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Improved oil formation volume factor (B_o) correlation for volatile oil reservoirs: An integrated non-linear regression and genetic programming approach

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Abstract In this paper, two correlations for oil formation volume factor (B_o) for volatile oil reservoirs are developed using non-linear regression technique and genetic programming using commercial software. More than 1200 measured values obtained from PVT laboratory analyses of five representative volatile oil samples are selected under a wide range of reservoir conditions (temperature and pressure) and compositions. Matching of PVT experimental data with an equation of state (EOS) model using a commercial simulator (Eclipse Simulator), was achieved to generate the oil formation volume factor (B_o). The obtained results of the B_o as compared with the most common published correlations indicate that the new generated model has improved significantly the average absolute error for volatile oil fluids. The hit-rate (R^2) of the new non-linear regression correlation is 98.99% and the average absolute error (AAE) is 1.534% with standard deviation (SD) of 0.000372. Meanwhile, correlation generated by genetic programming gave R^2 of 99.96% and an AAE of 0.3252% with a SD of 0.00001584.

The importance of the new correlation stems from the fact that it depends mainly on experimental field production data, besides having a wide range of applications especially when actual PVT laboratory data are scarce or incomplete.

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1. Introduction

The properties of reservoir fluids (PVT data) are critical in petroleum engineering computations, i.e. well test analysis, inflow performance, material balance and reserve calculations, as well as reservoir numerical simulations. In ideal cases, these properties are measured in laboratory based on down hole samples or recombined surface samples representing the reservoir zone of interest.

Most commonly these experimental measurements are very expensive and costly to obtain. Hence, the importance of the application of the modern PC-based programming, EOS, and simulation techniques, in addition to other statistical and empirical regression approaches, to provide better approximation and/or prediction of these properties, based on previously measured data (Lashin et al., 2006; Lashin, 2007; Fattah et al., 2009; Lashin and Serag El Din, 2013).

Oil formation volume factor (B_o) is the most important among other PVT properties that should be carefully measured for detailed reservoir characterization and other production computations. As far as the measured PVT properties are accurate and good (including B_o), the other dependent calculations of reservoir performance, production operations and formation evaluation, will be good (Fattah et al., 2009). Based on the reservoir fluid's nature, prevailing condition and type of applied correlations, many modern PVT simulator programs are developed and recently utilized in petroleum industry to predict preciously the different reservoir properties with different accuracies.

In the last few decades, extensive studies have been done by many researchers to develop a good correlation of B_o for better PVT calculations. Several previous correlations of B_o (back to 50 years ago) have been proposed and demonstrated in the literature. These correlations are based mainly on the assumption that the oil formation volume factor (B_o) is strongly a function of the solution gas–oil ratio (R_s), the reservoir temperature (T), the gas specific gravity (SG_g), and the oil specific gravity (SG_o), (Glaso, 1980; Standing, 1981; Kartoatmodjo, 1990; Kartoatmodjo and Schmidt, 1991, 1994; Al-Marhoun, 1992; Frashad et al., 1996; Velarde et al., 1997; El-Sebakhy, 2009; Fattah, 2005; Fattah et al., 2009). In the last few decades many statistical and PC-based programming methods are used to develop a good correlation of oil formation volume factor (B_o). Among these, nonlinear regression analysis and genetic algorithm methodologies are most commonly used (Soreide, 1989; Tang and Zick, 1993; Koza, 1992, 1997; Coats et al., 1998; Dalgaard, 2008; Souahi, 2008; Schebetov et al., 2010; Khan et al., 2012, etc.).

In nonlinear regression analysis, the observational data are modelled depending on one or more independent variables using a nonlinear function that utilizes a combination of modelled parameters. Least-squares regression technique is applied upon the nonlinear weighted values to minimize the sum-of-squared residuals between measured and simulated quantities. The data are fitted by a method of successive approximations (Dalgaard, 2008).

Genetic programming (GP) is evolution strategies that are based on the mechanics of natural selections. It belongs to the probabilistic search approach category known as "Evolutionary Algorithms" that uses natural PC-based models to develop computerized solutions of different problems (Fattah, 2012, 2014).

