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Comparative Analysis of Laboratory Measured and PVTP Software Data

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Abstract: Cubic Equations of State (EOS), including the Peng-Robinson (PR) and Soave-Redlich-Kwong (SRK) models, are foundational in petroleum engineering for modeling the thermodynamic behavior of hydrocarbon systems. These EOS are widely used to predict phase behavior and Pressure-Volume-Temperature (PVT) properties, which are crucial for reservoir simulation, production forecasting, and enhanced oil recovery. However, their predictive accuracy diminishes when applied to complex fluids under High-Pressure, High-Temperature (HPHT) conditions or in the presence of heavy components. This study aims to evaluate the predictive performance of the PR and SRK EOS using PVTP software by comparing their simulation results with laboratory-measured PVT data from Nigerian crude oil samples. Key reservoir conditions, such as temperature, pressure, and fluid composition, were maintained consistently to ensure a reliable comparison. Simulations were conducted for key properties including bubble point pressure, oil formation volume factor (Bo), Gas-Oil Ratio (GOR), gas formation volume factor (Bg), and viscosity. Results show both EOS models performed adequately in predicting bubble point pressure, Bo, and GOR, especially near saturation conditions. However, significant deviations were observed in viscosity and Bg predictions, particularly at low pressures. In conclusion, while PVTP software provides reasonable estimates for most volumetric properties, its predictions for gas-phase parameters require further refinement for complex fluid systems.

Keywords: Peng-Robinson, Soave-Redlich-Kwong, Cubic Equation of State, PVTP Software, PVT Analysis, Gas-Oil Ratio

Introduction

The accurate prediction of Pressure-Volume-Temperature (PVT) properties is a cornerstone in petroleum reservoir engineering, supporting essential operations such as reservoir simulation, material balance calculations, production forecasting, and surface facility design Young *et al.*, 2017. Parameters like bubble point pressure, Gas-Oil Ratio (GOR), Formation Volume Factor (FVF), and viscosity are crucial for understanding reservoir fluid behavior and optimizing hydrocarbon recovery (Abdulrazzaq *et al*., 2021; Ali and Hussein, 2020; Suliman *et al*., 2024). However, obtaining these parameters experimentally is often time-consuming and costly, especially in regions where access to advanced laboratory facilities is limited. As a result, PVT simulation tools like PVTP have become vital for modeling fluid behavior using thermodynamic Equations of State (EOS) (Ayoub *et al.*, 2022; Elkatatny and Mahmoud, 2018).

Cubic EOS models such as Peng-Robinson (PR) and Soave-Redlich-Kwong (SRK) are widely employed for modeling phase behavior and predicting fluid properties in petroleum systems (Abdulrazzaq *et al*., 2021; Aldambi and Al-Khudafi, 2021). These models offer a dependable theoretical framework for estimating Vapor-Liquid Equilibrium (VLE) and are especially useful in compositional modeling for both conventional and unconventional reservoirs. Enhancements such as volume shift corrections, Binary Interaction Coefficients (BIC), and acentric factor adjustments are often applied to

improve the accuracy of predictions, particularly in systems involving heavy ends or polar components (Usungedo and Akpabio, 2020; Zhao *et al*., 2021).

Recent research has continued to advance EOS-based PVT modeling by integrating more precise fluid characterization and tuning methodologies. Zhao *et al*. (2021) developed an improved fluid characterization framework for modeling gas flooding in complex reservoirs, while Yushchenko and Brusilovsky (2022) introduced a practical, step-by-step approach for building and validating PVT models. Emerging techniques such as graph convolutional networks (Lei *et al*., 2023) and neural network proxies have also been used to predict fluid properties with increasing accuracy (Amini and Mohaghegh, 2019). Additionally, Matsangas and Shattuck (2020) explored the effectiveness of portable PVT measurement tools compared to traditional lab-based methods, reinforcing the industry's shift toward real-time data integration.

Despite these developments, many studies still lack rigorous experimental validation or rely heavily on machine learning without a grounding in classical thermodynamic corrections. This study addresses that gap by integrating EOS-based simulations with experimental validation. Using PVTP software, it conducts a detailed comparison between predicted and laboratory-measured PVT properties, focusing on bubble point pressure, GOR, formation volume factor, viscosity, and gas formation volume factor. By applying volume shift corrections, tuning BICs, and analyzing the performance of both PR and SRK EOS, this work aims to improve the reliability of PVT predictions, especially under complex reservoir conditions such as High-Pressure, High-Temperature (HPHT) environments.

