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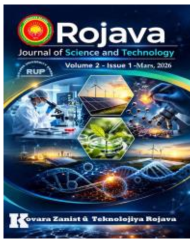

Development of New Models for Predicting the Solution Gas Oil Ratio of Rmelan Crude Oils

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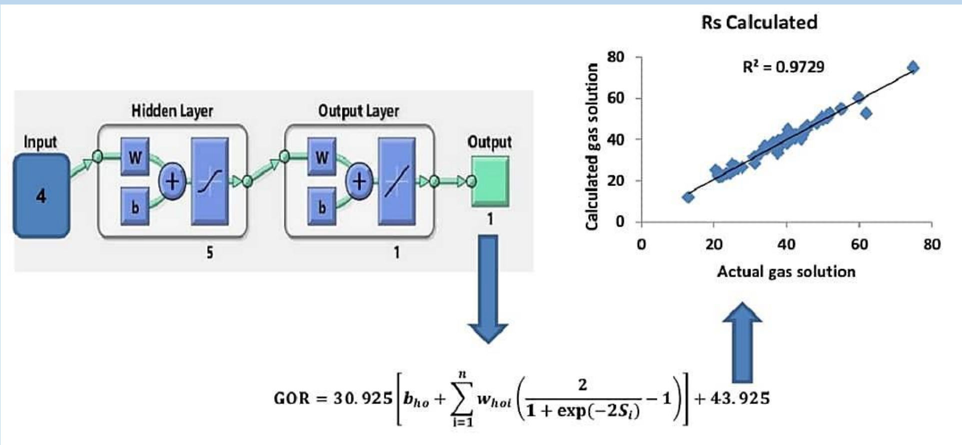
Abstract

Solution Gas Oil Ratio (SGOR) is an important reservoir fluid property. Many reservoir engineering calculations are relied upon for this property, such as reserve estimation, fluid production and injection rates, secondary and enhanced oil recovery, and prediction of the future production performance of oil and gas reservoirs. In some circumstances, in vitro PVT analysis is unavailable, the experimental-based PVT correlations are the best alternative. In this paper, new models were developed to predict the SGOR for Rmelan crude oil using non-linear multiple regression and artificial neural networks (ANN). 50 PVT datasets were collected from Rmelan oil fields for this purpose. The collected data include the SGOR, oil-specific gravity, gas-specific gravity, reservoir temperature, and bubble point pressure. A new SGOR correlation was developed using a nonlinear multiple regression technique with an R^2 of 0.81 Also, a new ANN model was developed for calculating the SGOR with an R2 of 0.97 and an average absolute relative error of 0.04. This study shows that the developed models are matched with Rmelan crude oil better than other published correlations. The developed models represent a road map for PVT properties of Rmelan crude oil saving time, effort, and money.



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1. Introduction

Petroleum (an equivalent term is crude oil) is a complex mixture consisting predominantly of hydrocarbons and containing sulfur, nitrogen, oxygen, and helium as minor constituents. The physical and chemical properties of crude oils vary considerably and are dependent on the concentration of the various types of hydrocarbons and minor constituents present (Hsu and Robinson 2019, Behrenbruch, Dedigama, and Engineering 2007).

An accurate description of the physical properties of crude oils is of considerable importance in the fields of both applied and theoretical science, especially in the solution of petroleum reservoir engineering problems. Physical properties of primary interest in petroleum engineering studies include fluid gravity, the specific gravity of the solution gas, solution gas oil ratio (GOR) or gas solubility, bubble-point pressure, oil formation volume factor, isothermal compressibility coefficient of undersaturated crude oils, oil density, total formation volume factor, crude oil viscosity, and surface tension. Data on most of these fluid properties are usually determined by laboratory experiments performed on samples of actual reservoir fluids (El-Hoshoudy and Desouky 2019, Arabloo et al. 2014, Elsharkawy and Engineering 2003). In the absence of experimentally measured properties of crude oils, it is necessary for the petroleum engineer to determine the properties from empirically derived correlations (Ahmed 2018).

