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Rigorous Modeling of Solution Gas – Oil Ratios for a Wide Ranges of Reservoir Fluid Properties

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Abstract

The reservoir fluid properties, the solution gas–oil ratio (GOR), are of great importance in various aspects of petroleum engineering. Therefore, a rapid means for estimating such parameters is much sort after. In this study, the linear interaction and general optimization method is applied in the development of a precise and reliable model for estimating the solution GOR. In order to develop a model that would be comprehensive, a reliable and extensive databank comprising of more than 1000 datasets collected from various geographical locations, including Asia, Mediterranean Basin, North America, Africa, and Middle East was compiled. Furthermore, the model developed was benchmarked against widely-used empirical methods in order to evaluate the performance of method proposed in predicting solution GOR data. The results show that the model proposed in this study outperforms the empirical methods to which it was compared. This study also investigated the influence of the reservoir fluid properties on the estimated solution GOR for the newly-developed model. Results show that bubble point pressure and gas gravity have the largest and the smallest influences on the predicted solution GOR, respectively. Finally, the Leverage approach was applied to determine the applicability domain for the proposed method via the detection of outlier data points. It was determined that only 26 data points, out of more than 1000 data, are identified as outlier data points.

Keywords: Reservoir fluid properties; Solution gas–oil ratio; GOR; API; Outlier data

Abbreviations: AARD: Average Absolute Relative Deviation; APRE: Average Percent Relative Error; API: Oil API Gravity; EOR: Enhanced Oil Recovery; LINGO: Linear Interactive And General Optimizer; OFVF: Oil Formation Volume Factor; Pb: Bubble Point Pressure, Psi; Rs: Solution Gas-Oil Ratio, SCF/STB; RMSE: Root Mean Square Error; SCF: Standard Cubic Feet; STB: Stock Tank Barrel; TR: Reservoir Temperature, °F; Γg: Gas Specific Gravity.

Introduction

The properties of reservoir fluids [1] are normally determined from bottom-hole and/or surface recombined samples. The fluid properties are required for a large number of reservoir engineering calculations, which include, selection of the most important enhanced oil recovery (EOR) method for a reservoir candidate, estimation of hydrocarbon reserves, performance prediction, calculations related to the production operation, production optimization, well-testing studies, fluid flow through porous media, etc [1-10]. In other words, reservoir fluid properties such as bubble point pressure, oil formation volume factor (OFVF), and solution GOR are key parameters in petroleum engineering calculations and are obtained through laboratory measurements, theoretical methods, and/or empirically derived correlations. Generally, petroleum engineers seek a rapid way to obtain these parameters, taking into account both economic and technical issues. The determination of reservoir fluid properties using laboratory experiments are not simple and can be time-consuming and expensive [11-13]. The reservoir fluid properties, in the absence of experimental measurements, must be determined through empirical methods.

Over the years, various empirical methods have been reported for the determination of reservoir fluid properties related to oil samples from different geographical locations worldwide. To this end, in one of the first attempts, Elam [14] in 1957 proposed a correlation for the estimation of saturation pressure as a function of temperature, gas specific gravity, oil gravity and solution GOR using as a basis of 231 data points for Texas crude oil. One year later, Lasater [15] presented a bubble point-pressure correlation for black oil data taken from Canada, western and mid-continental USA and South America. His model was developed using 158 samples of 137 various crude oils. He reported an average error of 3.8% for his model. He also observed that the existence of CO_2 in crude oil samples results in an increment in the saturation pressure. Vasquez and Beggs [16] proposed some empirically derived methods for the estimation of reservoir fluid properties using a universal databank collected from various regions of the world. Moreover, they separated the experimentally obtained data into two classes. The first group contained oils with gravities less than 30°API. The second group contained oils with gravities more than 30°API. In contrast with Lasater's results [15], they found that CO_2 content decreases the saturation pressure.

