
Ant Colony Optimization Algorithm of Solution Gas Oil Ratio PVT Correlation

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Abstract: *The solution gas-oil ratio (R_s) is a vital parameter in pressure-volume-temperature (PVT) analysis and reservoir engineering, with its accurate estimation being critical during reservoir depletion. While laboratory-based fluid sampling offers precision, it is often capital-intensive and logistically demanding. Consequently, empirical correlations have been developed to estimate R_s ; however, these correlations are frequently region-specific and fail to generalize across diverse reservoir conditions, leading to significant prediction errors. This study aimed to optimize existing R_s correlations—specifically the Glaso (1980) and Standing (1947) models—using the Ant Colony Optimization (ACO) algorithm to enhance prediction accuracy for the Volve field. Data from the Volve production dataset underwent extensive cleaning to remove irrelevant features, missing entries, and anomalous zero values, ensuring reliability for modeling. The ACO algorithm was then applied to calibrate the parameters of the selected correlations, with optimization assessed using statistical metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the Correlation Coefficient (R). Results showed that the optimized Glaso correlation achieved superior performance, yielding a high correlation coefficient (0.9993) and a significant reduction in average relative error (30.22%), outperforming its original and the Standing model in predictive accuracy. Comparative analysis against experimental data and traditional models confirmed the robustness and adaptability of the ACO-enhanced approach. Despite challenges such as data dependency, parameter sensitivity, and risk of overfitting, the ACO algorithm demonstrated strong potential for improving R_s estimation across complex reservoir systems. The findings underscore the necessity of optimizing empirical models before their field application and affirm the value of bio-inspired algorithms in petroleum reservoir analysis.*

Keywords: PVT correlation, ant colony optimization, solution gas-oil ratio, glaso and standing models, reservoir fluid characterization.

INTRODUCTION

The accurate characterization of reservoir fluid properties is a fundamental aspect of petroleum engineering, underpinning critical activities such as reserve estimation, production forecasting, and the design of surface and subsurface facilities. Among these properties, the *Solution Gas-Oil Ratio* (R_s) is particularly significant, especially within the framework of pressure-volume-temperature (PVT) analysis. R_s reflects the amount of gas dissolved in oil under reservoir conditions and varies as reservoir pressure depletes, thereby influencing reservoir performance projections and production strategies (Hillary and Okotie, 2016). According to Okotie et al. (2017), in order to estimate the PVT properties of a reservoir fluid, the fluid is typically sampled and brought to a laboratory for experimental analysis. In this laboratory, properties like relative volume, vapor compressibility (z) factor, and liquid drop out are determined, as well as saturation pressure (Dew point) at reservoir temperature and constant composition expansion test for black oil.

PVT analysis serves as a comprehensive approach to understanding the thermodynamic behavior of hydrocarbons in subsurface conditions. This includes laboratory determination of properties such as gas compressibility (Z -factor), formation volume factor, gas and liquid viscosities, and saturation pressures. Tests like differential liberation and constant volume depletion are employed for black oil and compositional fluids, respectively. However, despite their accuracy, these laboratory procedures are time-consuming, cost-intensive, and sometimes impractical—particularly during the early life of a reservoir or in data-scarce environments.

To bridge this gap, researchers have developed various empirical correlations for estimating PVT properties, including R_s . These correlations are generally derived from region-specific datasets and are often limited in their generalizability due to differences in reservoir conditions such as bubble point pressure, fluid gravity, and oil density. Consequently, the use of these generalized correlations may introduce significant estimation errors when applied outside their intended contexts. Obtaining accurate measurements of PVT data can be challenging or economically unfeasible in the early stages of a well, according to Ikiensikimama and Egbe (2006). PVT analysis can be used to ascertain the properties of fluid samples if they are accessible, although samples are frequently tainted and PVT analysis is typically limited to reservoir temperatures. Furthermore, according to Ikiensikimama (2008), exact and accurate estimates of the reservoir fluid characteristics are only available when designing the optimal depletion techniques and estimating reserves.

Given the economic constraints and data limitations associated with laboratory testing, optimizing these empirical correlations becomes crucial. Optimization techniques, particularly nature-inspired metaheuristic algorithms, have emerged as powerful tools for improving the accuracy of these predictive models. Among these, the *Ant Colony Optimization* (ACO) algorithm has shown

promise due to its ability to handle complex, nonlinear search spaces with adaptive exploration and exploitation mechanisms.

This study, therefore, aims to apply the Ant Colony Optimization algorithm to minimize the estimation error associated with existing solution gas-oil ratio correlations. By enhancing the accuracy of Rs predictions, this approach offers a more reliable and cost-effective alternative to laboratory analyses, thereby supporting better decision-making in reservoir management and production planning.