Gas solubility Rs is defined as the number of standard cubic feet (SCF) of gas that can dissolve in one barrel of crude oil tank at given conditions of pressure and temperature. When the pressure is increased until the bubble point pressure, we notice that Rs increases and reaches its maximum value at the bubble point pressure (Valko, McCain Jr, and Engineering 2003). As for increasing the pressure above the bubble point pressure until the initial reservoir pressure, Rs remains constant because all the available gases have dissolved in the crude oil (Lyons and Plisga 2011, Elmabrouk, Shirif, and Gas 2011). As a result Rs has reached its maximum value and is constant. The gas melting curve as a function of pressure in unsaturated crude oil is shown in **Figure (1)**. We notice that when the pressure decreases from the initial reservoir pressure Pi until the bubble point pressure Rs reaches its maximum value and is constant. When the pressure decreases below the bubble point pressure, Rs decreases due to the release of gases from the crude oil due to the decrease in pressure below the bubble point pressure (Ahmed 2018).

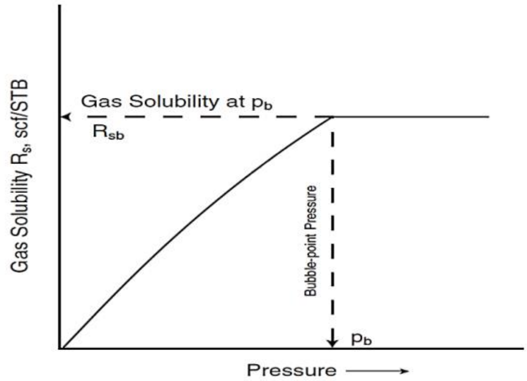

Figure 1. Gas-Solubility as a function of pressure (Ahmed 2018).

(Standing 1977) proposed a graphical correlation for determining the gas solubility as a function of pressure, gas-specific gravity, API gravity, and system temperature. The correlation was developed from a total of 105 experimentally determined data points on 22 hydrocarbon mixtures from California crude oils and natural gases. The proposed correlation has an average error of 4.8%. Standing (1981) expressed his proposed graphical correlation in the following more convenient mathematical form:

$$R_s = \gamma_g\left[\left(\frac{p}{18.2}+1.4\right)10^X\right]^{1.2048} \quad (1)$$

$$X = 0.0125API - 0.00091(T-460) \quad (2)$$

Where:

T = temperature, °R

p = system pressure, psia

γ_g = solution gas specific gravity

It should be noted that Standing’s equation is valid for applications at and below the bubble-point pressure of the crude oil.

The Vasquez Begg's Correlation

(Vazquez and Beggs 1977) presented an improved empirical correlation for estimating Rs. The correlation was obtained by regression analysis using 5,008 measured gas solubility data points. Based on oil gravity, the measured data were divided into two groups. This division was made at a value of oil gravity of 30°API. The proposed equation has the following form with the coefficients presented in **Table 1**.

$$R_s = C1 * \gamma_{gs} * p^{C2} \exp\left[C3\left(\frac{API}{T}\right)\right] \quad (3)$$

$$\gamma_{gs} = \gamma_g\left[1 + 5.912(10^5)(API)(T_{sep} - 460)\log\left(\frac{p_{sep}}{114.7}\right)\right] \quad (4)$$

Table 1. Values for the coefficients of Vasquez Begg's Correlation:

Coefficient	API<=30	API>30
C1	0.0362	0.0178
C2	1.0937	1.1870
C3	25.7240	23.931

Where:

γ_{gs} = gas gravity at the reference separator pressure.
γ_g = gas gravity at the actual separator conditions of p_{sep} and T_{sep}.
p_{sep} = actual separator pressure, psia.
T_{sep} = actual separator temperature, °R.

