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Fuzzy modeling of volume reduction of oil due to dissolved gas runoff and pressure release

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Abstract Oil formation volume factor (FVF) refers to the change in oil volume between reservoir and standard conditions at surface. It is a crucial oil property which is governed by reservoir temperature, amount of dissolved gas in oil, and specific gravity of oil and dissolved gas. This parameter plays a trivial role in petroleum reservoir and production calculations. Accurate determination of oil FVF is restricted by limitations on reliable sampling and high cost and time-consumption associated with laboratory experiments. Furthermore, available empirical correlations do not have satisfying generalization and accuracy owing to being calibrated on specific oil samples. Therefore, this study offers a Takagi–Sugeno (TS) fuzzy logic model for estimating oil FVF for the purpose of developing a precise model calibrated on regional Iranian oil using 367 training samples. TS fuzzy model utilizes subtractive clustering approach for determining number of rules and clusters. Evaluation of constructed fuzzy logic using 108 unseen test data points indicated achievement of fuzzy logic in prediction of oil FVF.

Keywords Dissolved gas in oil · Oil formation volume factor · PVT data · Fuzzy logic · Petroleum chemistry

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Introduction

Oil formation volume factor (FVF) is defined as the ratio of the volume of oil (plus the gas in solution) at the prevailing reservoir temperature and pressure to the volume of oil at standard conditions (Ahmed 2006). It is a crucial parameter playing a significant role in petroleum reservoir and production engineering calculations, such as material balance calculations, well testing, reserve estimates, inflow performance, reservoir simulation, production operations and design of surface facilities (Asoodeh and Kazemi 2013). Accurate determination of oil FVF is experimentally carried out through differential vaporization test on bottom-hole or recombined surface samples, while both sampling and running experiment are very time-consuming and expensive. Furthermore, sampling should be done at early stage of reservoir production which imposes some limitation on providing reliable samples (Dake 1998). Owing to these limitations, researchers have tried to establish empirical correlations for estimating oil FVF from available measured oil properties, including gas specific gravity, temperature, stock-tank oil gravity, and solution gas oil ratio (Katz 1942; Knopp and Ramsey 1960; Vazquez and Beggs 1980; Glaso 1980; Al-Marhoun 1988; Dokla and Osman 1992; Farshad et al. 1996; Petrosky and Farshad 1993; Omar and Todd 1993; Almehaideb 1997; Al-Shammasi 1999; Dindoruk and Christman 2001; El-Banbi et al. 2006; Hemmati and Kharrat 2007; Elmabrouk et al. 2010). These empirical correlations do not have flexible structure and consequently do not serve satisfying generalization. Recent years have been witnessing the growing tendency to utilize intelligent systems for solving complicated petroleum and chemistry problems (Asoodeh and Bagheripour 2012a, Asoodeh and Bagheripour 2012b, Asoodeh and Bagheripour 2012b, 2013; Asoodeh 2013a, b). These works proved that intelligent systems have more generalization capability and produce more reliable results. Therefore, in this study, a Takagi–Sugeno (TS) fuzzy logic model is employed to formulate gas specific gravity, temperature, stock-tank oil gravity, and solution gas oil ratio into formation volume factor. TS fuzzy model employs subtractive clustering as an effective approach for determining optimal number of rules and clusters. A set of 367 data points from Iranian oil samples were chosen for model construction and a set of 108 data points were used for assessment of constructed fuzzy model. Results indicated that fuzzy logic model can effectively estimate formation volume factor in a quick and cheap way. The proposed strategy was successfully applied to Iranian oil samples.

