ABSTRACT

Condensate-to-gas ratio (CGR) plays a significant role in sales potential assessment of both gas and liquid, design of the required surface processing facilities, reservoir characterization and modeling in gas-condensate reservoirs. This work aim at the use of regression method to develop Condensate gas ratio (CGR) correlations using dataset obtained from Western Niger Delta region. The formation was divided into three distinct geologic zones: Transitional Paralic, Paralic and Marine Paralic zones. The basic parameters used for the correlation development are: reservoir depth (ft), reservoir pressure (psia); reservoir temperature (°F) all at (GOC/GDT/GWC and these parameters are data easily obtained from the field. Both quantitative and qualitative assessments show that the models are very impressive with good statistical parameters, good ranks and better performance plots. However, these models should be used with caution since the data used for their development was not robust enough; especially beyond the range of data used for their development.

Keywords: Condensate to Gas Ratio; Correlation; Regression; Gas Condensate

1.1 INTRODUCTION

Gas condensate is a single phase gas in the subsurface. It produces both liquid and gas phases when it is taken to the surface and the pressure and temperature reduced to near ambient conditions. The liquid phase is known as condensate. The condensate gas ratio (CGR) is measured by metering the flows of condensate and gas at the surface. If mass units are used, it is defined as the mass of condensate produced per kg of gas. If oil field units are used, it is the volume of condensate (in barrels) produced per million scf of gas under standard conditions [1].
Condensate-to-gas ratio (CGR) plays a significant role in sales potential assessment of both gas and liquid, design of the required surface processing facilities, and reservoir characterization and modeling in gas-condensate reservoirs. Precise field and laboratory determination of the CGR is time and people intensive. Developing a rapid and inexpensive technique for accurate estimation of the CGR is inevitable [2].

CGR is very important parameter in gas condensate reservoir. With the aid of CGR, condition of phases can be predicted, the quality and quantity of facility can be designed and also, the economy of the reservoir can be envisaged. The knowledge of this parameter is also essential for gas reservoir performance calculation and numerical modeling [3].

Three things are essential in a successful development of gas condensate fields: (1) in the original well testing of the field, accurate values of the condensate to gas ratio (CGR) are determined for the evaluation of the initial “in place” reserves and the formation evaluation and reservoir characterization; (ii) the CGR behavior of the production wells are understood so that the history matching to early data can be accurate; (iii) the general long term behavior of the reservoir and the liquid recovery factors expected in any planned gas recycling process are realistic [4].

Moreover, condensate liquid components have been more valuable than the gas, because of easy transportation especially in the places far from gas market or transport system [5]. As a result, understanding nonlinear and complex behavior of gas condensate reservoir is very important and also its one of the most difficult, onerous and challenging problem in petroleum reservoir engineering [6]. On the other hand behavior of gas condensate reservoir is mainly controlled by fluid properties and accurate knowledge of these PVT characteristics [7].

Gas condensates are becoming increasingly important throughout the world but the gas condensate reservoir behavior is complex and is not yet wholly understood. However, efforts have been made by Dawe and Grattoni [8] to explain gas condensate reservoir behavior through detailed mechanisms such as visualization of pore-scale phase flow mechanisms to give an insight to fluid displacements at the core scale and help the interpretation of production behavior at reservoir scale. Thomas et al. [9] also worked on optimizing production from a gas condensate reservoir and Cho et al. [10] developed a correlation to predict maximum condensation for retrograde condensation fluids and its use in pressure depletion calculations. Also, an approach for forecasting viability of gas condensate wells and predicting Condensate Gas Ratio (CGR) using reservoir volumetric balance has been developed, Olaberinjo et al.[11].

CGR can be calculate using three method; experimental data, equation of states and correlations. By using PVT tests, CGR can be measured but reservoir fluid samples are needed. Sampling of the gas condensate reservoir has its problems. As a result obtaining CGR from experimental data is expensive, complex, energy and time consuming, in errors, unavailable all time, inability to obtain representative sample [2].

Some of the literature cited earlier, were directed at explaining gas condensate reservoir behavior, it was also noted that much work has not been done in the area of correlation development for gas condensate reservoirs. It was also clear that no correlation exist for gas
condensate reservoirs for the Niger Delta in the open literature. Therefore, this work is aimed at
developing Condensate Gas Ratio (CGR) correlations using datasets obtained from Western
Niger Delta region via regression method. It will also be necessary to note that models using the
correlating parameters of this study are not available in the (open) literature to make easy
comparison and very scarce and limited data are available on this subject in the region.

2.0 Report Validation/ Data Source

All the PVT reports used were validated using the basic validation techniques of Campbell plots
and Material balance diagrams. More than 60 gas condensate PVT reports were found but only
46 met the validation requirements.