(Glaso 1980) proposed a correlation for estimating the gas solubility as a function of the API gravity, pressure, temperature, and gas specific gravity. The correlation was developed from studying 45 North Sea crude oil samples. Glaso reported an average error of 1.28% with a standard deviation of 6.98%. The proposed relationship has the following form:

$$R_s = \gamma_g\left[\left(\frac{API^{0.989}}{(T - 460)^{0.172}}\right)(p_b^*)\right]^{1.2255} \quad (5)$$

where p_b^* is a correlating number and is defined by the following expression:

$$p_b^* = 10^X \quad (6)$$

$$X = 2.8869 - [14.1811 - 3.3093\log(p)]^{0.5} \quad (7)$$

(Al-Marhoun 1988) developed an expression for estimating the saturation pressure of the Middle Eastern crude oil systems. The correlation originates from 160 experimental saturation pressure data. The proposed correlation can be rearranged and solved for the gas solubility to give:

$$R_s = \left[a\gamma_g^b * \gamma_o^c * T^d * p\right]^e \quad (8)$$

Where:

γ_g = gas specific gravity
γ_o = stock – tank oil gravity
T = temperature, °R
$a - e$ = coefficients of the above equation having these values:
$a = 185.843208$, $b = 1.877840$
$c = -3.1437$ $d = -1.32657$ $e = 1.398441$

(Petrosky Jr and Farshad 1993) used a nonlinear multiple regression software to develop a gas solubility correlation. The authors constructed a PVT database from 81 laboratory analyses from the Gulf of Mexico crude oil system. Petrosky and Farshad proposed the following expression:

$$R_s = \left[\left(\frac{p}{112.727}\right)\gamma_g^{0.8439} * 10^X\right]^{1.73184} \quad (9)$$

With

$$X = 7.916(10^{-4})(API)^{1.5410} - 4.561(10^{-5})(T - 460)^{1.3911} \quad (10)$$

Where:
p = pressure, psia
T = temperature, °R

Sarit Dutta and J.P. Gupta. investigated PVT correlations for Indian crude using ANN (Dutta, Gupta, and Engineering 2010). They developed correlation for solution gas –oil ratio (GOR) for saturated and unsaturated oil for Indian (West Coast) crude oil. These were done using ANN technique. They also compared the results with other correlations currently available in the literature. They found that the developed models gave much lower values for the average absolute relative error of the studied parameters. The results were positive, and they could be integrated into reservoir modeling programs.

M. Khazam et al. studied new PVT correlations for Libyan crudes (Khazam, Alkhaboli, and Shlak 2016). They developed new correlations to predict gas solubility (GOR), for Libyan crude oil, using ANN and multiple linear regression using Minitab software. These models were developed by inputting several parameters taken from about 300 PVT datasets. which were collected from Libyan crude oil, especially from the Sirte, Ghams, Mazraq and offshore basins. The results showed after testing these models and comparing the results obtained with the results of the previous experimental correlations and the performance of the developed models was better than the performance of the published models in terms of the accuracy of the results.

The following equations were studied:

$$R_s = \gamma_g API \left[\left(\frac{P + 218.2}{172.4} \right) \left(\frac{T}{API\gamma_g} \right)^{-0.5592} \right]^{\frac{1}{0.5852}} \qquad (11)$$

Where:

$R_s =$ Total producing gas oil ratio from flash separation(scf /stb).

Aref Hashemi Fath et al. investigated **the** implementation of multilayer perceptron (MLP) and radial basis function (RBF) neural networks to predict the solution gas-oil ratio of crude oil systems (Fath, Madanifar, and Abbasi 2020).They developed new models using multiple neural networks (MLP) and radial basis function (RBF) to predict the solution gas-oil ratio. These models included bubble point pressure, reservoir temperature, oil gravity (API), and gas-specific gravity. The developed models used 710 data sets of PVT of oil collected from different fields around the world. The results showed that the developed models were better than all published correlations in terms of the accuracy of the results. In addition, the RBF model showed higher accuracy and efficiency compared to the MLP model.

Reda Abdel Azim et al. studied the estimation of solution gas oil ratio using ANN (Abdel-Azim 2022). They developed a new correlation using the ANN model to predict gas solubility. The development of this model included several parameters, API gravity, reservoir temperature, and gas-specific gravity. To develop this model, they used 450 PVT datasets collected from different oil fields around the world. They improved the performance of this model using 65% of the dataset for training, 20% of the dataset for testing, and 15% of the dataset to validate the developed correlations. The results showed that the average absolute relative error was 5.4% for solution gas. They compared the results obtained from the developed model with other known models to ensure the validity of the developed model. The results showed that the performance and results of the developed model using an ANN to predict solution gas outperformed other models.