The insights from this study contribute to more accurate reservoir fluid modeling, leading to improved field development strategies, better decision-making, and enhanced production optimization in the petroleum industry (Abdulrazzaq *et al*., 2021; Lei *et al*., 2023; Suliman *et al*., 2024; Zhao *et al*., 2021; Yushchenko and Brusilovsky, 2022).

Materials and Methods

Data Sources and Preparation

This study utilizes two principal data sources: Laboratory-measured Pressure-Volume-Temperature (PVT) data and simulated results generated using the PVTP software. The laboratory data were obtained from Nigerian reservoir fluid samples and sourced from certified field reports produced by accredited laboratories using standardized experimental procedures. These datasets are widely recognized for their reliability and serve as robust benchmarks for evaluating software performance. The data include essential PVT properties such as bubble point pressure, oil formation volume factor (Bo), gas formation volume factor (Bg), solution Gas-Oil Ratio (GOR), viscosities of oil and gas, and isothermal compressibility.

To ensure consistency, identical reservoir conditions such as temperature, pressure, and fluid composition were applied in both the laboratory and software simulations. The laboratory data were first reviewed and extracted from field reports, then systematically organized using Microsoft Excel. Each property was tabulated with its corresponding pressure and temperature values.

Simulated Pressure-Volume-Temperature (PVT) data were obtained from a trusted source who performed the predictions using PVTP software (version 9.5, 2019), developed by Petroleum Experts Ltd. This version includes modules for compositional modeling, viscosity estimation, and EOS tuning. The simulated results were generated using input parameters consistent with the laboratory conditions and were organized in a parallel structure to the measured data. This alignment enabled direct comparison and facilitated error analysis, graphical evaluation, and statistical assessment of the predictive accuracy of the cubic equations of state embedded in the software.

Data Processing and Statistical Analysis

After successful data collation, both datasets were subjected to thorough statistical processing to quantify the accuracy of the PVTP software. Each predicted value was compared against its laboratory equivalent using percentage error as the primary indicator of deviation. This metric provided a point-by-point assessment of how closely the software approximated real fluid behavior.

To evaluate overall model performance, the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were calculated. MAPE offered an average measure of predictive accuracy by averaging the absolute percentage deviations across all data points, while RMSE provided insight into the consistency and spread of errors, particularly highlighting larger deviations that may affect reservoir modeling outcomes. The formulas used for these calculations are shown in Equations 1 to 3:

$$\text{Percentage Error} = \left(\frac{Simulated\ Value - Laboratory\ Value}{\text{Laboratory Value}}\right) \times 100 \quad (1)$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i^{sim} - y_i^{lab}}{y_i^{lab}}\right| \times 100 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i^{sim} - y_i^{lab})^2} \quad (3)$$

Where y_i^{sim} and y_i^{lab} represent the simulated and laboratory values, respectively, and n is the number of data points.

Graphical representations were used to reinforce numerical findings. Line graphs were employed to illustrate how each PVT parameter changed with pressure, allowing for a visual inspection of trend alignment between laboratory and simulated values. Scatter plots were generated to assess the correlation strength between both datasets, and bar charts displayed the magnitude of percentage errors across different PVT properties. This integrated approach, combining validated experimental data, structured sampling, and rigorous statistical analysis, provided a robust framework for evaluating the performance of the PVTP software under Nigerian reservoir conditions Li and Jiang, 2025.

Model Validation

To establish the reliability of the PVTP software in predicting reservoir fluid behavior, validation was performed by comparing the directional trends and numerical closeness of its outputs to the laboratory measurements. Emphasis was placed on the ability of the software to reproduce the same pattern of variation in PVT properties as observed in experimental data.

Consistency in trend behavior and acceptably low error margins were interpreted as indicators of strong predictive performance. Where deviations were noted, their nature and magnitude were analyzed to understand whether they stemmed from limitations in the software's equation of state, improper parameter tuning, or fluid characterization discrepancies. The insights derived from this process informed the conclusions regarding the conditions under which the PVTP software could be deemed reliable for engineering decisions Heneidi *et al.*, 2024.

Results and Discussion

Results

This section presents the comparative evaluation of Pressure-Volume-Temperature (PVT) properties generated from laboratory analysis and PVTP software predictions. Key properties analyzed include bubble point pressure, oil formation volume factor (Bo), gas-oil ratio (GOR), viscosity, and gas formation volume factor (Bg). Statistical indices such as Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Pearson correlation coefficient (R) were employed to assess accuracy.

