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Refined Fluid Property Characterization in Data-Limited Reservoirs: Evaluating EOS and Black Oil Models for Optimized Simulation of The PSE Field in The Central Sumatra Basin

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ABSTRACT - The PSE Field, located in the Central Sumatra Basin, faces significant challenges due to outdated and incomplete fluid property data from Well X, where the last measurements were taken in 1992. This lack of comprehensive fluid data hampers accurate reservoir characterization, which is critical for optimizing production strategies. This study aims to bridge this gap by utilizing thermodynamic fluid characterization software (PVTp) to generate reliable fluid data, comparing two approaches: the Equation of State (EOS) model and the Black Oil model. Both models are evaluated based on key parameters such as saturation pressure (P_{sat}), gas-oil ratio (GOR), (FVF), density, and viscosity. EOS model, grounded in thermodynamic principles, is compared to the empirically based Black Oil model to assess their predictive accuracy. The average absolute error percentage (AAE%) is used as a benchmark for performance. Results indicate that EOS model achieved an average AAE% of 1.2%, significantly lower than the 10.94% observed for the Black Oil model. Specifically, EOS model showed 0% error for P_{sat}, 0.81% for relative volume, 3.7% for GOR, 1.4% for FVF, and 0.1% for density, while the Black Oil model demonstrated substantially higher errors, particularly for GOR (40.6%) and FVF (7.7%). This research highlights the limitations of the Black Oil model, especially in complex reservoirs where adjustments to laboratory data are necessary. In contrast, EOS model proves to be a more reliable alternative for accurate fluid characterization. The novelty of this study lies in its focus on the Central Sumatra Basin, where previous fluid property data was limited, making the validation of EOS model a valuable contribution to the field. The practical significance of this study extends beyond addressing the challenges of Well X, offering a framework that can be applied to other fields with similar data constraints. This research advocates for a transition from traditional Black Oil methods to more accurate EOS-based simulations, providing better decision-making tools for reservoir management and enabling greater efficiency and cost savings in future field operations

Keywords: physical properties of fluids, reservoir simulation, PVTp, EOS, black oil.

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INTRODUCTION

Reservoir Reservoir simulations are indispensable in oil and gas field development, serving as the backbone for understanding past, current, and future reservoir conditions. These simulations guide critical decisions about production strategies and field management, especially in mature basins where maximizing recovery is paramount. A vital component of this process is accurately determining the physical properties of fluids, as these properties directly influence how hydrocarbons behave under varying pressure and temperature conditions. Key characteristics such as specific gravity, gas solubility in oil, FVF, compressibility, and viscosity dictate not only reservoir performance but also the efficiency of recovery processes (Aulia et al. 2020). As fields mature, such as in the PSE field, and production continues, technicians often observe phenomena like partial drainage of oil. This is frequently attributed to the complex interplay between the physical properties of the reservoir rocks and the fluids they contain (Rita 2012). Understanding these fluid properties in detail is not just beneficial it is essential for optimizing production and mitigating unforeseen challenges, especially in older reservoirs where the data may be incomplete or outdated.

The PSE field, located within the prolific Central Sumatra Basin, exemplifies the challenges faced by mature oil fields. Known for its rich deposits of light and medium oil, the PSE field has produced hydrocarbons for decades, making it a critical component of Indonesia's energy output. The field belongs to the Sihapas Group, a major petroleum-producing stratigraphic unit that includes the Menggala, Bangko, Bekasap, and Duri Formations each contributing to the region's long history of successful oil production (Julikah et al. 2021).

One of the wells, Well X, suffers from a lack of complete fluid data—a common issue in mature fields. The most recent laboratory measurements for this well, collected in 1992, include relative volume, viscosity, FVF, and saturation pressure (P_{sat}). However, this dataset is far from comprehensive, and without detailed knowledge of the fluid properties, accurately identifying and characterizing the hydrocarbons within the reservoir becomes difficult. To address this, commercial Pressure-Volume-Temperature (PVT) software has been employed to estimate the missing data and predict the physical behavior of the fluids. The use of PVT software, including models based on both EOS and Black oil principles, has allowed engineers to simulate the behavior of reservoir fluids under changing pressure and temperature conditions. This simulation is critical in filling the gaps left by incomplete lab data, ensuring that production strategies are based on a solid understanding of reservoir dynamics.

Globally, numerous studies have shown the value of using commercial PVT software to predict reservoir fluid properties, often with notable accuracy. (Abdulrazzaq et al. 2021) successfully applied both EOS and Black oil models to simulate reservoir fluids in the Buzurgan oilfield. By performing simulations on the Mishrif Formation for wells BU-1, BU-6, BU-10, and BU-12, they highlighted the importance of calibration between original lab data and model predictions, reinforcing the need for accurate fluid characterization in reservoir management.

Aplin et al. (1999) investigated the North Sea reservoir fluids using EOS models, reporting AAE (Average Absolute Error) values of 12% for saturation pressure and 19% for GOR. Despite variability across different formations, the study underscores the robustness of EOS models in handling complex reservoir fluids, though significant discrepancies can still arise if model parameters are not properly calibrated.

Mansour et al. (2013) refined the Soave-Redlich-Kwong (SRK) equation within EOS model, significantly reducing errors from 111% to as low as 0.01%. This highlights the importance of continual model improvement to achieve better predictive accuracy, especially in fields where fluid properties are highly variable. Their work demonstrates how refining established equations can drastically enhance simulation reliability. Stochastic Black oil Reservoir

Simulation Modeling introduces a probabilistic approach that incorporates uncertainty into the modeling process (Alboudwarej & Sheffield 2016). By leveraging statistical techniques, these models generate more reliable fluid property correlations and offer a robust framework for managing uncertainty, particularly in fields where data is incomplete or unreliable. This approach has great potential to enhance the precision of reservoir simulations by providing a range of probable outcomes rather than a single deterministic result.

Machine Learning (ML) is also emerging as a transformative tool in fluid modeling. By utilizing vast datasets of lab-measured fluid properties, ML-based models are now capable of predicting key characteristics such as gas injection parameters and phase behavior with unprecedented accuracy (Ghorayeb et al. 2022). As these models evolve, they promise to revolutionize fluid property prediction, especially in complex reservoirs like PSE, where traditional methods might fall short.

Central Sumatra Basin

The Central Sumatra Basin (CSB), where the PSE field is located, remains one of Indonesia's most strategically important oil-producing regions. As a back-arc basin formed by the subduction of the India-Australia plate beneath the Asian plate, the CSB is geologically unique, with a sedimentary structure that has supported substantial oil and gas production for decades (Setiadi et al. 2021).

The basin is largely dominated by onshore exploration activities, particularly in its western regions, where significant light and medium oil deposits are found. However, the eastern part of the basin, especially in offshore areas like the Malacca Strait, remains underexplored due to the thick sediment layers that pose technical challenges. The stratigraphy of the CSB is a rich tapestry, ranging from the Paleogene to the Pliocene, including productive formations such as the Basement, Pematang Group, Sihapas Group, Farmer Formation, and Minas Formation (Julikah et al. 2021)some of the existing oil fi elds are heavy oil containing such as Duri, Sebanga, Rantau Bais, and Kulin fi elds with their API Gravity values of lower than 25o . Apart from those oil fi elds the Central Sumatra Basin is expected to bear signifi cant heavy oil potential. In this light, this paper emphasizes discussion of subsurface geological evaluation on suspected fi elds/areas that contain heavy oil. This evaluation serves as a preliminary step in investigation of heavy oil resources/reserves in the basin. Analysis results on stratigraphic sequence and seismic interpretation provide information support facts over presence of heavy oil that are usually associated to main faults of Dalu-Dalu, Rokan, Sebanga, Petapahan, Pulau Gadang, and Kotabatak. Large tectonic events as a compression phase in the Middle Miocene recent developed regional uplift and formed main thrust faults system, anticline structures due to the creature of basement highs, during which the F3 was deposited. The thrust faults system are important in the process of heavy oil generation in which surface water encroached into uplifted oil traps hence triggering heavy oil transformation mechanisms of biodegradation and water washing. This study provides illustration over sequences the heavy oil is generated in and their dimension in relation to area of structural anticlines. Based on available data, evaluation on subsurface geology has shown that anticlinal structures containing heavy oil tend to be characterized by near surface uplift (Basement up to 500 - 750 ms. These formations continue to support Indonesia's energy infrastructure, ensuring that the CSB remains a critical resource for the nation's energy security.

Reservoir Simulation

Reservoir simulation is a sophisticated technique that utilizes artificial models to represent the complex behavior of subsurface fluids within a reservoir. This process is crucial for understanding, investigating, and predicting fluid flow dynamics in oil and gas fields (Yunita 2017). To build an accurate simulation, the first essential step is to determine the physical properties of reservoir fluids. These properties serve as the foundation for constructing reliable models, without which it is impossible to simulate real-world fluid behavior under varying reservoir conditions.

Oil production rarely results in draining the reservoir completely. A range of phenomena, including variations in the physical properties of the reservoir rocks and fluids, often limits complete oil recovery (Rita 2012). Key physical properties such as specific gravity, gas solubility in oil, FVF, compressibility, and viscosity define the behavior of hydrocarbons in each layer of the reservoir. These characteristics are highly sensitive to changes in reservoir pressure and temperature, making accurate measurements essential for optimizing production and maximizing recovery (Aulia et al. 2020).