The following equations were studied:

$$Rs = 5472.1 * Rs_n + 2.1 \qquad (12)$$

Where:

$R_{s_n} =$ Is the normalized gas solubility.

2. Methodology

2.1. Data Description and Analysis

Before developing the correlation, we should firstly check the relation between the solution GOR and the input parameters. **Figure 2** shows the effect of the input parameters on the solution GOR for the correlation. As depicted from this figure, the solution GOR is directly proportional to reservoir temperature, bubble point pressure, oil formation volume factor, solution factor, specific oil gravity at standard conditions, and oil compressibility. On the other hand, the solution GOR is inversely proportional to oil viscosity at reservoir conditions, specific oil gravity and reservoir pressure. As shown also from this figure, the solution GOR is affected by reservoir temperature with R = 25%, bubble point pressure with R = 82%, oil formation volume factor with R = 88.5%, solution factor with R= 1.85%, specific oil gravity at standard condition with R = 0.62%, oil compressibility with R = 56.75%, oil viscosity at reservoir condition with R = -42.4%, specific oil gravity at reservoir condition with R = -74.73% and reservoir pressure with R = -15.61%. We neglected the oil viscosity at reservoir conditions, solution factor, oil specific gravity at standard conditions, oil compressibility and reservoir pressure from this correlation because of its small effect on the solution GOR.

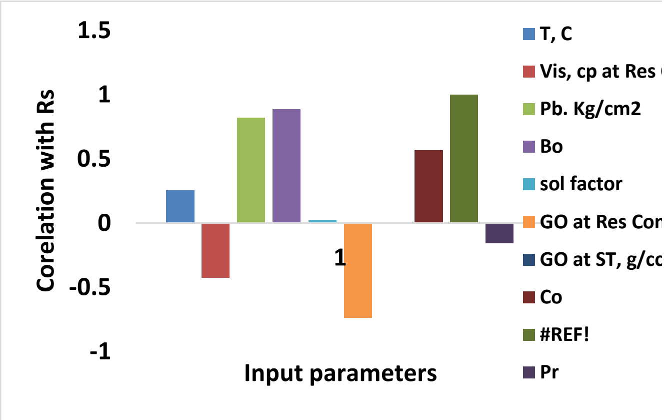

Figure2. Effect of input parameters on solution GOR for the this correlation.

2.2. Data Splitting

Before building ANN model to predict the bubble point pressures, the collected data sets are divided into three sets. The first set is employed for the process of model training, which represents 35 data sets out of 50 datasets (70% of all the data), while 15 data sets (30% of all the data) are used for the purpose of validation, and testing the performance of the model. Besides, all of the data are normalized between −1 and 1 to build the ANN model.

3. Results

3.1. Nonlinear Multiple Regression Model

The new correlation was developed to predict the solution GOR as a function of reservoir temperature, oil-specific gravity at reservoir conditions, bubble point pressure, and formation volume factor. To develop this correlation, 50 PVT datasets are collected from 50 Rmelan oil reservoirs.
The new solution GOR correlation can be expressed as:

$$\mathrm{GOR} = a_0 + a_1 * T + a_2 * \gamma_o + a_3 * P_b + a_4 * B_o \qquad (13)$$

Where:

$a_0 = -8.9 \quad a_1 = -0.047$

$a_2 = -132.87 \quad a_3 = 0.266 \quad a_4 = 133.35$

T = Reservoir temperature, °F.

γ_o = Oil specific gravity at reservoir conditions.

Pb = Bubblepoint pressure, psia.

B_o = Oil vormation volume factor, bbl/STB.

