International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Optimization of Solution Gas-Oil Ratio (R_S) Correlation for Niger Delta Field

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A B S T R A C T-

Solution gas-oil ratio which is said to be the most notable component of the PVT analysis specifies the total sum of cubic feet of natural gas dissolved in one barrel of crude oil at a distinct pressure. With the amount of solution gas-oil ratio at discrete reservoir pressure the amount of gas to be produced from a reservoir can be prognosticated giving the operators room to adequately plan for gas handling even before it's being produced. The ideal process to obtain PVT data (solution gas-oil ratio) is by sampling of reservoir fluids and performing laboratory studies on the samples. Sampling of fluids and performing of experiments are capital intensive and as such required properties are generated from existing PVT correlations. However, proliferation of correlations without optimization to minimize errors when applied to a specific field can lead to boundless errors which can be equivocal because these correlations was developed for a specific regions fluids with a specific bubble point pressure, gas specific gravity etc. This study is aimed at optimizing the solution gas-oil ratio correlation with the particle swarm optimization PSO algorithm. The correlations considered were Glaso, Vazquez and Beggs and Petrosky and Farshad correlations. After the implementation of the PSO algorithm, the coefficient of fitness of the correlations increased from 0.6534 to 0.9930, 0.7776 to 0.9936 and 0.7092 to 0.9994 for Glaso, Vazquez and Beggs and Petrosky and Farshad correlations respectively. The optimized Petrosky and Farshad correlation gave the best prediction performance for the Niger Delta field in concern with the least average relative percentage error of 1.0922.

Keywords: PVT correlation, Solution gas-oil ratio, Bubble point pressure, optimization, Particle swarm optimization, Coefficient of fitness.

1.INTRODUCTION

One of the main concerns in the handling of the different stages of oil field operations is the prediction of the physical fluid properties (Abdul-Majeed &Salmon, 1988). Pressure-Volume-Temperature (PVT) analysis is the study of the behaviour of vapor and/or liquids in the petroleum reservoirs as a function of pressure, volume, temperature in terms of the fluid composition and behavior in the phase envelope (Okotie & Okeke 2016;Okotie, 2018). Ahmed (2006) poised that to adequately evaluate the performance of a reservoir one of the key input data needed are the PVT properties which are essential in reservoir performance prediction, enhanced oil recovery, material balance, reserves estimations, optimization and design of the product. In addition, Ikiensikimama (2008) poised that the design of the best depletion strategy and estimation of reserves are feasible only when realistic and reasonable values of the reservoir fluid properties are available. Furthermore, Adeeyo and Mahourn (2013) added that the importance of PVT analysis is to simulate what takes place in the reservoir and at the surface during production and to provide relevant information about the thermodynamic and the physical behavior of the reservoir fluid.

These properties are ideally determined from the laboratory studies on samples collected from the surface or at the bottom of the wellbore. These experiments carried out to determine the PVT data includes the constant composition expansion test for both black oil and compositional reservoir,

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constant volume depletion (compositional only), differential liberation/vaporization (black oil only), separator test (black oil and compositional), viscosity measurement and compositional analysis, saturation pressure (dew point) at reservoir temperature etc. (Okotie, 2018).

Upon these experimental analyses, data such as liquid and gas viscosity,gas-oil ratio, gas density, vapor z factor, liquid density, liquid dropout, formation volume factor are derived. Amongst the data obtained from PVT experiment is the solution gas-oil ratio, which according to Fekete (2012) is the most essential and significant component of the PVT analysis. Solution gas evolves when the reservoir pressure drops below the bubble point in oil Reservoirs. The degree of undersaturation, production mechanisms of the reservoir, and other factors determines the rate of solution gas production (Ibukun,2016). The solution gas-oil ratio specifies the total sum of cubic feet of natural gas dissolved in one barrel of crude oil at a distinct pressure. With the amount of the solution gas-oil ratio at discrete reservoir pressure, the amount of gas to be produced from a reservoir can be prognosticated, giving the operators room to adequately plan for gas handling even before its being produced. As affirmed earlier, the ideal process to derive PVT Data is by sampling of Reservoir fluid and performing laboratory studies on the fluid samples. Nevertheless, in the truancy of laboratory tests, the use of correlations provides the only feasible alternative for the prediction of PVT properties for field applications (Adeeyo & Marhoun, 2013). Comparably sampling of fluids and performing of experiments are capital intensive and as such required properties are generated from existing PVT correlations. The correlations include Glaso (1980), standings (1947), Petrosky and Fashad(1993), Kartoatmodjo and Schmidt (1994), Ikiensikimama (2008) etc are used. Nevertheless, these correlations were developed for reservoir fluids of discrete composition from separate regions. Bubble point pressure of the reservoir fluids sampled to develop these correlations, yield accurate results. But for pressures below the bubble point pressure, the PVT properties may yield errors which make the application of these correlations in reservoir studies limited, because the values obtained from the correlations are not equal to the experimental results (Okotie, 2018). Consequently, there's exigency to optimize the developed correlations to suit distinct fields in other to make good and accurate prediction for the field with a Robust and accurate optimization algorithm.

1.1 PVT ANALYSIS

Petroleum is a complex mixture made up principally of hydrogen and carbon and consisting nitrogen, sulphur, helium and oxygen as slight constituents (Ahmed,2006). The physical and chemical properties of crude oil differ abruptly and hinge on the concentration of different kinds of hydrogen and carbon and minor constituents present.

According to Okotie (2018) pressure-volume-temperature (PVT) analysis is the study of behavior of vapor and/or liquid in petroleum Reservoirs as a function of pressure, volume and temperature in terms of the fluids composition and behavior in the phase envelope. Furthermore, Adeeyo and Marhoun (2013) added that PVT analysis is the study of the changes in volume of a fluid as a function of pressure and temperature. They also posited that the importance of PVT analysis is to simulate what takes place in the reservoir and at the surface during production and to provide relevant information about the thermodynamic and the physical behavior of the reservoir fluid.

