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Full Length Research

A novel correlation approach to predict total formation volume factor, using artificial intelligence

Sadegh Baziar[1]* and Habibollah Bavarsad Shahripour[2]

[1]Department of Petroleum Engineering, Amirkabir University of Technology, Tehran, Iran
[2]International Petro Offshore Niam Kish, Tehran, Iran

*Corresponding author. E-mail: baziar@aut.ac.ir. Tel: (+98) 9380162720.

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This paper presents a new correlation approach to predict total formation volume factor below the bubble point pressure for oil and gas mixtures. This correlation is obtained by using more than 450 experimental data points which are collected from samples of Iranian oil reservoirs. The important factors of influencing parameters are determined using an artificial neural network. Then an appropriate form of correlation is developed by multivariable regression. Finally by use of nonlinear optimization, the correlation coefficients are adjusted in an optimum level to minimize average absolute relative error. This new correlation is valid in a broad range of pressure and temperature and is more accurate than other ones for Iranian oil mixtures.

Key words: Artificial neural network, correlation, multivariable regression, nonlinear optimization, total formation volume factor.

INTRODUCTION

Pressure-volume-temperature (PVT) properties have a significant importance in reservoir studies and are used in field reserve calculation, enhanced oil recovery (EOR) processes, surface facilities design and simulation of fluid flow in porous media and pipelines. PVT data can be measured directly or indirectly. In the direct method, real sample properties are measured in PVT laboratories using PVT cell. But this process is expensive and takes much time to be done for all samples. A cheaper and faster method is using empirical correlations for estimating PVT properties. In this case, geological conditions must be considered as an important factor because the chemical composition of crude oil differs from one region to another. To take regional characteristics into account, PVT correlations need to be modified before their applications.

Total formation volume factor (FVF) is a key parameter for estimating initial oil in place of a field; therefore it must be measured carefully. Some empirical correlations have been stated for measuring this property in literature. But these correlations show high error level in case of Iranian oils; therefore, a new one is developed by using new methods to minimize deviation of estimated values from real values for total FVF of Iranian oils.

Literature review

In literature, many attempts have been done to obtain an appropriate correlation for prediction of total FVF. Standing used 387 experimental data points to develop a graphical correlation for predicting two-phase formation volume factor with a reported average error of 5% (Standing, 1947). Glaso proposed a new correlation for predicting the total FVF using 36 data points from 15 crude oil samples obtained mostly from North Sea region (Glaso, 1980). In 1988, Al-Marhoun presented a correlation based on a total of 1556 experimental data points gathered from 69 different crude oil samples from

Table 1. Ranges of data used to compare total FVF correlations.

Number of data points	900
Total FVF (res bbl/STB)	1.267-2.481
Pressure (psi)	1325-4426
Bubble point pressure (psi)	1996-4561
Temperature (°F)	110-238
Gas-oil ratio (SCF/STB)	504-1200
Gas relative density (Air=1)	0.898-1.182
Stock tank oil density (°API)	25.44-35.28

Table 2. Statistical output of oil total FVF correlations comparison.

Correlation	Average percent relative error (E_r)	Average absolute percent relative error (E_a)	Maximum error (E_{max})	Standard deviation (S)
Glaso	9.6	9.56	21.28	4.1385
Al-Marhoun-1	27.0	27.0	37.07	2.5570
Al-Marhoun-2	2.34	3.44	19.85	3.2581

Middle East reservoirs (Al-Marhoun, 1988). In 1992 he also expanded his previous work and developed a new correlation based on 4005 experimentally obtained data points from all over the world (Al-Marhoun, 1992).

Javadpour et al. (1998) have done a comparative investigation on oil and gas formation volume factor correlations below bubble point pressure. They have used data obtained from bottom-hole samples of oil wells from major Iranian onshore and offshore reservoirs. The ranges of these data are presented in Table 1 (Javadpour et al., 1998). The result of the comparison among different correlations is presented in Table 2. The Glaso and Al-Marhoun-1correlations have underestimation for total FVF. Their average absolute relative errors are 9.58 and 27.0%, respectively. Al-Marhoun-2 correlation shows the best predictions for total FVF with an average absolute relative error of 3.44%.

