Optimization of Formation Volume Factor and Solution Gas-Oil Ratio Correlations for Southern Iranian Oil fields Using Genetic Algorithm

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Abstract: Reservoir fluid properties have a critical role in reservoir engineering computations such as material balance calculations, well test analysis, reserve estimates, inflow performance analysis, recovery and numerical reservoir simulations. Ideally PVT properties are obtained by experimental methods which are expensive and time consuming. To resolve this problem empirical correlations are used. The prediction reliability of these correlations strongly depend on the range of data used for developing them originally and the fluid compositions of different geographical locations. In this research, the well-known correlations of two essential PVT parameters, formation volume factor and solution gas-oil ratio, are selected and optimized for southern Iranian oil fields. Genetic algorithm as an effective optimization method is applied to accomplish this task. The results for locally optimized correlations show significant improvements over the classical correlations.

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1.Introduction

Reservoir is a volume of porous rock which is filled with substantial amount of hydrocarbons such as crude oil and natural gas. High precision data of rock and fluid properties are essential for reliable reservoir modeling, reservoir engineering calculations, performance prediction by reservoir simulators and also for economic planning (Al-Hussainy and Humphreys, 1996). Generally reservoir properties consist of parameters which are used for characterization of geological information (Khouki. A ,2012).

Characterization of reservoir fluids have a major role in development of a strategy for reservoir production and operation.Since material balance calculations, well test analysis, reserve estimates, inflow performance analysis, recovery and numerical reservoir simulations all depend on the reservoir fluid properties, they are critical in reservoir engineering computations (El-Sebakhy A. E, 2009).

For characterization of any hydrocarbon reservoir, pressure, volume and temperature (P.V.T) are essential parameters. In general it is not possible to have accurate estimates for most of petroleum engineering problems without having accurate estimates of these properties. Furthermore, controlling the volume of reservoir and surface hydrocarbons and amount of underground withdrawal is only possible by knowing the oil PVT properties.

The volumetric and phase behavior of reservoir fluids is referred to as P.V.T. (pressure, Volume, Temperature). These properties include bubble point pressure, formation volume factor, solution gas–oil ratio (GOR), solution oil–gas ratio (OGR), liquid specific gravity, API specific gravity, gas specific gravity, saturation pressure and the likes, (Standing, 1962). Among these PVT properties, bubble point pressure (P_b) and oil formation volume factor B_o and solution gas-oil ration (R_s) are the most important parameters because they are the critical in reservoir and production computations (Standing 1962). PVT properties are obtained from experimental studies on samples collected from the bottom of the wellbore or on the surface. Obtaining these experimental data is very expensive and time consuming. The solution is to use state equations, statistical regression, graphical techniques and empirical correlations to predict these properties. Development of correlations for PVT computations has been the area of extensive research resulting in large volume of publications in this context. In the previous decade several graphical and mathematical correlations for both P_b and B_{ob} are proposed.

These correlations are based on the assumption that both P_b and B_{ob} are functions of solution gas-oil ratio (R_s), the reservoir temperature (T_f), the gas specific gravity (G_g), and the oil specific gravity (G_o). the reader can refer to El-Sebakhy et al (2007), Goda et al (2003), and Osman et al (2001) for more details. Equations of state involve many numerical calculations that require having detailed compositions of reservoir fluids which is an expensive and time consuming requirement. Moreover, their prediction is not reliable and mainly depends on range of data at which it was originally developed, geographical locations with similar fluid composition and API oil gravity. This is while the PVT correlations are based on field data that are available and can be easily measured such as reservoir pressure, reservoir temperature, and oil and gas specific gravity. (Khouki. A ,2012)

2.Empirical models for oil formation volume factor (B_o) and solution gas-oil ratio (Rs)

2.1.1Oil formation volume factor Bo

Oil formation volume factor is one of the most important PVT properties since it is one of the key factors in reservoir and production computations (Standing, 1962).Oil formation volume factor is defined as the volume of reservoir oil at the bubble point pressure and reservoir temperature that would be occupied by one stock tank barrel oil in addition to any dissolved gas (Olatunji , 2011)(3).