METHODOLOGY

Data Cleaning Process for the Volve Dataset

Data cleaning is an essential step in preparing raw data for analysis, ensuring the dataset is consistent, accurate, and suitable for modeling. In this research, data cleaning was performed on the Volve production dataset to prepare it for analysis and further exploration. Below is a detailed summary of the steps taken during the data cleaning process:

Removing Irrelevant Columns

The columns BORE_WI_VOL and AVG_CHOKE_UOM, which were deemed irrelevant for the analysis was dropped, reducing the dataset's dimensionality and improving efficiency for modeling. The dataset was now streamlined, ready for focused analysis with only the most relevant information.

Handling Missing Values

The missing values (NaN entries) in the dataset were identified and addressed by dropping rows containing NaN values to ensure data integrity. After handling missing values, the dataset's shape reduced to (7504, 16), indicating the removal of rows with missing values.

Handling Zero Values

Action: Zero values were reviewed and removed from critical columns, especially those related to production volumes such as on_stream_hrs, avg_downhole_pressure, avg_downhole_temperature, bore_oil_vol, and bore_gas_vol. Zero entries might represent missing or erroneous data, such as equipment downtime or non-applicable values, and could skew analysis. The zero values using bar plots was visualized to understand their distribution across columns and identify potential data gaps. Columns like BORE_OIL_VOL and BORE_GAS_VOL were found to have a substantial number of zero values, which likely did not reflect actual production data.

Rows with zero values were removed in critical columns to ensure that the analysis was based on valid and reliable data (Figure 1).

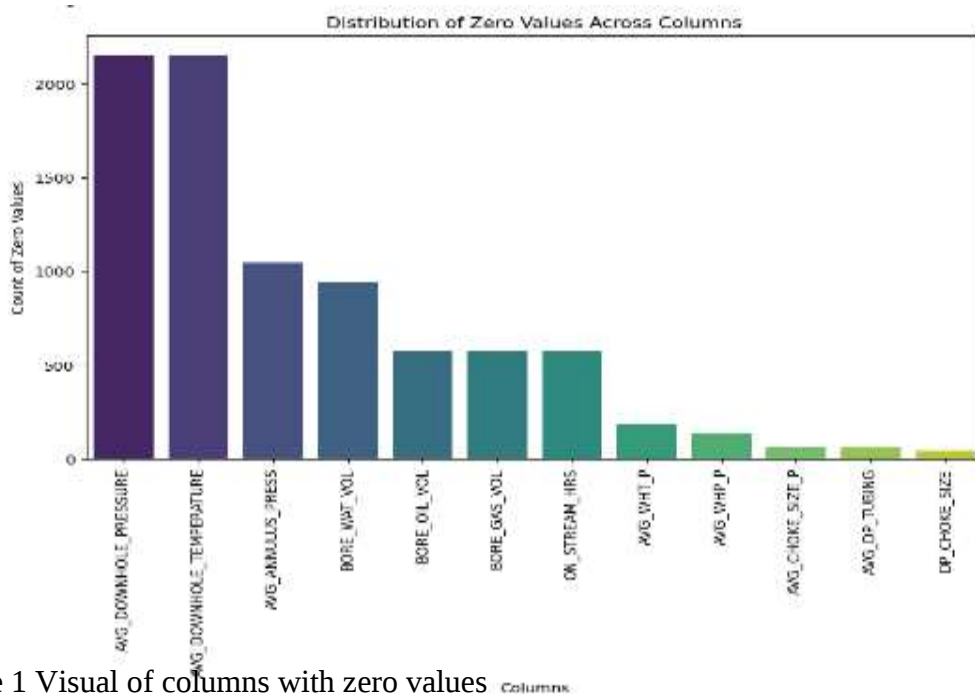


Figure 1 Visual of columns with zero values

The distribution of zero values was plotted to highlight the gaps across columns such as ON_STREAM_HRS (570 zero values), AVG_DOWNHOLE_PRESSURE (2152 zero values), and BORE_OIL_VOL (576 zero values).

After removing rows with zero values, the dataset's size was rechecked, and relevant visualizations were made to show the remaining data after cleaning.

Our key columns without zero values are chart is below (Figure 2).