In 1983, Ostermann [17] developed two correlations for the estimation of saturation pressure of crude oil samples taken from

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different regions in Alaska based on a limited number of data points. Al-Marhoun [9] developed an empirical correlation applying data gathered from the Middle East region. In 1990, Rollins et al. [18] proposed an empirically derived method to calculate the stock-tank gas–oil ratio as a function of oil API gravity, separator pressure and temperature, and gas gravity. In the same year, Sutton and Farshad [19] reviewed several PVT correlations and compared the accuracy of each model for several PVT parameters for application in the Gulf of Mexico. In their study, Glaso's correlations [20] provided acceptable results for calculation of saturation pressure, solution GOR, and OFVF. They reported that Vazquez and Begg's correlations [16] had higher accuracy for solution GOR for more than 1400 SCF/STB and saturation pressures more than 7000 psi. In 1992, Dokla and Osman [21] studied 51 crude oil samples from UAE and developed a new empirical methods for OFVF, saturation pressure and solution GOR. They reported that PVT correlations should be derived using local data sets because universal correlations are not always accurate enough. Moreover, Omar and Todd [22] developed models for OFVF and saturation pressure on the basis of Standing's correlations [23] using 93 PVT datasets from Malaysian oil reservoirs. Their models showed better accuracy for Malaysian oil samples. Furthermore, Petrosky and Farshad [24] proposed some empirically derived methods for the determination of reservoir fluid properties using data collected from the Gulf of Mexico. They showed that the empirical methods proposed outperformed other methods developed for the Gulf of Mexico, involving those reported by Standing [23], Vasquez and Beggs [16], Glaso [20], and Al-Marhoun [9]. Elsharkawy et al. [25] also compared different correlations to characterize Kuwaiti crude oils using a limited number of oil samples in this year.

Ghetto et al. [26] proposed some empirical methods for the calculation of saturation pressure, solution GOR, OFVF, oil compressibility, and oil viscosity for heavy and extra-heavy oils. The data used in developing the correlations came from reservoir fluid samples extracted from the Mediterranean Basin, Africa, and the Persian Gulf. In 1998, Khairy et al. [27] developed some empirical methods for the estimation of saturation pressure and bubble point OFVF. They compared their model with nine published correlations. In 1999, Velarde and McCain [28] developed a set of empirical methods for calculating solution GOR and OFVF, and modified OFVF using 195 laboratory tests. In 2007, Mazandarani and Asghari [29] tuned Al-Marhoun 's correlation [9] for Iranian field data to obtain a modified correlation using about fifty fluid samples collected from different Iranian oil fields. In 2008, Taghaz et al. [30] tested the accuracy of PVT correlations to determine the solution GOR of Libyan oils using about 1600 data points from different oil fields in the Sirte basin. They concluded that no correlation is suitable for Libyan oils. In 2012, Shafiie et al. [31] optimized Standing [23] and McCain correlations for solution GOR and OFVF, based on Iranian crude oil samples, and developed a new model using Genetic Algorithms. Very recently, Arabloo et al. [11] developed simple and accurate empirical methods for the prediction of saturation pressure and OFVF using a large databank compiled from various geographical locations. Here, it is worth mentioning that smart techniques have previously been implemented for the estimation of reservoir fluid properties and petroleum engineering problems in addition to empirical methods [32-40].

In this study, the LINGO (Linear Interactive and General Optimizer) [41] methodology is implemented to propose an efficient, precise, and rapid-to-use model for the determination of solution GOR. To achieve a comprehensive model covering properties for all regions, a reliable databank was collected which comprises an extensive range of reservoir conditions, as well as PVT properties. The widely-used empirically derived correlations were used for comparison to benchmark the performance of the model proposed in this study. To this end, an error analysis was conducted graphically and statistically. The influence of the reservoir fluid properties on the solution GOR values calculated were also studied. Finally, applicability domain of the proposed method was determined through the detection of outlier data points using Leverage approach.