One of the challenges for Reservoir and production engineers according to Henri et al.(n.d) is to maximize hydrocarbon Recovery with the least expenses in the minimum amount of time. This means asking a number of questions about the type of fluid the reservoir will produce, what will the primary recovery be, the amount of gas to be produced, and how large the reserves are etc. Answering these questions requires anticipating the volumetric and phase behavior of hydrocarbon produced as they advance from the reservoir tubing, through surface separators and lastly Into pipelines, and of hydrocarbons in place as the pressure of the reservoir declines with production (Henri, et al.,n.d).

A precise description of physical properties of crude oil is of a considerable importance in the fields of both theoretical and applied science and most significantly in the solution of petroleum reservoirs engineering problems (Ahmed,2006). Physical properties derived from PVT analysis include; oil density, bubble point pressure, fluid gravity, oil formation volume factor, solution gas-oil ratio,etc (Abdul-Majeed and Salman,1998; Ahmed, 2006; Okotie,2018).

These properties mentioned above are derived by sampling reservoir fluids from experiments. These experiments include the separator test, differential liberation/vaporization test, constant composition expansion test, constant volume depletion test etc. (Okotie,2018).

However El-Sebakhy et al. (2007) posited that the experimental processes are rigorous and capital intensive to obtain. In other to predict the PVT properties and boycott Rigorous laboratory experiments, mathematical correlations have been developed for distinct regions oils and gas density, fluid specification etc. These correlations include Standings (1947), Glaso (1980), Petrosky and Fashad (1993), Katoatmodjo and Schmidt (1994), Ikiensikimama (2008) etc.

As stated earlier in the first chapter, amongst the properties obtained from PVT analysis, this work is restricted to solution gas-oil ratio.

1.2 SOLUTION GAS-OIL RATIO

The solution gas-oil ratio is the quantity of gas dissolved in oil at any pressure: it increases linearly with pressure and it's a function of the oil and gas composition; the solution gas-oil ratio increase with pressure until the bubble point pressure is reached, after which it is a constant and the oil is said to be saturated (Fekete,2012).

According to Fekete (2012), the solution gas-oil ratio is the most notable component of PVT correlations. And it has a very major impact on the oil viscosity, the compressibility of oil, oil formation volume factor and used also for calculating the in-situ total reservoir fluid rate.

Saleh et al. (1987) evaluated empirical correlations for Egyptian oils and these correlations were; standings, Lasater, Vazquez and Beggs, and Glaso correlations for estimating solution gas-oil ratio. The use of Glaso's solution gas-oil ratio correlation was recommended for Egyptian crude with an average absolute percent error of 46.48

Also, Sutton and Fashad (1990) promulgated an evaluation of the four correlations studied by Ostermann using Gulf of Mexico crude oils. Standings, Vazquez and Beggs, Lasater and Glaso correlations were used for estimation of solution gas-oil ratio. From the study Glaso correlation for solution gas-oil ratio provided the optimum result of all the correlations evaluated with an average absolute error of 17.63

Furthermore, Al-Marhoun (2004) made evaluations on Standings, Vazquez and Beggs,and Al-marhoun solution gas-oil ratio correlation using the same data utilized for the evaluation of bubble point pressure correlations. Al-marhoun (1988) correlation gave the least average absolute error of 12.29

In addition Ikiensikimama (2008) conducted evaluation study of eleven correlations for their applicability to crude oil solution gas-oil ratio prediction of Niger Delta. A total of 237 data points was used for solution gas-oil ratio prediction evaluation. And it was concluded that the Petrosky and Fashad correlation is the best with maximum absolute error of 13.922 and a correlation coefficient of 0.9553

From the literatures presented above it was observed that no correlation provided a precise and accurate prediction of solution gas-oil ratio for reservoir fluids produced in areas in which it was good not developed for. Thus it Is of a great importance to optimize (minimize) these errors between the predicted and the actual measurements derived from laboratory experiments.

1.3 GLASO CORRELATION

Glaso (1980) proposed a correlation for evaluating the oil formation volume factor and gas solubility as a function of temperature, pressure, API gravity and gas specific gravity. Glaso claims that the correlation would be valid for all types of gas mixtures and oils after correcting for non-hydrocarbons in the surface gases and the paraffinicity of the oil.

This correlation however more accurately predicts oil properties of North Sea oil which provides the data of which it was formulated. The equation below is the correlation of solution gas-oil ratio proposed by Glaso;

$R_s = \gamma_g \left| \left(\frac{\gamma_{api}^{0.989}}{T^{0.172}} \right) 10^x \right|^{1.2255}$ .... (1)

$x = 2.8869 - (14.1811 - 3.3053 \log p)^{0.5}$ .... (2)

Where R_S is the solution gas-oil ratio, γ_g is the gas specific gravity, p is the reservoir pressure in psia, γ_{api} is the oil density in °API, and T is the reservoir temperature in °F.

1.4 VAZQUEZ AND BEGGS CORRELATION

Vazquez and Beggs (1980) correlation contains equations for the evaluation and prediction of oil formation volume factor, oil compressibility and solution gas-oil ratio. The correlation was developed by obtaining data from over 600 laboratory analysis of PVT assembled from different fields all over the world. The data used in the development of this correlation covers a large variety of temperature, pressure and oil properties. The correlation divides the data obtained into two categories; one for oil gravity over 30° API and the other at and below 30° API. Vazquez and Beggs correlations for solution gas-oil ratio is given in the equation below;

$R_s = C_1 \gamma_g P^{C_2} \exp \left| C_3 \left(\frac{\gamma_{api}}{T + 460} \right) \right|$ ....(3)

The coefficients C_1,C_2 and C_3 are given in table 1 below for the different oil densities.

Table-1: Coefficient of Vazquez and Beggs Correlation

Component	$\gamma_o \leq 30^{\circ}API$	$\gamma_o > 30^{\circ}API$
C_1	***0.362***	***0.0178***
C_2	***1.0937***	***1.1870***
C_3	***25.7240***	***23.931***

Where R_S is the solution gas-oil ratio, γ_g is gas specific gravity, p is separator pressure in psia, Y_{api} is oil density in °API and T is separator temperature in °F.

