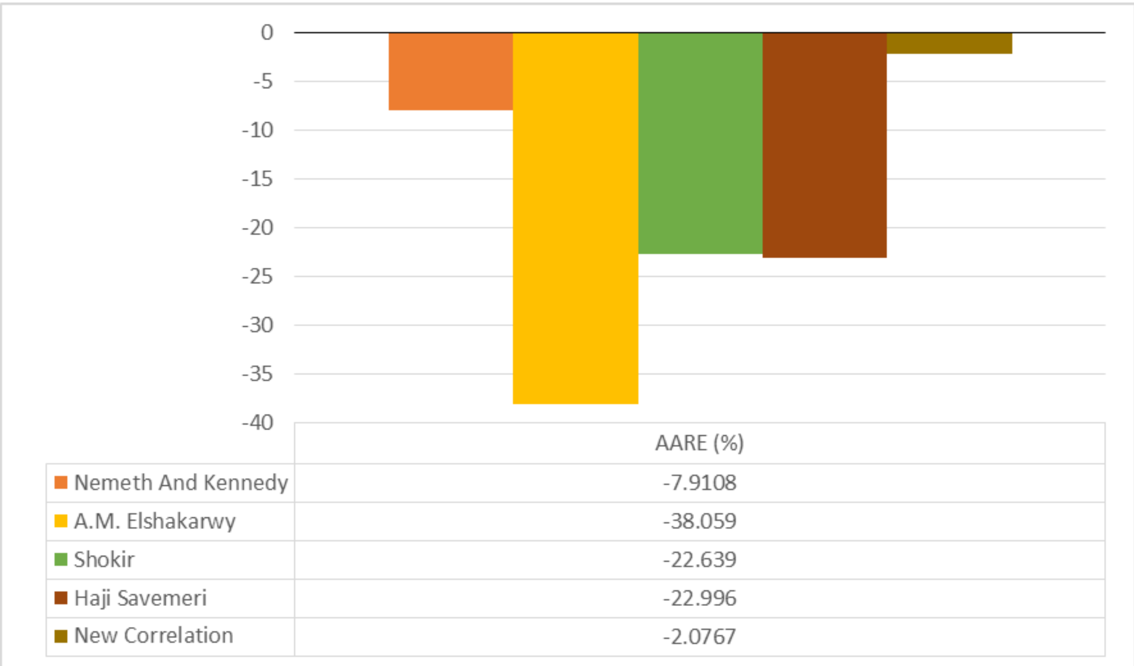

Figure 9a: *Comparison of the R^2 and AARE for the various model*

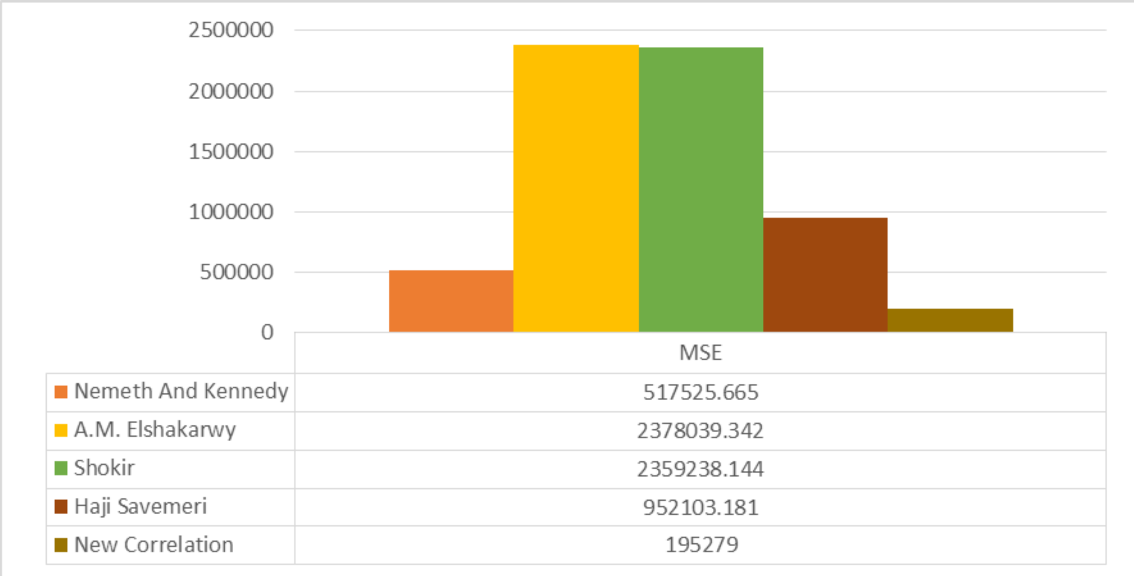

Figure 9b: *Comparison of the MSE for the various model*

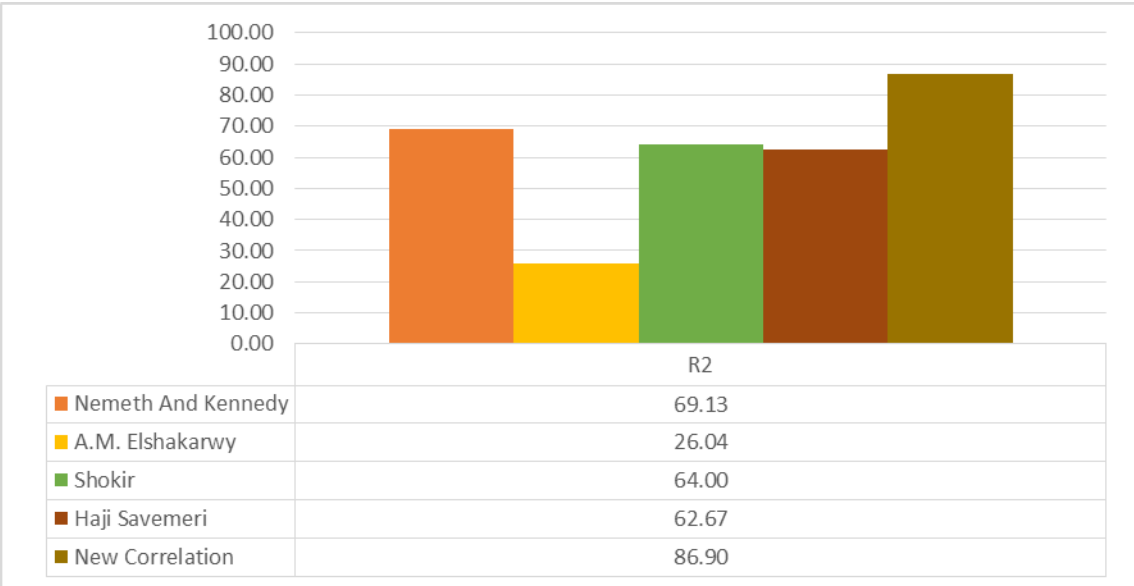

Figure 9c: *Comparison of the R^2 and AARE for the various model*

Figures 3 to 6 show the relationship between the dew point pressure (DPP) and the C_1 to C_{7+} MWC_{7+}, N_2, CO_2 and H_2S mole fractions. According to the findings, the dew point pressure is influenced to different extents by the temperature and composition of the fluid. Thus, the findings suggest that the molecular weight of the C_{7+} components has the greatest impact on the dew point pressure. On the other hand, the hydrogen sulphide mole fraction has the lowest impact. The specific gravity and mole fraction of the C_{7+} components and the reservoir temperature significantly impact the dew point pressure. According to Ahmadi et al. [4], an increase in the C_{7+} properties of the fluid leads to a rise in dew point pressure. In addition, an increase in temperature also increases dew point pressure.

Multiple regression scenarios were tested until the correlation with the lowest error analysis was obtained. The newly developed correlation was compared to existing models and performed better for the given data set. The cross-plot in Figure 7 shows how the Nemeth and Kennedy model, Shokir model, Elsharkawy model, and Haji-Savameri model performed, with the newly developed model (Figure 8) performing the best with a regression coefficient of 93% and an R^2 value of 0.869. The mean square error (MSE) and the average absolute relative error (AARE) were also calculated and showed that the newly developed correlation had the lowest deviation compared to the existing correlations for this data set (Table 3).

CONCLUSIONS

A model able to perform fluid characterisation and aid gas condensate reservoir development and management has been successfully developed. The model was constructed using Microsoft Excel with the Data Analysis Tool. The model includes an empirical correlation that estimates dew point pressure for gas condensate reservoirs based on multiple regression analyses using fluid compositional information and reservoir temperature as input. Comparing the prediction accuracies of formulas based on the developed model and other conventional methods indicated that this model is more accurate than other statistical methods in predicting DPP within the Niger Delta region. This model could produce a higher accuracy than other estimating methods, especially under conditions with limited field information and constrained working time. Furthermore, the developed correlation has a coefficient of determination, R^2 = 0.869, lower relative error AARE% = -2.0767, and root mean square = 195279, indicating the proposed correlation's high reliability.

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Received: December 2023; Revised: January 2024; Accepted: January 2024; Published: January 2024