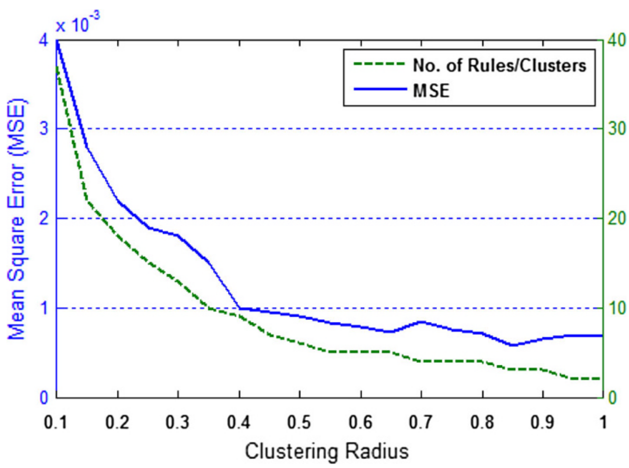
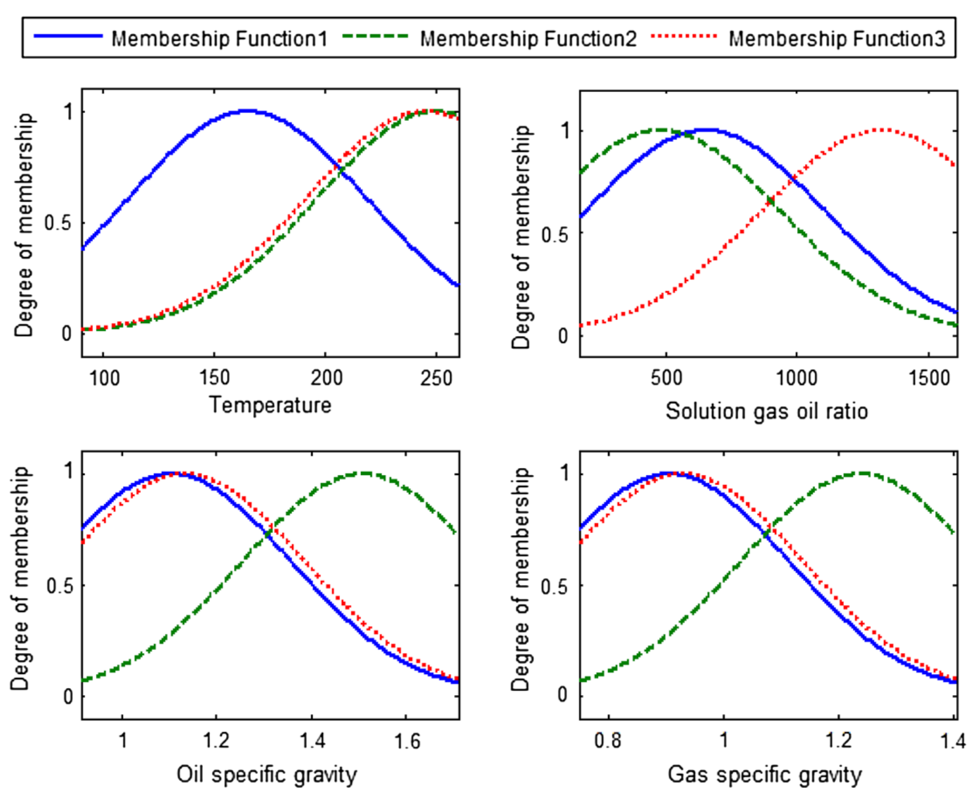


Fig. 1 Performance variation of fuzzy model versus clustering radius

Fuzzy logic

The basic idea of fuzzy logic originated from a work by Zadeh (1965). He introduced concepts of plastic boundaries in company with partial membership contrasting the prevailing crisp logic, which a value may or may not belong to one class. A fuzzy inference system (FIS) is the method of formulating from a given input to an output using fuzzy logic (MATLAB user's guide 2011). A FIS consists of five major steps: fuzzification of input variables, application of fuzzy operators (AND, OR, and NOT) in the rule's antecedent, implication from the antecedent to the consequent, aggregation of consequent across the rules, and defuzzification (Asoodeh and Bagheripour 2012a). Defining appropriate membership functions (fuzzy sets) which best fit the data set is an important task that is done by subtractive clustering algorithm in Takagi and Sugeno (1985) FIS. Subtractive clustering is an effective approach to estimate the number of fuzzy clusters and cluster centers in Takagi–Sugeno fuzzy inference system (Jarrah and Halawani 2001). Subtractive clustering is governed by a design parameter, called clustering radius. Clustering radius varies between the range of [0 1]. Specifying a smaller cluster radius will usually yield more and smaller clusters in the data (resulting in more rules). A large cluster radius yields a few large clusters in data (Chiu 1994). More details about fuzzy logic and subtractive clustering are available in works by Jarrah and Halawani (2001), Chiu (1994), and Mohaghegh (2000).

Fig. 2 Takagi–Sugeno fuzzy inference system generated input Gaussian membership functions (fuzzy clusters) for the model meant to predict oil formation volume factor



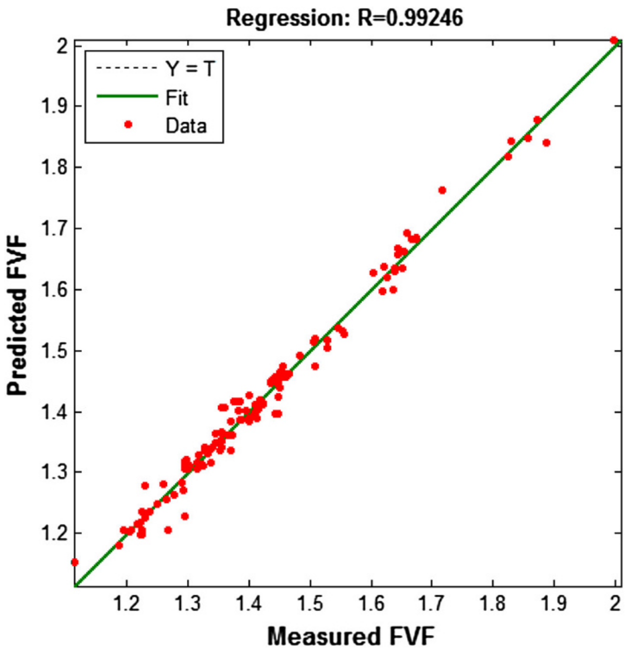


Fig. 3 Cross-plot showing correlation coefficient between measured and fuzzy predicted oil formation volume factor (FVF). High value of correlation coefficient, i.e., 0.99246 proves the robustness of fuzzy modeling