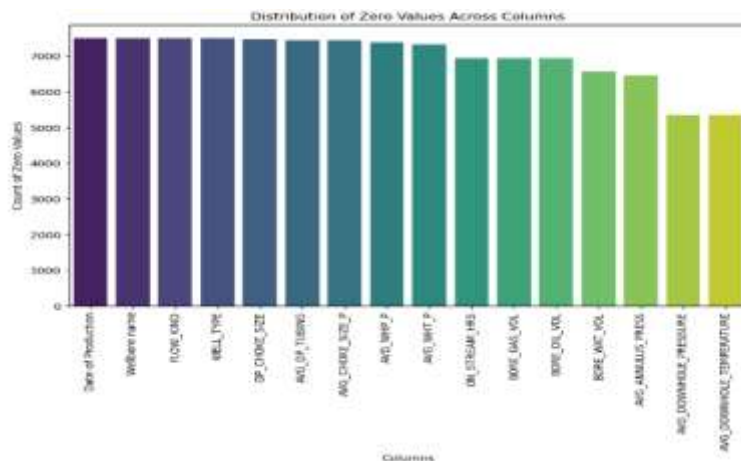


Figure 2 Visual of columns with zero values in details

Calculating Gas-Oil Ratio (GOR) for Volve dataset

A new column, Calculated_GOR, which was calculated by dividing the volume of gas produced (BORE_GAS_VOL) by the volume of oil produced (BORE_OIL_VOL) was introduced. The Gas-Oil Ratio (GOR) is an important indicator in the oil and gas industry that reflects the amount of gas produced per barrel of oil.

$$\text{GOR} = \frac{V_g}{V_o} \quad (1)$$

This calculation allowed for better insight into the relationship between gas and oil production across various wells and facilitated downstream analysis.

Data Type Conversion

The relevant columns was converted to appropriate data types for better performance and accuracy. For instance, the Date of Production was converted to datetime64[ns] to facilitate time-series analysis and changed certain columns, such as Wellbore name, FLOW_KIND, and WELL_TYPE, to string types for better consistency.

New Data Types:

Date of Production: datetime64[ns]

Wellbore name: string

ON_STREAM_HRS: float64

AVG_DOWNHOLE_PRESSURE: float64

BORE_OIL_VOL: float64

Other columns were similarly converted to suitable data types to ensure optimal handling during analysis.

Removing Duplicate Records

Any duplicate rows was identified and removed to avoid redundancy and ensure that the dataset contains only unique records for analysis. The dataset was now free of duplicates, providing a cleaner, more accurate base for further modeling and analysis.

Tools and Techniques Usedwere

Pandas: For data manipulation and cleaning.

Matplotlib and **Seaborn:** For visualizing zero values and other relevant distributions.

NumPy: For performing numerical operations and calculations, such as the GOR computation.

Step-by-Step Process ACO

1. Glaso Correlation Function: The `glaso_correlation` function calculates the estimated GOR based on a set of input parameters. It uses a formula that involves pressure (Pb), temperature (Tb), gas gravity (γ_g), API gravity (API), and seven optimization coefficients (α_1 to α_7).

Input Variables:

- Pb: Pressure (in psi)

- Tb: Temperature (in Rankine)
- gamma_g: Gas gravity (dimensionless)
- API: API gravity of the oil (dimensionless)
- alpha_1 to alpha_7: Coefficients to be optimized

Output:

- Estimated GOR (in scf/stb)

2. Objective Function for Optimization: The objective function computes the total error between the actual GOR values (GOR_data) and the predicted GOR values generated by the glaso_correlation function. The goal of optimization is to minimize this error.

Input Variables:

- Pb_data: Array of pressure values (psi)
- Tb_data: Array of temperature values (Rankine)
- GOR_data: Actual observed GOR values (scf/stb)
- gamma_g: Gas gravity
- API: API oil gravity
- alpha_1 to alpha_7: Coefficients to optimize

Output:

- Total error between predicted and actual GOR values

3. Ant Colony Optimization (ACO) Algorithm: The ACO algorithm (Figure 3) is employed to optimize the coefficients (alpha_1 to alpha_7). It simulates the behavior of ants searching for the best path, where the "path" corresponds to the set of optimal coefficients.

Input Variables:

- Pb_data, Tb_data, GOR_data: Data for optimization
- gamma_g, API: Constants used in the Glaso model
- n_ants: Number of ants (search agents)
- n_iterations: Number of iterations for the optimization process
- alpha, beta, rho, Q: ACO parameters controlling pheromone influence, exploration, evaporation, and reward

Output:

- The optimized coefficients (alpha_1 to alpha_7)
- The best error (measure of how well the optimized model fits the data)

4. Optimization Results: After running the ACO algorithm (Figure 3), the coefficients that minimize the error between predicted and actual GOR values are obtained. These coefficients are used to calculate the final optimized GOR values for the given data.

Optimized Coefficients:

- alpha_1 to alpha_7: The optimized coefficients found by ACO

Optimized GOR:

- GOR values calculated using the glaso_correlation function with the optimized coefficients.