The Darwinian principle that constitutes the basics of the GP involves four steps to solve a specific problem (Koza, 1992, 1997). These steps are, (1) generating an initial input to the problem based on population of random composition, (2) executing the specific program for each population and assigning the necessary fitness value, (3) creating a new computer programs (offspring population) and, (4) designing the best PC program that is appropriate for each generation.

The aim of this work is to generate new correlations for oil formation volume factor (B_o) regarding volatile oil reservoir. It involves two approaches; the first includes accurate determination of the B_o through comparing different correlations, while the second implies the development of a new correlation using an integrated non-linear regression and genetic programming methods. The B_o developed by Whitson and Torp (1983) is used to validate the new generated correlation.

2. Correlations of oil formation volume factor (B_o): a review

Many correlations are utilized to deduce oil formation volume factor (B_o) for black oil reservoir. One of the oldest correlations was that of Standing (1947) who published correlations for estimating oil formation volume factors of gas-saturated oils using field values of reservoir temperature, solution gas–oil-ratio at the bubble point, and the oil and gas gravities.

A large number of experimentally measured values (up to 105 readings), from 22 different California mixed oil–gas samples were used in the correlation development. More accurate correlations for estimating the bubble-point pressure, as well as the solution gas–oil ratio and the oil formation volume factor at the bubble-point for gas saturated black oils were presented by Glaso (1980). The analysis is based on dataset of 26 different crude oil systems, primarily from the North Sea region. Vasques and Beggs, 1980 used laboratory measurements resulted from more than 600 crude oil systems to develop empirical correlations for several oil parameters including the solution gas-oil ratio and the oil formation volume factor (both at bubble-point). Their database included approximately 6000 measured values over wide ranges of reservoir condition (pressure and temperature) and oil and gas gravities.

Al-Marhoun (1988) developed correlations for estimating the bubble-point pressure, as well as the solution gas–oil-ratio and oil formation volume factor for Middle East crude oils at bubble point pressure. These correlations were developed from a database of 69 bottom hole fluid samples and expressed as a function of reservoir temperature, gas gravity, solution gas–oil-ratio (at Pb), and the stock tank oil gravity. Al-Marhoun used nonlinear regression methods in the development of his correlations.

Kartoatmodjo and Schmidt (1994) presented what should be considered the most comprehensive study of black oil PVT properties. They developed a new set of empirical correlations based on a large data collection developed from reservoirs all over the world. The authors used two independent databases; the first database was used to develop the correlations while the second was used as a benchmark for verification purposes. The first database involved 740 different crude oil samples (5392 points) and the second database contained 998 data points.

Table 1 Properties of fluid samples used in this study (Fattah, 2005).

Property	Vo 1	Vo 2	Vo 3	Vo 4	Vo 5
Reservoir temperature (°F)	249	246	260	190	197
Initial reservoir pressure (psig)	NA	5055	5270	NA	13668
Initial producing gas–oil ratio (SCF/STB)	1991	2000	2032	2424	2416
Stock oil gravity (°API)	45.5	51.2	NA	36.8	34.1
Saturation pressure (psig)	4527	4821	4987	7437	9074
Components	Composition (Mole%)				
CO_2	2.14	2.18	2.4	0.1	0.34
N_2	0.11	1.67	0.31	0.16	0
C_1	55.59	60.51	56.94	69.84	72.47
C_2	8.7	7.52	9.21	5.37	4.57
C_3	5.89	4.74	5.84	3.22	2.79
iC_4	1.36	4.12	1.44	0.87	0.67
nC_4	2.69	0	2.73	1.7	1.33
iC_5	1.17	2.97	1.03	0.79	0.69
nC_5	1.36	0	1.22	0.88	0.82
C_6	1.97	1.38	1.96	1.41	1.52
$\mathbf{C_{7+}}$	**19.02**	**14.91**	**16.92**	**15.66**	**14.8**

C7 plus the heavier components of the oil fluid.

Fattah et al. (2009) developed a new set of correlations for volatile oil and gas condensate reservoirs. They modified the existing correlation for the solution gas-oil-ratio, the gas formation volume factor, the oil gas ratio and the oil formation volume factor to be more reasonable and accurate.

3. Dataset and methodology

3.1. Fluid samples

Five fluid samples of volatile oil (VO) were mainly used in this study. These fluids are taken from reservoirs denoting various locations and depths, and are chosen to cover an extensive range of volatile oil fluid properties (Fattah, 2005). Some of the utilized samples are representing near critical reservoir as clarified by McCain and Bridges (1994). Table 1 exhibits the main characteristics of these fluids.