1.5 PETROSKY AND FARSHAD CORRELATION

Petrosky and Farshad (1993) developed a set of correlation for Gulf of Mexico oils for the predictions of PVT properties such as: oil formation volume factor, solution gas-oil ratio. The correlation was developed by making use of fluid samples obtained from offshore region in Texas and Louisiana. The authors claim that these correlations provide accurate results over the Gulf of Mexico including those published by standings (1947), Glaso (1980), Vazquez and Beggs (1980), and Al-marhoun (1988). The solution gas-oil ratio correlation proposed by Petrosky and Farshad is given in equation 4 and 5;

$$R_s = \left|\left(\frac{p}{112.727} + 12.34\right)\gamma_g^{0.8439} 10^x\right|^{1.73184} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

$$x = -4.561 \times 10^{-5} T^{1.3911} + 7.916 \times 10^{-4} \gamma_{API}^{1.541} \ldots\ldots\ldots\ldots\ldots\ldots (5)$$

Where R_S is the solution gas-oil ratio, γ_g is the gas specific gravity, p is the reservoir pressure in psia, γ_{API} is the oil density in °API, and T is the reservoir temperature in °F.

1.6 PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

Minimizing loss and Maximizing earnings has always been an area of focus in engineering problems (Bruno and Victor, 2014). To maximize or minimize a function in other to get the optimum, there are disparate approaches that could be performed. Despite use of a wide variety of optimization algorithms that could be used, no particular one that is considered to be the best for any case study. One method of optimization that suits a particular problem might not be so for another one. It depends on several features, for example, whether the function is differentiable and its concavity (convex or concave). Depending on the problem's features, one must understand different optimization method so as to be able to select the algorithm that best fits to solve a problem.

Several studies with regards to the social behavior of animal groups were developed in the Early 1990's. Results from the studies showed that animals belonging to a certain group, that is: fishes and birds are able to disseminate information among their group and such capacity confers these animals a great survival advantages (Kennedy & Eberhart,1995).

Inspired by these works, Kennedy and Eberhart (1995) proposed the particle swarm optimization (PSO) algorithm. A metaheuristic algorithm suitable to optimize nonlinear continuous functions. The algorithm comprises of different components which are the inertial component, cognitive component and the social component.

Since the formulation of these algorithm, other modifications and versions have been proposed as variation of the classical formulation, they are; the linear decreasing inertial weight (Shi & Eberhart, 1999), the constriction factor weight, the dynamic inertia and the maximum velocity reduction models (Eberhart & Shi,2000).

This study will be making use of the inertial model (classical version) of the PSO that was first published by Kennedy and Eberhart (1995).

1.7 STATEMENT OF PROBLEM

Since solution gas-oil ratio is the most notable component of the PVT analysis Fekete (2012), the need to repeatedly discover its value as the pressure in the reservoir, declines cannot be overemphasized. Furthermore as continual sampling of Reservoir fluids and performing of laboratory tests are capital intensive, mathematical correlations were developed by different authors for the prediction of PVT properties. However these correlations was developed for a specific regions fluids with a specific bubble point pressure, gas specific gravity, oil density etc. Proliferation of correlations can lead to boundless errors which can be equivocal.

1.8 AIM AND OBJECTIVES

The aim of this work is to minimize the error allying results of developed correlations and experimental Results of solution gas-oil ratio.

Objectives:

The objectives developed for this project are

- To Relate and estimate different solution gas-oil ratio correlation.
- To apply the particle swarm optimization algorithm on the recognized correlations.
- To estimate and analyse the optimized solution gas-oil ratio correlation.

1. RESEARCH METHODOLOGY AND DESIGN

Particle Swarm Optimization Algorithm

The goal of an optimization problem is to determine a variable represented by a vector X = $[x_1, x_2, x_3 \ldots x_n]$ that minimizes or maximizes depending on the proposed optimization formulation of the objective function f(x). The variable vector X is known as position vector, this vector represents the variable model and it is an n dimension vector, where n represents the number of variables that may be determined in the problem. On the other hand, the function f(x) is called the fitness function or the objective function, which is a function that may assess how good or bad a position X is.

Considering a swarm with P particles, there is a position vector $X^t{}_i = [x^t{}_{i1}, x^t{}_{i2}, x^t{}_{i3} \ldots x^t{}_{in}]$ and a velocity vector $V^t{}_i = [v^t{}_{i1}, v^t{}_{i2}, v^t{}_{i3} \ldots v^t{}_{in}]$ at t iteration for each one of i particle that composes it. These vectors are updated through the dimension j according to the following equations;

$$V^{t+1}{}_{ij} = wV^t{}_{ij} + C_1 r^t{}_1 \left(Pbest_{ij} - X^t{}_{ij}\right) + C_2 r^t{}_2 \left(Gbest_j - X^t{}_{ij}\right) \quad (6)$$

$$X^{t+1}{}_{ij} = X^t{}_{ij} + V^{t+1}{}_{ij} \quad (7)$$

Where, i = 1, 2 … P and j = 1, 2 … n

V = velocity

w = inertial weight constant

C_1 = Cognitive acceleration term

C_2 = Social acceleration term

r_1 and r_1 = Random uniform distributed numbers from 0 to 1

Pbest = Particle personal best

Gbest = Swarm global best

$wV^t{}_{ij}$ = Inertial component

$C_1 r^t{}_1 \left(Pbest_{ij} - X^t{}_{ij}\right)$ = Cognitive component

$C_2 r^t{}_2 \left(Gbest_j - X^t{}_{ij}\right)$ = Social Component

Theoretical Concept of the PSO Implementation

The PSO algorithm can optimize an objective function with the following steps described below;

1. Choose the number of particles
2. Initialize the position of the particles
3. Evaluate the objective function at the initial position
4. Set the iteration number as t = i+1
5. Find the personal best for each particles
6. Find the global best
7. Find the velocities of the particles
8. Find the new value of the particles' position
9. Find the objective function value of the new particle' position
10. Set the stopping criterion
11. If the terminal rule is satisfied, stop the iteration and output result the results otherwise repeat step 4.