As it can be seen, Al-Marhoun-2 correlation has a good accuracy for total FVF prediction. But using these correlations for a more extended range of empirical data gathered from Iranian oilfields shows a high error level. Therefore it is needed to develop a new correlation for total FVF prediction. In this paper a new approach to develop a comprehensive correlation for Iranian oils is discussed. This correlation is developed using artificial neural networks, multivariable regression and nonlinear optimization.

Artificial neural networks (ANN)

ANN is a computational model which is inspired by the structure and/or functional aspects of biological neural networks. A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases an ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. ANN has been extensively employed in wide range of engineering problems (Valipour et al., 2013; Valipour and Montazar, 2012a, b; Valipour et al., 2012; Valipour and Montazar, 2012c). It has also been used in many studies in the field of petroleum engineering (Aminian and Ameri, 2005; Aminian et al., 2003; Baneshi et al., 2013; Baziar et al., 2014; Bhatt, 2002; Boadu, 2001; Carrasquilla et al., 2008; Chang et al., 1997; Goda et al., 2005, 2007; Hamada and Elshafei, 2009; Helle et al., 2001; Huang et al., 1996; Ibrahim and Potter, 2004; Irani and Nasimi, 2011; Jamialahmadi and Javadpour, 2000; Kamari et al., 2013; Kapur et al., 1998; Karimpouli et al., 2010; Lim and Kim, 2004; Mohaghegh et al., 1996; Mollajan and Memarian, 2013; Ouadfeul and Aliouane, 2012; Ouenes, 2000; Shokir, 2004; Singh, 2005).

Nonlinear programming optimization

Optimization is one of the most important areas of modern applied mathematics, with applications in various fields from engineering and economics to medicine. The general optimization problem is shown as Equations 1 to 3.

$$\min(\max) \quad f(x) \tag{1}$$

Subject to:

Table 3. Ranges of data for the new correlation.

Number of data points	505
Total FVF (RB/STB)	1.172-15.358
Pressure (psia)	150-4810
Bubble point pressure (psia)	365-5116
Temperature (°F)	120-290
Gas-oil ratio (SCF/STB)	48.82-1991.7
Gas relative density (air=1)	0.656-1.166
Stock tank oil density (API)	27.35-127.8

$$g_i(x) \leq 0 \qquad i = 1, 2....., m_1 \tag{2}$$

$$g_i(x) = 0 \qquad i = m_1, m_1 + 1, ...m \quad X \in R^n \tag{3}$$

In particular, if m = 0, the problem is called an unconstrained optimization problem. If the objective function or at least one of the constraints is nonlinear, then the program is called a nonlinear optimization problem. Many methods can be applied to solve problem and find optimum solution. In this study "*LINGO*" software is used to optimize total FVF correlation constants.

METHODOLOGY

The data set which is used in this investigation has been collected from PVT analysis of oil wells from major Iranian onshore and offshore reservoirs. Our samples mostly contain C_1 to C_{12}^+ and non-hydrocarbon components such as CO_2, H_2S and N_2. The experimentally obtained data were 505 data points for oil FVF below bubble point pressure. The ranges of the data are shown in Table 3. At first step, 459 data points were selected and introduced to an ANN. The neural network selected 367 of data points (about 80%) for training and the rest were used for testing. The neural network had 2 hidden layers, which had 3 and 2 nodes, respectively. The configuration of ANN is Multilayer Forward Network (MLFN) numeric predictor. The ANN worked with 7 independent variables consisting of (oil FVF at bubble point pressure (B_{ob}), bubble point pressure (P_b), Pressure, solution gas-oil ratio (R_s), stock tank oil relative density (γ_o), average gas relative density (γ_g), Temperature (°R) to identify importance factors of the parameters on total FVF. The tolerance value for acceptable predictions is set to 10%. Then, the five most important influencing parameters (B_{ob}, P_b, Pressure, R_s, γ_g) with 301 randomly selected data points in the appropriate wide range, were introduced to the "Data Fit" software. This software uses multivariable regression to find the best function predicting total FVF using these parameters. Then, the coefficients of the selected function had to be optimized with a nonlinear programming model. This model is based on minimization of the absolute relative error (ARE) by means of a written code in *"LINGO"* software. At this stage, we used the same 301 data points to optimize the coefficients of the function. Then the final correlation of Total FVF below bubble point pressure was obtained. The unconstrained optimization model is stated in Equation 4:

$$ARE = \sum_{i=1}^{301} \frac{(|B_{t\,actual} - B_{t\,correlation}|)}{B_{t\,actual}} \tag{4}$$

The average ARE for the 301 data points was 2.32%. The other 204 data points are remained to test the validation of the new correlation and to compare with the other correlations.

RESULT AND DISCUSSION

The result of the ANN with the least error level is shown in Figure 1. The residual chart and actual versus predicted values chart are shown in Figure 2 for the best case. Pressure, gas specific gravity, B_{ob}, P_b and R_s are selected for developing the new correlation. Two of the least impacting parameters have been eliminated and the rest of them have been used in the "Data Fit" software. The following function which has been found by the use of multivariable regression gives the most precise answers.

$$B_{t\,correlation} = a_1 \times B_{ob} \times (P/P_b)^d \tag{5}$$

$$d = a_2 \mathrm{Ln}(R_s) + a_3 \mathrm{Ln}(\gamma_g) + a_4 \mathrm{Ln}(P/P_b) \tag{6}$$

Then the above function was introduced to the *"LINGO"* software to optimize the coefficients. The final resultant coefficients are presented in the following:

Table 4. Statistical term of oil FVF correlations below Bubble point pressure.

Correlation	E_r	E_a	E_{max}	Standard deviation
Glaso	37.5	41	86.79	20.67
Standing	32.42	37.96	85.86	19.91
Al-Marhoun-2	22.06	22.11	107.65	18.96
New correlation	0.21	3.78	18.28	3.58