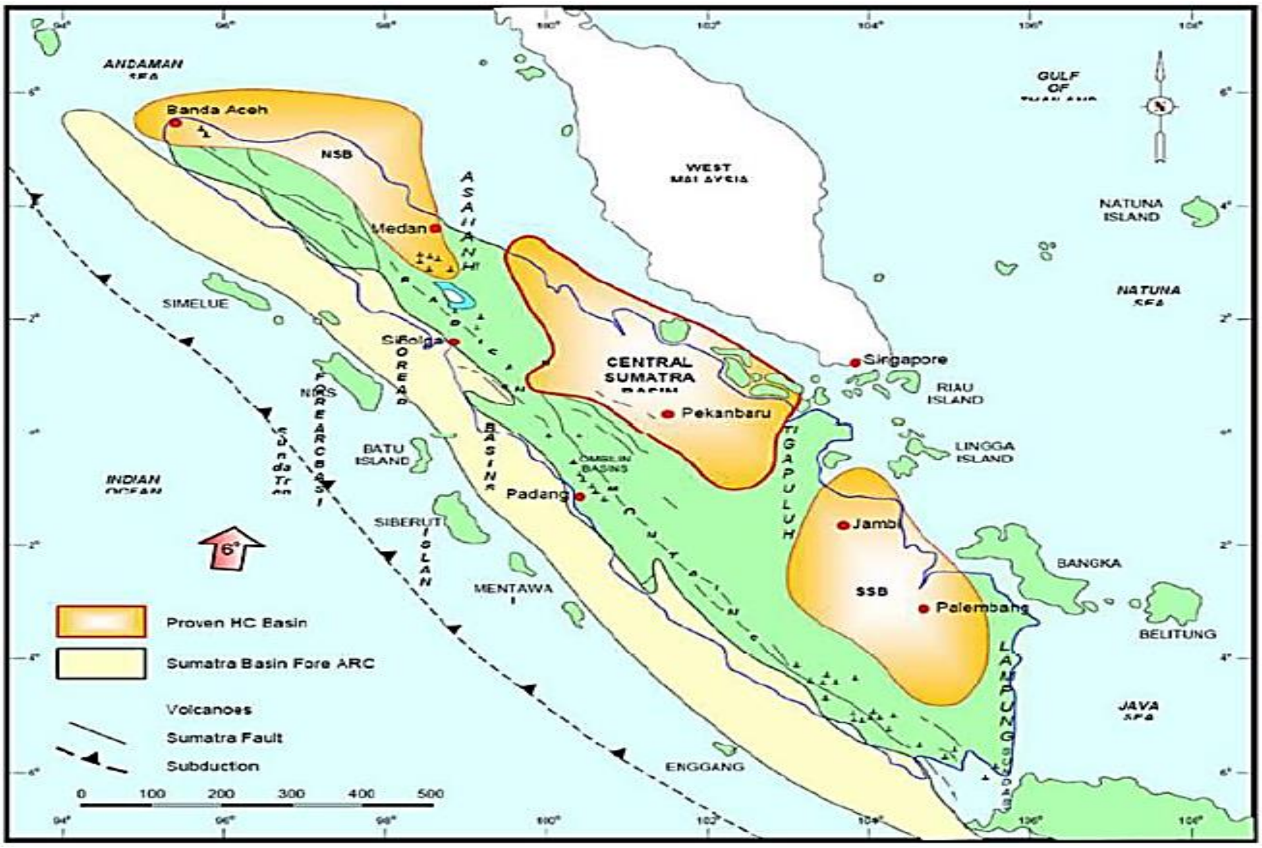

Figure 1
Map for Central Sumatra basin (Heidrick & Aulia 1993)

Understanding fluid behavior becomes even more critical when working with giant oilfields, where minor variations in fluid properties can significantly impact the economic viability of the entire project. Proper fluid characterization, accounting for both lateral and vertical variability in the reservoir, directly influences the success of enhanced oil recovery (EOR) strategies. Accurate PVT analysis is indispensable for determining key parameters such as mobility ratios and phase behavior, both of which are essential for effective field development (Meziani et al. 2018). Using advanced commercial PVT software helps estimate fluid properties more accurately, reducing the need for time-consuming and expensive laboratory tests during production phases (Nwankwo 2019).

Reservoir engineers rely on PVT analysis to characterize reservoir fluids accurately and simulate phase behavior during oil production (El-Hoshoudy & Desouky 2019). The process begins by obtaining representative fluid samples from the reservoir, followed by measuring and modeling the PVT data. This data is crucial for determining the relative volumes and phase states that occur under various pressure and temperature conditions. Two primary models dominate the field of fluid characterization: the Black oil model and EOS model.

Obtaining reliable PVT properties of reservoir fluids is a multi-step process that begins with acquiring adequate representative fluid samples from the reservoir. These samples must be accurately representative of the in-situ fluid composition to ensure the validity of the subsequent analyses. Once collected, the next critical step involves measuring the PVT data, which provides essential insights into the fluid's physical properties, including its compressibility, density, and viscosity under varying pressure and temperature conditions. Finally, this data is used to model the phase behavior of the reservoir fluids, enabling engineers to predict how the fluid will behave as pressure and temperature fluctuate during production. This comprehensive process ensures that the reservoir is properly characterized, allowing for optimized recovery strategies and more informed decision-making (Nagarajan et al. 2006). The Black oil model, known for its simplicity, uses empirical correlations based on separation data to estimate the necessary properties of reservoir fluids. While the model is straightforward and widely used, it lacks the precision of more sophisticated approaches when it comes to complex fluid systems. On the other hand, EOS model provides a more detailed and thermodynamically accurate representation of fluid composition and volumetric properties. It simulates the behavior of hydrocarbon fluids under specific reservoir conditions, allowing for more accurate predictions of fluid flow performance (Akpabio et al. 2015). PVT analysis and EOS generation are based on laboratory experiments. The commercial PVT software allows us to perform these tasks in the fluid model by matching the composition with available data on CCE, CVD, Differential Liberation Expansion (DLE), and separator tests (Khitrov et al. 2014). The choice of the appropriate EOS is crucial for proper fluid characterization, as it determines the accuracy of the PVT simulation. Commercial PVT software can replicate the results of laboratory experiments, including CCE, Constant Volume Depletion (CVD), and DLE tests. EOS model uses hydrocarbon component data to match saturation pressures and other lab-derived measurements, minimizing errors through the calculation of Absolute Average Error (AAE). Achieving a low AAE (less than or equal to 5%) ensures that the simulation closely represents the actual reservoir fluid properties (Abdulrazzaq et al. 2021). These parameters below are used in the PVT analysis, such as; 1). Component (C_1, C_2, C_3, C_4, C_5, pseudo components); 2). Pressure (p); 3).Temperature (T); 4). Gas Oil Ratio (R_s); 5).Oil (Oil FVF/B_o); 6). Viscosity (μ) and Density (ρ).

Correlations are an integral part of Black oil models, especially when detailed fluid composition data is not available. These correlations are derived from large datasets of measured PVT properties and are often region-specific, meaning they are tailored to specific types of reservoirs or formations. For instance, in the absence of detailed hydrocarbon component data, engineers can use correlation-based models to estimate fluid properties such as GOR, FVF, viscosity, and density based on analogous fields. However, it is critical to note that correlation models have limitations, as their accuracy depends on the similarity of the applied field data to the region for which the correlation was developed. Deviating from these conditions may lead to significant errors (El-Banbi et al. 2018). While Black oil models offer a practical solution in scenarios with limited data, EOS model provides a more accurate and robust approach for fluid characterization. EOS models, which are based on the fundamental thermodynamic properties of fluids, offer better precision in simulating complex reservoir conditions. The use of EOS models, combined with comprehensive PVT data and advanced commercial software, allows for better optimization of oilfield production, particularly in challenging reservoirs.

Correlations for Black Oil Method

The Black oil model remains a valuable tool for fluid modeling in scenarios where data on hydrocarbon compounds is unavailable or limited. When working in such cases, engineers must rely on correlations to estimate fluid properties based on similar fields or formations. Al-Marhoun emphasized the importance of reliable PVT data in reservoir engineering calculations, especially when direct fluid samples are difficult to obtain (Al-Marhoun 2021). It is essential to obtain samples of the reservoir fluid to determine the properties of the PVT. The correlation can be used for no-fluid samples to estimate PVT data. This is especially true during the early development when fluid properties are only available from surface flow tests.

Gas Oil Ratio (GOR)

GOR is one of the critical parameters in reservoir fluid correlations. GOR at the bubble point serves as an essential input for many fluid property correlations. It is typically determined by summing the GOR values from separator tests and stock tank measurements. (Whitson & Brule (2000) outlined how GOR can be calculated through DLE correlations and laboratory tests of separator data from the field. EOS models are then used to refine these calculations and predict GOR more accurately under reservoir conditions (Awadh & Al Mimar 2013). The formula is presented in Equation 1.

Where R_s is the Solution gas oil ratio, R_{sb} is the Solution gas oil ratio from the separator flash, R_{sd} is the Solution gas oil ratio from data lab correlation, R_{sdb} is the Solution gas oil ratio DLE at bubble point pressure, Bob is Bubble point-oil from separator flash, Bodb is Bubble point DLE.

$$R_s = R_{sb} - (R_{sdb} - R_{sd})\left(\frac{B_{ob}}{B_{odb}}\right) \quad (1)$$

Oil Gravity

Oil gravity, measured in API (American Petroleum Institute) units, is a key indicator of the quality and classification of crude oil. A higher API gravity suggests lighter, more valuable crude, while lower values indicate heavier oil, which is often less desirable due to more complex refining processes. When the API value is unknown, engineers can estimate it using Specific Gravity (SG), which serves as a proxy. The relationship between API gravity and SG is given by the formula:

$$API = \left(\frac{141.5}{SG}\right) - 131.5 \quad (2)$$

Where API is Degrees API Gravity, SG represents the Specific Gravity value. This equation provides a straightforward method for converting SG into API units, allowing for quick assessments of oil quality, even when detailed data is unavailable. This estimation is particularly useful when laboratory measurements are limited, or field data is incomplete, enabling engineers to make informed decisions about the production potential of the reservoir.

Gas Gravity, Salinity, Molecular Percent (H_2S, CO_2, N_2)

Gas gravity, salinity, and the molecular percentages of gases like H_2S, CO_2, and N_2 play a critical role in understanding the behavior of reservoir fluids. These values, typically derived from field correlations, offer insights into the composition and properties of the reservoir's gas phase. Correlations are often made with data from fields that share similar geological characteristics or are situated along the same migration pathways. In the absence of direct experimental data, reservoir engineers rely on production parameters and empirical correlations to estimate fluid properties accurately (Awadh & Al-Mimar, 2013). The accurate estimation of gas composition and salinity is crucial because these parameters directly affect the performance of the reservoir during production, including the gas-to-oil ratio (GOR), gas processing requirements, and the impact on surface facilities. Correlating such data ensures that production strategies are optimized for the specific characteristics of each reservoir, even when lab-tested data is not immediately available.