Oil formation volume factor at the bubble point pressure, can be defined as a function of solution gas oil ratio, average gas relative density, oil relative density and temperature (Hemmati et al 2007).

$$B_{ob} = \mathrm{F}\,(R_s, \gamma_o, \gamma_g, \mathrm{T}) \quad (1)$$

2.1.2.Empirical correlations for Bo

In the recent decades, engineers noticed the importance of developing empirical correlations for prediction of PVT properties. Studies conducted in this context resulted in development of different correlations such as Katz (1942), Standing (1947,1977), Vasquez et al (1980), Glaso (1980) and Al-Marhoun (1988, 1992).

The author in Glaso (1980) used 45 oil samples from a mixture of Northern Hydrocarbons to develop empirical correlations for oil formation volume factor. The author in Al-Marhoun (1988) used 160 datasets from 69 middle east reservoirs to obtain empirical correlations for B_o and P_b. The author in Almarhoun (1992) published his second correlation for formation volume factor at, below and above bubble point pressure based on 11728 experimental data points. The data were gathered from 700 oil reservoirs from all over the world mainly from middle east and north America. The reader can refer to Al-Shammasi (1997) and El-Sebakhy et al (2007) for more empirical correlations in this field.

The author in Labedi (1990) published correlations for oil formation volume factor for African crude oils. He used 28 data sets from Nigeria, 97 datasets from Libya and 4 datasets from Angola to develop his empirical correlations. The authors in (Dokla et al, 1992) used 51 datasets and developed correlations to estimate P_b and B_o for UAE crudes. They calculated new coefficients for Almarhoun middle east models (Almarhoun, 1988).

The authors in Macary et al (1992) used 90 dataset from 30 independent reservoirs in the Gulf of Suez to develop correlations for P_b and B_o. These new correlations were tested against data sets from Egypt in Saleh et al (1987) and showed improvements over the previously published correlations. The authors in Omar et al (1993) used 93 data sets from Malaysian oil reservoirs and published correlations for B_o based on standing model.

The authors in Kartoatmodjo et al (1994) used 740 oil samples including 5392 data sets from all over the world to develop correlations for all of PVT properties. The authors in Petoskey et al(1993) developed a new correlation based on Gulf of Mexico crude oil and also reported that the best correlation for oil formation volume factor is the Al-Marhoun correlation. The authors in McCain et al (1991) used a global database and performed a comprehensive evaluation of all PVT correlations. They also recommended the standing correlation (1947) for formation volume factor at and below the bubble point for future use.

The authors in Ghetto et al (1994) performed an extensive study on correlations of PVT properties based on a global database collected from the Mediterranean Basin, Africa, Middle East, and the North Sea reservoirs. They recommended both Vasquez and Beggs correlations for oil formation volume factor. The author in Elshakawy et al (1994) evaluated PVT correlations for Kuwait crude oils using 44 oil samples. They concluded that Almarhoun correlation (1988) gives satisfactory results for oil formation volume factor and Standing correlation provides the best results for bubble point pressure.

The authors in Mahmood et al(1996) performed and evaluation of PVT correlations for Pakistan crude oils. They used 166 datasets from 22 different crude oil samples. the authors in Hanafy et al (1997), evaluated the most accurate correlation for formation volume factor based on Macary et al (1992) to apply to Egyptian crude oils. The results showed the average absolute error of 4.9%, while the results in Dokla et al(1992) was 3.9%. Thus the study strongly recommends the application of a local correlation instead of a global one.

In Al-Fattah et al (1994) an evaluation of all the oil formation volume factor correlations is performed. In this study 674 datasets in the published literature are used and they pointed out that Almarhoun correlation (1992) has the least error for global dataset. Finally the author in Al-Shammasi (1997) evaluated the accuracy and flexibility of published correlations and neural networks for bubble point and oil formation volume factor for various mixtures of hydrocarbons from different geographical locations worldwide. He concluded that statistical and trend performance analysis shows that some of the correlations violate the physical behavior of hydrocarbon solutions (El-Sebakhy A. E, 2009). (1)

The paper is organized as it follows: In section 2 the basic definitions of formation volume factor and solution gas oil ratio are presented and the most common empirical correlations are discussed. Section 3 is dedicated to description of genetic algorithm optimization method and its details. In section 4, the correlations used in this study are presented and the obtained results are discussed .Section 5 concludes the paper.

