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Toward an intelligent approach for determination of saturation pressure of crude oil

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ABSTRACT

Bubble point pressure is a crucial PVT parameter of reservoir fluids, which has a significant effect on oil field development strategies, reservoir evaluation and production calculations. This communication presents a new mathematical model to calculate the saturation pressures of crude oils as a function of temperature, hydrocarbon and non-hydrocarbon reservoir fluid compositions, and characteristics of the heptane-plus fraction. The model was developed and tested using a total set of 130 experimentally measured compositions and saturation pressures of crude oil samples from different geographical locations covering wide ranges of crude oil properties and reservoir temperatures. In-depth comparative studies have been carried out between this new model and five well known predictive models for estimation of saturation pressure of crude oils. The results show that the developed model is more accurate and reliable with the average absolute relative deviation of 4.7% and correlation coefficient of 0.992. In addition, it is shown that the proposed model correctly captures the physical trend of changing the saturation pressure as a function of the input variables. Finally, the applicability domains of the proposed model and quality of the existing experimental data were examined by outlier diagnostics.

1. Introduction

Knowledge of reservoir fluid properties is important in petroleum engineering computations, including material balance calculations, well test analysis, reserve estimates, inflow performance calculations, surface facility design, and numerical reservoir simulation [1–4]. These properties can be obtained either by conducting a laboratory study on reservoir fluids or estimation from models or correlations. Among all PVT properties, the bubble point pressure (P_b) is one of the most essential factors in reservoir and production computations [5–7].

The bubble point pressure of a hydrocarbon system is defined as the maximum pressure at which the first bubble of gas begins to evolve from the oil. This important property can be measured experimentally for a crude oil system by conducting a constant-composition expansion (CCE) experiment. As bubble point pressure is used, either directly or indirectly, in almost all correlations for prediction of crude oil properties, any error in estimation of bubble point pressure will propagate throughout estimates of other fluid properties such as oil formation volume factor, oil viscosity, oil density, etc. Hence, it is absolutely necessary that the prediction for bubble point pressure be as accurate as possible [5–7].

Although PVT sampling and experiments provide reliable results, they are relatively expensive, time consuming and also results are heavily dependent on the validity of the reservoir fluid samples, especially when the reservoir has depleted below the bubble point pressure [1,3,8]. Numerous numbers of equations of states (EOS) [9–12] have been published in the literature to model reservoir fluid phase behavior but none of them can be considered to be so accurate to predict all properties of reservoir fluids at all conditions [13–15]. Moreover, the equation of state requires the extensive knowledge of the detailed compositions of the reservoir fluids and the determination of such quantities is expensive and time consuming [16]. Furthermore, the accuracy of the EOS prediction depends heavily on the nature of the fluid, on the type of selected equation and on the operator-dependent tuning procedures. This method also involves several numerical computations [16,17].

To overcome the aforementioned problems, equations of state and several empirically derived correlations and eventually soft computing techniques have been developed based on available data of different regions of the world. A large number of correlations for estimation of bubble point pressure have been offered in the literature over the last few years to go with a handful of correlations published earlier [18–26]. Many of these new correlations are based on data from a single geographical area and cannot be used globally due to different characteristics of fluids in each area [16,24].

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Since the 1950s, many researchers have tried to develop correlations for predicting saturation pressure of reservoir fluids with different degrees of accuracy. The first work was done by Standing [18] on 22 hydrocarbon systems in California. Standing's correlation was based on the assumption that the bubble point pressure is a function of gas solubility, gas gravity, oil gravity, and reservoir temperature. Based on Henry's law, Lasater [20] developed a correlation for estimation of bubble point pressure on 158 samples from 137 reservoirs in Canada, the United States and South America. This correlation is based on systems essentially free from non-hydrocarbon components. Glaso [21] used a total of 45 oil samples from the North Sea to develop graphical form models for bubble point pressure, saturated oil formation volume factor, total oil formation volume factor and dead oil viscosity. This correlation provides corrections for the presence of non-hydrocarbon components such as H_2, N_2, H_2S and the paraffinicity of the oil. Al-Marhoun [22] used 160 data set points to develop correlations for estimating bubble point pressure and oil formation volume factor from 69 Middle Eastern hydrocarbon mixtures. In 1992, Dokla and Osman [27] presented correlations for estimating the bubble point pressure and the oil formation volume factor for UAE crude oil. In 1993, Petrosky and Farshad [28] developed correlations for the Gulf of Mexico crude oil samples using 90 PVT analysis data set. Velarde et al. [29] proposed a new correlation for bubble point pressure based on 2097 PVT data sets from 97 laboratory reports by introducing a new coefficient in the equation presented by Petrosky and Farshad [28]. In addition, other correlations were also proposed by researchers through different regression techniques. Valko and McCain [24] provided an in-depth analysis of various bubble point correlations.

Although, large numbers of correlations for estimation of bubble point pressure of reservoir oils have been offered in the literature over the last few years, many of these new correlations are based on data from a single geographical area. Most of these correlations were derived using petroleum service company laboratory fluid property data [24].