3.2. Approach

Equations of state models were used in commercial simulator software "Eclipse Simulator 2009.1" to develop a special model for each sample in Table 1 (Schlumberger, 2005). The approach generated by Coats and Smart (1986) was followed to match the laboratory results, while Peng and Robinson (1976) model, that implies volume shift correction (3-parameter EOS), was used to develop a consistent EOS models. Whitson and Torp (1983) procedure is utilized to develop Equations of state models for each of the five samples that were further used to output the modified black oil (MBO) PVT properties (R_v, R_s, B_o, and B_g) at six different separator conditions. The extracted data from the PVTi program for the MBO PVT properties, involve more than 1200 points from the different five volatile oil samples (Fattah, 2005).

Two techniques were used to generate the new B_o for volatile oil reservoir. The first was executed using non-linear regression technique, while the second by applying genetic programming.

3.2.1. Non-linear regression technique

The regression analysis technique is similar in calculations to the correlation coefficient. The linearity or nonlinearity of the pattern of data is checked using a specific plotting or what is called scatter gram. The results of a regression analysis, usually demonstrates the regression equation and coefficients, their significance levels and variances of both regression coefficients and residuals (Pidwirny, 2006). Data fitting is enhanced by choosing coefficients to minimize the sum of the squares of the errors. Excel's optimization tool (Solver) can be used to do this task and executing the regression analysis.

3.2.2. Genetic programming

Commercial GP software named Discipulus was utilized to obtain the new B_o correlation (Foster, 2001; Francone, 2004). It is GP steady-state software that makes use of the tournament selection. It uses two pairs of individuals that complete each round for regeneration and enable usual parameters to be regulated, (i.e. mutation and crossover rates, population size, instruction set, and initial program sizes distribution) (Foster, 2001). For each run, setting of parameters, randomizing and optimizing of the GP parameters are usually automated and performed by Discipulus. The tournament selection is used in this study along with other default parameters of 90% for probability of mutation rate frequency, 50% for crossover frequency and 500 as a population size (number of population runs).

Discipulus utilizes two important parameters to control the size of the programs.

A fitness function is usually used in the genetic programming algorithms. This function depends mainly on whether a classification problem or a regression problem is presented to Discipulus. In General, the better the training data are

Table 2 Statistical comparison of all correlations using observed data.

Correlation	Absolute error (average) (%)	Standard deviation	Correlation of determination % (R^2)
Standing (1947)	4.55	0.0028	95.52
Vasques and Beggs (1980)	3.52	0.0019	93.85
Glaso (1980)	2.51	0.0012	97.49
Al-Marhoun (1988)	10.68	0.0163	80.35
Kartoatmodjo and Schmidt (1994)	3.27	0.0013	98.77
Fattah et al., 2009	1.967	0.00073	98.68
New correlation by non-linear regression	1.534	0.00037	98.99
New correlation by genetic program	0.325	0.000016	99.99