Solution Gas–Oil Ratio

As mentioned above, the solution GOR plays a key role in PVT analysis related to petroleum engineering calculations. As a consequence, solution GOR affects the OFVF, the viscosity compressibility of oil, and it is also needed to determine the in-situ total reservoir fluid rates. As a definition, solution GOR is the amount gas dissolved in oil with regards pressure. Here, it should be noted that reservoirs containing light oils have more dissolved gas than a reservoir with heavy oils. With an increase in pressure, solution GOR increases approximately linearly until the attainment of bubble point/saturation pressure (P_b); after which it is a constant and the oil is supposed to be under-saturated (Figure 1). Figure 1 is a typical illustration of the trend of solution GOR versus pressure.

As a result, most of empirically derived methods reported in the open literature for the determination of reservoir fluid properties have been developed on the basis of data related to a specific region and limited PVT studies [42]. This drawback can decrease the precision of these methods in predicting reservoir fluid properties at a particular solution gas–oil ratio. This means that the aforementioned empirical correlations may lead to significant deviation when they are utilized for the estimation of reservoir fluid properties for other geographical locations. For that reason, it is of important to collect a comprehensive databank covering a wide range of reservoir fluid properties for all regions in the world. Therefore, a reliable and comprehensive databank [9,17,21,22,26,43-47] comprising more than 1000 data series collected from various geographical locations including Asia, Mediterranean Basin, North America, Africa, and Middle East was compiled in this study. The databank collected includes reservoir fluid properties, viz. solution GOR (R_s, SCF/BBL), bubble point pressure (P_b, psi), reservoir temperature (T_R, °F), and gas gravity (γ_g), as well as oil gravity (API). A statistical description of the properties, including maximum, minimum, and average values is summarized in Table 1.

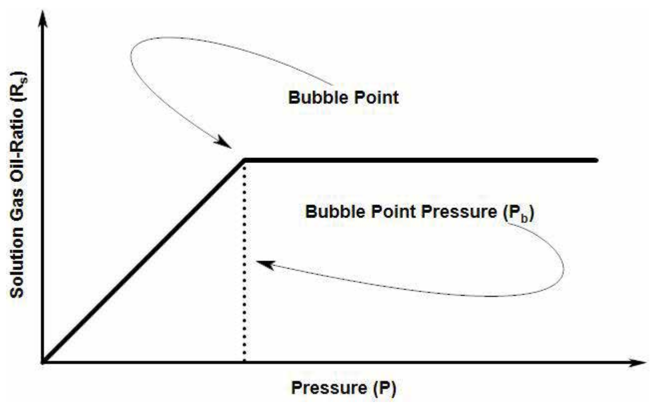

Figure 1: Typical trend of solution GOR versus pressure.

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Property	Unit	Minimum	Average	Maximum	Role
R_s	SCF/STB	7.08	515.32	3298.66	Output
γg	–	0.52	1.00	3.44	Input
T_R	°F	54.9	173.30	360.93	Input
API	–	6.00	33.41	56.8	Input
P_b	psi	58.01	1755.58	7127.01	Input

Table 1: Statistical analysis of reservoir fluid properties used for the estimation of solution gas–oil ratio.

Proposing the New Model

The key aim of the present study is to propose a comprehensive, accurate and reliable model for the determination of solution GOR using data collected from various crudes worldwide. To this end, the LINGO methodology [41] is used for pursuing our objective in this study. Basically, the technique is an interactive linear and discrete tuning tool. As a result, the methodology has been utilized in mathematics, science, and industry, and employed to solve computer problems mathematically [48-50]. Furthermore, quadratic programming, as well as linear and nonlinear, and integer programming are the most important problems solved by LINGO software [11]. Additionally, the LINGO methodology can solve the root and algebraic equations/problems linearly and nonlinearly. It should be mentioned that the LINGO software includes a number of common mathematical functions within the programming language to use by operators for finding/solving their programming problem [51]. In this study, the LINGO methodology is used to develop a reliable model to determine the solution GOR as a function of reservoir fluid properties, including bubble point/saturation pressure, reservoir temperature, and gas gravity, as well as oil gravity (API) as follows:

$$R_s = f(\gamma_g, T_R, API, P_b) \tag{1}$$

In the development of the model, the databank collected was separated into two sets of data, viz. the training and test sets. Approximately 80% of entire the databank was used in the development of model (training set), and the rest (20%) was assigned to the test set for checking the model developed and evaluating its accuracy, performance, and capability. To measure the accuracy of the model developed, the average absolute relative deviation (AARD) is selected as an objective function. Finally, a simple form of equation with four easy functions including ×,+,–,/ was obtained as follows:

$$RS = A+B -15.849 \tag{2}$$

$$A = 0.14624 P_b - 0.14624\, API + \frac{802.44}{P_b} + \frac{(2.727 P_b - API T_R + 2715.5)^2}{(API - 995.53)^2} \tag{3}$$

$$B = (0.0064332\, P_b + 0.0064332\, API\, _g) \times (API\, \gamma_g - 14.811) \tag{4}$$

where P_b denotes the bubble point pressure (psi), API stands for oil API gravity, T_R denotes the reservoir temperature (°F), and γ_g is gas specific gravity.

Variables Relevancy Analysis

To show the degree of dependency of the reservoir fluid properties selected as input variables (*i.e.* saturation pressure, reservoir temperature, and gas specific gravity as well as oil API gravity) on the solution GORs estimated by Eq. (2), a sensitivity analysis was performed. Hence, the relevancy factor (r) [52] is utilized in this study for measuring the degree of effect of each reservoir fluid property applied in Eq. (2) for the determination of solution GOR. Regarding the relevancy factor approach, an input variable has a higher influence on the output parameter if the calculated absolute value of r between the input and output variables is greater than the r values for other input variables. Consequently, the positive or negative influence of input variables (saturation pressure, reservoir temperature, and gas specific gravity as well as oil API gravity) on the solution GORs is however not determined by an absolute value of r. Consequently, following equation is used to calculate the r values through the relevancy analysis [40]:

$$r(\mathrm{Inp}_k, \mu_g) = \frac{\sum_{i=1}^{n} (\mathrm{Inp}_{k,i} - \overline{\mathrm{Inp}_k})(\mu_i - \overline{\mu})}{\sqrt{\sum_{i=1}^{n} (\mathrm{Inp}_{k,i} - \overline{\mathrm{Inp}_k})^2 \sum_{i=1}^{n} (\mu_i - \overline{\mu})^2}} \tag{5}$$

where $\mathrm{Inp}_{k,i}$ stands for i^{th} value of the *k*th input variables and $\overline{Inp_k}$ denotes the average value of the *k*th input variables (*i.e.* bubble point pressure, reservoir temperature, and gas gravity as well as oil gravity), μ_i indicates the *i*th value of the solution gas–oil ratios determined by Eq. (2), and $\overline{\mu}$ is the average value of the solution gas–oil ratios determined by Eq. (2).

Results and Discussion

Performance evaluation of the new model

A graphical and statistical error analysis was conducted to evaluate the performance of the method over a wide range of the reservoir fluid properties, and to compare the results obtained using the model against the most widely used empirically derived correlations. Hence, AARD, root mean square error (RMSE), and average relative percent error (ARPE) were considered as statistical error parameters, and a parity diagram or scatter plot, as well as a relative distribution error curve are used as two graphical illustrations to evaluate the performance of the method proposed to estimate the solution GORs. The results of error analysis are summarized in Table 2. The results in the table indicate that the model proposed has acceptable accuracy with respect to the large number of data points and the wide range of reservoir fluid properties employed in its development. The AARD value reported for the model is 19.83%. The value indicates that the method output values are in agreement with corresponding experimental records of the solution GOR. Furthermore, the calculated APRE and RMSE values are 1.73% and 203.05, respectively.