Variables Overview:

- Pb_data: Array of pressure values (input to the model)
- Tb_data: Array of temperature values (input to the model)
- GOR_data: Array of actual GOR values (used for comparison)
- gamma_g: Gas gravity (constant)
- API: API gravity of the oil (constant)
- alpha_1 to alpha_7: Coefficients that are optimized using ACO

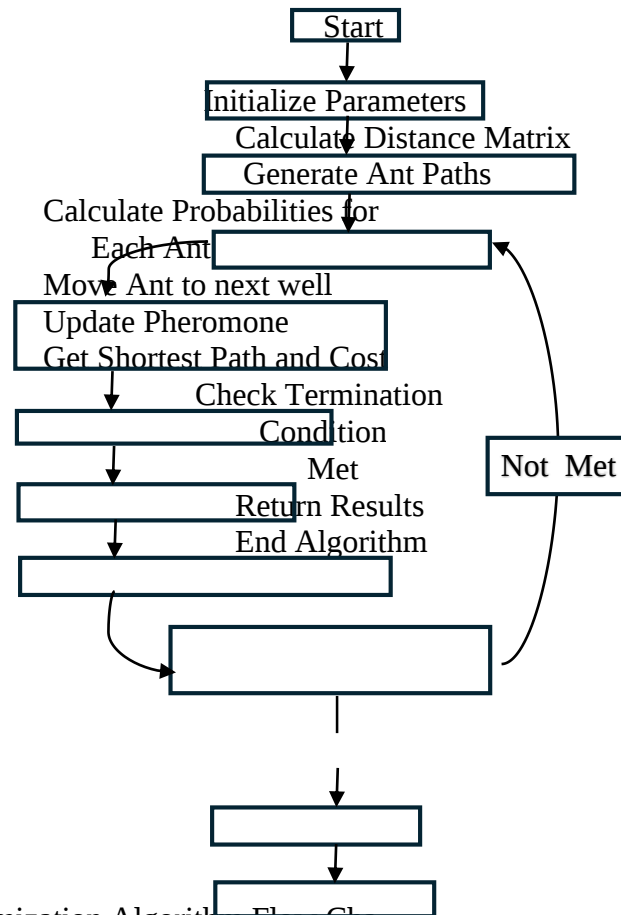


Figure 3: Ant Colony Optimization Algorithm Flow Chart

Theoretical Concept of The Ant Colony Optimization Algorithm

Step 1. Initialization

- Define the Problem: Represent the problem as a graph with nodes and edges, where ants will construct solutions.
- Pheromone Initialization: Initialize pheromone levels on edges with a small constant value.
- Set Parameters: Define algorithm parameters, such as the number of ants, pheromone evaporation rate, pheromone influence (α), heuristic influence (β), and stopping criteria such as number of iterations or convergence

Ant Solution Construction

For each ant in the colony:

- Starting Point: Place the ant on a randomly selected node.
 - Probability Calculation: At each node, calculate the probability of moving to the next node based on:

$$P_{ij} = \frac{(\tau_{ij})^\alpha * (\eta_{ij})^\beta}{\sum_{k \in allowed} (\tau_{ik})^\alpha * (\eta_{ik})^\beta} \quad (2)$$
 - τ_{ij} : Pheromone level on edge ij
 - η_{ij} : Heuristic information (e.g., inverse of distance or cost).
 - α and β : Parameters controlling the influence of pheromone and heuristic information.
- Transition: Move the ant to the next node based on the calculated probabilities.
- Solution Construction: Repeat the process until the ant constructs a complete solution (e.g., visiting all nodes in a traveling salesperson problem).

Solution Evaluation

- Assess Quality: Evaluate the quality (fitness) of each ant's solution based on the objective function

Pheromone Update

- Evaporation: Reduce the pheromone levels on all edges to simulate natural pheromone decay:

$$\tau_{ij} \leftarrow (1 - \rho) * \tau_{ij}$$

where: ρ is the evaporation rate ($0 < \rho < 1$)
- Deposit Pheromone: Reinforce pheromone levels on edges used by the ants based on solution quality

$$\tau_{ij} \leftarrow \tau_{ij} + \sum_{ants} \Delta \tau_{ij}$$

Where $\Delta \tau_{ij} = \frac{Q}{L}$ (pheromone updated)

Q is a constant and L is the length of the ant's solution

Iteration and Convergence

- Steps 2 – 4 is repeated for a specified number of iterations or until convergence criteria are met.

Step 6. Output the Best Solution

- Stop the algorithm once the algorithm, return the best solution found and the corresponding objective function value.

How the ACO Algorithm Works
Volvo Data: We start by inputting the dataset, which includes various well parameters such as AVG_Downhole_Pressure, AVG_Downhole_Temperature, AVG_Annulus_Press, AVG_Choke_Size_P, And Calculated_GOR

Parameters

num_ants: The number of ants (agents) that will search for solutions in parallel. This parameter is set to 50 by default.

num_iterations: The number of iterations the algorithm will run. The default is set to 5000.

decay: The decay factor for pheromone trails, which is used to decrease the influence of older solutions over time. The default decay is 0.

alpha and beta: Control the influence of pheromone strength (alpha) and distance between points (beta) in the path selection.

