Petroleum xxx (2017) 1–9

Contents lists available at ScienceDirect

Petroleum

journal homepage: www.keaipublishing.com/en/journals/petlm

Development of new correlations for the oil formation volume factor in oil reservoirs using artificial intelligent white box technique

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ARTICLE INFO

Article history:
Received 1 January 2017
Received in revised form
27 August 2017
Accepted 27 September 2017

Keywords:
Oil formation volume factor
Artificial intelligent
Reservoir management
Artificial neural network

ABSTRACT

Oil formation volume factor (OFVF) is considered one of the main parameters required to characterize the crude oil. OFVF is needed in reservoir simulation and prediction of the oil reservoir performance. Existing correlations apply for specific oils and cannot be extended to other oil types. In addition, big errors were obtained when we applied existing correlations to predict the OFVF. There is a massive need to have a global OFVF correlation that can be used for different oils with less error.

The objective of this paper is to develop a new empirical correlation for oil formation volume factor (OFVF) prediction using artificial intelligent techniques (AI) such as; artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and support vector machine (SVM). For the first time we changed the ANN model to a white box by extracting the weights and the biases from AI models and form a new empirical equation for OFVF prediction. In this paper we present a new empirical correlation extracted from ANN based on 760 experimental data points for different oils with different compositions.

The results obtained showed that the ANN model yielded the highest correlation coefficient (0.997) and lowest average absolute error (less than 1%) for OFVF prediction as a function of the specific gravity of gas, the dissolved gas to oil ratio, the oil specific gravity, and the temperature of the reservoir compared with ANFIS and SVM. The developed empirical equation from the ANN model outperformed the previous empirical correlations and AI models for OFVF prediction. It can be used to predict the OFVF with a high accuracy.

1. Introduction

1.1. Importance of oil formation volume factor

The properties of the reservoir oil are crucial in reservoir engineering computational applications. These properties include; oil formation volume factor, bubble point pressure, gas solubility in oil, etc. The oil formation volume factor (B_o) determines the ratio between the oil volume in the reservoir with the dissolved gas to the volume of the oil at the surface (stock tank). All material balance calculations need the oil formation volume factor to determine the reservoir volume after the depletion process. The oil formation volume factor is a strong function of the reservoir pressure and in certain cases the data for the oil formation volume factor (OFVF) is not available. Correlations and models were developed to predict the FVF that can be used in reservoir computational models.

Reservoir engineering applications such as material balance equation, reservoir simulation, and well testing need the PVT properties of the petroleum reservoir fluids and one of these properties is the oil formation volume factor.

Several empirical correlations were developed to predict the OFVF for specific regions and for specific oils. Labedi [1] came up with an empirical correlation to determine the OFVF at the bubble point pressure. He developed the correlation using 129 data sets. Al-Marhoun [2] developed a correlation for the FVF at the bubble point pressure. He used 11,728 measured values to develop the correlation for 700 reservoirs from North America and Middle East.

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Peer review under responsibility of Southwest Petroleum University.

Production and Hosting by Elsevier on behalf of KeAi

https://doi.org/10.1016/j.petlm.2017.09.009
2405-6561/

Please cite this article in press as: S. Elkatatny, M. Mahmoud, Development of new correlations for the oil formation volume factor in oil reservoirs using artificial intelligent white box technique, Petroleum (2017), https://doi.org/10.1016/j.petlm.2017.09.009

He used the least square linear regression method to develop the correlation and he obtained the following correlation:

$$B_{ob} = 1 + a_1 R_s + a_2 R_s \left(\frac{\gamma_g}{\gamma_o}\right) + a_3 R_s \left(\frac{T-60}{1-\gamma_o}\right) + a_4(T-60) \quad (1)$$

where R_s is the solution gas oil ratio, go is the oil gravity, gg is the gas gravity, T is the reservoir temperature, °F, $a_1 = 0.177342 \times 10^{-3}$, $a_2 = 0.220163 \times 10^{-3}$, $a_3 = 4.292580 \times 10^{-6}$, and $a_4 = 0.0.528707 \times 10^{-3}$. The average absolute percentage error of the developed correlation to predict the FVF was as maximum as 0.5.

Vazquez and Beggs [3,4] developed empirical correlation for the oil formation volume factor. They used 6004 data points from different oil reservoirs worldwide. Glasø [5] used 41 data points for oil collected from the North Sea to develop a correlation for the oil formation volume factor.

Macary and El-Batanoney [6] developed empirical correlations for the oil formation volume factor for 30 different oil reservoirs in the Gulf of Suez area, Egypt. They used 90 data sets in their correlation. Dokla and Osman [7] generated differently correlation for the UAE oils to determine the oil formation volume factor and bubble point pressure. They used 51 data sets to develop these correlations. Omar and Todd [8] proposed correlations for the formation volume factor and bubble point pressure based on Standing [9] correlation for oil reservoirs in Malaysia. They developed the correlations using 93 data sets. Kartoatmodjo and Schmidt [10,11] developed several correlations for different PVT properties (including the oil formation volume factor) using 5392 data sets collected from different oil reservoirs worldwide. Al-Mehaideb [12] developed set of correlations for PVT properties of the UAE oils using data from UAE oil reservoirs, he used 62 data sets. Petrosky and Farshad [13] developed different PVT correlations for Gulf of Mexico crude oils and they used 90 data sets to develop their correlations.