To assess the performance of the proposed model graphically, a scatter diagram, as well as a relative distribution error plot of values estimated using Eq. (2) were plotted. Figure 2 shows a comparison of values estimated by the model developed in this study versus experimental values of solution GOR on a parity diagram. It is clear

Method	AARD, %	APRE, %	RMSE
Glaso [20]	79.25	32.37	468.33
Petrosky and Farshad [24]	62.70	-48.16	217.38
Kartoatmodjo and Schmidt [54]	57.80	-48.15	395.93
Standing [23]	47.84	-38.61	312.88
Farshad et al. [2]	43.07	-28.87	267.08
Vazquez and Beggs [16]	42.29	-31.99	389.08
Al-Marhoun [9]	42.01	-21.28	348.17
Dindoruk and Christman [56]	36.89	-13.78	254.27
Macary and El-Batanony [53]	36.54	1.40	238.87
Al-Shammasi [55]	32.95	-16.72	242.81
Baniasadi et al. [42]	23.15	2.29	197.39
This present study	19.83	1.73	203.05

Table 2: Error analysis performed for the proposed model and comparable methods investigated in this study.

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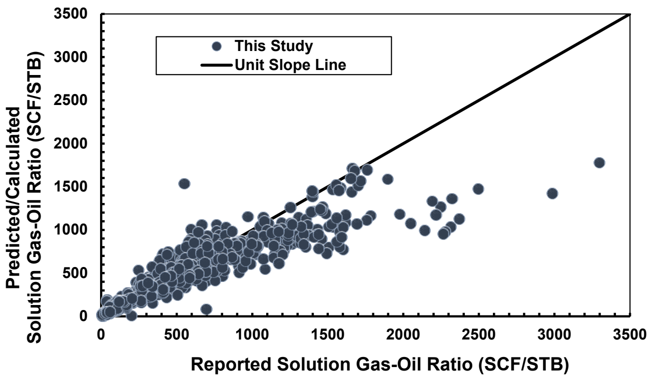

Figure 2: Scatter diagram of the predicted solution gas-oil ratio values versus the experimental records.

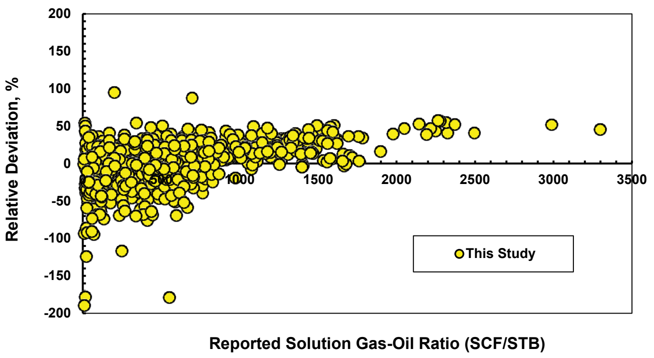

Figure 3: Relative error distribution plot of the predicted solution gas-oil ratio values versus the experimental records.

from the figure that the estimated GOR values approximately match the experimental values, resulting in data clustered around the parity line. This shows the capability of the model proposed in this study in predicting more than 1000 data values for solution GOR. Another graphical comparison is shown in Figure 3, which illustrates the calculated average relative percent error between the model and experimental data for solution GOR. As can be seen in the figure, the relative errors for the estimated data are clustered around the zero line. This demonstrates that there is acceptable agreement between the model predictions and experimental data for solution GOR. Figure 4 shows the plot of the predicted values against experimental data for the solution GOR with respect to the sorted data index.

A comprehensive comparison analysis was undertaken between the model developed in this study and widely-used empirically derived methods including the Farshad et al. method [2], Macary and El-Batanony method [53], Petrosky and Farshad method [24], Vazquez and Beggs method [16], Al-Marhoun method [9], Kartoatmodjo and Schmidt method [54], Al-Shammasi method [55], Standing method [23], Glaso [20], Baniasadi et al. method [42], and Dindoruk and Christman method [56] in order to evaluate the performance of the method in predicting solution GOR data. Table 2 reports the statistical results obtained for the comparisons undertaken. The table shows that the model developed in this study performs the best model for the calculation of solution GOR. Figure 5 illustrates graphically the calculated AARD for the model developed, as well as all comparative methods investigated in the study. From Table 2 and Figure 5, it can be concluded that the methods of Baniasadi et al. [42], Al-Shammasi [55], Macary and El-Batanony [53], Dindoruk and Christman [56], and Al-Marhoun [9] are, after the method proposed in this study, the most accurate for the calculation of solution GOR with AARD values of 23.15, 32.95, 36.54, 36.89, and 42.01%, respectively. Table 3 lists some random data points selected from the databank, and Table 4 summarizes the estimated values for the data points presented in Table 3 using method developed and empirical methods discussed above. Table 4 also confirms superior performance of the model developed in this study over the empirical methods to which it was compared.