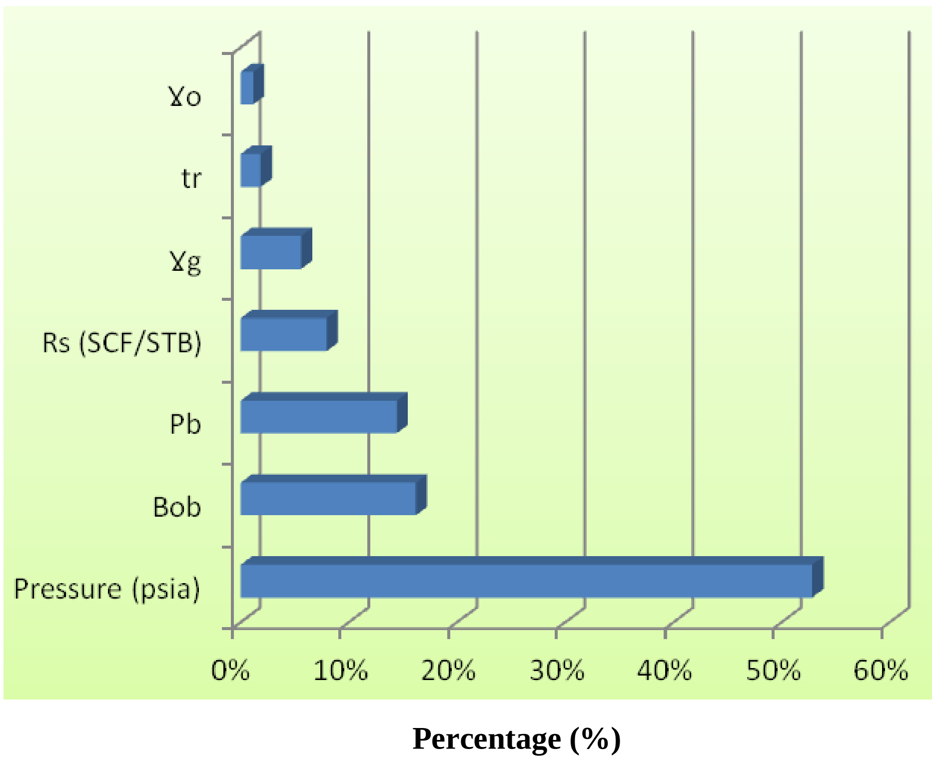

Figure 1. Importance factors of the influencing parameters.

$a_1 = 0.9817570$ $\quad a_3 = -0.087755$

$a_2 = -0.06559381$ $\quad a_4 = 0.1988700$

Validation

A reliable method for checking this correlation is using validation tests. To validate the new correlation, some of the data points are selected. The obtained total FVF from new correlation versus pressure and R_s were plotted for these data and are shown in Figure 3. In general state total FVF increases as pressure decreases. Also the lower values of R_s, the higher values of total FVF. The figure has compatibility with these general rules that implies validation of the new correlation.

Accuracy

To measure accuracy of the proposed correlation with other mentioned correlations, Glaso, Standing, Al-Marhoun-2 and the new correlation are tested with the 204 remaining data points and the results are shown in Table 4. Al-Marhoun-1 correlation didn't take part in this comparison due to larger errors than the second one. Figure 4 shows this comparison. This figure confirms that the proposed correlation is the most accurate one for prediction of total FVF. Also the residual range in this new correlation has the lowest values compared to other ones. As shown in Table 4, the range of the used data which are used is so much wider in comparison with the ranges of the data used by Javadpour et al. (1998) which is shown in