METHODOLOGY

The methodology for simulating reservoir fluid properties relies on the use of secondary data sourced from previous laboratory tests. This data serves as the input for commercial PVT software to simulate the behavior of fluids in the reservoir. In this research, the simulation focuses on Well X from the PSE field, where limited lab data is available. The following steps outline the fluid simulation process:

1). Data Collection: Gather existing data from laboratory tests and field measurements related to the reservoir fluid; 2). Data Processing: Process and clean the data to ensure accuracy and consistency, addressing any discrepancies between lab results and field conditions; 3). Model Input: Input the prepared data into the PVT software for two distinct models—EOS and Black oil. These models are selected based on their ability to capture different aspects of reservoir fluid behavior, with EOS model offering a more thermodynamic approach and the Black oil model relying on empirical correlations; 4). Initialization: Initialize the simulation by aligning the generated data with actual lab results. The success of this step is measured by the Absolute Average Error (AAE), which should be less than 5% to indicate a good match between the simulation and real-world conditions. This step is critical for ensuring that the model accurately represents the physical properties of the reservoir fluids; 5). Comparative Analysis: Analyze the results of the simulations, comparing the data generated by EOS and Black oil models against the laboratory data to assess which model offers better alignment with the actual reservoir conditions; 6). Discussion and Conclusion: Generate comprehensive discussions based on the comparison, drawing conclusions about the effectiveness of each model and its implications for field development and production optimization and 7). The flow chart in Figure 2 shows the research scenario based on EOS and Black oil approaches.

General Info of The PSE Field

The PSE field, situated in Central Sumatra, Indonesia, is an important onshore oil field characterized by its significant hydrocarbon reserves.

The field is part of a mature oil-producing region known for light and medium oil production. Below are the specifics related to Well X, one of the key wells in this field:

Well X data

It has a total depth of 5850 ft, a reservoir temperature of 308^0 F, and a Pressure of 1875 psig. The following is data from well X in the PSE field.

RESULT AND DISCUSSION

The PSE field benefits from a comprehensive set of laboratory data on reservoir fluid characteristics, which are crucial for optimizing production strategies and accurately modeling the reservoir's behavior. The research concludes by comparing the laboratory-measured fluid properties with the data generated by PVTp simulations, using both EOS and Black oil models. This comparison is vital to determine which model provides the most accurate representation of the reservoir fluids.

Equation of State

In EOS approach, data matching is a critical step to ensure that the model's predictions align closely with the lab-measured fluid properties. This process involves adjusting EOS model parameters to minimize the differences between the predicted values and the actual laboratory results. EOS model is based on thermodynamic principles, and by fine-tuning it, the model can accurately represent the reservoir fluid's behavior.

Saturation Pressure (P_{sat})

P_{sat} in this context represents the pressure at which the first bubble of gas forms in a liquid at a given temperature, also known as the bubble point pressure. According to the reference (Ikpabi & Akinsete 2024); (Prince Benard Ikpabi & Oluwatoyin Olakunle Akinsete 2022), this P_{sat} data matches the measured bubble point pressure from lab tests, which is indicated by the green cross (X) on the phase envelope.

The fitting line seen passing through or near the green cross (X) represents the model's prediction of the bubble point pressure. The proximity of this line to the lab data point (green cross) validates that the model accurately fits the experimental bubble point pressure.

The green cross (X) indicates the bubble point

Table 1
The data of reservoir fluid

Component	Mol (%)
H_2S	0
CO_2	12.78
N_2	1.05
C_1	4.3
C_2	1.79
C_3	3.36
i-C_4	1.44
n-C_4	1.93
i-C_5	1.26
n-C_5	2.44
C_6	4.04
C_{7+}	65.61
Total	100

SG (gr/cm^3)	Mol Weight C_{7+}	Water Salinity (ppm)
0.818	89.73	1200

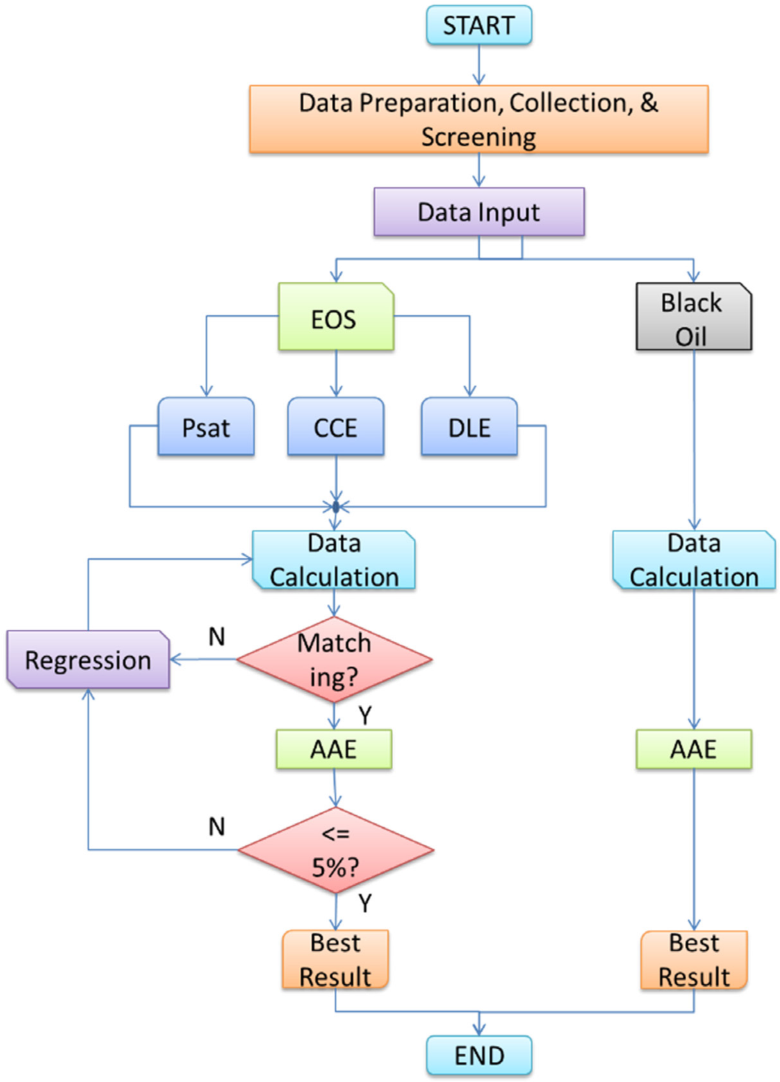

Figure 2
Research flow diagram

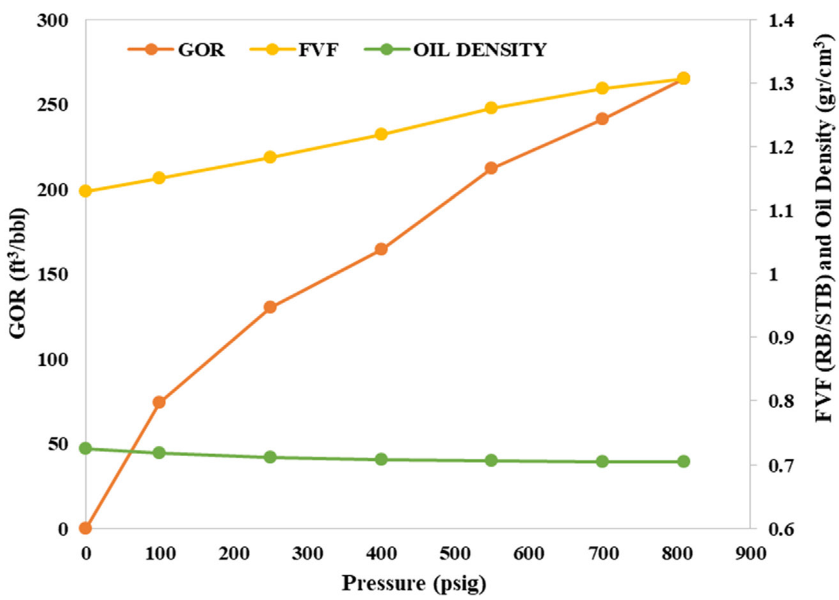

Figure 3
DLE test results

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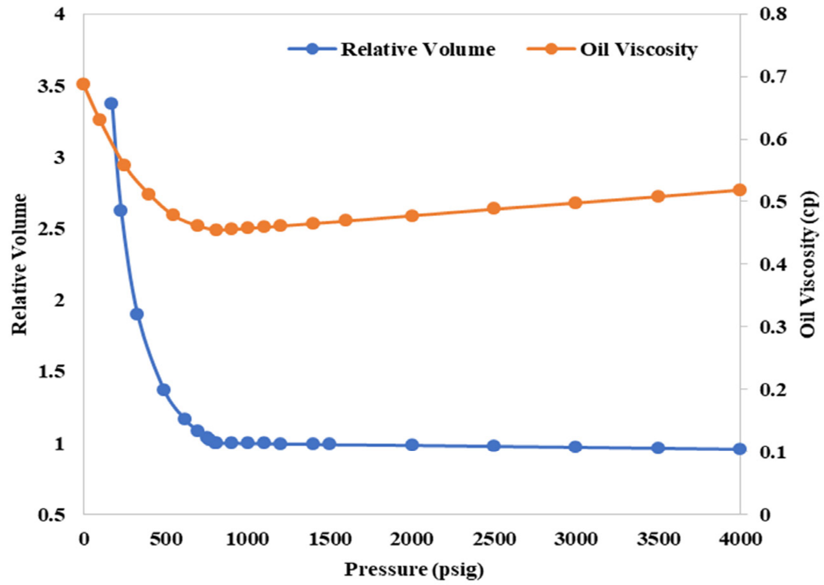

Figure 4
Constant composition expansion test results

derived from laboratory experiments, suggesting that the model predictions align well with actual lab measurements. This validation is crucial in ensuring that the phase behavior model is reliable for predicting fluid behavior in real reservoir conditions.

Constant Composition Expansion (CCE)

CCE is a critical test in PVT analysis that aims to assess how a reservoir fluid sample behaves under varying pressure conditions while maintaining its composition constant. This test is essential to understanding the physical properties of the fluid under actual reservoir conditions, such as relative volume (the fluid's volume relative to its original state) and liquid viscosity. According to (Syahrial 2022) the most appropriate fluid sample was chosen for fitting an equation of state to experimental data through regression. Based on data analysis and quality control of all PVT data suggested that fluid from UP-1 DST-3 is the best representative of XYZ field. The PR3-EOS and LBC correlation are applied to the UP-1 DST-3 data sets under conditions of predictions and regression. Agreement between laboratory data and regressed EOS results is generally good to excellent. The results show that that regression on critical properties of components is sufficient for good data matches. In this work, a good agreement with experimental data was obtained with grouping (lumping), the objectives of CCE in PVT Analysis are determining fluid behavior, bubble point pressure identification, and measurement of relative volume, the CCE test provides a detailed understanding of how the fluid transitions from a liquid phase to a two-phase (liquid and gas) system, enabling better reservoir management.