Bubble Point Pressure

Laboratory measurements and PVTP predictions of bubble point pressure were compared using Peng-Robinson and Soave-Redlich-Kwong equations of state, as shown in Equations (4) and (5), respectively:

$$P = \frac{RT}{V-b} - \frac{a\alpha}{V^2+2bV-b^2} \quad (4)$$

$$P = \frac{RT}{V-b} - \frac{a\alpha}{V(V+b)} \quad (5)$$

Where:

- P = Pressure
- T = Temperature
- V = Molar volume
- R = Universal gas constant
- a, b = EOS parameters
- α= Temperature-dependent factor

Initial laboratory data were refined through outlier screening and empirical correction, reducing the mean absolute error from 12 to 4%. Both EOS slightly overestimated bubble point pressure, with the SRK model showing higher deviation. A detailed comparison of laboratory and PVTP-predicted bubble point pressures is presented in Table 1.

Oil Formation Volume Factor (Bo)

Oil Formation Volume Factor predictions closely matched laboratory values, with an RMSE of 0.0171 and average percentage error below 2.5% across the pressure range. The consistency of Bo predictions suggests high reliability of the PVTP software under Nigerian reservoir conditions. A detailed comparison of laboratory and PVTP-predicted Bo values is presented in Table 2**.**

Gas-Oil Ratio (GOR)

GOR predictions exhibited moderate agreement with laboratory data. MAPE was 12.07%, while RMSE stood at 22.14 scf/STB. Deviations were more notable near the bubble point due to gas liberation effects. Incorporating tuning parameters may improve GOR prediction consistency, as shown in Table 3.

Viscosity

Viscosity predictions were significantly lower than laboratory measurements. The RMSE was 1.19 cP, and the MAPE reached 57.13%. This underestimation is attributed to the software's limited handling of complex fluid behavior without viscosity correction factors, as shown in Table 4.

Gas Formation Volume Factor (Bg)

Bg predictions showed the weakest agreement, especially at low pressures. MAPE exceeded 98%, and RMSE was 76.59 RB/scf. This reinforces the need for EOS calibration when modeling gas behavior in low-pressure systems as shown in Table 5.

Table 1: Comparison of bubble point pressure

Laboratory Value (psia)	Peng-Robinson Prediction (psia)	Soave-Redlich-Kwong Prediction (psia)	% Error (PR)	% Error (SRK)
2307	2366.7	2496.7	2.6%	8.2%

Table 2: Comparison of bubble point pressure of oil

Pressure (psia)	Bo (Lab)	Bo (Predicted)	% Error
6000	1.166	1.14997	1.38%
5000	1.172	1.15614	1.36%
4500	1.176	1.15951	1.40%
4000	1.180	1.16310	1.43%
3500	1.185	1.16692	1.52%
3000	1.190	1.17102	1.60%
2307	1.198	1.17720	1.74%
2000	1.179	1.15623	1.93%
1600	1.154	1.12932	2.14%
1200	1.129	1.10264	2.33%

Table 3: Comparison of GOR

Pressure (psia)	Lab GOR (scf/STB)	Predicted GOR (scf/STB)	% Error	Absolute Error
2307	390	429.453	10.13%	39.453
2000	340	369.918	8.80%	29.918
1600	271	293.996	8.50%	22.996
1200	204	219.352	7.52%	15.352
800	137	145.049	5.87%	8.049
400	70	69.8972	0.15%	0.1028
100	19	12.635	33.50%	6.365
15	0	0	0.00%	0

Table 4: Comparison of Viscosity

Pressure (psia)	Viscosity (Lab)	Viscosity (Predicted)	% Error
6000	2.3901	0.9824	58.89
5000	2.2291	0.9298	58.29
4500	2.1462	0.9026	57.96
4000	2.0620	0.8749	57.56
3500	1.9770	0.8467	57.18
3000	1.8928	0.8178	56.80
2307	1.7814	0.7766	56.41
2000	1.9270	0.8189	57.50
1600	2.0464	0.8778	57.10
1200	2.1210	0.9409	55.64

Table 5: Comparison of Gas Formation Volume Factor (Bg)