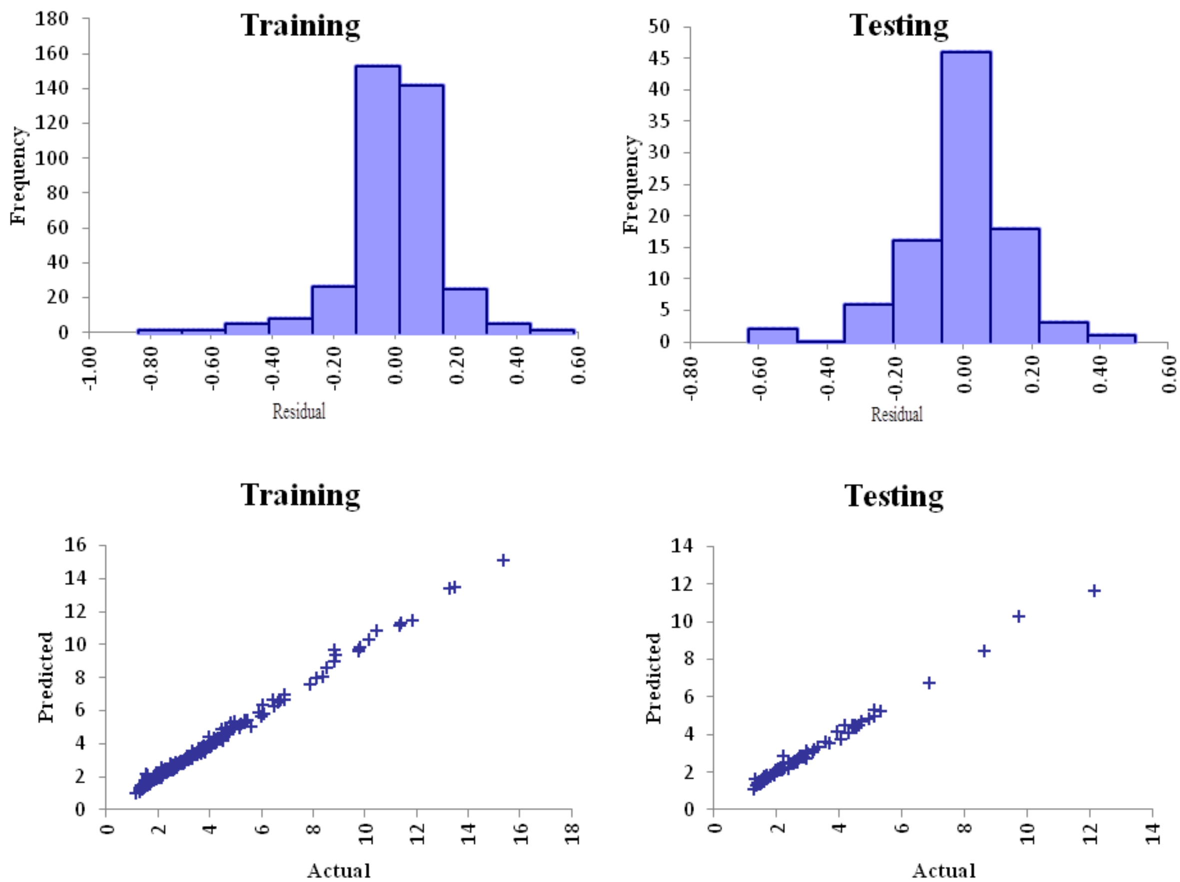

Figure 2. Residual and actual versus ideal values of the best ANN.

Table 1. Therefore this correlation is more comprehensive and applicable in many operational ranges.

Conclusion

ANN is a useful method to identify the most influencing parameters on a dependent parameter. In case of total FVF, 5 parameters consisting of pressure, R_s, B_{ob}, P_b and gas specific gravity are influencing. The new correlation developed based on minimizing ARE is valid in operational ranges and has more accuracy than the other correlations.

Conflict of interest

Authors have none to declare

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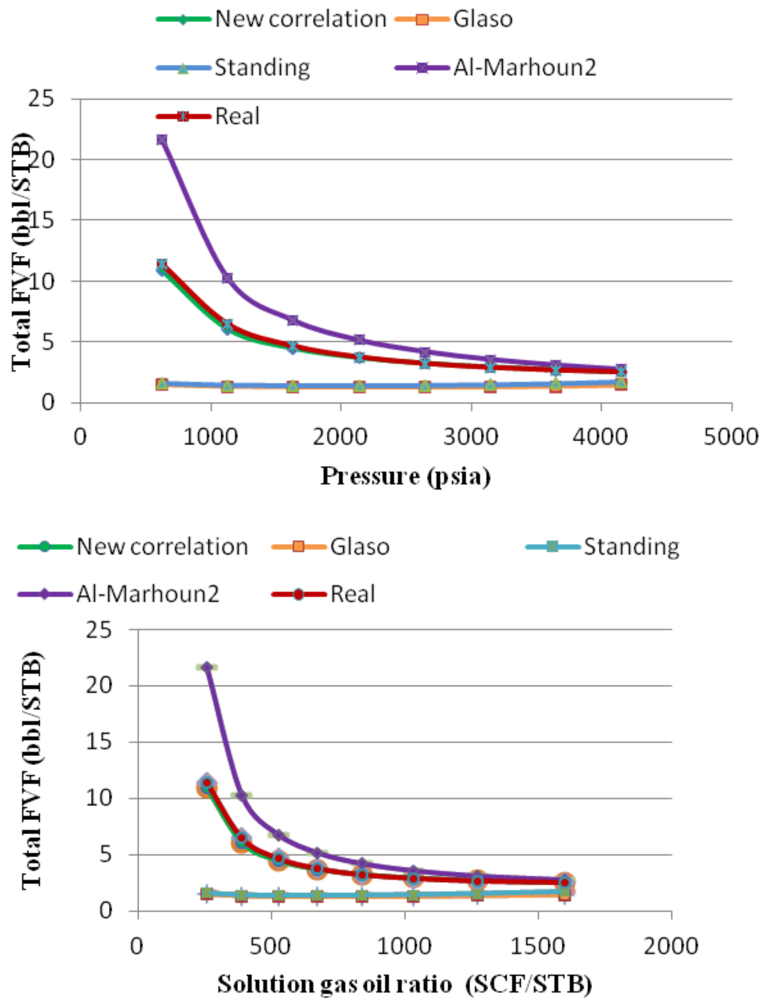