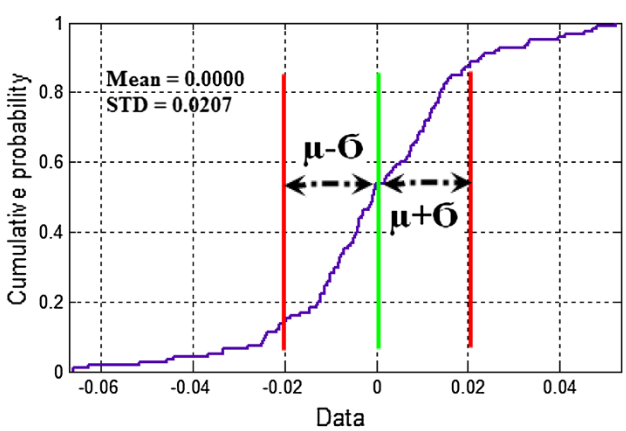


Fig. 4 Cumulative probability of error distribution statistics for fuzzy model meant to predict oil formation volume factor (FVF). Small values of mean and standard deviation (STD) reveal high performance of fuzzy modeling. Error distribution indicates 68 % of predicted values have errors in range of 0.0000 ± 0.0207

Results and discussion

In this stage of study, a Takagi–Sugeno fuzzy inference system was constructed to estimate oil formation volume factor from gas specific gravity, temperature, stock-tank oil gravity, and solution gas oil ratio. To achieve optimal fuzzy model, different clustering radii were introduced to subtractive clustering algorithm and the performance of consequent fuzzy model was investigated. Figure 1 illustrates performance variation of Takagi–Sugeno fuzzy model using concept of mean square error versus different clustering radii. The model with the lowest mean square error of prediction was chosen as optimal model. As Fig. 1 shows by specification of 0.85 for clustering radius, optimal fuzzy model is achieved. Figure 2 illustrates input membership functions for extracted optimal fuzzy model. The linguistic rules for handling this problem are defined as below.

Rule 1 If (T is membership function 1) and (Rs is membership function 1) and (γ_o is membership function 1) and (γ_g is membership function 1) Then (FVF is membership function 1).

Rule 2 If (T is membership function 2) and (Rs is membership function 2) and (γ_o is membership function 2) and (γ_g is membership function 2) Then (FVF is membership function 2).

Rule 3 If (T is membership function 3) and (Rs is membership function 3) and (γ_o is membership function 3) and (γ_g is membership function 3) Then (FVF is membership function 3).

To assess performance of constructed fuzzy model, unseen test data were input into it and formation volume factor was computed. Figure 3 shows a cross-plot of predicted oil FVF versus measured values. High value of correlation coefficient verifies that fuzzy model performed satisfyingly. More statistical details about performance of fuzzy model are shown in Fig. 4. Figure 4 illustrates cumulative probability error distribution of fuzzy logic predictions. Mean and standard deviation of error distribution are equal to 0.0000 and 0.0207, respectively. This figure obviously shows that error for most of data points is located in acceptable proximity of zero that is another indicator for confirmation of fuzzy model accomplishment. Since fuzzy

Table 1 Statistics of dataset used in this study

Parameters	Minimum		Maximum		Average	
	Training	Test	Training	Test	Training	Test
Temperature	90	92.24	260	254.17	182.27	183.92
Solution gas oil ratio	169.53	173.51	1,608.26	1,594.2	698.75	691.31
Oil specific gravity	1.06572	1.06148	1.2373	1.2223	1.12596	1.1253
Gas specific gravity	0.7647	0.782	1.4029	1.3920	1.19849	1.11979

models have an excellent interpolation capability and really bad extrapolation capability, it should be borne in mind that constructed model is only valid in range of training data points. Table 1 shows statistics of data used in this study. For any dataset within the ranges provided in Table 1, the proposed model is valid.

Conclusions

Oil formation volume factor (FVF) has obvious significance in petroleum engineering. In this study, a quantitative formulation between oil FVF and available oil properties, including gas specific gravity, temperature, stock-tank oil gravity, and solution gas oil ratio was established using fuzzy logic. Fuzzy logic is a quick, accurate, and convenient-to-use method for determining oil FVF. It can be simply implemented on any set of PVT data to develop a sophisticated method calibrated on desired regional data with specific physical and chemical characteristics. Zero valued relative error (i.e., mean of error distribution) and near unity value of correlation coefficient between measured and predicted oil FVF data confirms accomplishment of fuzzy modeling. Therefore, the proposed method is a good alternative for following situations:

(a) In situations where samples are not reliable.
(b) In situations where sampling is not applicable due to long time production of reservoir.
(c) In situations where it is desired to save time and money by eliminating laboratory experiments.

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