Christanti et al. (2023) and Sholahudin et al. (2022) highlight the importance of CCE in capturing the physical properties of reservoir fluids under pressure conditions close to actual reservoir states, making it crucial for optimizing production strategies and accurately characterizing the reservoir's fluid dynamics.

Figure 6 illustrates the relative volume behavior of the reservoir fluid as a function of pressure, with the lab measurements and EOS model predictions being compared; Lab Data (CCE Results): Represented by the green plus signs (+), the lab data comes from a CCE test, which directly measures the relative volume of the reservoir fluid sample under varying pressures. EOS Model Predictions; The red line represents the relative volume calculated using EOS model. This is a predictive approach that estimates the fluid's behavior under the same pressure conditions. Both the lab data and EOS model follow the same general trend. At lower pressures (below 500 psig), the relative volume is higher and decreases rapidly as pressure increases. At higher pressures (above 1000 psig), the relative volume stabilizes and approaches 1.0, indicating that the fluid is becoming more compressed.

The AAE is 0.81%, which indicates a very close match between the lab results and EOS model's predictions. This low error suggests that EOS model accurately captures the fluid's behavior across the

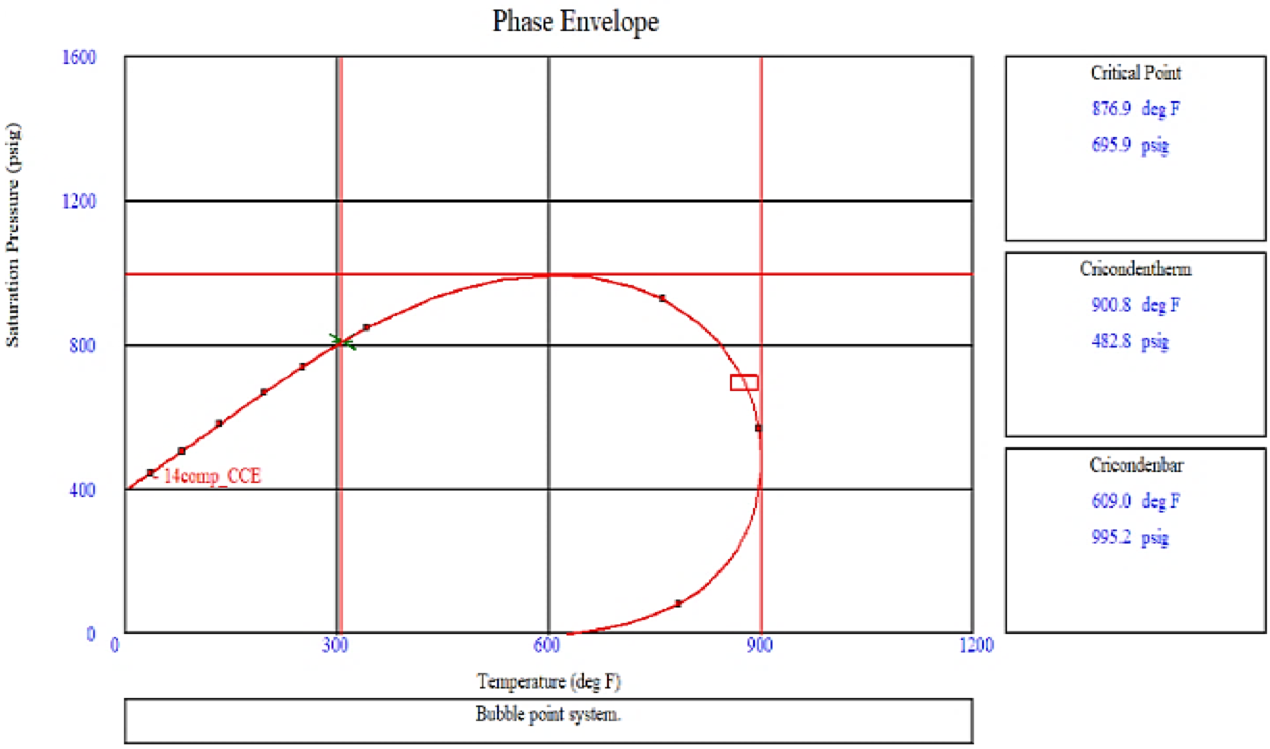

Figure 5
Chart of phase envelope

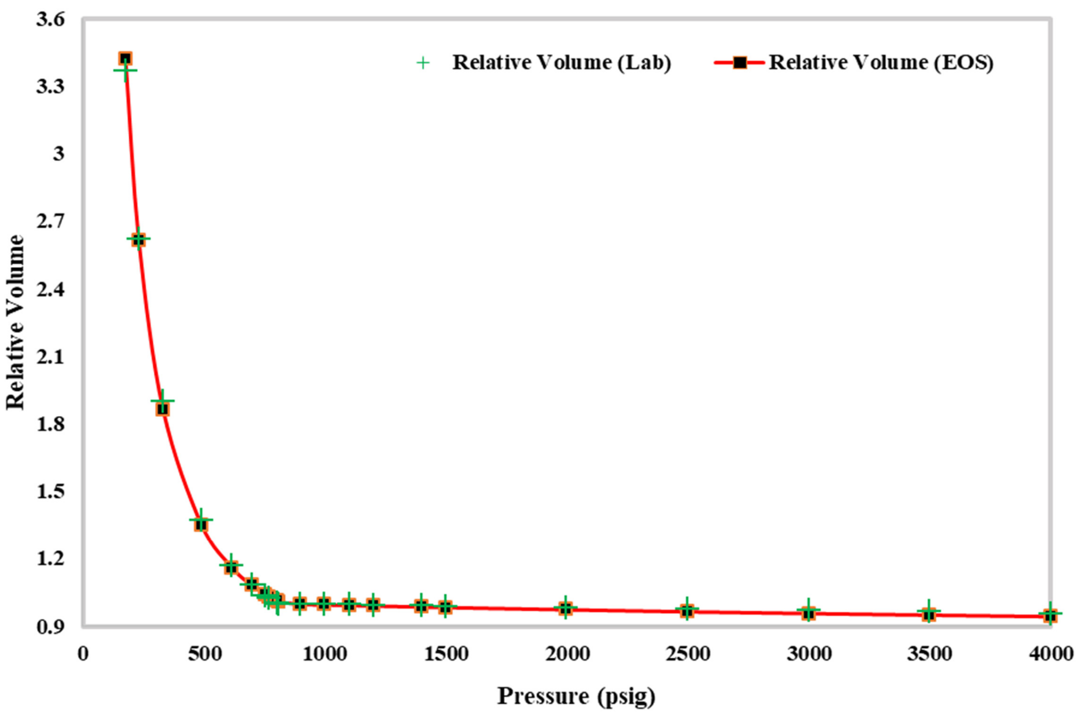

Figure 6
Comparision betwen relative volume test and EOS model

pressure range.

The graph clearly shows an inverse relationship between pressure and relative volume. As pressure increases, relative volume decreases, particularly in the lower pressure range. At lower pressures (below the bubble point), the fluid is more expansive, resulting in higher relative volumes. This is due to the presence of gas in the two-phase region, causing the fluid to occupy more volume. As the pressure increases, especially beyond the bubble point, the gas compresses, and the fluid behaves more like a single-phase liquid, reducing the relative volume significantly. While both the lab and EOS model data show similar trends, the lab-measured relative volumes tend to be slightly higher than EOS model predictions at lower pressures (near or below the bubble point). As pressure increases beyond the bubble point, the discrepancy between the lab data and EOS predictions narrows, indicating that both methods converge toward similar values at higher pressures.

Differential Liberation Expansion

Figure 7 presents the Gas Oil Ratio (GOR) as a function of pressure, comparing experimental laboratory data DLE with the predictions from EOS model. As pressure increases, the GOR also increases, reflecting a positive correlation between pressure and GOR. This trend is expected, as higher pressures tend to retain more gas in the oil phase, resulting in more gas liberation as pressure drops. At lower pressures, the lab data tends to show slightly higher GOR values than EOS model predictions. However, this discrepancy diminishes as pressure increases, and the two data sets converge more closely at higher pressures.

The last data point shows a slight mismatch, where EOS model predicts a lower GOR than what was observed in the lab. This could be due to specific complexities in the lab sample or variations in the fluid's behavior under test conditions.

The calculated AAE between the lab data and EOS model is 3.7%, which is lower than the acceptable threshold of 5% mentioned (Fetoui 2021). Despite the slight difference at certain pressure points, the model is considered sufficiently accurate for matching purposes.

The lab-measured GOR is generally higher than EOS-predicted values. This could suggest that the fluid sample releases gas more readily under lower pressure conditions than what EOS model anticipates. Both the lab measurements and EOS model align more closely, indicating that EOS model performs better under higher pressure conditions. The deviation at the last point suggests possible differences in the fluid's behavior near critical points, such as near the bubble point.

Figure 8 illustrates the relationship between Oil FVF and pressure, comparing experimental data from DLE lab tests. The Oil FVF increases with increasing pressure, showing a positive correlation. This trend is expected, as oil typically expands and retains more gas at higher pressures, which increases its volume under reservoir conditions.

Across the entire pressure range, the lab data (green plus signs) are slightly higher than EOS predictions (red squares). This suggests that, in the lab, the oil retains more volume at these pressures than what EOS model calculates. Although the lab data is consistently higher, the difference between the lab measurements and EOS model is small, indicating a good fit between the two. There are five points that appear to deviate slightly from the general trend, potentially due to experimental or sample variability. Despite these small outliers, the average absolute error (AAE) is 1.4%, which is well within acceptable limits and suggests a good match between EOS model and lab results.

At low pressures (below 200 psig), the oil FVF increases steeply, which may be due to gas evolution from the oil as the fluid approaches the bubble point. At higher pressures (above 500 psig), the oil FVF continues to increase but at a slower rate, as the fluid becomes more compressed and retains less gas.

Figure 9 presents the relationship between oil density and pressure, comparing laboratory measurements with the predictions. The oil density decreases as pressure increases, indicating an inverse relationship between the two variables. This trend is expected, as oil becomes less dense when gas is dissolved into it at higher pressures, making the fluid expand and reducing its density.