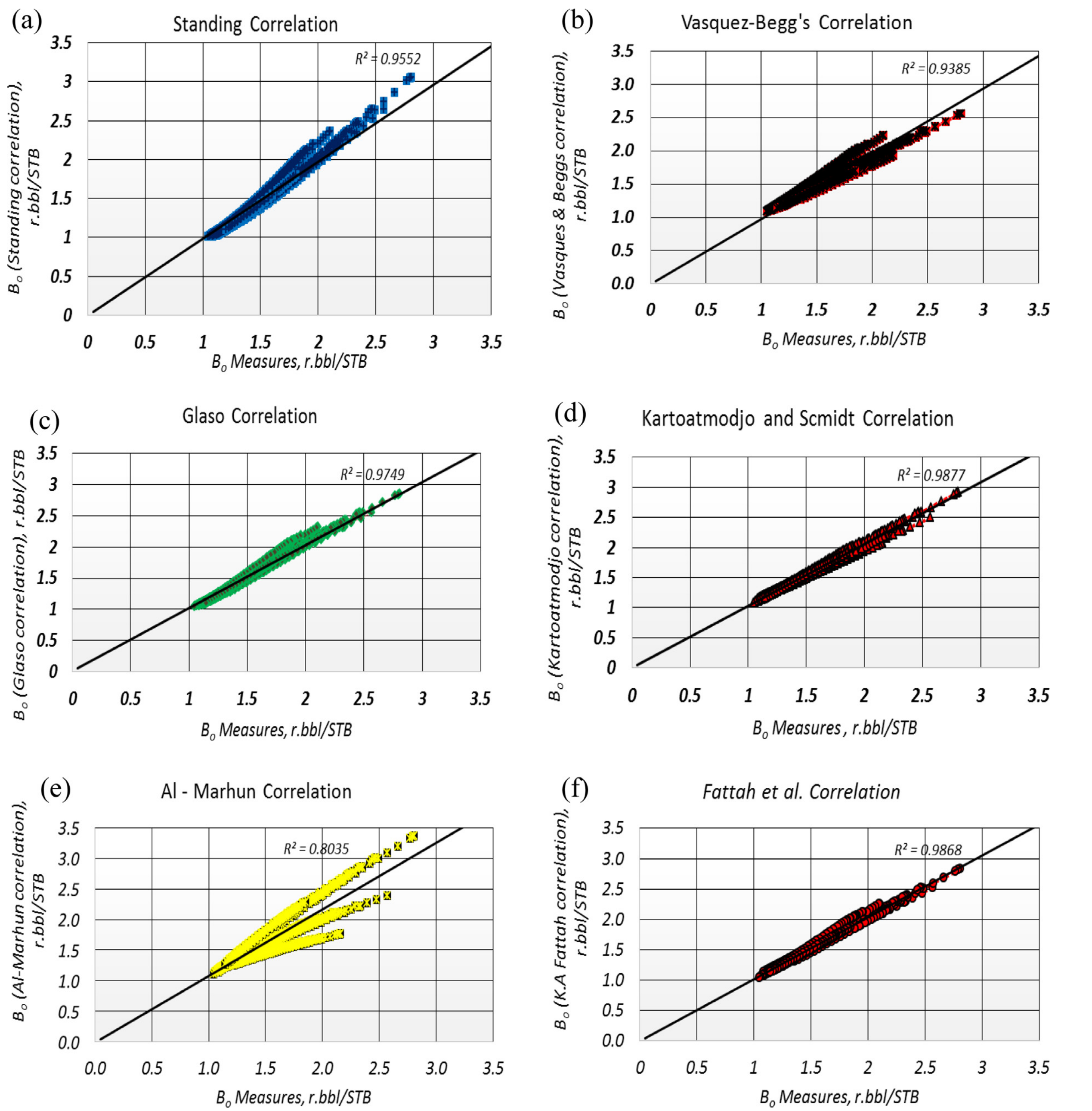

Figure 1 Crossplot for B_o correlation for volatile oil samples (a. Standing (1947), b. Vasques and Beggs (1980), c. Glaso (1980) correlation, d. Kartoatmodjo and Schmidt (1994), e. Al-Marhoun (1988), f. Fattah et al. (2009)).

modelled by an evolved program, the more fit will be the result (the closer the match of data, the fitter the generated program). Discipulus determines the fitness of generated programs by checking the matching between final outputs and initial training data. Two parameters are very important as a fitness measurement, (i.e. the hit-rate (R^2) and the fitness variance), (Fattah, 2014). The program input data are further differentiated into three semi-equal sets, (training set, validation set and applied set). A group of input files, including both input and output parameters, are utilized to enhance the intended B_o correlation. Usually the input parameters are the reservoir temperature (R^o), the solution gas oil ratio (R_S), the surface gas specific gravity (SG_g) and the surface oil specific gravity (SG_o), while the output is the oil formation volume factor (B_o).