2.2.1.Solution gas-oil ratio Rs

Solution gas oil ratio is an important factor in reservoir engineering computations. Correlations are used when the experimental data for PVT properties of a specific field are not available. Saving of time and cost are other advantages of correlations. Saving of cost and time are other advantages of correlations. Solution gas oil ratio, R_s, is the number of standard cubic feet of gas solved in a stock tank barrel oil in a specific pressure and temperature. The solubility of gas in crude oil is a function of pressure, temperature, API gravity and gas gravity. The solubility of gas in crude oil in a constant temperature increases by increasing the pressure until the saturation pressure is reached. At this pressure no more gas is solved and the gas solubility is at its maximum value. Figure 1 shows the solution gas oil ratio as a function of pressure for an under saturated crude oil. When the pressure decreases from the initial reservoir pressure P_i to the bubble point pressure P_b, no gas is liberated from the oil and the solubility remains at its maximum value R_{sb}. Below the bubble point the solved gas is liberated and R_s decreases as the pressure decrease. When solution gas oil ratio for a crude oil system is not available, it is necessary to determine this value by empirical correlations.

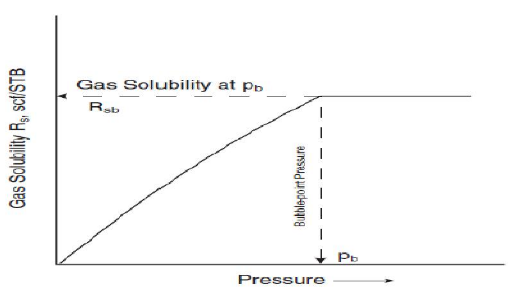

Fig. 1 Typical gas solubility/pressure relationship

2.2.2.Empirical correlations for solution gas oil ratio Rs

Many empirical correlations for solution gas oil ratio are discussed in this research. The correlations cover oils from USA, North Sea, Middle East, Gulf of Mexico, Iran and Libya. Three of them are based on global databases (Vasquez et al, 1980; Kartoatmodjo, 1994; Mazandarani et al, 2007). Standing (1947) presented a graphical correlation for solution gas oil ratio as a function of pressure, gas specific gravity, API gravity and system temperature. The correlation used 105 experimental data points obtained from a mixture of 22 hydrocarbons from California crude oil and natural gases. Standing (1987) presented his graphical correlation in mathematical form. Vasques and Beggs (1980) published an improved empirical correlation for estimation of R_s. They used 5000 data points and categorized them based on API gravity. Glaso (1980) published a correlation for solution gas oil ratio as a function of API gravity, pressure, temperature and gas specific gravity. The correlation is based on 45 crude oil samples from Northern sea. Marhoun used more than 60 different crude oil samples from middle east to develop a correlation for saturation pressure. He used nonlinear multiple regression analysis and a trial and error method for this purpose. The correlation can be rearranged and solved for solution gas oil ratio. Farshad and Petrosky (1993) published new correlations for Gulf of Mexico crudes. Standing correlation for solution gas oil ratio was used as the basic correlation to develop new coefficients. The approach was to apply nonlinear regression analysis to give the correlation the maximum flexibility in order to obtain the best empirical correlation. 90 data sets from the gulf of Mexico were used to develop this correlation.

Velarde, Blasingame and McCain (1999) published new correlations for solution gas oil ratio for pressures at and below the bubble point. In contrary to previous approaches, this correlation for solution gas oil ratio is not obtained by rearranging the correlation for bubble point pressure.

Two sets of dimensionless functions were considered for this correlation “reduced pressure” and “reduced solution gas oil ratio”. The reduced pressure variable is defined as the pressure divided by bubble point pressure and reduced solution gas-oil ratio variable is defined as the solution gas-oil ratio divided by the gas oil ratio at the bubble point. Mazandarani and Asghari (2007) tuned the Al-Marhoun’s correlation for Iranian oil reservoirs. They collected about 50 oil samples from different Iranian oil fields (Hassan. F. O, 2011).

2.3.Most common correlations for Bo and Rs

The most commonly applied correlations for Bo and Rs are provided below: (Standing, 1947; W. D. McCain, 1989).

$$\boldsymbol{B_o = 0.9759 + 12\left(10^{-5}\right)\left(CN\right)^{1.2}_{B_{ob}}} \quad (2)$$

$$(CN)_{B_o} = R_s \left(\frac{\gamma_s}{\gamma_{STO}}\right)^{0.5} + 1.25T \quad (3)$$

Where B_o is res bbl/STB, γ_o is the specific gravity of the stock-tank oil and T is the reservoir temperature in °F. Solution gas-oil ratio, in SCF/STB, at the bubble point is used for R_s to calculate B_{ob}; solution gas-oil ration at any pressure below the bubble point is used for R_s to calculate B_o at that pressure.

$$R_s = \gamma_g \left[\left(\frac{P}{18.2} + 1.4\right) 10^X\right]^{1.2048} \quad (4)$$

X= 0.00125 API-0.00091 [T-460]

Where T is the reservoir temperature in Ranking, γ_g is the gas specific gravity, P is the pressure in psi and R_s is the solution gas- oil ratio is in SCF/STB.