Gharbi and Elsharkawy [14] introduced a neural network model to predict the oil formation volume factor. They collected 498 experimental data points for different oil sample from the Middle East. They introduced a black box model that can accurately predict the oil formation volume factor.

Al-Marhoun and Osman [15] developed new models to predict the oil formation volumed factor at the bubble point pressure using artificial neural networks (ANN). They developed the models for Saudi oil reservoirs based on 283 data sets measured for oil samples from the field. The models predicted the oil formation volume factor with high accuracy and the absolute relative error was 5.9%. They used 142 data sets to train the ANN model, 71 data sets for validation, and 70 data sets for testing the developed models. Their model was a black box and they did not generate empirical correlations out of the ANN models. Osman and Al-Marhoun [16] used the Multi-Layer-Preceptor (MLP) and Radial Basis Function (RBF) neurula networks to develop models for PVT for oil and brine samples. Their models predicted the PVT properties accurately compared to the published correlations but they did not introduce mathematical equations, they only presented black box models.

The objective of this research is to develop a new empirical correlation to determine the oil formation volume factor (OFVF) based on the specific gravity of gas (γ_g), the dissolved gas to oil ratio (R_s), the oil specific gravity (API), and the temperature of the reservoir (Tf). Three artificial intelligent techniques were used to develop the OFVF model such as; artificial neural network (ANN), adaptive neuro-fuzzy inference system (ANFIS), and support vector machine (SVM). The obtained results of the three models will be compared and the one who will gave the highest correlation coefficient and lowest average absolute error percent will be used to change the AI to a white box by extracting the weight and biases to develop the new empirical equation for OFVF prediction.

1.2. Artificial intelligent techniques

Artificial Neural network is the most powerful statistical tool to recognize and classify complex patterns and system which human brain cannot do [17]; in fact the artificial neural network technique is inspired from biological neurons that are found in human brain [18].

An ANN model consists of fundamental processing unit, termed as neurons. The neural network models are structured on three components, learning algorithm, transfer function and network architecture [19] (Lippmann 1987). The network model comprises of at-least three layers, input layer, hidden layer and output layer. Each layer connects with other layers with the help of weights. The network performance is solely based on the adjustment of weights between these layers [20,21]. Hidden layers assigned with transfer function usually 'log-sigmoidal' or 'tan-sigmoidal'. Output layer is assigned with 'pure linear' activation function.

Adaptive neuro-fuzzy inference system (ANFIS) is also gained dominant importance in petroleum industry. Many researchers used ANFIS to delineate complex concepts in the petroleum industry [22,23]. ANFIS is the combination of neural network and fuzzy logic and its very robust supervised learning technique. It is the kind of neural network that uses Sugeno fuzzy inference system [24]. ANFIS has the capability to extract the benefits of both mentioned AI techniques in single platform. In order to get best out of this technique one should use any evolutionary algorithm to optimize the parameters of ANFIS [25].

Fuzzy logic maps input parameters to input membership functions, converting input membership functions to set of fuzzy rules, converting set of fuzzy rules to output characteristics, then convert output characteristics to output membership functions and finally this membership function to one valued output or any classification based on output [26]. In ANFIS instead of just fixing the shape of membership function, it automatically assigned the type and shape of membership function by analyzing the data [27].

Support Vector machine is the type of supervised learning that is mostly used for regression and pattern recognition purposes [28,29]. Based on soft margin hyper-plane support vector machine have been introduced as new artificial intelligence tool framework for both classification and function approximation [30,31]. Instead of sigmoidal type transfer function like in artificial neural network, support vector machine stands on the kernel neuron function which definitely allows projection to higher planes and able to solve more complicated and complex highly nonlinear problems [32]. SVM applications can be found in many fields like medical, business, civil and electrical [33].

1.3. Application of artificial intelligence in petroleum engineering

Artificial intelligence models were applied in many areas in petroleum engineering. Semi-clathrate hydrate pressure of carbon dioxide, methane, nitrogen, and hydrogen sulfide in the presence of TBAB ionic was obtained using SVM and coupling of SVM with genetic algorithm (GA-SVM). The obtained correlation coefficient was 0.97759 and 0.99944 for SVM and GA-SVM, respectively between the experimental and predicted values [34]. The clathrate hydrate formation pressure of carbon dioxide in the presence of 1,4-dioxine was predicted using ANFIS with a correlation coefficient of 0.9969 and a mean square error of 0.0034, [35].

The moisture content of natural gas dried by calcium chloride dehydrator units was predicted using least squares support vector machines (LSSVM) coupling with genetic algorithm (GA-LSSVM)