4. Results and discussion

4.1. B_o correlations

Comparisons between the most common correlations that are utilized to calculate the oil formation volume factor (B_o) for volatile oil (presented in the literature) are shown in Table 2. The comparison of the Standing (1947) correlation with the measured oil formation volume factor B_o for volatile oil reservoirs results in AAE of 4.554% with a SD of 0.0028. Fig. 1.a presents cross-plots for B_o (Standing correlation) vs B_o from laboratory reports for the volatile oil samples. The Vasques and Beggs correlation 1980 exhibits an AAE of 3.515% with a SD of 0.00185 and a coefficient of determination of 95.5%. Fig. 1b shows cross-plots for B_o (Vasques and Beggs, 1980) vs. measured B_o for volatile oil samples. The Glaso correlation (1980) is represented in Fig. 1c. It shows good correlation of 97.5% with an AAE of 2.506% and SD of 0.00119. Al-Marhoun correlation (1988) is represented in Fig. 1d. It shows lower correlation of determination (80%) and high AAE (10.681%) compared to other methods. Kartoatmodjo and Schmidt (1994) correlation gave good coefficient of determination 98.7% low AAE and SD of 3.2682% and 0.0013, respectively (see, Fig. 1e). Among the demonstrated correlations, the best result was given by Fattah et al. (2009). It gives low AAE of 1.966%, low SD of 0.00073 and good coefficient of determination of 98.68% (Fig. 1f).

4.2. Developed B_o correlation using non-linear regression technique

Using the non-linear regression analysis, the following relation for oil formation volume factor (B_o) was developed.

$$B_o = a_1 + a_2 * R_s + a_3 * (T - 460) * \left(\frac{\gamma_o}{\gamma_g}\right)$$

where B_o is the oil formation volume factor, r.bbl/STB, R_S is the solution gas oil ratio, MSCF/STB, T is the reservoir temperature, R^o, and $T \geqslant 580$, γ_o is the specific gravity of surface oil, γ_g is the specific gravity of surface gas, and

$$a_1 = 1.77682494, \quad a_2 = 0.000560993, \quad a_3 = 1.22421E - 05$$

Fig. 2 presents the crossplot of B_o new correlation by non-linear regression vs the measured B_o of volatile oil samples. Good coefficient of determination (R^2) of 98.99% with an average low absolute error and standard deviation of 1.534% and 0.000372 were obtained. Fig. 3, on the other hand, is a crossplot of the PVT-related B_o and non-linear regression-derived B_o against pressure for one selected sample (sample one "Vo 1", see Table 1). It shows good correlation fit with the measured data.

Figure 2 Crossplot for B_o New correlation by non-linear regression for volatile oil samples.

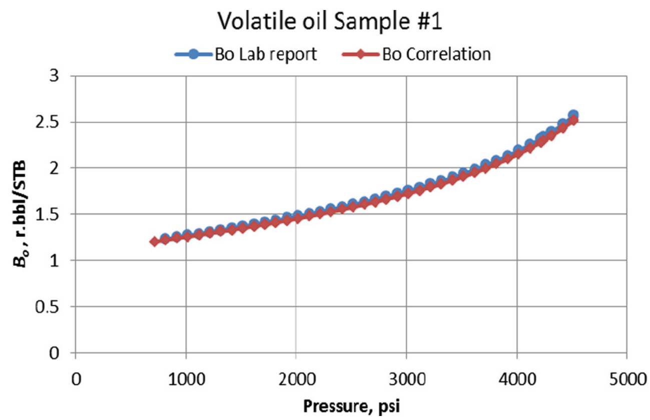

Figure 3 Crossplot of B_o extracted from PVT Lab measurements and new correlation using non-linear regression vs pressure for sample 1.

However, the improvement in the performance of the new correlation compared with the common correlation is not significant; therefore, genetic programming technique was applied to develop new correlation with much improved performance/accuracy.

4.3. Developed B_o correlation using genetic programming

The improved performance of each run, its progress and associated data and charts can be clearly indicated in Discipulus program. It can create thousands of runs (models) from a given inputs data sets that enable good prediction of the outputs (performance is judged by the hit-rate (R^2) and the fitness variance). The best GP is selected based on its hit-rate (R^2) and fitness variance to be applied in deriving the oil formation volume factor (B_o).

