CHEMICAL ENGINEERING RESEARCH AND DESIGN 92 (2014) 891–902

Contents lists available at ScienceDirect

Chemical Engineering Research and Design

journal homepage: www.elsevier.com/locate/cherd

Evolving an accurate model based on machine learning approach for prediction of dew-point pressure in gas condensate reservoirs

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ABSTRACT

Over the years, accurate prediction of dew-point pressure of gas condensate has been a vital importance in reservoir evaluation. Although various scientists and researchers have proposed correlations for this purpose since 1942, but most of these models fail to provide the desired accuracy in prediction of dew-point pressure. Therefore, further improvement is still needed. The objective of this study is to present an improved artificial neural network (ANN) method to predict dew-point pressures in gas condensate reservoirs. The model was developed and tested using a total set of 562 experimental data point from different gas condensate fluids covering a wide range of variables. After a series of optimization processes by monitoring the networks performance, the best network structure was selected. This study also presents a detailed comparison between the results predicted by this ANN model and those of other universal empirical correlations for estimation dew-point pressure. The results showed that the developed model outperforms all the existing methods and provides predictions in acceptable agreement with experimental data. Also it is shown that the improved ANN model is capable of simulating the actual physical trend of the dew-point pressure versus temperature between the cricondenbar and cricondenterm on the phase envelope. Finally, an outlier diagnosis was performed on the whole data set to detect the erroneous measurements from experimental data.

Keywords: Retrograde gas condensate; ANN; Dew-point pressure; Statistical error analysis; Outlier detection

1. Introduction

Well deliverability in gas condensate reservoirs, is declined rapidly by condensate banking when the flowing bottom-hole pressure falls below the dew point pressure. The liquid dropout around wellbore causes the productivity decreases. This ring of increased condensation saturation around the wellbore reduces effective permeability to gas and results in rapid well-productivity decline (Elsharkawy, 2002). Therefore accurate prediction of dew-point pressure of gas condensate reservoirs is a critical element in planning the development of gas condensate reservoirs.

Dew-point pressure of a gas condensate sample is determined through the constant mass expansion test. Although the experimentally measurement of dew-point pressure is very accurate and reliable, but it is very time consuming and costly process for gas condensate reservoirs (Grieves and Thodos, 1963; Pedersen et al., 1988; Sage and Olds, 1947).

There are generally two methods to estimate dew-point pressure of gas condensate reservoirs. The first method uses the equations of state and the second one uses empirical correlations. Equations of state do not have ability to simulate the phase behaviour of light oil and gas condensate reservoirs, especially in the retrograde area. Besides, all the developed empirical correlations have not enough accuracy (Shokir, 2008). Therefore, there is a need to methods for predicting the dew-point pressure of gas condensate reservoirs accurately.

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Received 16 October 2012; Received in revised form 4 July 2013; Accepted 13 August 2013

http://dx.doi.org/10.1016/j.cherd.2013.08.014

Nomenclature

AAPE	average absolute relative percent error (%)
ANN	artificial neural network
APE	average percent relative error (%)
C_{7+}	heptane-plus fraction
H	hat value
R, R^2	correlation coefficient
RMSE	root mean square error (%)
MW_{c7+}	molecular weight of heptane plus fraction
P_d	dew-point pressure (psia)
Res	standardized residual
SG_{c7+}	specific gravity of heptane plus fraction
T	temperature (°F)
z_i	mole fraction of i component (hydrocarbon and non-hydrocarbon)

In 1942, Kurata and Katz (1942) developed a correlation to estimate critical properties of light hydrocarbon mixtures. They used a limited number of dew-point pressure to develop their correlation, but the effect of fluid composition were neglected.

Olds et al. (1945) used the compositions of oil and gas samples obtained from primary separator of a well in the Paloma field, to develop a new correlation for prediction of dew-point pressure of gas condensate reservoirs in graphical and tabular form. They also investigated the effect of omission of intermediate molecular weight on dew-point pressure. They showed that intermediate molecular weight components have a considerable effect on dew-point pressure. Olds et al. (1949) experimentally investigated the volumetric behaviour for different mixtures of gas condensate reservoirs from San Joaquin Valley field. They presented a correlation which relates dew-point pressure to stock tank API oil gravity, gas–oil ratio, and temperature in tabulated and graphical forms.