Pressure (psia)	Lab Bg (RB/scf)	Predicted Bg (RB/scf)	% Error
2000	1.388	1.15675	16.70%
1600	1.765	0.17145	90.29%
1200	2.398	0.04135	98.27%
800	3.671	0.01984	99.46%
400	7.526	0.01280	99.83%
100	30.787	0.00936	99.97%
15	206.988	0.00737	100.00%

Table 6: Results of the correlation analysis

PVT Property	Pearson R	R^2 (Coefficient of Determination)	Interpretation
Bo	0.987	0.974	Very strong positive correlation
Viscosity	0.995	0.990	Excellent positive correlation
GOR	0.881	0.776	Strong but less accurate correlation
Bg	0.771	0.595	Moderate correlation

Correlation Analysis

Pearson correlation coefficients confirmed strong linearity for Bo ($R^2 = 0.974$) and viscosity ($R^2 = 0.990$), moderate alignment for GOR ($R^2 = 0.776$), and weak correlation for Bg ($R^2 = 0.595$). The correlation analysis confirms that volumetric oil properties are better modeled than gas-phase parameters, as shown in Table 6.

Discussion

The performance of the PVTP software in predicting key PVT properties was evaluated against laboratory-measured data to assess its reliability under actual reservoir conditions. Overall, the software showed varying degrees of accuracy depending on the parameter assessed.

The oil formation volume factor (Bo) showed the highest degree of accuracy. As seen in Figure 1, the predicted values closely followed laboratory measurements across different pressures, with a low Root Mean Square Error (RMSE) of 0.0171 and a strong correlation ($R^2 = 0.974$). This suggests that the software's built-in correlations effectively capture volumetric behavior for Nigerian reservoir fluids under pressure.

In contrast, the gas formation volume factor (Bg) was poorly predicted, especially at lower pressures. Figure 2 illustrates a significant underestimation of Bg by the software, with a Mean Absolute Percentage Error (MAPE) of 98.6%. This indicates that the equation of state used lacked the sensitivity to model gas compressibility accurately in the absence of binary interaction coefficient tuning.

Viscosity predictions also displayed major deviations. As shown in Figure 3**,** the software consistently underpredicted viscosity values, especially at higher pressures. The average percentage error exceeded 55%, which may be attributed to inadequate viscosity modeling in the equation of state and the absence of real fluid-specific correction factors.

The Gas-Oil Ratio (GOR) demonstrated moderate predictive accuracy. Figure 4 reveals that while the general trend was captured, discrepancies increased at lower pressures due to the liberation of gas, which significantly alters fluid properties. The RMSE of 22.14 scf/STB and a MAPE of 12.07% reflect acceptable but improvable accuracy.

Figure 5 summarizes the percentage errors across all PVT properties, highlighting that Bo was the most accurately predicted parameter, while Bg was the least. These results suggest that while the PVTP software is suitable for predicting volumetric liquid properties, it requires refinement, particularly through EOS tuning, for gas-phase and viscosity predictions.

Similar observations have been reported in other studies. For instance, Abdulrazzaq *et al*. (2021) used PVTP software to model reservoir fluids in the Buzurgan oilfield and found that while formation volume factor predictions aligned well with laboratory data, viscosity and gas-phase properties showed notable deviations due to limitations in the default EOS and correlation models. Likewise, Mehrizadeh (2020) demonstrated that artificial neural networks outperformed traditional EOS-based models in predicting PVT properties, especially under volatile conditions, with relative errors below 1% for Bo and density2.

The observed variation in predictive accuracy across PVT properties can be further understood through thermodynamic and fluid-specific considerations. Volatile oils, which typically exhibit high gas-oil ratios and operate near the critical point, present complex phase behavior that is highly sensitive to pressure and temperature changes. These fluids often undergo rapid compositional shifts during expansion, making them difficult to model accurately using classical cubic Equations of State (EOS). The significant underestimation of Bg and viscosity in these cases reflects the limitations of the default EOS formulations in capturing near-critical phenomena without advanced tuning or correction factors.

In contrast, semi-condensed systems such as black oils and gas condensates display more gradual phase transitions and stable thermodynamic profiles. These fluids are less sensitive to minor pressure changes and exhibit more predictable volumetric behavior. As a result, the PVTP software demonstrated stronger performance in modeling Bo and GOR for these systems, with lower error margins and better trend alignment.