3. Genetic Algorithm

Genetic algorithms are a class of search algorithms that simulate the process of natural selection and evolution inspired by the Darwin's theory. They are also referred to as stochastic optimization algorithms and it is shown to work well in many engineering work grounds. Stochastic optimization algorithms are a family of optimization methods in which the solution space is searched by candidate solutions produced by a pseudo-random number generator. Since GA is a stochastic optimization algorithm it only needs to evaluate the objective function value in each set of decision variables in order to guide the search through the solution space ;no other specific information is required. This algorithm employs a binary coding of decision variables not the decision variables their selves. It searches a population of decision variable sets simultaneously not a single set of decision variables in each iteration (Goldberg, 1989). Different versions of genetic algorithm are developed but in general, the following elements are essential to implement a GA (Coello et al, 2002):

1.Initializing the potential solutions for the problem.

2.An objective function that evaluates the aggregated effect of decision variables. The algorithm proceeds to maximize or minimize the objective function.

3.A set of constraints for the decision variables that express the feasible set of combinations for the decision variables.

4.GA operators (cross over and mutation).

In genetics terminology, the solution space is referred to as environment, the potential solutions of the optimization problem are called chromosomes (solutions that represent a set of decision variables) and the total number of solutions is called population size. Every iteration of the optimization procedure is named a generation (G).

In general, reproduction, cross over, mutation and an elitist method are the basic components of an standard genetic algorithm. The GA proceeds by evaluating every set of decision variables in the population at each generation. Figure (2) illustrates the typical framework for the genetic algorithm. The first step in GA is to generate an initial population of P points randomly each involving n decision variables in the solution space. The decision variables are encoded as binary digits or real numbers.

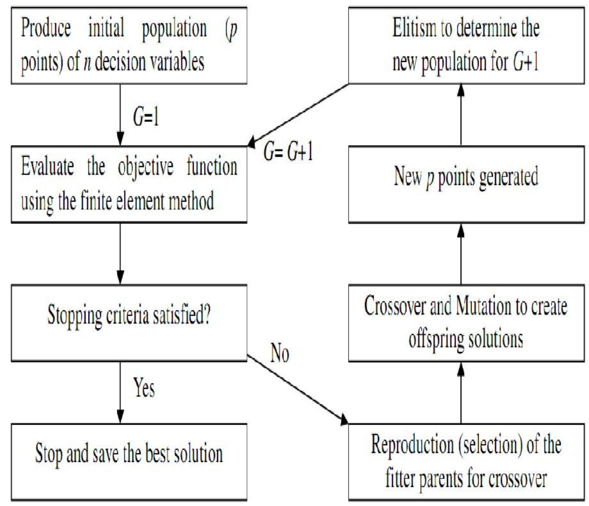

Figure (2). A generic framework for a simple genetic algorithm

The objective function value (fitness) is then calculated for each set of decision variables. Next, two points in the population are selected and are compared based on the objective function values. The point with a better objective function value will have a higher chance to survive. In minimization problems, points with lower objective function values have a higher chance for selection in the next generation. Then the two points are mated to generate a new point using genetic operators like cross over and mutation. This step is repeated until a population with P new points is generated. An elitist method is then applied to determine the final points in the new generation G+1. Thus the new generation is a collection of points with better fitness values from both P newly generated points and those in the previous generation. When the new generation is created the objective function of each individual is calculated. After some generation cycles, GA guides the population in the solution space towards solutions with better performance. The result is a more concentrated population around the optima. The GA algorithm stops progressing if a stopping criteria (number of generations, improvement of the best solution over the successive generations) is met (Lijie Cui et al, 2005).

3.1.Applying Genetic Algorithm to the correlations

Equations (4) and (5) show the correlations and their coefficients (indicated by letter C) that should be optimized by the genetic algorithm. Both correlations include 5 coefficients for optimization. The genetic algorithm changes all the coefficients simultaneously in each iteration over the search space until the stopping criteria is met. The objective function is to obtain the least mean square error between the correlation output and the specified experimental data points. In this study 150 experimental data sets have been used to optimize the correlation and 50 unseen datasets are applied to evaluate the validity of the optimized correlations. The data are obtained from 7 different oil reservoirs in one of the southern Iranian oil fields.