The iterative process of the PSO algorithm is presented with the flowchart in the figure 1 below;

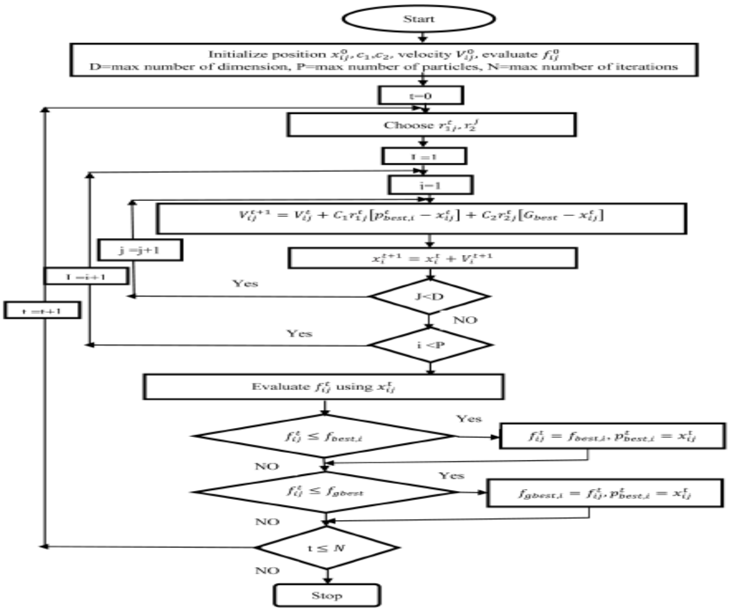

Fig. 1- Work flow algorithm for the PSO (Source: Satyobroto 2011)

Generation of Objective Functions

The cost or objective functions are developed for the Vazquez and Beggs (1980), Glaso (1980), and the Petrosky and Farshad (1993) solution gas-oil ratio correlations.

For the Glaso (1980) correlation

$$R_s = \gamma_g \left| \left(\frac{\gamma_{API}^{\ldots}}{\ldots} \right) 10^x \right|^{\ldots} \tag{8}$$

$$x = 2.8869 - (14.1811 - 3.3053 logP)^{0.5} \tag{9}$$

Hence,

$$R_{sestim} = \gamma_g \left| \left(\frac{\gamma_{API}^{\alpha_1}}{\ldots} \right) 10^x \right|^{\ldots} \tag{10}$$

$$x = \alpha_4 + (\alpha_5 + \alpha_6 logP)^{\alpha_7} \tag{11}$$

Therefore the objective function is defined as

$$\min f(x) = \sum \left| R_{sexper} - R_{sestim} \right| \tag{12}$$

$$\min f(x) = \sum \left| R_{sexper} - \gamma_g \left| \left(\frac{\gamma_{API}^{\alpha_1}}{\ldots} \right) 10^{\alpha_4 + (\alpha_5 + \alpha_6 logP)^{\alpha_7}} \right|^{\ldots} \right| \tag{13}$$

α_1, α_2, α_3, α_4, α_5, α_6, and α_7 are the optimization parameters to be determined by the PSO algorithm.

For the Vazquez and Beggs (1980) correlation

$$R_s = C_1 \gamma_g p^{C_2} e \left(C_3 \left(\frac{\gamma_{API}}{\ldots} \right) \right) \tag{14}$$

Hence,

$$R_{sestim} = \theta_1 \gamma_g p^{\theta_2} e \left(\theta_3 \left(\frac{\gamma_{API}}{\ldots} \right) \right) \tag{15}$$

Therefore the objective function is defined as

$$\min f(x) = \sum \left| R_{sexper} - R_{sestim} \right| \tag{16}$$

$$\min f(x) = \sum \left| R_{sexper} - \theta_1 \gamma_g p^{\theta_2} e \left(\theta_3 \left(\frac{\gamma_{API}}{\ldots} \right) \right) \right| \tag{17}$$

Where, R_{sexper} is the solution gas-oil ratio derived from laboratory text.

R_{sestim} is the solution gas-oil ratio estimated by the model.

θ_1, θ_2, and θ_3 are the optimization parameters to be determined by the PSO algorithm.

For the Petrosky and Farshad (1993) correlation

$$R_s = \left| \left(\frac{p}{\ldots} + 12.34 \right) \gamma_g^{0.8439} 10^x \right|^{\ldots} \tag{18}$$

$$x = -4.561 \times 10^{-5} T^{1.3911} + 7.916 \times 10^{-4} \gamma_{API}^{1.541} \tag{19}$$

Hence,

$$R_{sestim} = \left|\left(\frac{p}{\beta_1} + \beta_2\right)\gamma_g^{\beta_3} 10^x\right|^{\beta_4} \tag{20}$$

$$x = \beta_5 T^{\beta_6} + \beta_7 \gamma_{API}^{\beta_8} \tag{21}$$

Therefore the objective function is defined as

$$\min f(x) = \sum \left| R_{sexper} - R_{sestim} \right| \tag{22}$$

$$\min f(x) = \sum \left| R_{sexper} - \left|\left(\frac{p}{\beta_1} + \beta_2\right)\gamma_g^{\beta_3} 10^{\beta_5 T^{\beta_6} + \beta_7 \gamma_{API}^{\beta_8}}\right|^{\beta_4} \right| \tag{23}$$

β_1, β_2, β_3, β_4, β_5, β_6, β_7 and β_8 are the optimization parameters to be determined by the PSO algorithm.

The table 2 below presents the data for the optimization of these correlations;

Table-2: Differential Liberation Test Data for Rs for a xyz field

Oil density, γ_{API} @ 60 ^{0}F	**37**
$\gamma_g(from\ separator\ air = 1)$	**0.743**
Temperature, T	**60 ^{0}F**
Pressure (psia)	**R_s (scf/STB)**
2419.7	**737**
2214.7	**684**
1964.7	**620**
1714.7	**555**
1464.7	**492**
1214.7	**429**
964.7	**365**
714.7	**301**
464.7	**235**
214.7	**155**

The optimization algorithm was implemented using MATLAB programming language. The code for the implementation can be found in the appendix section.