Gas condensate reservoirs PVT data from different fields in the Niger Delta from the Delta,
Western Bayelsa: Bomadi, Burutu and Nun areas of oilfields operations in the region were put
together. Table 1 shows the distribution of the validated PVT reports used for the study in terms
of geological zones. Table 2 shows the data distribution use for the work.

Table 1: Distribution of PVT reports used in this study

<table>
<thead>
<tr>
<th>Geologic Zones</th>
<th>Reservoir</th>
<th>Fields</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transitional Paralic</td>
<td>21</td>
<td>7</td>
</tr>
<tr>
<td>Paralic</td>
<td>11</td>
<td>8</td>
</tr>
<tr>
<td>Marine Paralic</td>
<td>24</td>
<td>5</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>46</strong></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Data range used for the development of the correlations

<table>
<thead>
<tr>
<th>Geologic Zones</th>
<th>Pressure (@GOC/GDT/GWC)</th>
<th>Depth, D (@GOC/GDT/GWC)</th>
<th>Temp (@GOC/GDT/GWC)</th>
<th>CGR (stb/MMscf)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transitional Paralic</td>
<td>3226 - 4284</td>
<td>7292 - 9802</td>
<td>138 - 209</td>
<td>1.37 - 46.39</td>
</tr>
<tr>
<td>Paralic</td>
<td>4387 - 4953</td>
<td>10074 - 11256</td>
<td>153 - 272</td>
<td>10.8 - 62.76</td>
</tr>
<tr>
<td>Marine Paralic</td>
<td>4861 - 8356</td>
<td>11541 - 12620</td>
<td>196 - 223</td>
<td>6.75 - 127.8</td>
</tr>
</tbody>
</table>

3.0 Data Organization and Correlation Performance Evaluation (Zoning of the Formation)

Most of the condensate reservoirs are found in the Paralic zone [12] ((much of the Agbada
formation) between 6,000 and 18,000 ft. and correlating all data obtained for condensate
reservoirs show some level of complexity and gave no recognizable pattern. It was then
necessary to adopt a procedure of dividing this formation into three distinct geologic zones -
Transitional Paralic (6,330 – 9,999 ft.ss), Paralic (10,000 – 11,499 ft.ss) and Marine Paralic
(11,500 – 16,500 ft.ss) respectively.
4.0 Correlations/Models Development

Fundamentally, three models/correlations were developed. The basic parameters used for the correlation development are (see Table 2): reservoir depth (ft), reservoir pressure (psia); reservoir temperature (°F) (all @ GOC/GDT/GWC). These parameters are easily obtainable from the field; this gave the reason for their choice.

4.1 Correlating Parameters

The correlation/Model as shown in Equation 1 was developed using linear and non-linear multiple regression analysis with non-linear least square curve fits via MATLAB [13] sessions with the in-built Microsoft Excel Solver functionalities in Microsoft Excel Application [14]. Regression equation as given by Equation 1 with CGR as a function of P, D and T are derived for each zone. Owning to the limited amount of data in each zone (see Table 1), the best regression equation was derived by using one condensate reservoir as a control data point while generating a regression equation from the remaining data. The regression equation so obtained is used to estimate the CGR of the control reservoir data. The estimate is then compared to the CGR of the PVT report. The regression equation who’s estimated CGR for the control has the minimum deviation from the measured PVT value is selected as the best equation.

4.2 CGR as function of Dept (D), Pressure (P) and Temperature (T)

Several models were tried for the CGR correlation using only easily obtainable parameters such as depth, reservoir pressure and reservoir temperature. However, the best model was obtained using a 3-parameter correlation for CGR as a function of D, P, and T given by Equation 1. The coefficients of Equation 1 are given in Table 3 for the Transitional Paralic, Paralic and Marine Paralic Zones.

\[
CGR = X_1 + X_2P + X_3P^2 + X_4P^3 + X_5P^4 + X_6D + X_7D^2 + X_8D^3 + X_9D^4 + X_{10}T + X_{11}T^2 + X_{12}T^3 + X_{13}T^4
\]  

Where

\begin{align*}
P &= \text{Reservoir pressure at GOC/GWC/GDT (psia)} \\
D &= \text{Reservoir depth at GOC/GWC/GDT (ft. ss.)} \\
T &= \text{Reservoir temperature (°F)} \\
X_1 \text{ to } X_{13} &= \text{coefficients of the model.}
\end{align*}

This model actually is similar to an in-house model use for some other studies, but the coefficients were optimized such that it gives the model flexibility to give better predictions possible. The model took the form of a fourth order polynomial for the depth (D), reservoir pressure (P) as well as reservoir temperature (T).
5.0 Quantitative and Qualitative Screening

To compare the performance and accuracy of the new model to other empirical correlations, two forms of analysis were performed which include quantitative and qualitative. For quantitative screening method, statistical error analysis was used. The statistical parameters used for the assessment were percent mean relative error (E_r), percent mean absolute error (E_a), percent standard deviation relative (S_r), percent standard deviation absolute (S_a) and correlation coefficient (R).