Formation Volume Factor

$$B_o = C_1 + C_2(10^{-5})\,(CN)_{B_o}^{C_3} \qquad (4)$$

$$(CN)_{B_o} = R_s\left(\frac{\gamma_s}{\gamma_{STO}}\right)^{C_4} + C_5\,T$$

Solution gas-oil ratio

$$R_s = \gamma_g\left[\left(\frac{P}{C_1} + C_2\right)10^{X}\right]^{C_3} \qquad (5)$$

$$X = C_4\,API - C_5\,[T - 460$$

4. Results

Table (1) and (2) present a comparison between the classical and optimized correlations versus experimental data for solution gas oil ratio and oil formation volume factor. The root mean square error (RMSE) and absolute relative error (ARE) for the optimized correlations show much better agreement with experimental data compared to classical correlations. Figures (2) and (3) also validate the results obtained by error analysis.

Table (1). Comparison between classical and optimized correlations versus experimental data for solution gas-oil ratio

Solution gas oil ratio			
Statistical Index	RMSE	ARE	R^2
Experimental data V.S. Optimized correlation	45.7474	0.0699	0.9905
Experimental data V.S. classical correlation	123.2496	0.2108	0.9708

Table (2). Comparison between classical and optimized correlations versus experimental data for formation volume factor

Oil formation volume factor			
Statistical Index	RMSE	ARE	R^2
Experimental data V.S. Optimized correlation	0.0227	0.0118	0.9913
Experimental data V.S. classical correlation	0.0402	0.0227	0.9906

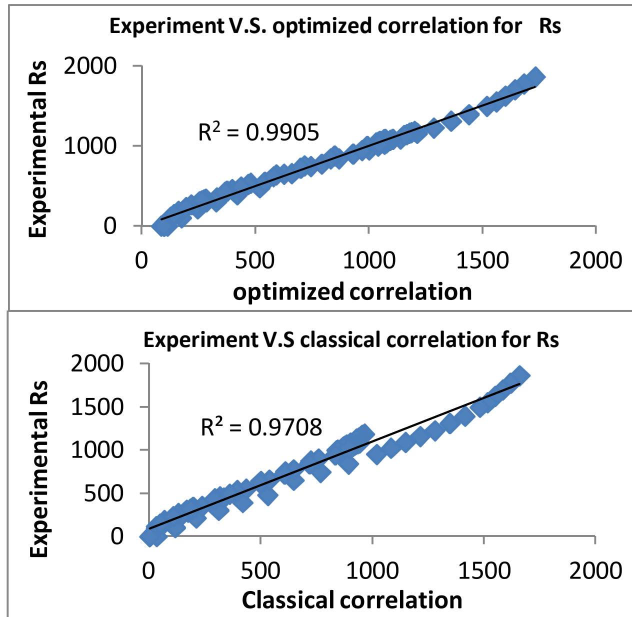

Figure (2): Regression analysis for solution gas-oil ratio

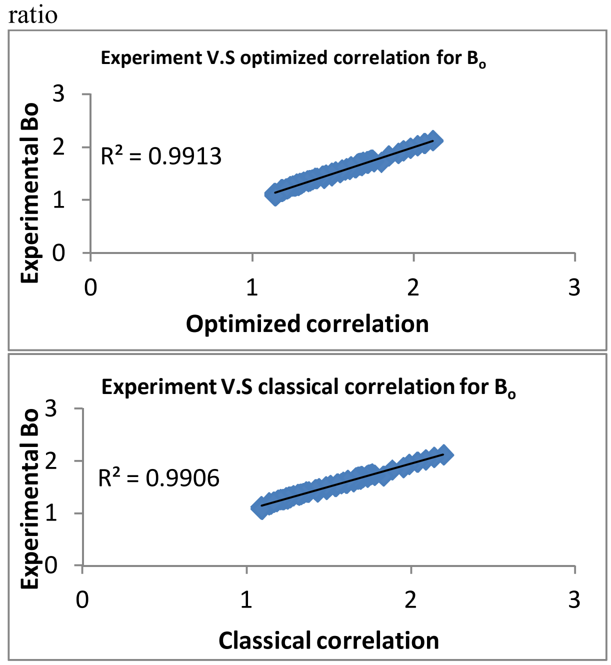

Figure (3): Regression analysis for oil formation volume factor

5.Conclusion

In this research, two critical PVT parameters are selected and optimized for southern Iranian oil fields. The selected parameters are referred to as formation volume factor and solution gas oil ratio. The optimization task was performed by genetic algorithm, which is an effective multivariable optimization technique. The results of the optimized correlations showed notable improvement over the classical equations in the literature.