Influence of the reservoir fluid properties on solution GOR

As pointed out earlier, reservoirs containing light oils have more dissolved gases than reservoir with heavy oils. Therefore, it would be interesting to determine the accuracy of the model developed for various ranges of oil API gravity. To this end, the capability of the model presented in this study for estimating the solution GOR was observed across the spectrum of the light to heavy oils. The solution GORs estimated by the proposed model was partitioned into four classes of oil API gravities, viz. 6-15, 15-25, 25-35, and 35-56.8°. The results of analysis in terms of the calculated AARD values is shown in Figure 6. As can be seen in the figure, the model errors for the estimation of solution GORs of light oils is less than that for heavy oils. In other words, it can be concluded that the model developed in this study is more applicable for crudes with higher values of oil API gravity. To further investigate the influence of the reservoir fluid properties, including saturation pressure, reservoir temperature, gas specific gravity, and oil API gravity, a sensitivity analysis was performed in this study using the relevancy factor approach. Figure 7 shows the results of sensitivity analysis. The figure indicates that bubble point pressure and

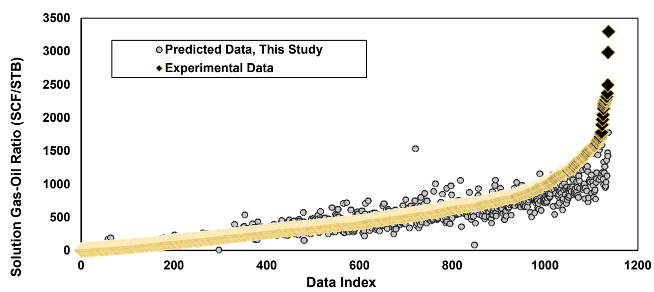

Figure 4: Fitting curve, as sorted data index, for the predicted solution gas-oil ratio values versus the experimental records.

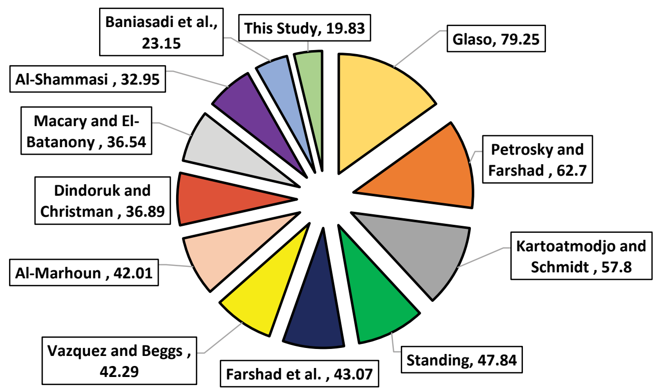

Figure 5: Graphical comparison of the developed model against the comparative methods studied in terms of statistical error parameter of AARD.