3.2. Neural Network Model

Before building the ANN model to predict the solution GOR, the collected data sets are divided into three sets. The first set is employed for the process of model training, which represents 35 data sets out of 50 datasets (70% of all the data), while 15 data sets (30% of all the data) are used for validation and testing the performance of the model. Besides, all the data are normalized between −1 and 1 to build the ANN model. In this work, an ANN model was developed to estimate the solution GOR as a function of reservoir temperature, oil-specific gravity at reservoir conditions, bubble point pressure, and oil formation volume factor. The model is built based on three layers. The first layer is the input layer, which has four neurons for inputs. There are 13 neurons that contribute to the hidden layer, which is the second layer. The output layer, which has one neuron to predict the output parameter, solution GOR, is the third layer. we firstly examined the Log-sigmoid as a transfer function at different numbers of hidden neurons (5, 6, 7, 8, 9,10, 11, 12, and 13) as presented in **Table 2**. We found that the highest coefficient of determination and the lowest RMSE at n = 6. Then we examined the Tan-sigmoid as a transfer function at numbers of neurons of (5, 6, 7, 8, 9,10, 11, 12, and 13) as presented in **Table 3**. We found that the optimum transfer function is Tan-sigmoid with 5 neurons where the coefficient of determination is 0.97 and MAE is 4 %. To reach this fact a Levenberg-Marquardt technique was selected as a training algorithm and the pure-linear was examined to be the output function. **Figure 3** shows the layout of the proposed model and the characteristics of the proposed model are presented in **Table 4.**

Table 2. Solution GOR model accuracy at various numbers of neurons in the hidden layer with log–sigmoid transfer function.

Neuron #	5	6	7	8	9	10	11	12	`13
$\mathbf{R^2}$	0.74	0.95	0.93	0.8188	0.9056	0.92	0.9421	0.8863	0.4315
SD	15.66	7.26	9.15	12.6685	10.629	10.5	8.7667	13.524	13.0734
AE	11.1	5.76	6.8	9.823	5.3255	7.65	6.4089	7.505	9.9357

Table 3. Solution GOR model accuracy at various numbers of neurons in the hidden layer with a tan–sigmoid transfer function.

Neuron #	5	6	7	8	9	10	11	12	`13
$\mathbf{R^2}$	0.97	0.7854	0.8392	0.7602	0.9372	0.9155	0.8966	0.7216	0.904
SD	5.9	17.6	10.9751	14.5063	9.9673	9.1759	11.7711	12.1602	10.6673
AE	4.0	11.4156	7.4207	8.8507	5.8802	6.5089	8.3034	7.8015	7.3168

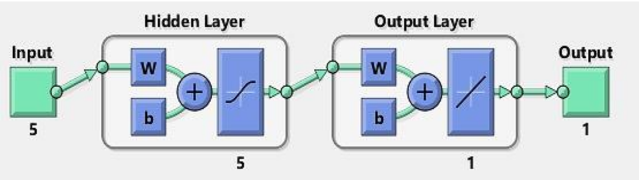

Figure 3. Layout of the proposed ANN model for solution volume factor.

Table 4. Characteristics of the ANN model for the solution GOR.

Parameter	Value
ANN layers number	3
neurons number in the input layer	4
optimum neuron number in the hidden layer	5
training algorithm for the neural network	Levenberg–Marquardt
transfer function of the hidden layer	Tan sigmoid
transfer function of the output layer	pure linear

The developed model for solution GOR using the ANN can be expressed as follows:

First, the input parameters are normalized using the following expressions:

$$GOR_n = 0.032336 * Rs - 1.420372 \qquad (14)$$

$$API_n = 0.11928 * API - 4.151871 \qquad (15)$$

$$P_{b_n} = 0.021739 * P_b - 1.25 \qquad (16)$$

$$B_{o_n} = 11.76471 * B_o - 13.35294 \qquad (17)$$

For i = 1 to no of neurons and for j = 1 to no of inputs, the inputs for the hidden are calculated from the following expression:

$$S_{i,j} = \sum_{j=1}^{N} (w_{i,j} x_j) + b_i \qquad (18)$$

The solution GOR can be calculated by the following function:

$$GOR = 30.925 \left[b_{ho} + \sum_{i=1}^{n} w_{hoi} \left(\frac{2}{1 + \exp(-2S_i)} - 1 \right) \right] + 43.925 \qquad (19)$$

The solution GOR model's coefficients are listed in **Table 5**. Regression plots for the pore pressure model, as indicated in **Figure 4**, present the relation between network outputs and targets for training, validation, testing, and all data points. The fit is good for all the datasets in this work, and the R-squared values are 0.9711

Table 5. Weights and Biases of the solution GOR ANN Model.