2.RESULT AND DISCUSSION

Results

The results obtained from the particle swarm optimization algorithm implementation are illustrated below in subsections for the three different correlations' objective function. The particle swarm movement, Best cost or solution, solution gas-oil ratio plot, and the error analysis of the various correlations are illustrated.

Results for Glaso (1980) Correlation

$$R_{sestim} = \gamma_g \left|\left(\frac{\gamma_{API}^{\alpha_1}}{(T-460)^{\alpha_2}}\right)10^{x}\right|^{\alpha_3} \quad (10)$$

$$x = \alpha_4 + (\alpha_5 + \alpha_6 logP)^{\alpha_7} \quad (11)$$

After the implementation of the algorithm, the various correlation optimized variables were derived as;

$\alpha_1 = -5.01108$

$\alpha_2 = 5.2194$

$\alpha_3 = 0.9251$

$\alpha_4 = 13.3343$

$\alpha_5 = 10.3724$

$\alpha_6 = 5.2736$

$\alpha_7 = 0.58398$

The figure 2, 3, and 4 below presents the particles movement, best cost (value of minimize objective function) and the solution gas-oil ratio plot for the Glaso correlation.

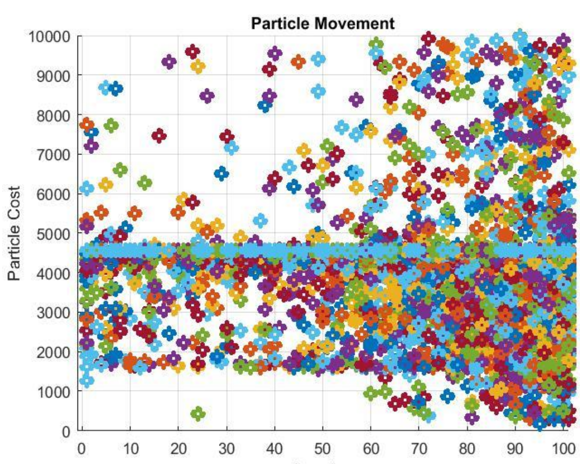

Fig. 2- Particles' Movement for the Glaso (1980) Correlation Optimization

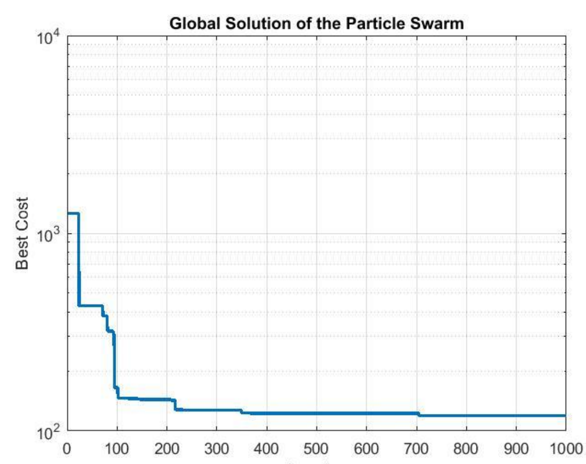

Fig. 3- Objective Function Solution for the Glaso (1980) Correlation Optimization

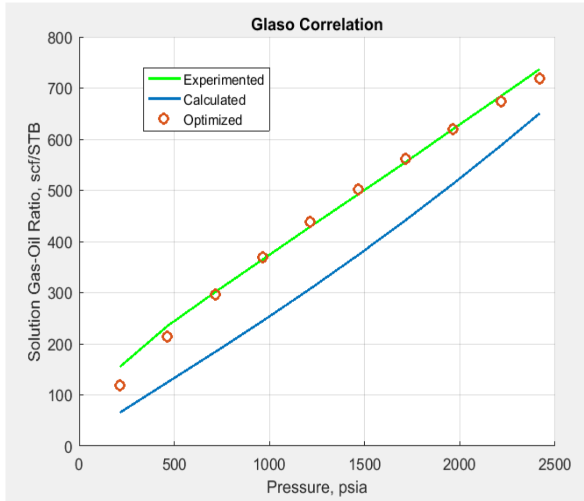

Fig. 4- Solution Gas-Oil Ratio Solution with Glaso (1980) Correlation

Results for Vazquez and Beggs (1980) Correlation

$$R_{sestim} = \theta_1 \gamma_g p^{\theta_2} e\left(\theta_3\left(\frac{\gamma_{API}}{\cdots}\right)\right) \quad (15)$$

After the implementation of the algorithm, the various correlation optimized variables were derived as;

$\theta_1 = 1.1287$

$\theta_2 = 0.7449$

$\theta_3 = 13.4439$

For oil API gravity greater than 30.

The figure 5, 6, and 7 below presents the particles movement, best cost (value of minimize objective function) and the solution gas-oil ratio plot for the Vazquez and Beggs correlation.

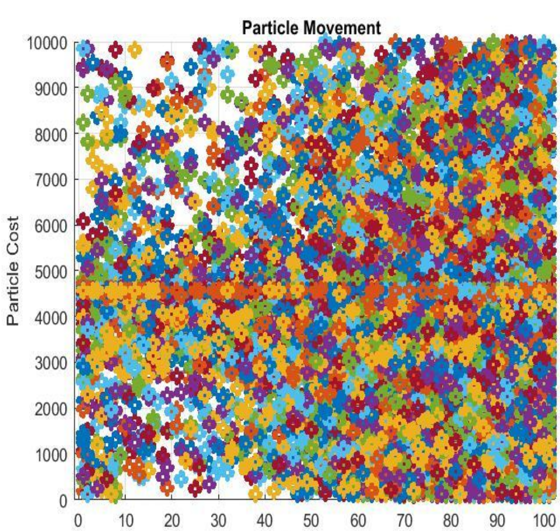

Fig. 5- Particles' Movement for the Vazquez and Beggs (1980)