Data Index	P_b	γ_g	API	T_R	R_{si}
1	2082.77	0.756	7.5	153.5	208.7
2	2076.97	0.815	10.5	152.6	260.0
3	554.99	0.68	12	74.9	52.4
4	599.98	0.74	14.8	82.8	68.0
5	825.28	1.411	19.4	172.4	177.8
6	3199.97	0.75	20.9	110.5	556.2
7	285	0.74	23	114.8	32.5
8	430.04	1.04	25	99.4	95.5
9	1499.98	0.64	27	107.7	239.9
10	909.97	0.67	30	88.25	171.8
11	3057	0.778	32	175	679.0
12	400.01	0.8	34	71.6	76.6
13	2775.01	0.823	35.7	140.5	689.4
14	1340	0.8	36.3	87.8	313.4
15	1415	1.2468	37.2	248	486.0
16	5760.99	0.924	40.1	302	1760.6
17	1153.05	0.85	40.4	105.5	299.6
18	2221	0.693	45.3	238	547.0
19	1386.97	0.763	46.5	116.03	367.6
20	1962.07	0.78	52.5	138.25	636.7
21	1170.47	0.649	56.8	140.7	300.9

Table 3: Records of some data points existing in the databank compiled in this study.

gas specific gravity has the largest and smallest influences, respectively, on the solution GOR values predicted by the model.

Detection of outlier solution GOR data points

The detection of outlier data points that exist in a databank used to develop a predictive model is important to know in order to determine the applicability domain of the model developed. To this end, the Leverage methodology [57-59] is utilized in this study to identify outlier data points in the solution GOR databank that was compiled. Detailed information on the Leverage methodology in terms of mathematical equations, as well as a step-by-step procedure is reported elsewhere [57-59]. The Williams diagram is sketched to show graphically the applicability domain of the proposed method. The existence of a majority of solution GOR data in the domain $0 \leq H \leq 0.1428$ and $-3 \leq$ Standardized Residuals $\leq$ demonstrates that the method is statistically valid. The data points which are located in the domain range-3 $\leq$ Standardized Residuals $\leq$ are recognized as valid solution GOR data, and data which are outside the range are considered as outliers. The results show that only 26 data points in the solution GOR databank (among more than 1000 data points) were identified as outlier data points (Figure 8).

Conclusion

The linear interaction and general optimization method, as a modeling approach, was applied in the development of an accurate and reliable model for calculating solution GOR data. A comprehensive databank comprising more than 1000 data samples collected from various geographical locations was compiled and used to develop a comprehensively applicable model. The performance of the model developed was compared to some widely-used empirical methods. The influence of the reservoir fluid properties on the estimated solution GOR data was also investigated. Finally, applicability domain of the proposed method was determined through the detection of outlier data points using the Leverage approach. It is found that only 26 data points (among more than 1000 data values) are identified as outlier data points. The results obtained indicate that the model proposed in this study outperforms all comparable models studied with an AARD value of 19.83%. The sensitivity analysis conducted in this study indicates that bubble point pressure and gas gravity have the largest and smallest influences, respectively, on the predicted solution GOR data. Furthermore, the model proposed in this study has greater applicability for the estimation of solution GORs for reservoirs containing light oils.