Reamer and Sage (1950) used five different pairs of fluids from a field in Louisiana. They studied the effects of temperature and gas–oil ratio on dew-point pressure. The results are presented in graphical forms. Moreover, they concluded that due to complex effect of fluid composition on dew-point pressure, a general correlation for this purpose is not possible.

Organick and Golding (1952) introduced a simple correlation in the form of working charts for prediction of dew-point pressure in gas condensate reservoirs. Nemeth and Kennedy (1967) proposed a mathematical relationship between the dew-point pressure of a hydrocarbon fluid and its composition, temperature and characteristics of the C_{7+} fraction. They used 579 data sets from 480 hydrocarbon systems. Their correlation contains 11 coefficients with an average deviation of 7.4%.

Later, Crogh (1996) improved the Nemeth and Kennedy correlation for better prediction of dew-point pressure. One should note here that, reservoir temperature was not considered in the developed correlation.

Humoud and Al-Marhoun (2001) developed an empirical correlation to estimate dew-point pressure in gas condensate systems using available field data. They used different gas condensate fluid samples in Middle East. The newly proposed correlation predicts with an average absolute error of 4.3%, and a maximum relative error of 15.1%.

Elsharkawy (2002) published another mathematical model to predict dew-point pressure of gas condensate reservoirs using parameters involved in Nemeth and Kennedy correlation. Their correlation contains 19 constants with an average absolute deviation of 7.68%.

Shokir (2008) developed another new mathematical genetic programming based model. In the proposed model the effect of SG_{C7+} was not considered. The comparison indicated that the developed model is more accurate than Elsharkawy (2002) correlation and Peng–Robinson EOS. Although numerous number of equations of state (Martin, 1979; Soave, 1972; Zudkevitch and Joffe, 1970), have been developed to model reservoir fluid phase behaviour, but they could not simulate the phase behaviour of complex hydrocarbons such as gas condensates in the retrograde region (Sarkar et al., 1991).

Nowadays, with the aid of computers, artificial intelligence has become an inseparable part of engineering predictions especially in chemical and petroleum engineering (Ahmadi et al., 2013; Ali Ahmadi et al., 2013; Arabloo et al., 2013; Chamkalani et al., 2013; Farasat et al., 2013; Hemmati-Sarapardeh et al., 2013; Kumar, 2009; Morooka et al., 2001; Rafiee-Taghanaki et al., 2013; Roosta et al., 2011; Shokrollahi et al., 2013; Zendehboudi et al., 2012). The complexity, fuzziness and uncertainty existent in addition to non-linear behaviour of most reservoir parameters such as dew-point pressure in gas condensate reservoirs require a powerful tool to overcome these challenges. To this end, objective of this study is to predict dew-point pressure of retrograde gas condensate reservoirs using a wide range of experimental data points by applying artificial neural network. In addition, results of estimated dew-point pressure by developed intelligent model are also compared with predictions of other empirical correlations. Finally, validity and sensitivity of the proposed model is examined against variation in temperature.

2. Artificial neural networks (ANN)

A detailed description of neural networks is given elsewhere (Haykin, 1994). ANNs imitates the behaviour of biological neurons and learn by trial and error. These methods have large numbers of computational units connected in a massively parallel structure and do not require an explicit formulation of the mathematical or physical relationships of the handled problem (Chouai et al., 2002). The overall computational model consists of a reconfigurable interconnection of simple elements, or units. Fig. 1 depicts a sample network, where units are denoted by circles and interconnections are shown as lines. Notice that some units in Fig. 1 interface directly with the outside world, whereas others are “hidden” or internal. Individual units implement a local function, and the overall network of interconnected units displays a corresponding functionality. In other words, the system’s knowledge, experience, or training is stored in the form of network interconnections. Analysis of this functionality, except through training and test examples, is often difficult. To be useful, neural systems must be capable of storing information (i.e., they must be “trainable”). Neural systems are trained in the hope that they will subsequently display correct associative behaviour when presented with new patterns to recognize or classify (Schalkoff, 1997).

To optimize the network performance function, during training process the connection weights and biases are adjusted by a trial and error process. There are many different types of neural networks that differ from each other in network structure and/or learning algorithm. Many parameters