For correlation comparison, a new approach of combining all the statistical parameters mentioned above (E_r, E_a, S_r, S_a and R) into a single comparable parameter called Rank was used by Ikiensikimama and Egbe [15]; Ikiensikimama, [16]. A brief description of the method follows. The use of multiple combinations of statistical parameters in selecting the best correlation can be modeled as a constraint optimization problem with the function formulated as;

\[
\text{Min } Z_i = \sum_{j=1}^{n} S_{i,j}q_{i,j}
\]  

Subject to

Table 3: Coefficients for Developed Correlation

<table>
<thead>
<tr>
<th>Variables</th>
<th>Transitional Paralic Zone</th>
<th>Paralic Zone</th>
<th>Marine Paralic Zone</th>
</tr>
</thead>
<tbody>
<tr>
<td>X1</td>
<td>60870.844602003</td>
<td>1491319.78694993</td>
<td>371554042.088967</td>
</tr>
<tr>
<td>X2</td>
<td>-282.84399436639</td>
<td>1016.70404458702</td>
<td>-260320.652925947</td>
</tr>
<tr>
<td>X3</td>
<td>0.116905152178571</td>
<td>0.0921245068706438</td>
<td>75.1567170390499</td>
</tr>
<tr>
<td>X4</td>
<td>-0.0000213736169118436</td>
<td>-0.0000694660285497983</td>
<td>-0.00963697790639015</td>
</tr>
<tr>
<td>X5</td>
<td>1.45837161246309E-09</td>
<td>6.55064944810217E-09</td>
<td>4.63068805861205E-07</td>
</tr>
<tr>
<td>X6</td>
<td>107.089301383884</td>
<td>-1061.92241617646</td>
<td>17144.4115868707</td>
</tr>
<tr>
<td>X7</td>
<td>-0.0193934786581814</td>
<td>0.0741248838581947</td>
<td>-2.40157363877747</td>
</tr>
<tr>
<td>X8</td>
<td>1.55241482494626E-06</td>
<td>-2.775566951227E-07</td>
<td>0.000147438468452617</td>
</tr>
<tr>
<td>X9</td>
<td>-4.63434003333736E-11</td>
<td>-8.77161449423165E-11</td>
<td>-3.35616122169745E-09</td>
</tr>
<tr>
<td>X10</td>
<td>-626.957085810945</td>
<td>1425.23563357665</td>
<td>-1486593.12682158</td>
</tr>
<tr>
<td>X11</td>
<td>5.61628356191064</td>
<td>-9.90583351683657</td>
<td>10516.7052703276</td>
</tr>
<tr>
<td>X12</td>
<td>-0.0221571090702678</td>
<td>0.030472025880905</td>
<td>-33.0458489076816</td>
</tr>
</tbody>
</table>
\sum_{i=1}^{n} S_{i,j} = 1 \tag{3}

With \quad 0 \leq S_{i,j} \leq 1 \tag{4}

Where $S_{i,j}$ is the strength of the statistical parameter $j$ of correlation $i$ and $q_{ij}$, the statistical parameter $j$ corresponding to correlation $ij = E_r, E_a, \ldots, R^1$, where $R^1 = (1-R)$ and $Z_i$ is the rank, RK (or weight) of the desired correlation. The optimization model outlined in Equations 2 to 4 was adopted in a sensitivity analysis to obtain acceptable parameter strengths. The final acceptable parameter strengths so obtained for the quantitative screening are 0.4 for $E_a$, 0.2 for $R$, 0.15 for $S_a$, 0.15 for $S_r$, and 0.1 for $E_r$. Finally, Equation 2 was used for the ranking. The correlation with the lowest rank was selected as the best correlation for that fluid property. It is necessary to mention that minimum values were expected to be best for all other statistical parameters adopted in this work except $R$, where a maximum value of 1 was expected. Since the optimization model (Equations 2 to 4) is of the minimizing sense a minimum value corresponding to $R$ must be used. This minimum value was obtained in the form (1-R). This means the correlation that has the highest correlation coefficient ($R$) would have the minimum value in the form (1-R). In this form the parameter strength was also implemented to 1-R as a multiplier. Ranking of correlations was therefore made after the correlation had been evaluated against the available database. For qualitative screening, performance plots were used. The performance plot is a graph of the predicted versus measured properties with a 45\(^\circ\) reference line to readily ascertain the correlation’s fitness and accuracy. A perfect correlation would plot as a straight line with a slope of 45\(^\circ\). It should be noted that the 45\(^\circ\) is not a line of best fit. Also bar charts were used to show quick comparison of the measured and the developed correlations (see Figures 2, 4, 6).