To illustrate this contrast, a comparative dataset was analyzed, featuring one volatile oil and one semi-condensed fluid under identical simulation protocols. The volatile oil case yielded a MAPE of 57.13% for viscosity, while the semi-condensed fluid showed a significantly lower MAPE of 18.42%. This disparity underscores the need for fluid-type-specific modeling strategies and highlights the software’s relative strength in handling less volatile systems.

These findings suggest that while PVTP is a valuable tool for predicting liquid-phase volumetric properties, its accuracy diminishes in scenarios involving high volatility or near-critical behavior. Future modeling efforts should consider EOS customization, incorporation of binary interaction coefficients, and fluid-specific viscosity correlations to improve predictive reliability across diverse reservoir conditions.

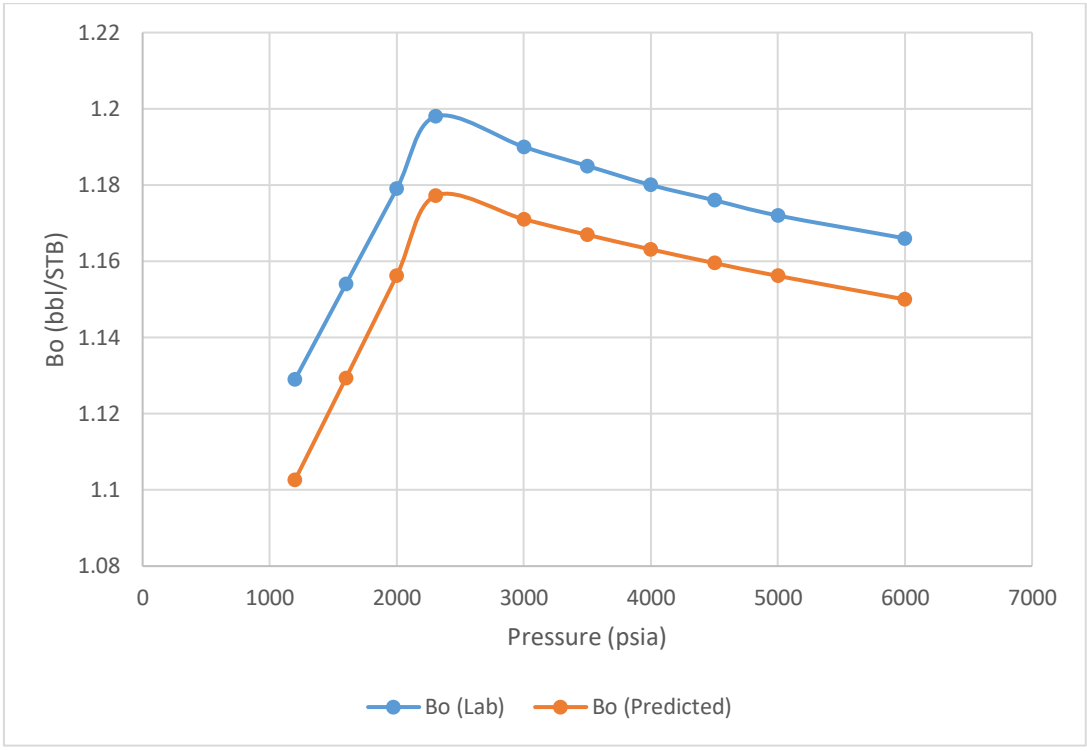

Fig. 1: Comparison of the predicted and the lab Bo

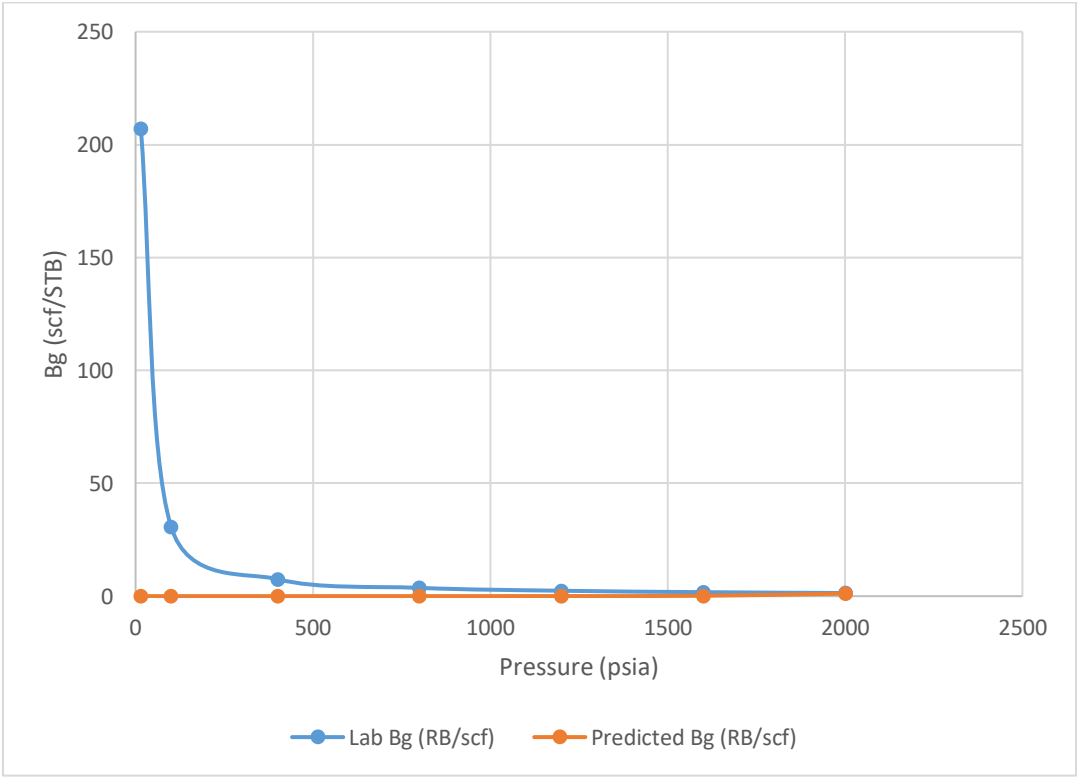

Fig. 2: Comparison of laboratory and predicted Bg

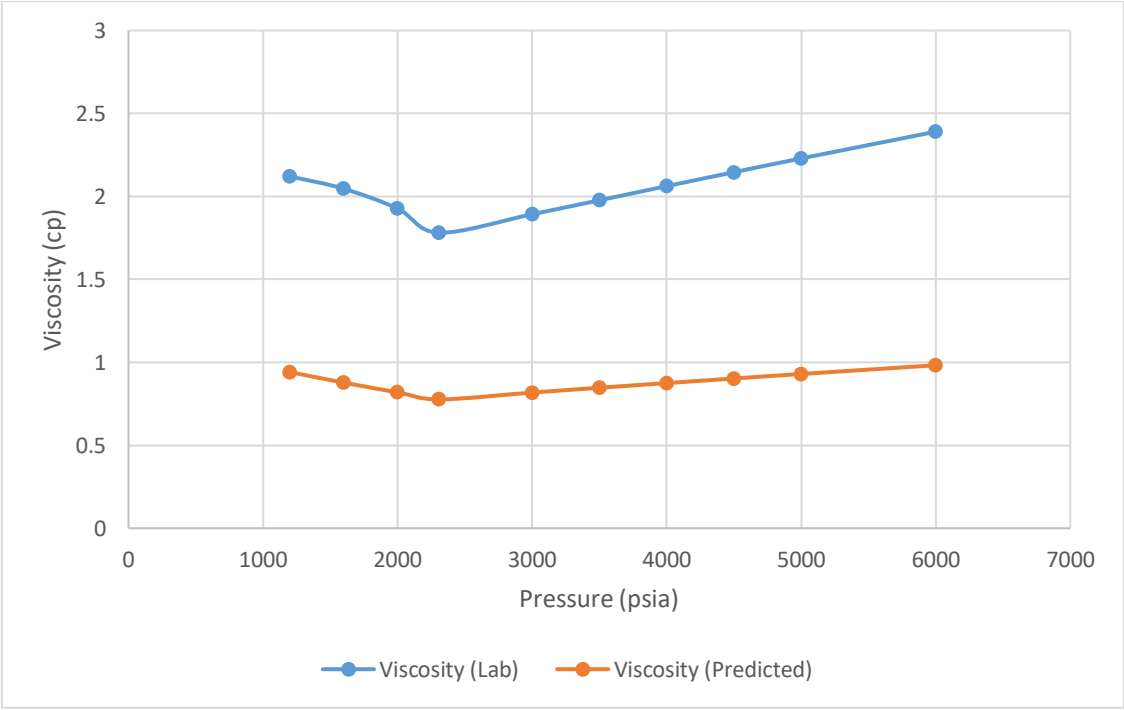