References

1. Al-Fattah, S. M. and Al-Marhoun, M. A.: "Evaluation of empirical correlation for bubble point oil formation volume factor," J. Pet. Sci. & Eng. 11(1994) 341.
2. Al-Hussainy, R., Humphreys, N., 1996. Reservoir management principles and practices. Journal of Petroleum Technology 48 (12), 1129–1135
3. Al-Marhoun, M. A., "New Correlation for formation Volume Factor of oil and gas Mixtures," JCPT (March 1992) 22.
4. Al-Marhoun, M., "PVT Correlations for Middle East Crude Oils," Journal of Petroleum Technology, pp 650-666, 1988.
5. Al-Marhoun, M.A., and Osman, E. A., "Using Artificial Neural Networks to Develop New PVT Correlations for Saudi Crude Oils," Paper SPE 78592, presented at the 10th Abu Dhabi International Petroleum Exhibition and Conference (ADIPEC), Abu Dhabi, UAE, October 8-11, 2002.
6. Al-Shammasi, A. A.,: "Bubble Point Pressure and Oil Formation Volume Factor Correlations," paper SPE 53185 presented at the 1997 SPE Middle East Oil Show and Conference, Bahrain, March 15–18.
7. Al-Shammasi, A. A.: "A Review of Bubble Point Pressure and Oil Formation Volume Factor Correlations," SPE Reservoir Evaluation & Engineering (April 2001) 146-160. This paper (SPE 71302) was revised for publication from paper SPE 53185.
8. Al-Shammasi, A. A.: "Bubble Point Pressure and Oil Formation Volume Factor Correlations," SPE Middle East Oil Show, Bahrain, 20–23 February 1999. SPE53185.
9. Coello CA, Montes EM. Constraint handling in genetic algorithms through the use of dominance-based tournament selection. Adv Eng Informatics 2002;16(3):193–203.
10. Dokla, M. and Osman, M.: "Authors' Reply to Discussion of Correlation of PVT Properties for UAE Crudes," 12 SPEFE (March 1993) 82. 13
11. Dokla, M. and Osman, M.: "Correlation of PVT Properties for UAE Crudes," SPEFE (March 1992) 41.
12. El-Sebakhy A. E., Hadi A. S., and Faisal A. K., (2007), "Iterative Least Squares Functional Networks Classifier", IEEE Transactions Neural Networks Journal, 18, vol.3, 844-850, May 2007.
13. El-Sebakhy, E., 2009. "Data mining in forecasting PVT correlations of crude oil systems based on type 1 fuzzy logic inference systems ". Computers & Geosciences 35 (9), 1826–1917.
14. El-Sebakhy A. E., Hadi A. S., and Faisal A. K., (2007), "Iterative Least Squares Functional Networks Classifier", IEEE Transactions Neural Networks Journal, 18, vol.3, 844-850, May 2007.
15. Elsharkawy, A. M. Elgibaly, A. and Alikhan, A. A.: "Assessment of the PVT Correlations for Predicting the Properties of the Kuwaiti Crude Oils," paper presented at the 6th Abu Dhabi International Petroleum Exhibition & Conference, Oct. 16-19, 1994.
16. Ghetto, G. De, Paone, F. and Villa, M.: "Reliability Analysis on PVT correlation," paper SPE 28904 presented on October 25-27, 1994 at the SPE European Petroleum Conference, London, UK.
17. Goda M. H., Shokir E. M. El-M, Fattah K. A., and Sayyouh H. M., "Prediction of the PVT Data using Neural Network Computing Theory". The 27th Annual SPE International Technical Conference and Exhibition in Abuja, Nigeria, August 4-6, 2003: SPE85650.
18. Glaso, O.: "Generalized Pressure-Volume Temperature Correlations," JPT (May 1980), 785.
19. Goldberg DE. Genetic algorithms in search, optimization and machine learning. Reading, MA: Addison-Wesley; 1989.
20. Hanafy, H.H., Macary, S.A., Elnady, Y. M., Bayomi, A.A. and El-Batanoney, M.H.: " Empirical PVT Correlation Applied to Egyptian Crude Oils Exemplify Significance of Using Regional Correlations," paper SPE 37295 presented at the SPE Oilfield Chemistry International Symposium, Houston, Feb. 18–21, 1997.
21. Hassan. F. O : "correlation for solution gas -oil ratio of iraqi oils at pressures below the bubble point pressure" Iraqi Journal of Chemical and Petroleum Engineering. Vol.12 No.2 (June 2011) 1 - 8
22. Kartoatmodjo, T. and Schmidt, Z.: "Large data bank improves crude physical property correlations," Oil and Gas Journal (July 4, 1994) 51.
23. Katz, D. L.: "Prediction of Shrinkage of Crude Oils," Drill&Prod. Pract., API (1942), pp 137-147.
24. Khouki. A. "Hybrid soft computing systems for reservoir PVT properties prediction" Computers & Geosciences 44 (2012) 109–119.