To overcome the shortcomings associated with the earlier correlation methods, researchers have utilized artificial intelligence based methods foremost of which is the classical artificial neural network (ANN) and its variants [30–36].

Gharbi and Elsharkawy [37] presented models for prediction of bubble point pressure as functions of solution gas–oil ratio, gas specific gravity, oil specific gravity, and temperature for Middle Eastern crude oils. Gharbi et al. [34] used universal multilayer perceptron based models for prediction of bubble point pressure using 5200 data points from all over the world. Al-Marhoun and Osman [32] presented correlations for bubble point pressure of Saudi Arabian crudes using ANN. This study shows a significant increase in accuracy over Al-Marhoun's previous correlations [22,38], also developed for Saudi crude. El-Sebakhy et al. [39] used support vector regression for generating correlations for bubble point pressure and saturated oil formation volume factor using three different published PVT databases. Moghadam et al. [40] used ANN for prediction of bubble point pressure based on 218 crude oil PVT data points from different locations in Iranian reservoirs.

The developed neural network correlations often do not perform to expectations and generally have several shortcomings that include; ANN is normally a black box modeling scheme that is based on the trial-and-error approach in which its architectural parameters have to be guessed in advance, such as, number and size of hidden layers, learning rate, training algorithm parameters, initial random weights and most importantly the tendency to be stocked at the local minima, and its inability to handle uncertainties [16,41]. The hidden layer is also disadvantageous since it does not reflect the physical phenomena of the process that is being simulated. Hence, while it shows precision within the training data set, it cannot predict accurately the 'unseen' data sets. This is indicated in McCain et al. [42].

The existent complexity, fuzziness and uncertainty existent in addition to nonlinear behavior of most reservoir parameters require a powerful tool to overcome these challenges [43]. The recent development and success of applying support vector machine modeling to solve various difficult engineering problems has drawn the attention to its potential applications in the petroleum industry [4,44–46]. In the last decades, various prediction models have been proposed that include artificial neural network models [47,48], adaptive neuro-fuzzy inference system (ANFIS) models [49,50] and support vector machine (SVM) [4,46]. This study presents a new model for the estimation of bubble point pressure for reservoir crude oils based on support vector machine modeling approach. The model was built and tested using a comprehensive data set collected from previously published literature. A quantitative analysis of the model was carried out to establish the adequacy and accuracy of the developed model. In addition, the model efficiency was tested against the measured saturation pressures, and the prediction made by available empirical correlations in the literature, the PR [9], and SRK-EOS [10]. Next, the model was used to simulate the results of gas injection or isothermal swelling test. Finally, outlier diagnosis was performed for detection of the probable doubtful experimental saturation pressure data.

2. Data acquisition

The reliability of the models for prediction of physical properties and phase behaviors of fluids generally depends on the comprehensiveness of the employed data set for their development [4,51]. For this purpose, a comprehensive data set was assembled from previously published literature [14,15,52–69]. A total of 130 experimental data points were obtained, each containing experimental values for temperature, crude oil compositions of C_1 through C_{7+}, non-hydrocarbon composition (N_2, CO_2, and H_2S), specific gravity of the heptane-plus fraction (SG_{C7+}), molecular weight of the heptane-plus fraction (MW_{C7+}), and the corresponding saturation pressure (P_b) measurement. The data set consists of data from a variety of crude oils of various composition ranges and from various geographical locations i.e. Middle East, North America and North Sea. Table 1 shows the range and the corresponding statistical parameters of the variables that have been used to develop and test the model. As can be seen, the data represent wide ranges of experimental conditions. Reservoir temperatures vary from 128 to 314 °F, specific gravities of the heptane-plus from 0.743 to 0.942, molecular weights of the heptane-plus from 134 to 324, and bubble point pressures from 313 to 6880 psia.

3. Model development

3.1. Background of the support vector machine

The support vector machine has been preliminary proposed for classification problems utilizing the hyper-planes to define decision boundaries between the experimental data points of different classes [70,71]. In this regression technique, the experimental data points from the input space are mapped into a high-dimensional or even

Table 1
Ranges of input/output variables used for developing and testing the model.

Parameter	Minimum	Maximum	Average
Temperature (°F)	128	324	177.3
Molecular weight of heptane-plus (MW_{C7+})	134	324	230.9
Specific gravity of heptane-plus (SG_{C7+})	0.743	0.942	0.861
Bubble point pressures (psi)	313	6880	2283.2
Methane	5.63	74.18	33.10
Ethane	0.84	12.45	7.35
Propane	0.43	11.87	6.33
Butanes	0.95	8.40	4.58
Pentanes	0.40	6.65	3.27
Hexanes	0	6.65	3.20
Heptane-plus	10.72	83.20	40.63
Nitrogen	0	1.67	0.36
Carbon dioxide	0	9.11	1.09
Hydrogen sulfide	0	3.68	0.14