Neuron #	Wi,1	Wi,2	Wi,3	Wi,4	bi	Whi	bh
1	0.6219	-1.8302	-2.05	1.4131	-2.0845	1.1492	0.52508
2	0.1042	0.25216	1.8967	-1.5544	-0.57408	0.41177	
3	-0.53165	-2.2646	-1.5205	1.7123	0.56092	0.4792	
4	1.4088	3.4885	1.727	1.0391	0.65132	0.45873	
5	-0.5674	0.097096	1.0379	0.41352	1.3177	0.29678	

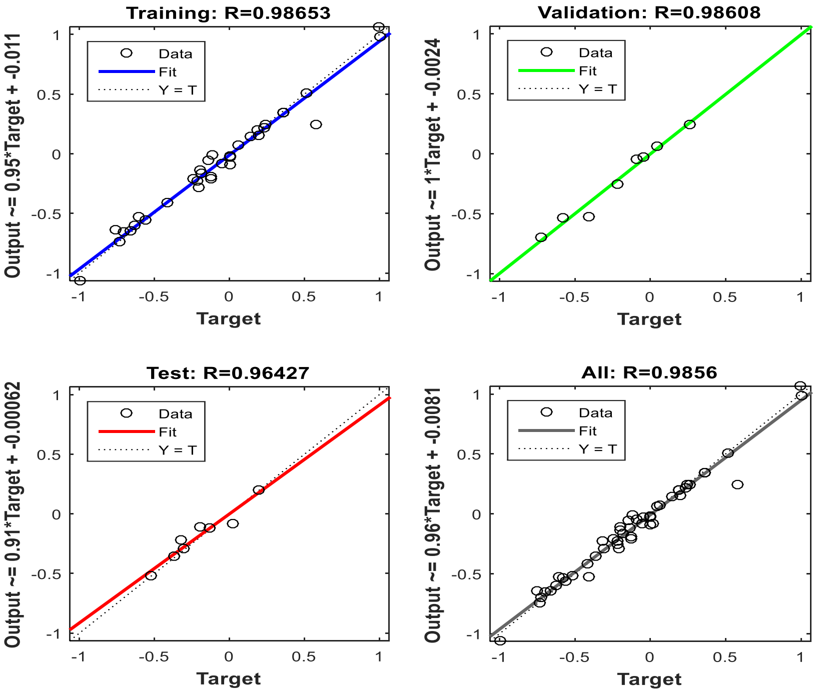

Figure 4. Cross plots of ANN model of solution GOR.

4. Discussion

- In this section, the accuracy of the developed solution GOR in this study was compared versus five of the most published and applied solution GOR correlations to predict the gas solubility of Rmelan crude oil. The developed solution GOR correlation in this thesis achieved the highest coefficient of determination of 0.81 as shown in **Figure 5**.
- Marhoun's solution GOR correlation gives a very low coefficient of determination of -1.37 as shown in **Figure 6**.
- The Standing's solution GOR correlation gives a very low coefficient of determination of -2.99 as shown in **Figure 7**.
- Glaso's solution GOR correlation gives a very low coefficient of determination of -3.86 as shown in **Figure 8**.

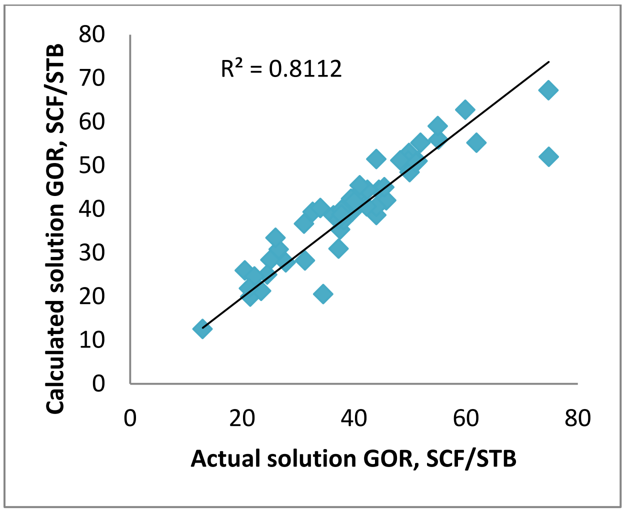

Figure 5. Cross plot of the solution GOR (after this study).