Fig. 4 presents the best raised genetic program with is improved fitness with time for the new correlation. The R^2 of the best GP is found to be 99.96% with fitness variance of 0.0000303. Since the input data for the Discipulus program are differentiated into three groups of data (training, validation and applied), Fig. 5 displays the matching between the

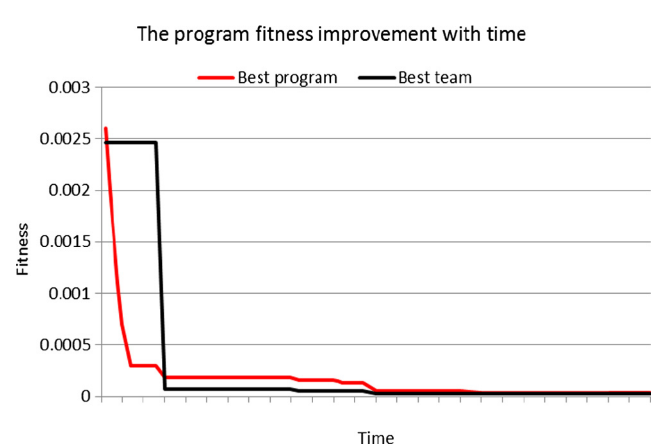

Figure 4 The program fitness improvement with time.

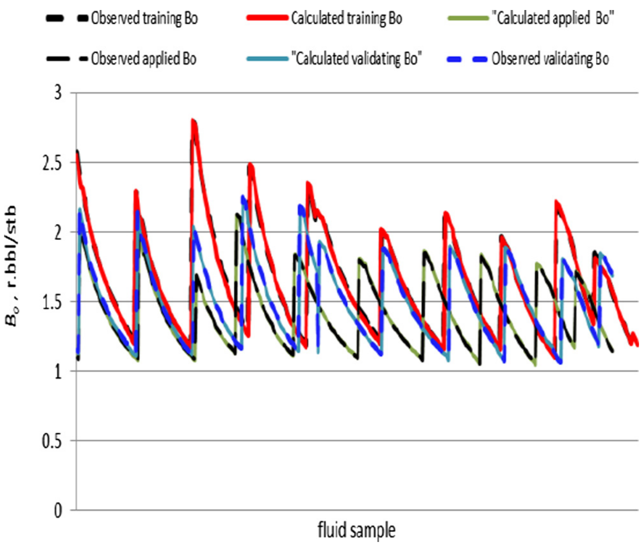

Figure 5 The observed vs calculated B_o data form input data.

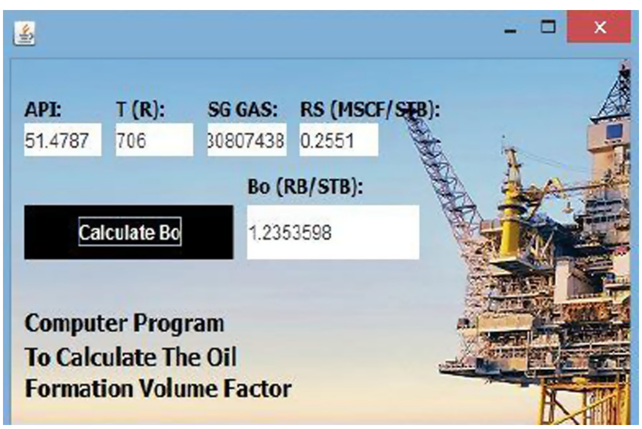

Figure 6 The windows interface of the genetic program.

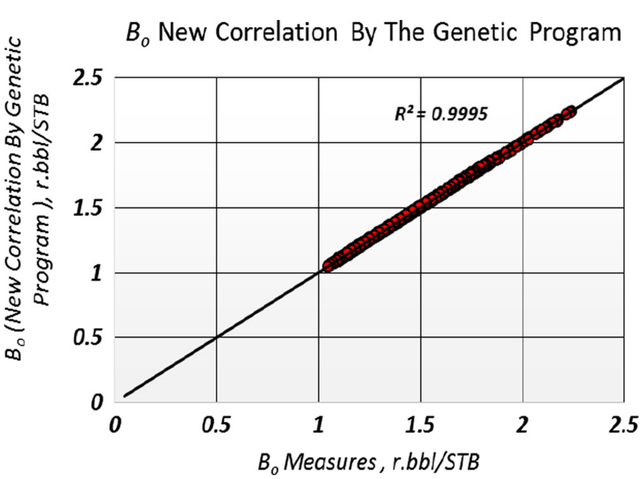

Figure 7 Crossplot of measured and new generated B_o correlation by genetic program for volatile oil samples.

measured and the calculated B_o for each input data category. The matching between the measured and the calculated B_o inputs is obtained from the best run enhanced by the software.