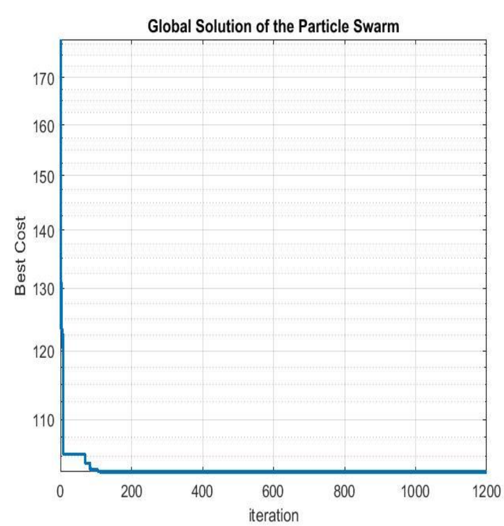

Fig. 6- Objective function solution for the Vazquez and Beggs (1980) correlation optimization

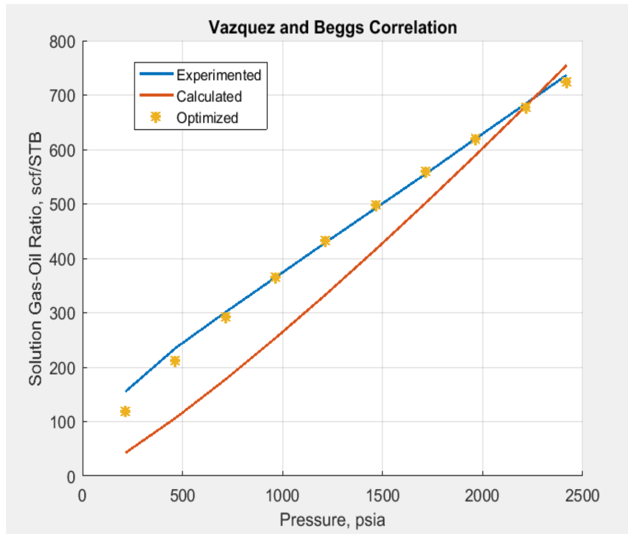

Fig. 7- Solution Gas-Oil Ratio Solution with Vazquez and Beggs (1980) Correlation

Results for Petrosky and Farshad (1993) Correlation

$$R_{sestim} = \left|\left(\frac{p}{\beta_1} + \beta_2\right)\gamma_g^{\beta_3}10^{x}\right|^{\beta_4} \tag{20}$$

$$x = \beta_5 T^{\beta_6} + \beta_7 \gamma_{API}^{\beta_8} \tag{21}$$

After the implementation of the algorithm, the various correlation optimized variables were derived as;

$\beta_1 = 18.248$

$\beta_2 = 22.541$

$\beta_3 = -5.852$

$\beta_4 = 0.973$

$\beta_5 = 2.2426 \times 10^{8}$

$\beta_6 = -4.0056 \times 10^{12}$

$\beta_7 = -1.6174 \times 10^{9}$

$\beta_8 = -5.0154 \times 10^{6}$

The figure 8, 9, and 10 below presents the particles movement, best cost (value of minimize objective function) and the solution gas-oil ratio plot for the Petrosky and Farshad correlation.

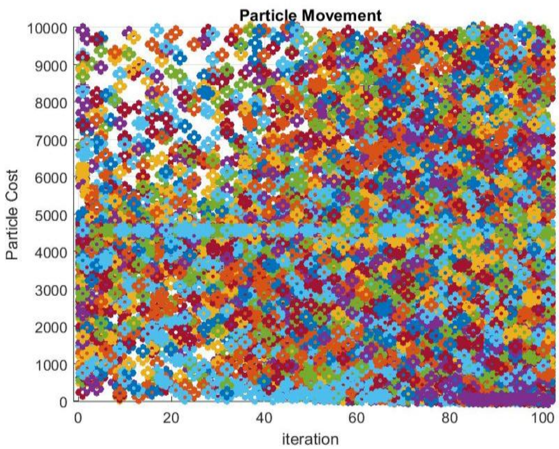

Fig. 8- Particles' Movement for the Petrosky and Farshad

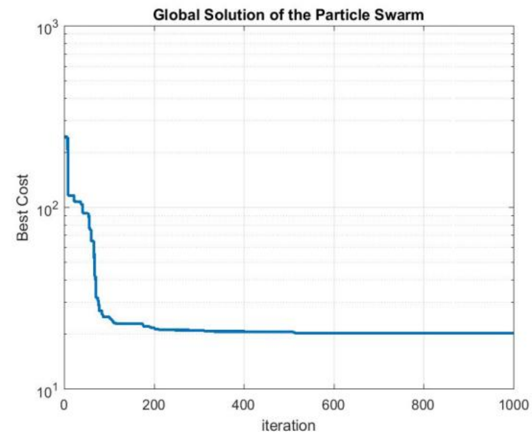

Fig. 9- Objective Function Solution for the Petrosky and Farshad

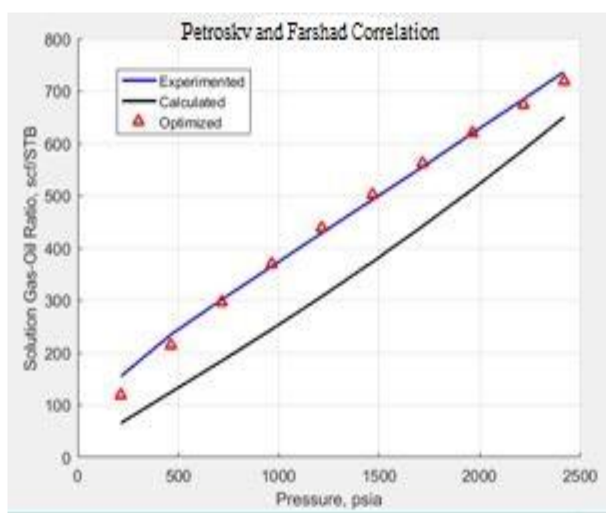

Fig. 10- Solution Gas-Oil Ratio Solution with Petrosky and Farshad

(1993) Correlation

Error Analysis

The error analysis for the various correlations (calculated and optimized) is presented in the table 4.1 below in terms of the sum of squared error, sum of squared residual, average percent relative error, coefficient of fitness and standard deviation.