Figure 3. Total FVF versus pressure (top) and Solution gas oil ratio (bottom) for different correlations

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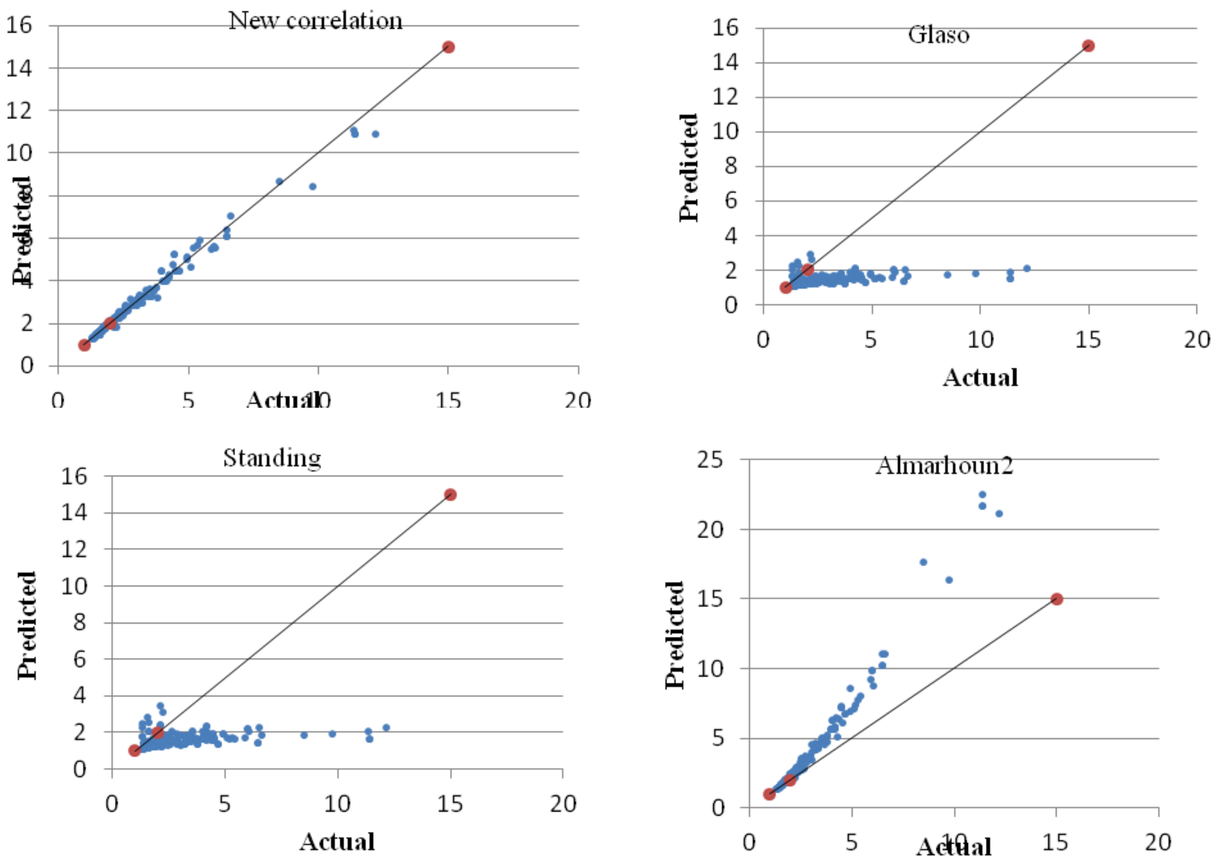

Figure 4. Total FVF predicted by different correlations versus actual values.

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