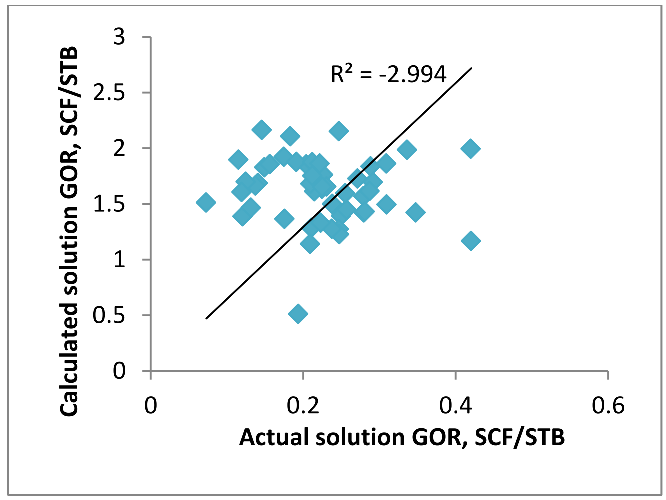

Figure 7. Cross plot for solution GOR (Standing's correlation)

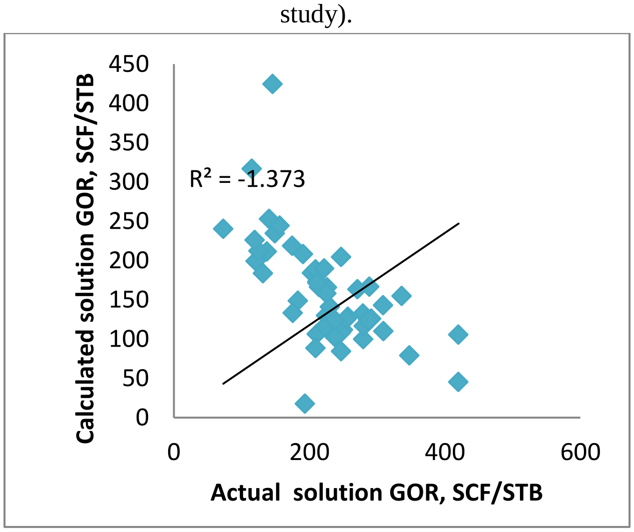

Figure 6. Cross plot for gas solution GOR (Marhoun's correlation).

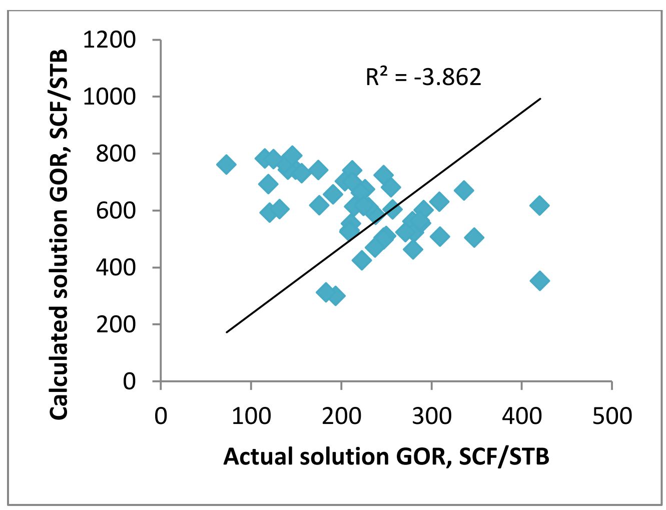

Figure 8. Cross plot for solution GOR (Glaso's correlation).

5. Conclusions

50 PVT datasets are collected from 50 Rmelan oil reservoirs for developing new PVT correlations using nonlinear multiple regression and ANN. From the work, the following conclusions may be drawn:

- A new correlation based on nonlinear multiple regression was developed to predict the solution GOR with a coefficient of determination, R^2 of 0.8112.
- An ANN-based model was developed to predict the solution GOR with an R^2 of 0.97.
- This study shows that the developed models are matched with Rmelan crude oil better than other published correlations.
- The developed models represent a road map for PVT properties of Rmelan crude oil saving time, effort, and money.

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