Table-3**: Results Error Analysis**

Parameters	*Glaso*		*Vazquez and Beggs*		*Petrosky and Farshad*	
	Cal.	*Optim.*	*Cal.*	*Optim.*	*Cal.*	*Optim.*
Sum of Squared Error (10^4)	11.833	2.310	7.5920	0.21874	9.9273	0.021327
Sum of Squared Residual (10^5)	4.7101	3.6112	5.8949	3.6966	3.3432	3.3217
Coefficient of Fitness (R^2)	0.6534	0.9930	0.7776	0.9936	0.7092	0.9994
Average Relative Error (%)	29.2471	4.3825	25.4181	4.1855	20.8248	1.0922
Standard Deviation	1.9838	2.0021	2.4448	2.02528	1.6528	1.9211

The results above indicates that the particle swarm optimization algorithm is a good algorithm for the optimization of solution gas-oil correlations, as it does not depends 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 three (Glaso, 1980;Vazquez and Beggs, 1980; Petrosky and Farshad, 1993) correlations was able to predict the solution gas-oil ratio of the xyz field in the Niger Delta 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 Vazquez and Beggs (1980) that their correlation can be generalized for any field didn't hold in this case.

However, with the implementation of the PSO algorithm, the efficiency of the prediction of the various correlations increased as the PSO found the best combination of the constant parameters that will give the best prediction as the xyz field is concerned.

The optimized Petrosky and Farshad correlation was found to have the best prediction performance with the highest coefficient of fitness of 0.9993, the lowest sum of squared error of 0.021327 and the least average relative percentage error of 1.0922. Therefore, for any pressure and temperature, the optimized Petrosky and Farshad Correlation can be used to predict the solution gas-oil ratio of the xyz field without any fear of enormous error.

3.CONCLUSION AND RECOMMENDATION

According to Fekete (2012), solution gas-oil ratio is the most notable component of the PVT analysis. Therefore, the need to continually determine its value as the reservoir pressure declines cannot be overemphasized. Also, as earlier stated that the regular sampling of reservoir fluids and the performing of laboratory tests are capital intensive, and as such, mathematical correlations were developed by different authors for the prediction of PVT properties. These correlations however, was developed for a specific region's fluids with a specific bubble point pressure, oil density, gas specific gravity etc.

globalization of correlations can lead to boundless errors which can be equivocal. However, this work was restricted to the Glaso (1980), Vazquez and Beggs (1980), and Petrosky and Farshad (1993) 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 correlation was 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 particles swarm optimization increased the performance accuracy of all three correlations. Their coefficient of fitness was increased from 0.7776 to 0.9936, 0.6534 to 0.9930 and from 0.7092 to 0.9994 for the Vazquez and Beggs (1980), Glaso (1980), and Petrosky and Farshad (1993) correlations respectively. Hence, the optimized Petrosky and Farshad correlation gives the best prediction performance for the xyz field reservoir fluid.

From the results derived and presented in this research, the following recommendation was made.

- Before a PVT (solution gas-oil ratio) correlation is employed for the prediction of reservoir properties, it should first be optimized with previously observed properties.
- Because of the simplicity and non gradient dependence of the PSO, it is recommended to be used in the optimization of PVT correlations.
- Reservoir fluid properties all over the world should be made available to researchers in other to be able to develop a robust and generalized or globalized solution gas-oil ratio correlation.

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APPENDICES

MATLAB CODE FOR METHODOLOGY

GLASO OBJECTIVE FUNCTIONs

```
function Rs = Glaso(x)
rhog = 0.743;
rhoApi = 37;
T = 60;
P = [2419.7,2214.7,1964.7,1714.7,1464.7,1214.7,...
   964.7,714.7,464.7,214.7];
Rt = [737,684,620,555,492,429,365,301,235,155];s
z = x(4)+(x(5)+x(6)*log10(P)).^x(7);
Rs = sum(abs(Rt-rhog*((rhoApi^x(1)/T^x(2)).*10.^z).^x(3)));
end
```

VAZQUEZ AND BEGGS OBJECTIVE FUNCTION

```
function Rs = Beggs(x)
rhog = 0.743;
rhoApi = 37;
P = [2419.7,2214.7,1964.7,1714.7,1464.7,1214.7,...
   964.7,714.7,464.7,214.7];
Rt = [737,684,620,555,492,429,365,301,235,155];

T = 60+459.67;
Rs= sum(abs(Rt-x(1).*rhog.*(P.^x(2)).*exp(x(3)*(rhoApi/T))));
end
```

PETROSKY AND FARSHAD

```
function Rs = Petrosky(x)
rhog = 0.743;
rhoApi = 37;
P = [2419.7,2214.7,1964.7,1714.7,1464.7,1214.7,...
   964.7,714.7,464.7,214.7];
Rt = [737,684,620,555,492,429,365,301,235,155];
T = 60;
z = (x(5)*T^x(6))+(x(7)*rhoApi^x(8));
Rs = sum(abs(Rt-(((P/x(1))+x(2)).*(rhog^x(3))*10.^z).^x(4)));end
```