Data Index	This Study	ARD%	Baniasadi	ARD%	D& Christman	ARD%	Al-Marhoun	ARD%	Macary	ARD%	Al-Shamasi	ARD%
1	219.0	4.9	102.8	50.8	291.9	39.9	194.7	6.7	288.9	38.4	199.0	4.6
2	250.2	3.8	150.2	42.2	323.3	24.4	260.2	0.1	310.8	19.5	236.7	9.0
3	52.4	0.0	39.5	28.5	78.5	42.3	35.6	35.5	64.2	42.3	43.6	3.4
4	66.1	2.9	57.7	15.2	92.7	36.3	50.8	25.4	75.5	36.0	59.4	6.9
5	174.6	1.8	36.5	6.5	91.1	133.6	40.2	3.0	40.0	2.5	28.5	27.0
6	555.0	0.2	38.9	22.5	53.7	69.0	20.2	36.4	44.3	70.9	27.4	5.9
7	30.3	6.6	170.0	17.6	167.8	18.7	142.0	31.2	161.5	4.1	170.4	1.2
8	80.2	16.1	669.0	12.1	631.0	17.1	856.4	12.5	1107.4	78.3	900.9	45.0
9	240.4	0.2	241.8	0.8	184.0	23.3	163.4	31.9	233.7	19.4	264.7	35.2
10	152.3	11.3	167.3	2.6	123.2	28.3	106.1	38.2	132.3	5.6	163.9	16.9
11	658.8	3.0	776.1	10.2	729.1	3.5	996.8	41.5	1094.5	90.4	1064.8	85.2
12	75.8	1.1	324.2	5.2	257.2	24.7	364.2	6.5	265.4	4.9	366.0	31.2
13	678.0	1.6	749.8	23.6	653.9	7.8	665.6	9.7	909.5	83.7	967.1	95.3
14	311.7	0.5	331.2	5.7	250.8	20.0	344.2	9.8	252.9	1.1	362.2	41.6
15	490.7	1.0	366.7	3.8	404.7	6.2	591.2	55.2	200.3	47.4	356.3	6.5
16	1694.3	3.8	473.4	0.4	376.5	20.2	595.1	26.2	369.2	4.1	546.3	41.9
17	299.5	0.0	616.6	22.1	492.0	37.8	510.4	35.5	535.7	32.3	692.3	12.5
18	547.4	0.1	633.3	0.1	461.5	27.2	440.4	30.5	493.2	22.2	702.5	10.8
19	371.2	1.0	426.7	16.1	265.6	27.8	376.6	2.5	290.3	3.2	487.6	62.5
20	601.4	5.5	690.7	8.5	478.9	24.8	699.1	9.8	526.9	1.4	889.1	71.1
21	323.9	7.6	400.1	33.0	177.6	41.0	230.1	23.5	240.0	20.2	497.8	65.4

Table 4: A point-to-point comparison between the results obtained with the proposed model and comparative methods for the experimental records reported in Table 3.

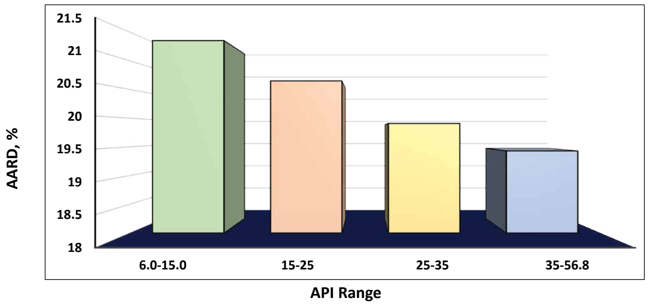

Figure 6: Accuracy of the model developed in this study in different API ranges.

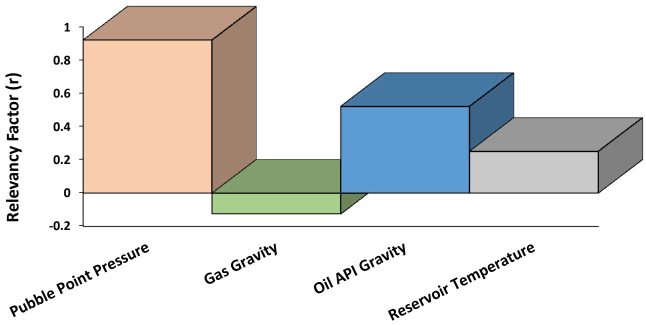

Figure 7: Degree of importance for each input parameter for the prediction of solution gas-oil ratio.

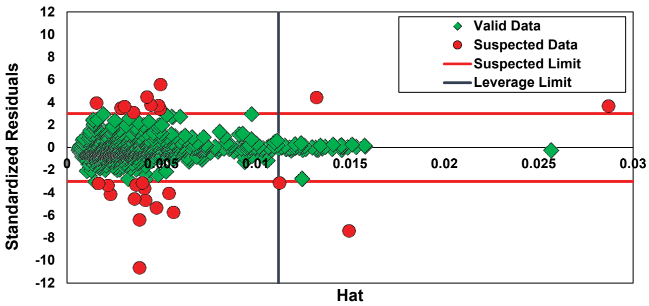

Figure 8: Graphical plot of the leverage analysis for the recognition of outlier data points.

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