At lower pressures (below 200 psig), the lab measurements show slightly higher oil density than EOS model predictions. This may be due to gas evolving from the oil at lower pressures, which increases the density of the liquid phase in the lab tests.

As pressure increases, the lab data and EOS model predictions converge closely, particularly above 500 psig. This suggests that EOS model accurately predicts the behavior of oil density at higher pressures. The average absolute error (AAE) between the lab measurements and EOS model is 0.1%, indicating a very close fit between the two datasets. This extremely low error suggests that EOS model provides a reliable estimate of oil density across the range of pressures analyzed.

At lower pressures, the oil density is higher because less gas is dissolved in the oil, making the fluid more compact.

As the pressure increases, more gas dissolves in the oil, leading to expansion and a reduction in oil density. This relationship stabilizes as the pressure moves into the higher range, with both the lab data and EOS predictions reflecting similar behavior.

Black Oil

The Black oil model is a simplified fluid modeling approach commonly used when detailed hydrocarbon component data is not available, making it a practical solution for fields lacking extensive fluid characterization. In the case of smaller fields or mature fields with limited data, such as the PSE field, correlations are employed to estimate essential fluid properties. The Black oil model works by using basic production data and empirical relationships to predict the behavior of fluids under reservoir conditions.

Data Collection for Black Oil

The input data required for the Black oil model in the PSE field includes GOR, oil gravity, gas gravity, salinity, molecular percentages of H_2S, CO_2, and N_2. Since component data is unavailable for the PSE field, these properties are derived using empirical correlations based on fields with similar geological characteristics or located on the same migration path.

Fluid Data Properties from Black Oil Method

After running the model, the black oil method's result is compared with lab test data. Below are comparisons of both the Black oil model and the lab test. The chart of the phase envelope of the Black oil model has an AAE, which is excellent for matching with the lab test. Figure 10 exhibits a significant difference between lab tests (plus sign) and the Black oil model (red line). The curve explains low pressure (0 - 200 psig): The GOR increases steadily as pressure rises, showing a gradual increase in gas released per oil unit. Mid-range pressure (200 - 600 psig) describes the GOR continuing to increase as pressure rises, but the curve starts to plateau, showing a slower increase. Pressure reaches approximately 600 psig. The GOR reaches its maximum value at about 700 psig. It indicates the point at which the

Table 2
The data for the black oil method

Parameter	Value
GOR (ft^3/STB)	256
Oil Gravity (API)	41.5
Gas Gravity	0.5
Water Salinity (ppm)	1200
H_2S (%)	0
CO_2 (%)	12.8
N_2 (%)	11