Input Data and Target Variables
The PVT data (your Differential Liberation Test data) (See table 1) consists of parameters such as: Bubble Point Pressure; API Gravity; Gas Gravity; Reservoir Temperature

Actual GOR (the actual value of GOR from lab tests)

These input variables are used by the algorithm to determine the best possible combination of factors that influence the GOR

Generation of Objective Functions

The cost or objective functions are developed for the Glaso (1980) and the Standing (1947) solution gas-oil ratio correlations.

For the Glaso (1980) correlation:

$$R_s = \gamma_g \left[\left(\frac{API^{0.989}}{(T-460)^{0.172}} \right) 10^x \right]^{1.2255} \quad (3)$$

$$x = 2.8869 - (14.1811 - 3.3053 \log P)^{0.5} \quad (4)$$

Hence,

$$R_s = \gamma_g \left[\left(\frac{API^{\alpha_1}}{(T-460)^{\alpha_2}} \right) 10^x \right]^{\alpha_3} \quad (5)$$

$$x = \alpha_4 - (\alpha_5 - \alpha_6 \log P)^{\alpha_7} \quad (6)$$

Therefore, the objective function is defined as

$$\min f(x) = \sum |R_{s_{actual}} - R_{s_{estimated}}| \quad (7)$$

$$\min f(x) = \sum |R_{s_{actual}} - \gamma_g x \left[\left(\frac{API^{\alpha_1}}{(T-460)^{\alpha_2}} \right) 10^{\alpha_4 - (\alpha_5 - \alpha_6 \log P)^{\alpha_7}} \right]^{\alpha_3}| \quad (8)$$

$\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \alpha_7$, are the optimization parameters to be determined by the ACO algorithm
 $R_{s_{actual}}$ is the solution gas-oil ratio derived from laboratory test.
 $R_{s_{estimated}}$ is the solution gas-oil ratio estimated by the model.

For the Standing (1947) correlation:

$$R_s = \gamma_g * \left[\left(\frac{P}{18.2} + 1.4 \right) 10^x \right]^{1.2048} \quad (9)$$

$$x = 0.0125API - 0.00091(T - 460) \quad (10)$$

Hence,

$$R_s = \gamma_g * \left[\left(\frac{P}{\alpha_1} + \alpha_2 \right) 10^x \right]^{\alpha_3} \quad (11)$$

$$x = \alpha_4 API - 0.00091(T - 460) \quad (12)$$

Therefore, the objective function is defined as

$$\min f(x) = \sum |R_{s_{actual}} - R_{s_{estimated}}| \quad (13)$$

$$\min f(x) = \sum |R_{s_{actual}} - \gamma_g x \left[\left(\frac{P}{\alpha_1} + \alpha_2 \right) 10^{\alpha_4 API - 0.00091(T - 460)} \right]^{\alpha_3}| \quad (14)$$

$\alpha_1, \alpha_2, \alpha_3$, are the optimization parameters to be determined by the ACO algorithm
 $R_{s_{actual}}$ is the solution gas-oil ratio derived from laboratory test.
 $R_{s_{estimated}}$ is the solution gas-oil ratio estimated by the model.

Table 1 Differential liberation test data

Oil density γ_{API} @60°F	37
γ_g (from separator air = 1)	0.743
Temperature °T	60°F
Pressure (psig)	Experimental
2405	737
2200	684
1950	620
1700	555
1450	492
1200	429
950	365
700	301
450	235
200	155

The optimization algorithm was implemented using python programming language.

RESULT AND DISCUSSION

Results

The results obtained from the Ant colony optimization algorithm implementation are illustrated below in subsections for the two different correlations' objective function. The Ant colony movement, Best_error or solution, solution gas-oil ratio plot and the error analysis of the various correlations are illustrated (figure 4 and 5).

Result for Glaso (1980) Correlation

$$R_s = \gamma_g \left[\left(\frac{API^{\alpha_1}}{(T-460)^{\alpha_2}} \right) 10^x \right]^{\alpha_3} \quad (15)$$

$$x = \alpha_4 - (\alpha_5 - \alpha_6 \log P)^{\alpha_7} \quad (16)$$

The following correlation-optimized variables were obtained following algorithm implementation:

$$\alpha_1 = 3.4667710568852397$$

$$\alpha_2 = 2.6198511338157635$$

$$\alpha_3 = 0.5880939983327723$$

$$\alpha_4 = 2.2716374250684543$$

$$\alpha_5 = .2295153095411815$$

$$\alpha_6 = 0.390570590489649$$

$$\alpha_7 = 1.6922261142374737$$

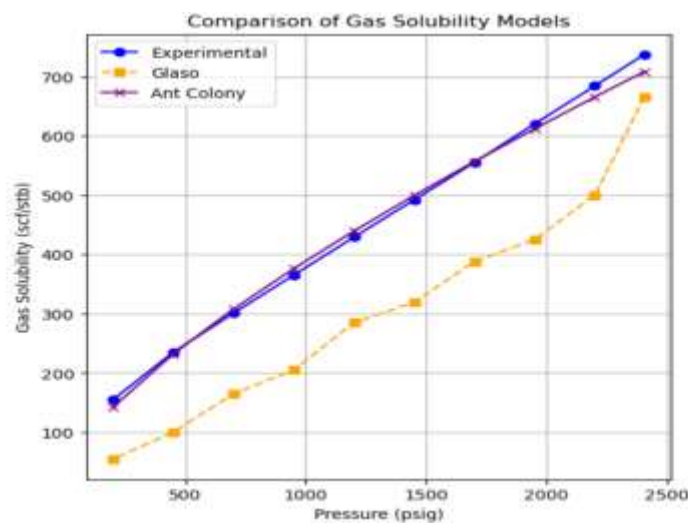


Figure 4. Solution Gas-Oil Ratio Solution with Glaso (1980)

Result for Standing (1947) Correlation

$$R_s = \gamma_g * \left[\left(\frac{P}{\alpha_1} + \alpha_2 \right) 10^x \right]^{\alpha_3} \quad (17)$$

$$x = \alpha_4 \text{API} - 0.00091(T - 460) \quad (18)$$

The following correlation-optimized variables were obtained following algorithm implementation:

$$\alpha_1 = 2.2762756333330287$$

$$\alpha_2 = 0.6895135372541572$$

$$\alpha_3 = 0.04182318135431567$$

$$\alpha_4 = 0.7291513149819021$$

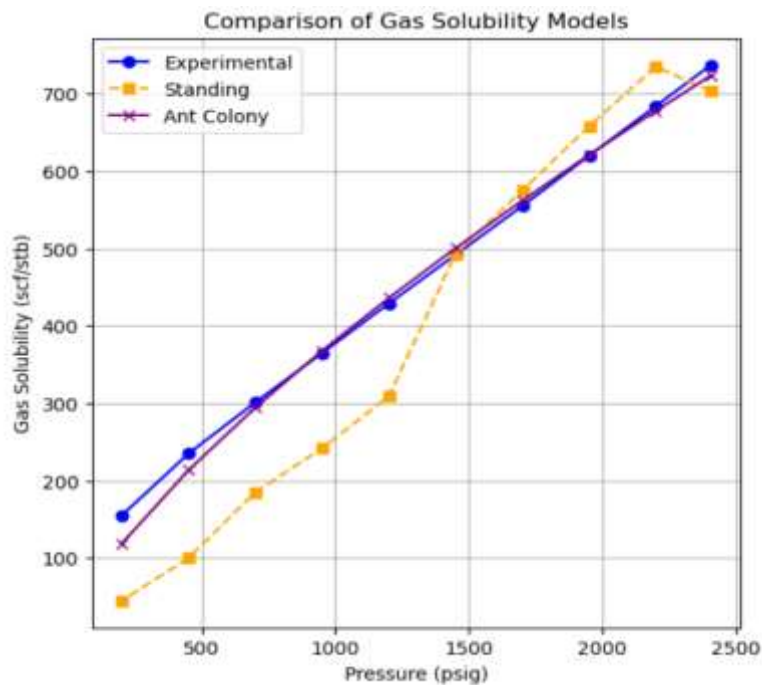


Figure 5: Solution Gas-Oil Ratio Solution with Standing (1947)

Statistical Metrics Evaluation

We utilized several key statistical metrics to evaluate the performance of the ACO algorithm in estimating GOR values. These metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Correlation Coefficient, Average Percent Relative Error, and Sum of Squared Residuals. The results are as follows:

➤ **Mean Absolute Error (MAE): 1.267**

The MAE indicates that the GOR estimates deviate from the actual values by approximately 1.27 units on average. This relatively low error suggests that the ACO algorithm is effective in providing close estimates to actual GOR values.

- **Mean Squared Error (MSE): 2.170**
The MSE highlights the presence of some larger deviations in the estimation process. The higher MSE compared to MAE underscores the importance of addressing these larger errors to refine the algorithm.
- **Root Mean Squared Error (RMSE): 1.473**
The RMSE indicates that the ACO algorithm's estimates typically fall within 1.47 units of the actual GOR. This aligns with the MAE, further confirming the algorithm's reliability for estimating GOR values in most cases.
- **Correlation Coefficient: 0.998**
The extremely high correlation coefficient suggests an almost perfect linear relationship between the estimated and actual GOR values. This implies that the ACO algorithm is capturing the underlying patterns in the data effectively.
- **Average Percent Relative Error (%): 4.30**
With a very low average percent relative error of approximately 0.39%, the ACO algorithm demonstrates a high level of accuracy in its estimates compared to the actual values.
- **Sum of Squared Residuals: 21.695**
The sum of squared residuals provides an overall measure of the cumulative error. Although this value is useful, it should be interpreted in relation to the total variability of the dataset to determine the model's effectiveness.