The model output is generated as a computer program, (i.e. Java, C++ code, or assembler). The result program was further used with C++ compiler to build a windows-based interface to be used in calculating B_o value (Fig. 6). This code can be changed and modified, when needed, to generate an oil formation volume factor (B_o) array for different reservoir regimes. Cross plotting of measured B_o against the calculated one was used to validate the model (Fig. 7). The AAE and the SD for the new correlation are found to be 0.3252% and 0.00001584, respectively (coefficient of determination > 99.9%). Table 2 exhibits the statistics of the different correlations as compared with the new generated one. One can easily recognize that the new GP correlation is the most accurate correlation among those developed and tested.

5. Conclusions

The data used in this study are in the form of more than 1200 measurements that are collected from the PVT laboratory analysis of five representative volatile oil fluid samples. These samples were selected under a wide range of reservoir composition and condition (temperature and pressure) and were utilized mainly in generating a new oil formation volume factor (B_o), for volatile oil reservoir. Two B_o correlations were developed using non-linear regression and genetic programming (GP) techniques. Based on the results obtained, the following can be concluded:

1. A new correlation that depends mainly on experimental field production data and has a wide range of applications is evolved in this work. It can be further incorporated with other aspects of correlations to generate reservoir fluid properties (PVT data) without further EOS calculations, especially when actual PVT laboratory data are scarce or incomplete.
2. Comparison of different correlations, previously approached by many researchers indicates that Fattah et al. (2009) correlation was found to be the best in terms of the low AAE of 1.97%, low SD of 0.00074, and correlation coefficient of 98.68%.
3. The obtained results of B_o correlations as compared with the most common published correlations indicate that the new proposed model has improved significantly the average absolute error for volatile oil fluids.
4. The coefficient of determination (R^2) of the new correlation by non-linear regression was 98.99% and the average absolute error was 1.534% with a standard deviation of 0.00037.
5. A very good new correlation of 99.99% is generated based on genetic programming technique with a fitness variance of 0.0000303, AAE of 0.3252% and a SD of 0.00001584.

References

Al-Marhoun, M.A., 1988. PVT correlation for Middle East crude oils. J. Pet. Technol. 40 (5), 650–666.

Al-Marhoun, M.A., 1992. New correlations for formation volume factors of oil and gas mixtures. J. Can. Pet. Technol. 31 (3), 22. http://dx.doi.org/10.2118/92-03-02, PETSOC-92-03-02.

Coats, K.H., Smart, G.T., 1986. Application of a regression-based EOS PVT program to laboratory data. SPERE, 277–299.

Coats, K.H., Thomas, L.K., Pierson, R.G., 1998. Compositional and black oil reservoir simulation. SPE Res. Eval. Eng. 1 (4), 372–379. http://dx.doi.org/10.2118/50990-PA, SPE-50990-PA.

Dalgaard, P., 2008. Nonlinear Regression Analysis. Department of Biostatistics, University of Copenhagen.

El-Sebakhy, A.E., 2009. Forecasting PVT properties of crude oil systems based on support vector machines modeling scheme. J. Pet. Sci. Eng. 64, 25–34.

Frashad, F., LeBlanc, J.L., Garber, J.D., 1996. Empirical PVT correlations for Colombian crude oils. In: SPE Latin American and Caribbean Petroleum Engineering Conference, Port of Spain, Trinidad and Tobago, SPE-36105-MS. http://dx.doi.org/10.2118/36105-MS.

Fattah, K.A., 2005. Volatile Oil and Gas Condensate Fluid Behavior for Material Balance Calculations and Reservoir Simulation (Ph.D. thesis). Cairo University, Egypt.

Fattah, K.A., El-Banbi, A.H., Sayyouh, M.H., 2009. New correlations to calculate volatile oil, gas condensate PVT properties. Oil Gas J., 41–46.

Fattah, K.A., 2012. *K*-value program for crude oil components at high pressures based on PVT laboratory data and genetic programming. J. King Saud Univ. Eng. Sci. 24 (2), 141–149.

Fattah, K.A., 2014. Gas–oil ratio correlation (RS) for gas condensate using genetic programming. J. Pet. Explor. Prod. Technol. 4 (3), 291–299.

Foster, J.A., 2001. Review "discipulus": a commercial genetic programming system. Register Machine Learning Technologies.

Francone, F.D., 2004. Discipulus, owner's manual. Machine Learning Technologies.