GENERAL PSO IMPLEMENTATION

```
function [P,G] = pso
clc;
clear;
```

```
close all;
%% problem definition
CostFunction = @(x) Petrosky(x);        %Cost or Objective Function
nVar = 8;                    %number of decision or unknown variables
Varsize = [1 nVar];              %matrix size of decision variable
VarMin = -10;                   %lower bound of decision variable
VarMax = 10;                    %upper bound of decision variable


%% Parameters of PSO
MaxIt = 1000;                      %Maximum iteration
nPop = 1000;                       %Population or swarm size
w = 1;                        %inertial coefficient
c1 = 2;                       %personal acceleration coefficient
c2 = 2;                       %social acceleration coefficient
wdamp = 0.99;                    %damping ratio of inertial coefficient
%% Initialization
%The particle template
empty_Particle.Position = [];
empty_Particle.Velocity = [];
empty_Particle.Cost = [];
empty_Particle.Best.Position = [];
empty_Particle.Best.Cost = [];

%create population array
Particle = repmat(empty_Particle,nPop,1);

%initial global best
GlobalBest.Cost = inf;
%initiatlize population members

for i = 1:nPop
   %create random solution
   Particle(i).Position = unifrnd(VarMin,VarMax,Varsize);

   %initialize velocity
   Particle(i).Velocity = zeros(Varsize);

   %Evaluation
   Particle(i).Cost = CostFunction(Particle(i).Position);

   %Update the personal best
   Particle(i).Best.Position = Particle(i).Position;
   Particle(i).Best.Cost = Particle(i).Cost;

   %update global best
   if Particle(i).Best.Cost<GlobalBest.Cost
   GlobalBest = Particle(i).Best;
   end
end

% Array told best cost afer every iteration
BestCosts = zeros(MaxIt,1);

%%main loop
for it = 1:MaxIt
   for i = 1:nPop
      %update velocity
       Particle(i).Velocity = w*Particle(i).Velocity+c1*rand(Varsize).*...
          (Particle(i).Best.Position- Particle(i).Position)+c2*...
          rand(Varsize).*(GlobalBest.Position-Particle(i).Position);
       Particle(i).Position = Particle(i).Position + Particle(i).Velocity;

       %Evaluation
       Particle(i).Cost(it) = CostFunction(Particle(i).Position);

       %update personal best

       if Particle(i).Cost(it)<Particle(i).Best.Cost
          Particle(i).Best.Position = Particle(i).Position;
          Particle(i).Best.Cost =  Particle(i).Cost(it);
       end
```

```
        if Particle(i).Best.Cost<GlobalBest.Cost
            GlobalBest = Particle(i).Best;
        end
    end
    % Store best cost value
    BestCosts(it) = GlobalBest.Cost;

    %Display iteration
    disp(['iteration' num2str(it) ': BestCost = ' num2str(BestCosts(it))])

    %Damping Inertia coeeficient
    w = w*wdamp;
end

%%Results
P= Particle;
G = GlobalBest;

figure
semilogy(BestCosts,'LineWidth',2)
xlabel('iteration')
ylabel('Best Cost')
title('Global Solution of the Particle Swarm')
grid on
figure
axis([-1 101 -10 10000])
l = 1:MaxIt;
for i = 1:nPop;
hold on
loglog(l,P(i).Cost,'o','LineWidth',4)
end
xlabel('iteration')
ylabel('Particle Cost')
title('Particle Movement')
grid on
end
```

ERROR EVALUATION ALGORITHM

```
function result = evaluation

rhog = 0.743;
rhoApi = 37;
P = [2419.7,2214.7,1964.7,1714.7,1464.7,1214.7,...
    964.7,714.7,464.7,214.7];
Rt = [737,684,620,555,492,429,365,301,235,155];
[Rs,Rsc] = G(rhog,rhoApi,P);
me = mean(Rt);
result.Optim.sse = sum((Rt-Rs).^2);
result.Optim.ssr = sum((Rs-me).^2);
result.Optim.sst = sum((Rt-me).^2);
sst = result.Optim.sst;
sse = result.Optim.sse;
result.Optim.R_sq = 1-sse/sst;
result.Optim.sd = std(Rs);
result.Optim.Erc = 100*mean(abs(Rs - Rt)./Rt);

result.Calc.sse = sum((Rt-Rsc).^2);
result.Calc.ssr = sum((Rsc-me).^2);
result.Calc.sst = sum((Rt-me).^2);
sstc = result.Calc.sst;
ssec = result.Calc.sse;
result.Calc.R_sq = 1-ssec/sstc;
result.Calc.sd = std(Rsc);
result.Calc.Erc = 100*mean(abs(Rsc - Rt)./Rt);
figure
hold
%plot(P,Rt,P,Rsc,P,Rs,'*','LineWidth',1.5)
plot(P,Rt,'b',P,Rsc,'k',P,Rs,'^r','LineWidth',1.5)
%plot(P,Rt,'g',P,Rsc,P,Rs,'o','LineWidth',1.5)
xlabel('Pressure, psia')
ylabel('Solution Gas-Oil Ratio, scf/STB')
```

```
grid on
legend('Experimented','Calculated','Optimized')
%title('Glaso Correlation')
%title('Vazquez and Beggs Correlation')
%title('Petrosky and Farshad Correlation')

function [Rs,Rsc] = B(rhog,rhoApi,P)
T = 60+459.67;
x = [1.1287,0.7449,13.4439];
c = [0.0178,1.1870,23.931];
Rs= x(1).*rhog.*(P.^x(2)).*exp(x(3)*(rhoApi/T));
Rsc = c(1).*rhog.*(P.^c(2)).*exp(c(3)*(rhoApi/T));
end

function [Rs,Rsc] = Pe(rhog,rhoApi,P)
T = 60;
x = [18.248,22.541,-5.852,0.973,2.2426e8,-4.0056e12,-1.6174e9,-5.0154e6];
c = [112.727,12.34,0.8439,1.73184,-4.561e-5,1.3911,7.916e-4,1.541];
z = (x(5)*T^x(6))+(x(7)*rhoApi^x(8));
Rs = (((P/x(1))+x(2)).*(rhog^x(3))*10.^z).^x(4);
z1 = (c(5)*T^c(6))+(c(7)*rhoApi^c(8));
Rsc = (((P/c(1))+c(2)).*(rhog^c(3))*10.^z1).^c(4);
end

function [Rs,Rsc] = G(rhog,rhoApi,P)
T = 60;
x = [-5.01108,5.2194,0.9251,13.3343,10.3724,5.2736,0.58398];
c = [0.989,0.172,1.2255,2.8869,14.181,-3.3053,0.5];
z = x(4)+(x(5)+x(6)*log10(P)).^x(7);
Rs = rhog*((rhoApi^x(1)/T^x(2)).*10.^z).^x(3);
z1 = c(4)-(c(5)+c(6)*log10(P)).^c(7);
Rsc = rhog*((rhoApi^c(1)/T^c(2)).*10.^z1).^c(3);
end
end
```