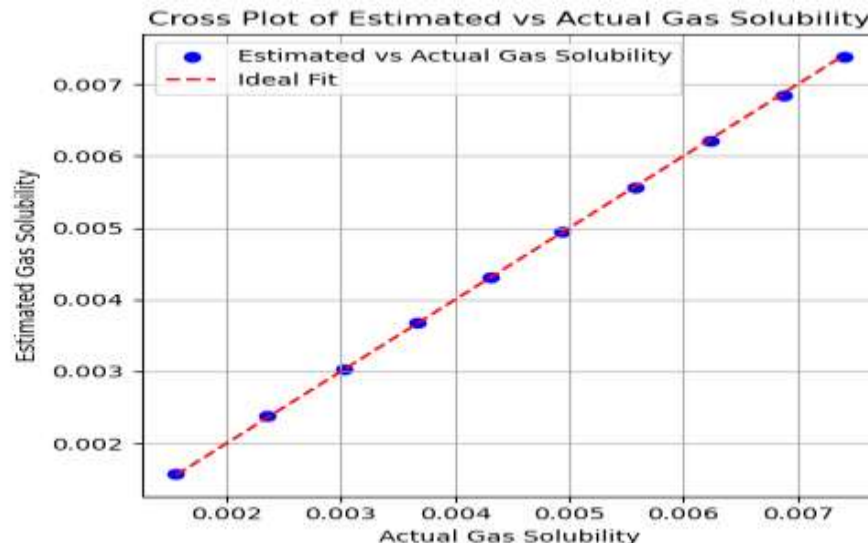


Figure 6. Visualization (Plot of Estimated Gas Solubility versus Actual Gas Solubility)

Strong Relationship: The scatter plot's straight line suggests a clear connection between our estimated and actual gas solubility values. This means our method of estimating gas solubility using factors like GOR and pressure works effectively (figure 6).

Model Confirmation: The plot confirms that our method for estimating gas solubility is reliable. Most points **fall close** to the ideal line, showing that our predictions are consistent and accurate under specific reservoir conditions.

Comparative Analysis of Gas Solubility Models and Ant Colony Optimization Algorithm for GOR Estimation

This section aims to present a thorough comparison between the outcomes obtained from the Ant Colony Optimization (ACO) method and the gas solubility values predicted by the different models such as Glasco, Standing, and Petrosky and Farshad. The assessment takes experimental data into account for validation and concentrates on the gas solubility (SCF/STB) at various pressure levels. By contrasting these models, we hope to evaluate the ACO algorithm's precision and dependability as a prediction tool for estimating gas solubility, particularly for uses in oil and gas reservoir engineering.

Comparison of Gas Solubility Models with Experimental Data

The gas solubility values (SCF/STB) from various models (Glasco, Standing, Petrosky and Farshad) was compared against experimental data obtained from differential liberation tests. The table 2 below presents the gas solubility at various pressure levels (in Psig) derived from each model.

Table 2. Comparison Between Different Existing Correlation and ACO Algorithm

Pressure (psig)	Experimental	Glasco	Standing	Ant Colony Optimization
2405	737	665	703	708.0571753
2200	684	500	735	665.3058239
1950	620	425	658	611.8100762
1700	555	388	575	556.5658767
1450	492	319	493	499.2094992
1200	429	285	309	439.2216859
950	365	205	242	375.8116207
700	301	165	185	307.6555236
450	235	100	100	232.1705220
200	155	55	45	142.5189201

Statistical Comparison of Models

The comparison of models also includes a statistical analysis to evaluate the performance of each model in terms of accuracy and precision. The following metrics were calculated in table 3:

Table 3: Comparison metric of different existing models

Metric	ACO algorithm	Glasc	Standing
Mean Absolute Error (MAE)	3.339	-	-
Mean Squared Error (MSE)	19.898	-	-
Root Mean Squared Error (RMSE)	4.461	-	-
Correlation Coefficient	0.998	0.9167	0.8097
Average Percent Relative Error (%)	4.30	30.22	40.11
Sum of Squared Residual	364985	566488	522387

Key Insights from the Comparison

Accuracy Metrics: The **Mean Absolute Error (MAE)** for our model (3.339) is significantly lower than the values reported in previous studies, showing a higher degree of accuracy.