Glaso, O., 1980. Generalized pressure–volume–temperature correlations. J. Pet. Technol. 32 (5), 785–795.

Kartoatmodjo, T., 1990. New Correlations for Estimating Hydrocarbon Liquid Properties (MS thesis). University of Tulsa, Tulsa, Oklahoma.

Kartoatmodjo, T., Schmidt, Z., 1991. New correlations for crude oil physical properties. Soc. Pet. Eng., Unsolicited paper 23556-MS

Kartoatmodjo, T., Schmidt, Z., 1994. Large data bank improves crude physical property correlations. Oil Gas J. 92 (27), 51–55.

Khan, N.M., Bilal, H.M., Shoaib, M., Manzoor, A., Shaukat, W., Shakil, T., 2012. Fluid characterization of a retrograde gas condensate reservoir for the simulation study. In: SPE/PAPG Annual Technical Conference, Islamabad, Pakistan, 3 5 December, Paper SPE163134.

Koza, J.R., 1992. Genetic Programming: On the Programming of Computers by Means of Natural Selection. The MIT Press, Cambridge, MA.

Koza, J.R., 1997. Genetic programming. In: Encyclopedia of Computer Science and Technology, 18 Aug.

Lashin, A., 2007. Velocity modeling of the upper cretaceous Bahariya reservoir, using variogram and principal component analyses, North of Qattara Depression, Western Desert-Egypt. J. Appl. Geophys. 6 (1), 279–303.

Lashin, A., Serag El Din, S., 2013. Reservoir parameters determination using artificial neural networks: Ras Fanar field, Gulf of Suez, Egypt. Arab. J. Geosci. 6, 2789–2806.

Lashin, A., Ahmed, G., Abd El Aal, M., 2006. Improving and predicting the petrophysical parameters of the reservoirs using Monte Carlo Simulation and Stochastic analysis. J. Egypt. Geophys. Soc. (EGS) 4 (1), 1–16.

McCain Jr, W.D., Bridges, B., 1994. Volatile oils and retrograde gases what's the difference? Pet. Eng. Intern. 66 (1), 45–46.

Pidwirny, M., 2006. Fundamentals of Physical Geography, second ed. (Chapter 3 Sec. H).

Peng, D.Y., Robinson, D.B., 1976. A new two-constant equation of state. Ind. Eng. Chem. Fundam., 15–59

Schebetov, A., Rimoldi, A., Piana, M., 2010. Quality check of gas-condensate PVT studies and EOS modeling under input data uncertainty. In: Paper SPE 133258 Presented at the SPE Gas Technical Conference and Exhibition Held in Moscow, Russia, 26–28 October.

Schlumberger, 2005. Eclipse Simulator. ECLIPSE suite of programs. User manual.

Soreide, I., 1989. Improved Phase Behavior Prediction of Petroleum Reservoir Fluids from a Cubic Equation of State (Ph.D. theses). Norwegian Institute of Technology, Department of Petroleum Engineering.

Souahi, F., 2008. Developing correlations for prediction of petroleum fraction properties using genetic algorithms. Oil Gas Sci. Technol. 63 (2), 229–237.

Standing, M.B., 1947. A Pressure–Volume–Temperature Correlation for Mixture of California Oils and Gases. Drilling and Production Practice. API, New York, pp. 275–287.

Standing, M.B., 1981. Volumetric and Phase Behavior of Oil Field Hydrocarbon Systems, ninth ed. Society of Petroleum Engineers of AIME, Richardson, Texas.

Tang, D.E., Zick, A.A., 1993. A new limited compositional reservoir simulator. In: SPE Symposium on Reservoir Simulation, New Orleans, Louisiana, 28 February-3 March. http://dx.doi.org/10.2118/25255-MS, SPE-25255-MS.

Vasques, M., Beggs, H.D., 1980. Correlation for fluid physical property prediction. JPT, 968–970.

Velarde, J., Blasingame, T.A., McCain Jr., W.D., 1997. Correlation of black oil properties at pressures below bubble point pressure – a New approach. In: Presented at the Annual Technical Meeting of CIM, Calgary, Alberta, 8-11 June. PETSOC-97-93.

Whitson, C.H., Trop, S.B., 1983. Evaluating Constant-Volume Depletion Data. SPE, Richardson, Paper SPE 10067.