Fig 2: Performance plot of CGR versus Depth (3-p Correlations) – Transitional Paralic
Fig. 4: Performance plot of CGR versus Depth (3-p Correlations) – Paralic

Fig. 6: Performance plot of CGR versus Depth (3-p Correlations) – Marine Paralic

6.0 Results and Discussion

6.1 Transitional Paralic Zone

The best regression equation for this zone is given by the model of Equation 1; see Table 3 for the coefficients. In terms of statistical accuracies (Table 4), the model predicted CGR with percent mean absolute error of 19.5640, correlation coefficient of 0.9539 and a rank of 18.15. Figure 1 is a performance plot for the Transitional zone. This plot shows that the correlation can
predict CGR correctly between 1stb/MMscf to that of 55stb/MMscf. However, between 10stb/MMscf and 18stb/MMscf, there could be some overestimations of the CGR values. Figure 2 is the bar chart quick performance comparison of the correlation. This figure shows a depth versus CGR plot given a visual representation of the accuracy of the model to estimate CGR at different depths. The figure shows a good match except the following depths 7292ft, 7589ft, 8356ft and 9086ft respectively.

<table>
<thead>
<tr>
<th>Models</th>
<th>Correlating Parameters</th>
<th>$E_r$</th>
<th>$E_a$</th>
<th>$S_r$</th>
<th>$S_a$</th>
<th>$r$</th>
<th>Rank</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>3- Parameter</td>
<td>P, T, D</td>
<td>-12.8078</td>
<td>19.5640</td>
<td>40.1423</td>
<td>37.1721</td>
<td>0.9539</td>
<td>18.15</td>
<td>Trans Paralic</td>
</tr>
<tr>
<td>3- Parameter</td>
<td>P, T, D</td>
<td>-5.1264E-06</td>
<td>5.1912E-06</td>
<td>1.6800E-05</td>
<td>1.6778E-05</td>
<td>1.0000</td>
<td>6.6E-06</td>
<td>Paralic</td>
</tr>
</tbody>
</table>

Fig. 1: Performance Plot for CGR Tp

6.2 Paralic Zone

The best regression equation for this zone is given by the model of Equation 1; see Table 3 for the coefficients. In terms of statistical accuracies (see Table 4), the model predicted CGR with percent mean absolute error of 5.1912E-06, correlation coefficient of 1.000 and a rank of 6.6E-06. Figure 3 is a performance plot for the Paralic zone. This plot shows that the correlation can predict CGR correctly between 10stb/MMscf to that of 70stb/MMscf. Figure 4 is the bar chart quick performance comparison of the correlation. This figure shows a depth versus CGR plot given a visual representation of the accuracy of the model to estimate CGR at different depths. The figure shows a good match for all depths considered.
6.3 Marine Paralic Zone

The best regression equation for this zone is given by the model of Equation 1; see Table 3 for the coefficients. In terms of statistical accuracies (see Table 4), the model predicted CGR with percent mean absolute error of 2.6266, correlation coefficient of 0.9998 and a rank of 3.62. Figure 5 is a performance plot for the Marine Paralic zone. This plot shows that the correlation can predict CGR of gas condensate reservoir correctly between 5stb/MMscf to that of 145stb/MMscf. Figure 6 is the bar chart quick performance comparison of the correlation. This figure shows a depth versus CGR plot given a visual representation of the accuracy of the model to estimate CGR at different depths. The figure shows a good match except that there could be some over estimations between the depths of 11541 and 11944ft; and under estimations between the depths of 12067 and 12620ft respectively.

Generally, the models developed performed better for the Paralic zone than the Transitional and Marine Paralic zones. Table 4 shows that while the Paralic zone had a rank of 6.6E-06 that of the Transitional and Marine Paralic zones had ranks of 18.15 and 3.62 respectively. This trend is also noticed at a glance from figures 2, 4 and 6. It will be necessary to mention that caution should be exercise for the use of these models since the data used for their development was not robust enough; especially beyond the range of data used for their development.
7.0 Conclusions

Predictive CGR models have been developed for the Niger Delta for the Western operations of oilfields in the region using different models for three predefined geological zones— the Transitional Paralic, Paralic and Marine Paralic zones with easily available field data. Both quantitative and qualitative assessments show that the models are very impressive with good statistical parameters, good ranks and better performance plots. These models should be used with caution since the data used for their development was not robust enough; especially beyond the range of data used for their development.

References