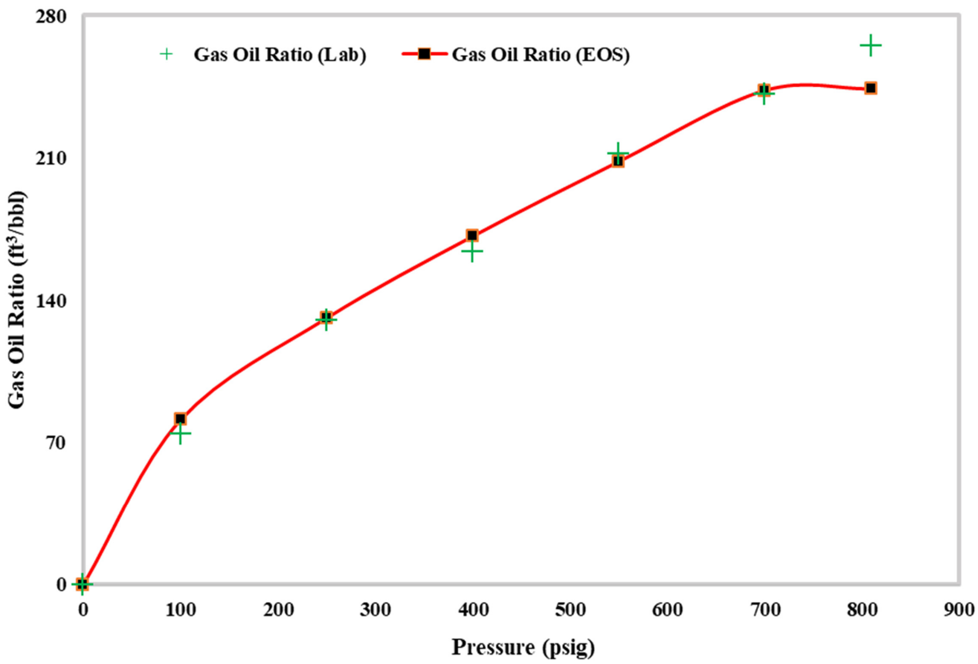

Figure 7
Gas oil ratio versus pressure

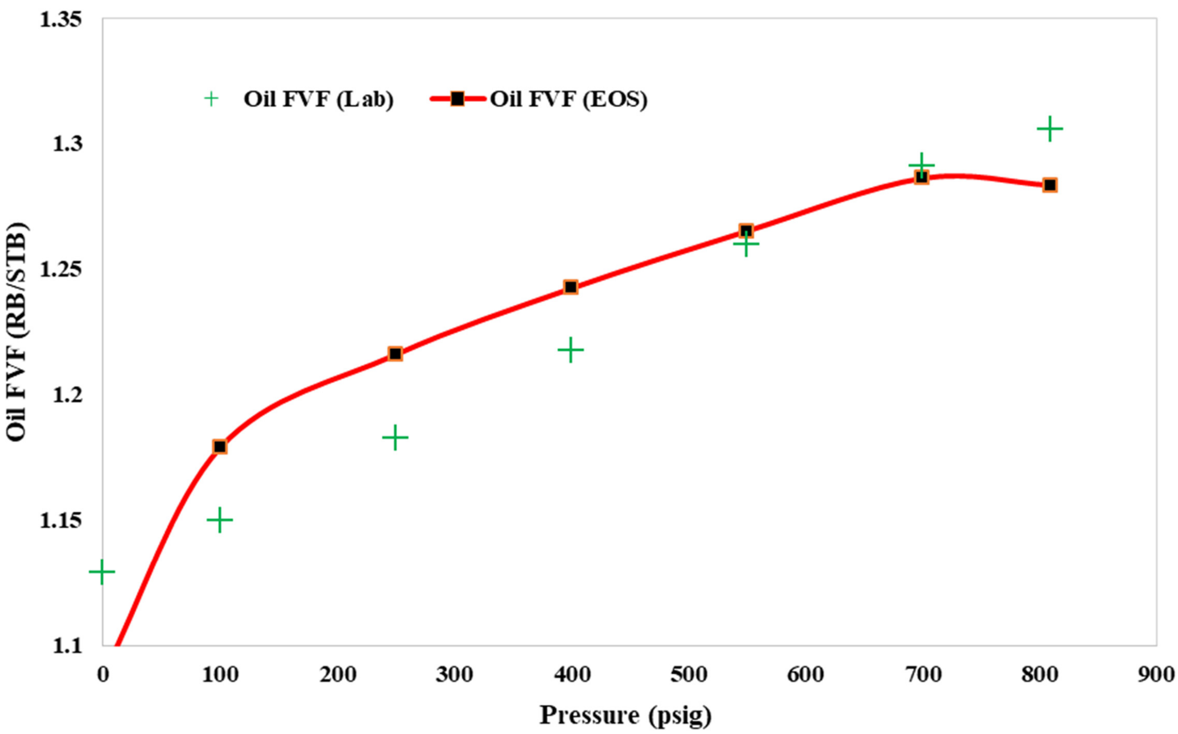

Figure 8
Formation volume factor versus pressure

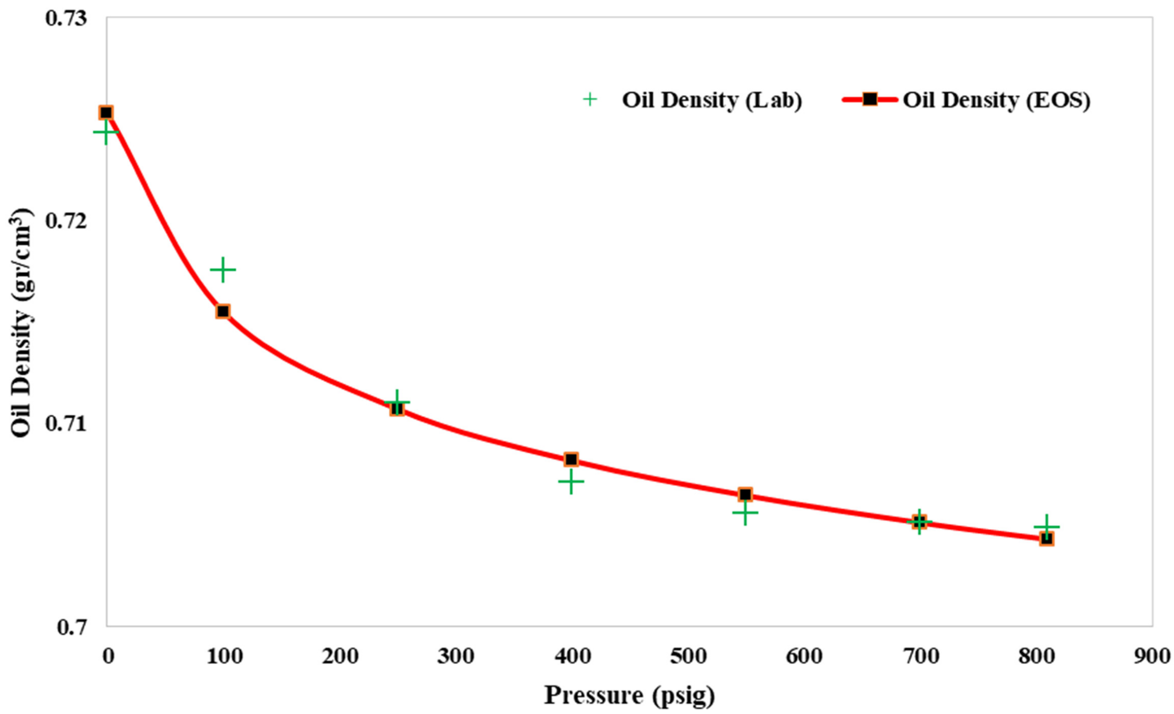

Figure 9
Oil density versus pressure

gas content in the oil is the highest. After reaching the peak, the GOR sharply decreases as pressure approaches 800 psig. This drop suggests that the gas is being reabsorbed or no longer released from the oil at higher pressures. Especially in the last point, above 800 psig, the gas dropped drastically due to it dissolving into a liquid phase, according to the Black oil model, which is opposite the DLE lab test. The AAE is 40.6% Figure 11 demonstrates the comparison between the Oil FVF as measured in laboratory tests and calculated using the Black oil method. The chart reveals a significant deviation between the two curves, indicating discrepancies in the FVF values predicted by the Black oil model relative to the actual lab data. Both the lab data and the Black oil model show a general decrease in Oil FVF as pressure increases, which is consistent with the behavior of oil under compression. As the pressure increases, the oil contracts, reducing its . The lab-measured Oil FVF values (green plus signs) are consistently higher than those predicted by the Black oil model (red squares), especially at lower pressures. This indicates that the Black oil model underestimates the actual expansion of the oil in the reservoir, particularly when the pressure is below 300 psig. The calculated AAE (Average Absolute Error) between the lab data and the Black oil model is 7.7%, which exceeds the acceptable threshold of 5%. This higher error margin suggests that the Black oil model's assumptions and correlations may not fully capture the fluid behavior in this particular reservoir, leading to significant differences in the predicted FVF. The deviation in the curves, particularly at lower pressures, suggests that the correlation or formula used in the Black oil model may be inaccurate for this specific fluid system or pressure range. This reinforces the need to carefully assess the suitability of the Black oil method for reservoirs with complex fluid behaviors.

Figure 12 presents a comparison of oil viscosity values measured in the lab versus those calculated using the Black oil method. The chart shows a closer match between the two sets of data than was observed in the Oil FVF comparison (Figure 11), with both the lab data and the model predictions following a similar trend of decreasing viscosity as pressure increases.

Figure 12 demonstrates that the Black oil model is effective in predicting oil viscosity for the given pressure range, with a low AAE of 3.2%, indicating a good match with the lab data. Although the lab measurements show slightly higher viscosity at lower pressures, the overall trend and values are closely aligned, suggesting that the Black oil method can be reliably used to estimate oil viscosity in this case. This contrasts with the less accurate results observed for Oil FVF in Figure 11, reinforcing the importance of validating model outputs for different fluid properties on a case-by-case basis.

Figure 13 compares the oil density values measured in laboratory tests with those predicted by the Black oil method. The chart highlights differences between the two datasets, though the scale of these differences remains relatively small. Both the lab data and model calculations show an overall increase in oil density as pressure rises. The lab-measured density values (green plus signs) are generally lower than those predicted by the Black oil method (red squares), especially at lower pressures (below 400 psig). The Black oil method tends to overestimate oil density in this range, suggesting that the empirical correlations used in the model may not fully capture the fluid's behavior under these conditions. At higher pressures, the difference between lab-measured and model-calculated densities narrows, indicating a better alignment between the two as pressure increases. The AAE for this comparison is 3.2%, which falls within the acceptable threshold of 5%.

Table 3
Comparison of results

Parameter	AAE (%)	
	EOS	Black Oil
P_{sat} (psig)	0	0.001
Relative Volume	0.81	-
GOR (ft^3/bbl)	3.70	40.60
FVF (RB/STB)	1.40	7.70
Density (gr/cm^3)	0.10	3.20
Viscosity (cp)	-	3.20
Mean	1.2	10.94

While there is some deviation between the lab data and model results, the error is small enough to consider the Black oil method a reasonably accurate tool for predicting oil density in the PSE field.

Comparison Between EOS and Black Oil Methods

Table 3 presents comparison of AAE values resulted from EOS and Black Oil Methods.

The analysis of AAE percentages obtained in this study clearly demonstrates that EOS method delivers significantly better accuracy than the Black oil method. With an overall mean AAE of 1.2% for EOS versus 10.94% for the Black oil model, the study confirms that EOS method is far more suitable for comprehensive fluid property analysis in this case. These results support the conclusion that the Black oil model lacks the precision needed to effectively capture the complex behavior of reservoir fluids,

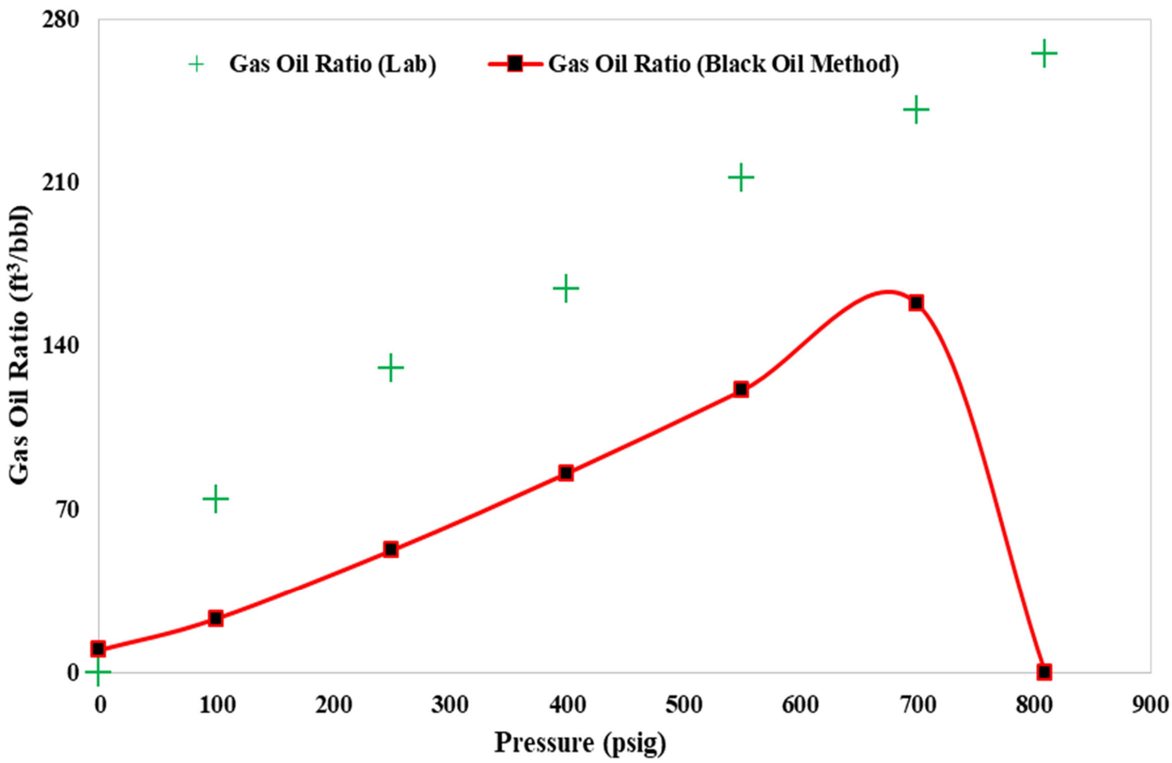

Figure 10
Comparison of gas oil ratio values between laboratory data and black oil methods

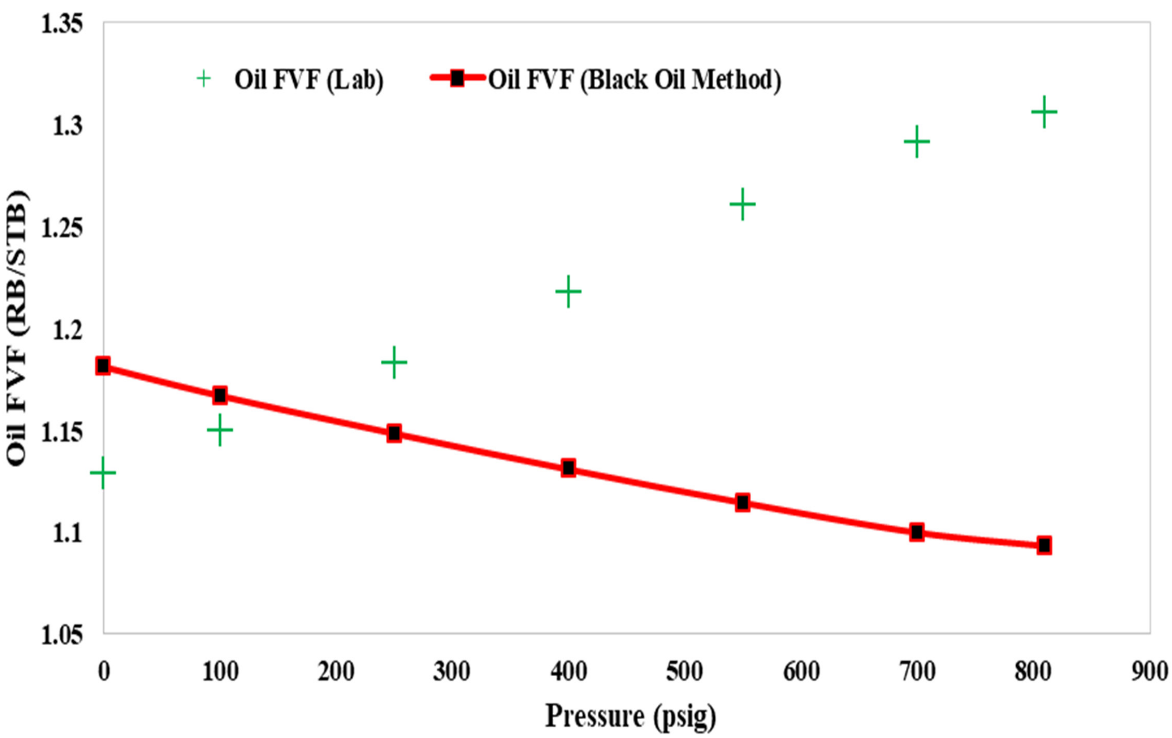

Figure 11
Comparison of oil formation volume factor values between laboratory data and black oil methods