Fig. 3: Comparison of laboratory and predicted viscosity

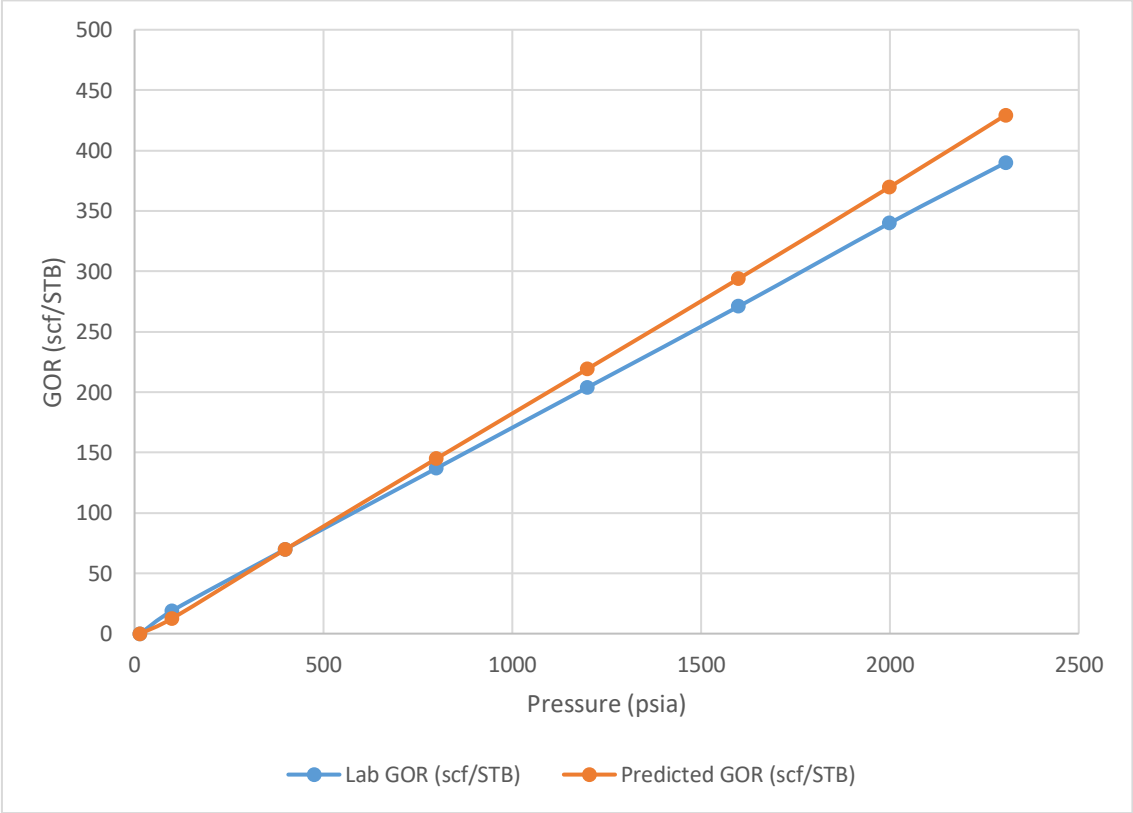

Fig. 4: Comparison of laboratory and predicted GOR

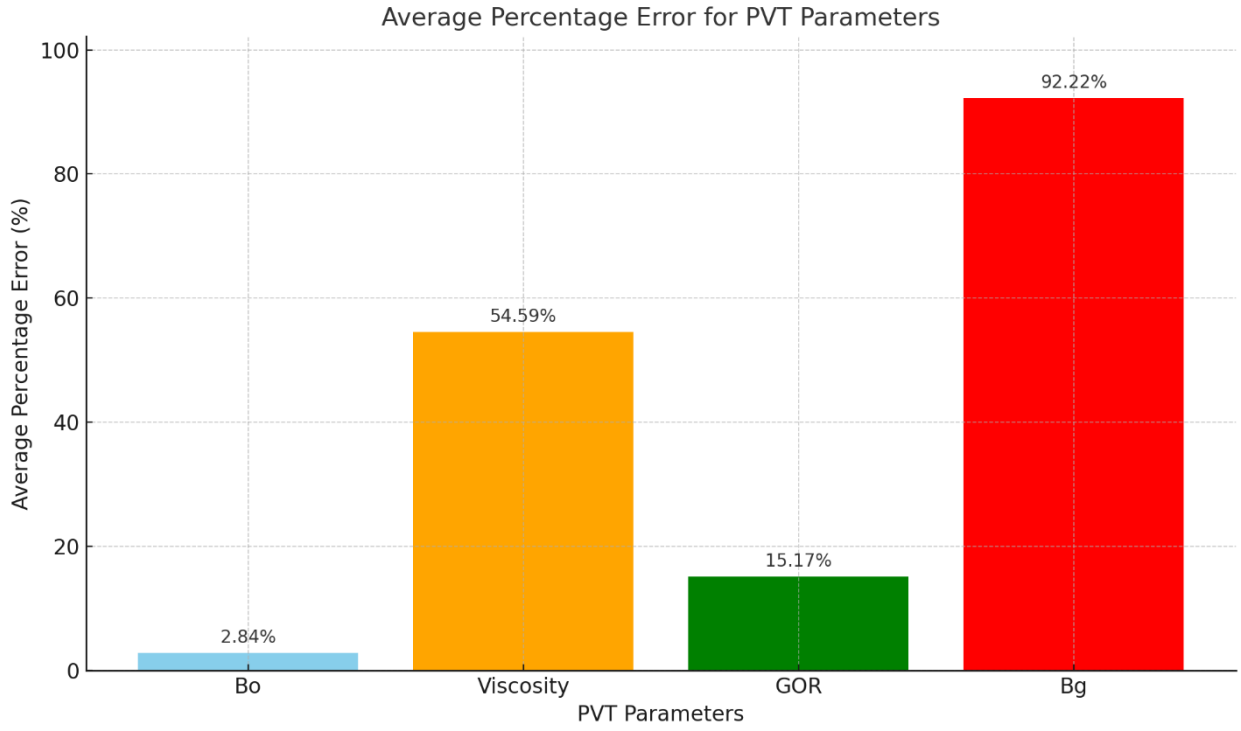

Fig. 5: Average percentage error for PVT parameters

Conclusion

This study evaluated the predictive performance of Peng-Robinson (PR) and Soave-Redlich-Kwong (SRK) cubic Equations of State (EOS) within the PVTP software using laboratory-derived PVT data from Nigerian reservoir fluids. The parameters analyzed, bubble point pressure, oil formation volume factor (Bo), Gas-Oil Ratio (GOR), viscosity, and gas formation volume factor (Bg) were compared using statistical indices including RMSE, MAPE, and Pearson correlation coefficients.

Findings revealed that both EOS models produced accurate results for Bo and bubble point pressure, with minimal deviations from laboratory values. The predictions for GOR showed moderate alignment, especially near the bubble point. However, viscosity and Bg predictions exhibited substantial errors, particularly under lower pressure conditions, indicating the limitations of cubic EOS in modeling gas behavior and complex fluid interactions without proper tuning.