25. Labedi, R.: "Use of Production Data to Estimate Volume Factor Density and Compressibility of Reservoir Fluids." J. Pet. Sci. & Eng., 4(1990) 357.
26. Lijie Cui, Daichao Sheng : "Genetic algorithms in probabilistic finite element analysis of geotechnical problems" Computers and Geotechnics 32 (2005) 555–563.
27. Macary, S. M. & El-Batanoney, M. H.: "Derivation of PVT Correlations for the Gulf of Suez Crude Oils," Paper presented at the EGPC 11th Petroleum Exploration & Production Conference, Cairo, Egypt (1992).
28. Mahmood, M. M. and Al-Marhoun, M. A: "Evaluation of empirically derived PVT properties for Pakistani crude oils," J. Pet. Sci. & Engg. 16 (1996) 275.
29. Mazandarani, M. T. and Asghari, S. M., (September 2007), "Correlations for Predicting Solution Gas-Oil Ratio, Bubblepoint Pressure and Oil Formation Volume Factor at Bubblepoint of Iran Crude Oils", European Congress of Chemical Engineering, Copenhagen McCain, W. D.: " Reservoir fluid property correlations-State of the Art," SPERE, (May 1991) 266.
30. M.N. Hemmati and R. Kharrat, SPE, Petroleum U. of Technology Research Center. "A Correlation Approach for Prediction of Crude-Oil PVT Properties" 15th SPE Middle East Oil & Gas Show and Conference held in Bahrain International Exhibition Centre, Kingdom of Bahrain, 11–14 March 2007
31. Omar, M.I. and Todd, A.C.: "Development of New Modified Black oil Correlation for Malaysian Crudes," paper SPE 25338 presented at the 1993 SPE Asia Pacific Asia Pacific Oil & Gas Conference and Exhibition, Singapore, Feb. 8-10.
32. Osman, E. A., Abdel-Wahhab, O. A., and Al-Marhoun, M. A., "Prediction of Oil Properties Using Neural Networks," Paper SPE 68233, 2001.
33. Petrosky, J. and Farshad, F.: "Pressure Volume Temperature Correlation for the Gulf of Mexico." paper SPE 26644 presented at the 1993 SPE Annual Technical Conference and Exhibition, Houston, TX, Oct 3-6.
34. Saleh, A. M., Maggoub, I. S. and Asaad, Y.: "Evaluation of Empirically Derived PVT Properties for Egyptian Oils," paper SPE 15721, presented at the 1987 Middle East Oil Show & Conference, Bahrain, March 7-10.
35. Standing M.B.: "A Pressure-Volume-Temperature Correlation for Mixtures of California Oils and Gases," Drill&Prod. Pract., API (1947), pp 275-87.
36. Standing, M. B.: Volumetric and Phase Behavior of Oil Field Hydrocarbon System. Millet Print Inc., Dallas, TX, (1977) 124.
37. Standing,M. B. (1962). ''Oil-system correlation'': Petroleum production handbook. New York City: McGraw-Hill Book Co.
38. Sunday Olusanya Olatunji, Ali Selamat, Abdul Azeez Abdul Raheemb: Predicting correlations properties of crude oil systems using type-2 fuzzy logic systems .Expert Systems with Applications 38 (2011) 10911–10922.
39. W. D. McCain " The properties of petroleum fluid" , 2nd ed, 1989, Tulsa, Oklahama.

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