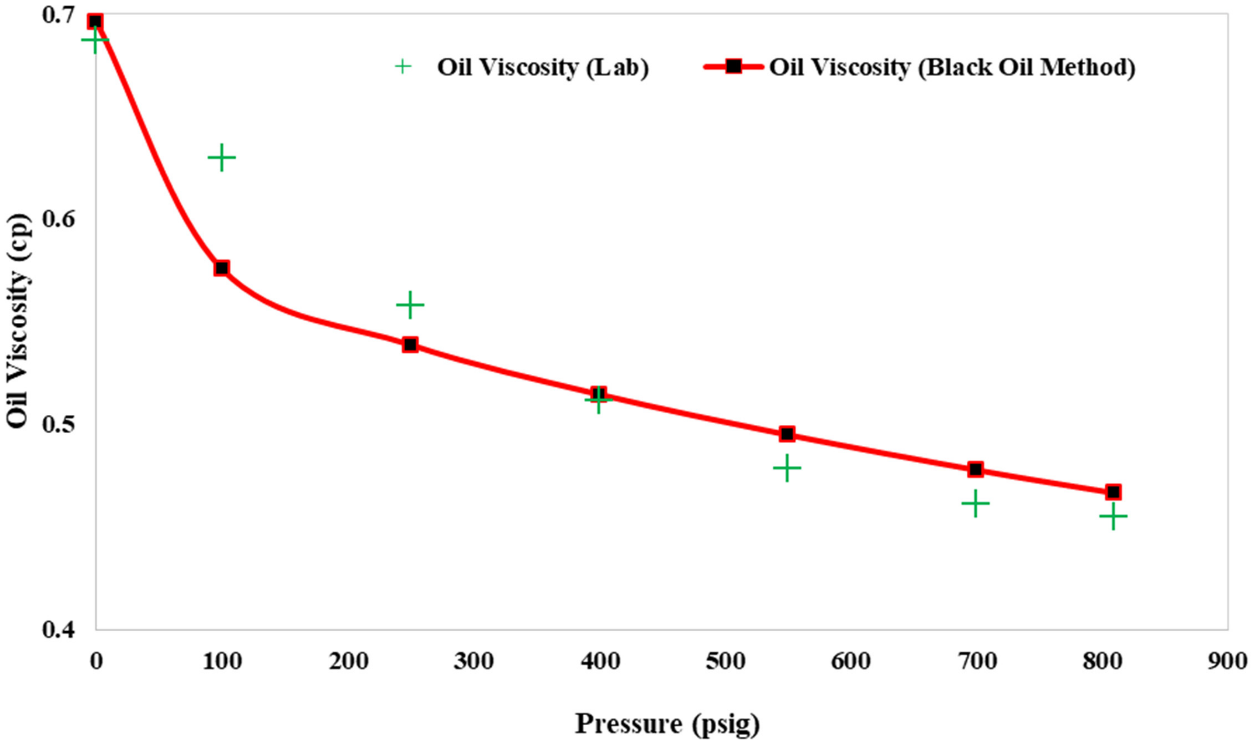

Figure 12
Comparison of oil viscosity values between laboratory data and black oil methods

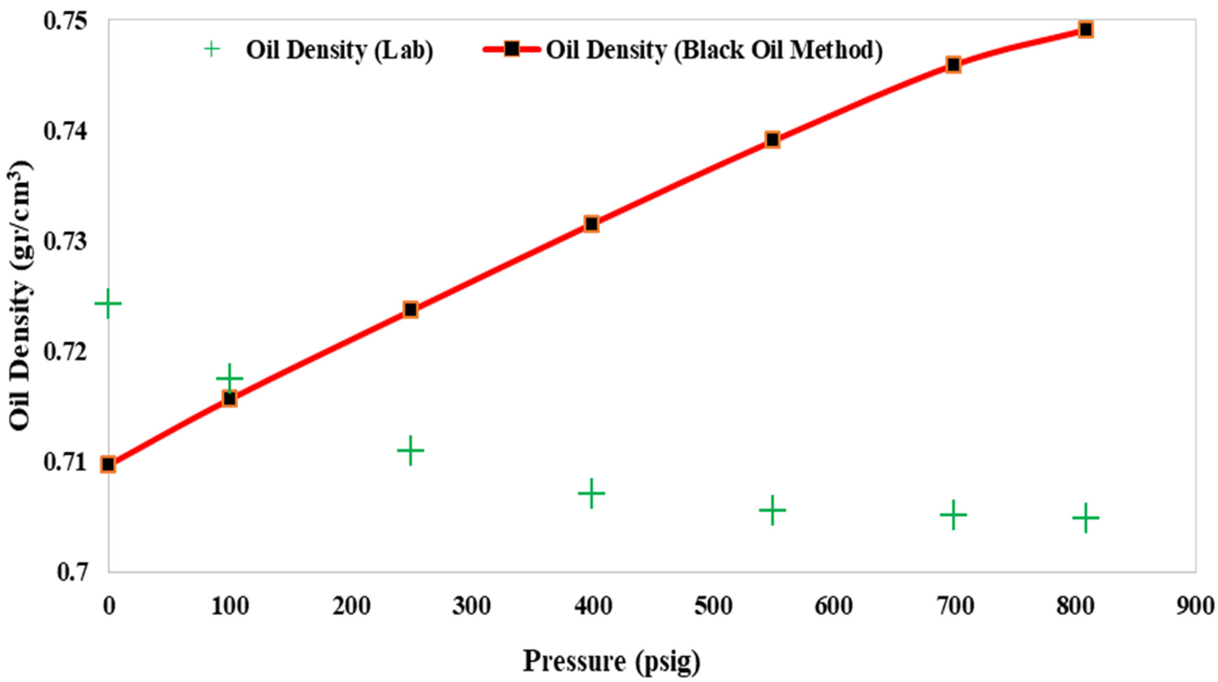

Figure 13
Comparison of oil density values between laboratory data and black oil methods

particularly when applied to fields with diverse and intricate fluid systems, such as the PSE field. The study's findings reinforce that the Black oil method, in its current form, is insufficient for analyzing comprehensive fluid properties. The relatively high AAE, especially for critical parameters like GOR and FVF, highlights the need for advanced modifications to the traditional Black oil approach. One promising avenue for improvement involves incorporating probabilistic and statistical approaches to better handle the variability and uncertainties inherent in fluid property predictions.

Several researchers have made significant strides in refining the Black oil model to enhance its predictive capabilities:

Whitson & Torp (2000) introduced a method that brought the Black oil approach closer to the accuracy of EOS models. By refining correlations and improving fluid property predictions, they significantly increased the precision of the Black oil method in various scenarios.

Kanu & Ikiensikim (2014) advanced Black oil PVT correlations by addressing the limitations that confined the traditional model to specific local conditions. Their work expanded the model's applicability to a broader range of oil types, reservoir temperatures, and pressures, making it more versatile for modern reservoir analysis.

El-Banbi et al. (2006) builds on Whitson and Torp's methodology, El-Banbi et al. developed a globalized Modified Black oil (MBO) PVT dataset, which provided more generalized and adaptable correlation models. This modification used statistical techniques to improve the accuracy of predictions across various reservoir conditions, offering a significant improvement in the Black oil model's reliability and making it applicable to a wider range of real-world reservoir environments. These advancements demonstrate that with appropriate adjustments, the Black oil method can be refined to better approximate the accuracy of EOS models. By integrating probabilistic models and using statistical techniques, researchers have already enhanced the predictive power of the Black oil model, making it more versatile and reliable for different reservoir settings.

The Reservoir Fluid Properties

Following the comparison of lab data and model results, a set of equations describing the physical properties of the reservoir fluid has been obtained. These data are processed and stored in a PVT file, which can be imported into reservoir simulation software. The PVT file serves as a crucial reference for the development of production scenarios, particularly for infill well planning, development strategies, and optimizing production over the reservoir's lifespan.

In the context of geological and geophysical reservoir studies, the fluid properties derived from such simulations provide vital insights into reservoir dynamics during the production period. This data plays an essential role in forecasting reservoir performance, guiding field development, and informing decisions on enhanced oil recovery (EOR) strategies. With accurate fluid characterization from the PVT file, engineers can simulate different operational scenarios, ensuring the most effective use of reservoir resources and maximizing recovery potential.

Figure 14 illustrates the relationship between oil density and gas density as a function of pressure at a constant temperature of 308°F. The chart highlights contrasting trends for oil and gas density, demonstrating how these two fluids behave differently under increasing pressure.

The contrasting behaviors of oil and gas densities reflect the fundamental differences in compressibility between liquids and gases. While gas density increases dramatically due to the compressive forces at higher pressures, oil density only decreases slightly, indicating a reduced compressibility in comparison to gas.

These trends are important for reservoir simulations and fluid modeling, as they impact predictions of fluid flow behavior and reservoir performance. Understanding the interplay between oil and gas densities helps engineers optimize production strategies, particularly in scenarios involving gas injection or pressure maintenance. Figure 15 illustrates the viscosity behavior of oil and gas as a function of pressure at a constant temperature of 308°F. The chart highlights the different responses of gas and oil viscosities under varying pressure conditions. The viscosity behavior of gas and oil as depicted in Figure 15 shows the strong influence of pressure on gas viscosity, which increases sharply under compression before leveling off. Oil viscosity, however, remains relatively stable, indicating that oil is far less affected by pressure changes in this range. These differences are critical for reservoir engineering and production planning, as gas viscosity plays a more dynamic role in fluid flow and production behavior, while oil's viscosity remains relatively stable, offering more predictable flow characteristics. Understanding these trends helps in optimizing production strategies, especially in fields with high-pressure environments. Figure 16 displays the relationship between the FVF for both oil and gas as a function of pressure at a constant temperature of 308°F. The chart reveals how the FVF for oil and gas behaves differently as pressure increases. The increase in oil FVF as pressure rises shows that the oil's volume is significantly influenced by the amount of dissolved gas. This makes oil more expansive in the reservoir than at surface conditions. The sharp decline in gas FVF reflects the compressibility of gas. As pressure increases, gas occupies a progressively smaller volume, underscoring how sensitive gas is to pressure changes in terms of volume reduction. Figure 17 illustrates the relationship between Relative Volume and GOR as a function of pressure at a constant temperature of 308°F. The graph highlights how both relative volume and GOR respond to changes in pressure, reflecting the interactions between the gas and oil phases. The simultaneous increase in relative volume and GOR as pressure rises suggests that more gas is dissolving into the oil, which expands the overall volume of the mixture. This behavior is typical of oil-gas systems under compression, where the dissolution of gas into the oil phase increases the volume the oil occupies in the reservoir. The increasing GOR demonstrates that at higher pressures, the gas-to-oil ratio becomes larger, indicating that more gas is available in solution within the oil phase. This is critical in understanding how the gas phase influences the overall behavior of the reservoir fluids.