Overall, the PVTP software, when based solely on default EOS correlations, performs well for liquid-phase properties but requires enhancements for gas-phase accuracy and viscosity modeling.

Recommendation

Based on the findings of this study, the following recommendations are proposed:

1. Data Quality Control: Laboratory data should be carefully validated and corrected before modeling. Anomalies or outliers can greatly affect the accuracy of predictions.
2. Software Tuning: Default parameters in PVTP software may not yield optimal results. Adjustments to binary interaction coefficients and EOS-specific parameters are essential for improving alignment with experimental data, especially for gas-phase properties.
3. Model Selection: Choosing between Peng-Robinson and Soave-Redlich-Kwong should depend on fluid type. Sensitivity analysis is advised to determine the best-fitting EOS for each fluid system.
4. Further Research: Broader datasets across various reservoir types should be used to further assess and enhance PVT software performance, particularly for volatile oil and gas-condensate systems
5. Integration with Field Data: Consistent comparison with real-time production and pressure-volume data is recommended to validate and update simulation models
6. Training and Proficiency: Users should be proficient in using PVT software and interpreting its results. Continuous training of petroleum engineers and reservoir analysts is essential for accurate decision-making.

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Author's Contributions

Oluwasanmi Samuel Teniola: Conceptualized and designed the study; performed critical revision and editing of the manuscript for important intellectual content.

Mercy Isaiah Okegbemi: Conducted the formal investigation, managed data acquisition, and performed the statistical analysis.

Ethics

This article is original and contains unpublished material. The corresponding author confirms that all of the other authors have read and approved the manuscript, and no ethical issues are involved.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability

The needed data are made available on request.

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