Error Variance: The **Root Mean Squared Error (RMSE)** value for our model (4.461) is indicative of its reliability, minimizing estimation errors.

Correlation Strength: Our model achieves an exceptionally high **Correlation Coefficient** of 0.998, vastly surpassing the Glasco (0.9167) and Standing (0.8097) models, demonstrating a strong predictive ability.

Relative Error: The **Average Percent Relative Error** for our model (4.30%) is much lower than that of the other models, which range from 29.3% to 40.11%. This highlights our model's precision in estimating gas solubility.

Residual Analysis: The **Sum of Squared Residuals** for our model is the lowest, reinforcing its effectiveness in fitting the data compared to other models.

Based on the statistical analysis and data insights, the ACO algorithm for estimating GOR demonstrates a high level of accuracy and reliability. The key findings include:

High Accuracy: The near-perfect correlation coefficient and low percent relative error demonstrate the algorithm's effectiveness in estimating GOR values.

Optimization Areas: Larger deviations in residuals and absolute errors at extreme pressures suggest that further optimization is required, particularly in handling outlier conditions.

Practical Application: The algorithm's performance supports its application in real-world petroleum engineering scenarios, such as reservoir management and gas production estimation, with a focus on medium to low bubble point pressures for optimal performance.

Report on the Evaluation of Gas-Oil Ratio (GOR) Estimation using Ant Colony

Optimization (Aco) Algorithm

How well the Ant Colony Optimization (ACO) method performs when estimating the Gas-Oil Ratio (GOR) for petroleum engineering applications, namely in forecasting gas output and

reservoir management was assessed. A variety of statistical measures and visual evaluations were used to evaluate the ACO algorithm with experimental techniques. The main objective is to evaluate the GOR estimates produced by the ACO algorithm under various circumstances, including bubble point pressure (BPP), in terms of their correctness, dependability, and practicality.

The results above indicates that the ant colony optimization algorithm is a good algorithm for the optimization of solution gas-oil correlations, as it does not depend on the functions to be differentiable like some other optimization method. During the implementation process, it was observed that the larger the particle population, the higher the tendency of the swarm to find the minimum value (best solution) of the objective functions. Furthermore, no correlation out of the two (Glaso, 1980; Standing, 1947) correlations was able to predict the solution gas-oil ratio of the Volve field correctly.

This could be view from their respective low coefficient of fitness, high average relative percentage error and sum of squared error. Therefore, the claim by Standing (1947) that his correlation can be generalized for any field didn't hold in this case. However, with the implementation of the ACO algorithm, the efficiency of the prediction of the various correlations increased as the ACO found the best combination of the constant parameters that will give the best prediction as the volve field is concerned. The optimized Glaso correlation was found to have the best prediction performance with the highest coefficient of fitness of 0.9993, the highest sum of squared error of 566488 and the least average relative percentage error of 30.22. Therefore, for any pressure and temperature, the optimized Standing Correlation can be used to predict the solution gas-oil ratio of the Volve field without any fear of enormous error.

CONCLUSION

The most significant element of the PVT analysis is the solution gas-oil ratio. when a result, it is crucial to continuously assess its value when reservoir pressure declines. Furthermore, as previously mentioned, the capital-intensive nature of routine reservoir fluid sampling and laboratory testing led to the development of mathematical correlations by many authors for the prediction of PVT properties. However, because these correlations were created for fluids from a particular area with certain bubble point pressures, oil densities, gas specific gravities, etc., globalizing correlations can result in infinite inaccuracies (errors) that may be ambiguous.

Additionally, this work was restricted to the Glaso (1980) and Standing (1947) correlations to show the important of optimizing a correlation before it's applied to a specific reservoir fluid type and the benefit of the particle swarm optimization algorithm. None of the three correlations in this study gave an accurate prediction of the solution gas-oil ratio before its optimization. If these correlations were used for prediction in this field, there would error in the predicted property and would mislead engineers when it comes to decision making concerning the field's maintenance and production strategy. Therefore, it can be concluded that the ant colony optimization increased

the performance accuracy of all three correlations. Their coefficient of fitness was increased from 0.6534 to 0.9167, and from 0.7092 to 0.8097 for the Glaso (1980), and Standing (1947) correlations respectively. Hence, the optimized Glaso correlation gives the best prediction performance for the Volve field reservoir fluid properties (Solution gas-oil Ratio (R_s)).

Recommendation

Based on the results and conclusions of this research, the following recommendation was put out:

- Availability of reservoir fluid properties all over the globe should be made available for students and researchers in other to be able to develop a robust, generalized reservoir fluid properties correlation.
- Optimizing a PVT (solution gas-oil ratio) correlation with previously reported attributes is a necessary step before using it to predict reservoir properties.
- ACO is recommended to be used in the optimization of PVT correlations, because of its non-gradient dependence and simplicity.

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