CONCLUSION

The results of this study unequivocally demonstrate the superiority of EOS method over the Black oil method in accurately predicting reservoir fluid properties. The remarkably low Average Absolute Error (AAE) of just 1.2% across all key parameters solidifies EOS model as an exceptionally precise and reliable tool for evaluating the comprehensive physical characteristics of reservoir fluids. By contrast, the Black oil method, with a significantly higher average AAE of 10.94%, consistently fails to provide the accuracy needed for in-depth PVT analysis. In cases where a detailed understanding of fluid behavior is critical for optimizing reservoir performance and making informed decisions, the Black oil model simply does not meet the standard required for high-fidelity fluid simulations.

This study not only confirms the critical advantage of using EOS method when sufficient data particularly chemical composition is available,

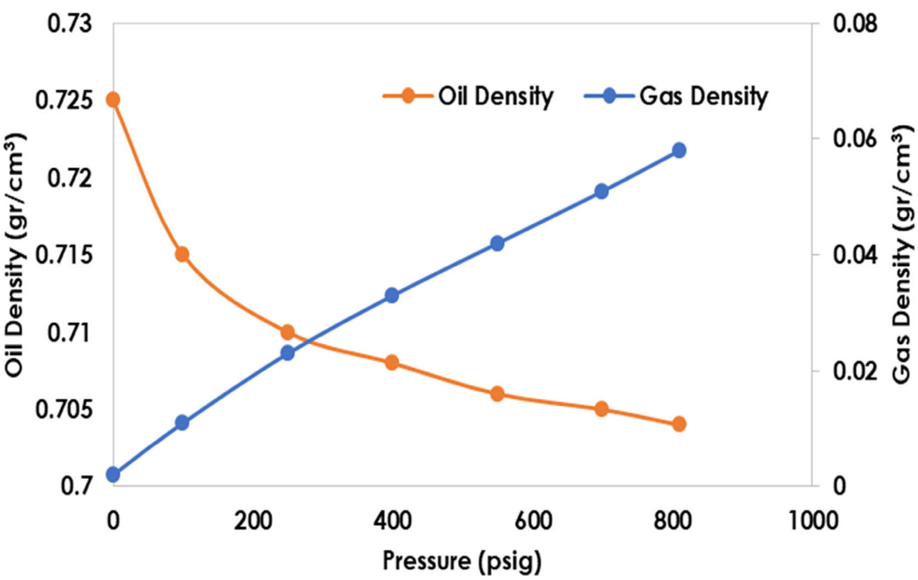

Figure 14
Oil and gas density @ 308 °F

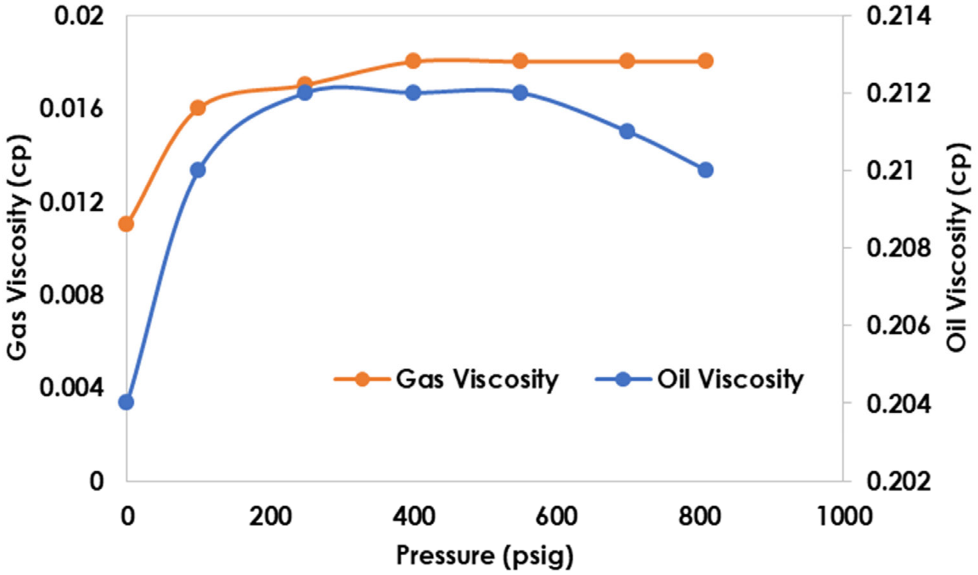

Figure 15
Chart of viscosity @ 308 °F

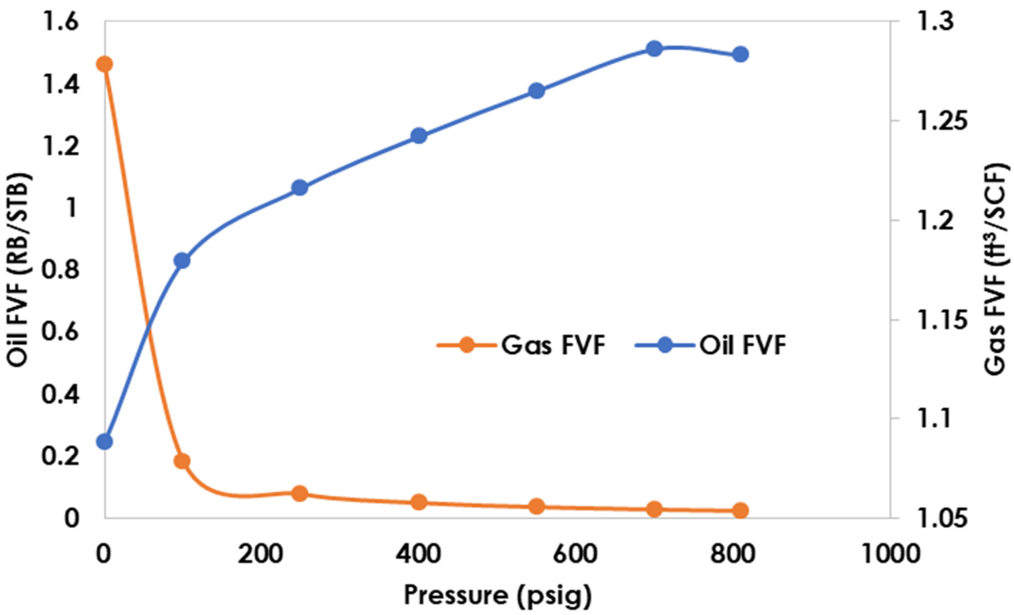

Figure 16
Chart of FVF @ 308 °F

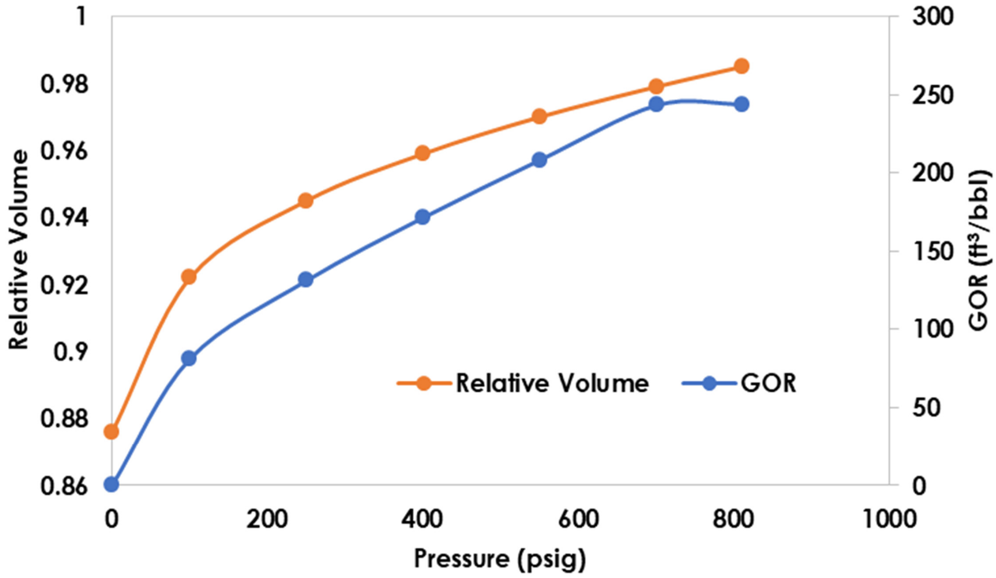

Figure 17
Chart of GOR and RV @ 308 °F

but it also underscores the limitations of the Black oil approach. EOS model excels in delivering highly accurate simulations that closely match field conditions, making it the preferred method for comprehensive fluid property analysis. Its ability to capture the intricacies of fluid behavior under varying pressure and temperature conditions ensures that reservoir characterization is more precise, leading to better-informed strategies for production optimization and enhanced recovery techniques. In contrast, while the Black oil method may still hold some utility in scenarios where data is severely limited, it remains a compromised approach. The lack of precision inherent in this method makes it unsuitable for scenarios where an accurate understanding of fluid dynamics is essential. Given the complexity and economic stakes involved in modern reservoir management, relying on a model with such a high margin of error can lead to suboptimal decision-making and underperformance in recovery strategies.

Thus, for thorough and reliable fluid property analysis, EOS method is strongly recommended. Its superior accuracy ensures that the reservoir is characterized with a higher degree of confidence, enabling optimized production strategies that maximize recovery potential and minimize uncertainty. In today's competitive and data-driven oil and gas landscape, choosing the right model is no longer a matter of convenience but a strategic imperative. EOS method is clearly the best tool for this task, offering high-fidelity modeling that aligns with the industry's need for precision and efficiency.

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GLOSARRY OF TERMS

Simbol	Definisi	Unit
PVTp	Thermodynamic fluid characterization software	

EOS	Equation Of State	
AAE	Average Absolute Error	%
GOR	Gas Oil Ratio	Fraction
FVF	Formation Volume Factor	Bbl/STB
P_{sat}	Saturation Pressure	Psia
CSB	Central Sumatra Basin	
RV	Relative Volume	Fraction
PVT	Pressure Volume Temperature	
API	American Petroleum Institute	
CCE	Constant Composition Expansion	
DLE	Differential Liberation Expansion	
ML	Machine learning	
MBO	Modified Black Oil	
R_s	Solution gas oil ratio	
CVD	Constant Volume Depletion	Fraction
BO	Black Oil	

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