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Application of expert systems for accurate determination of dew-point pressure of gas condensate reservoirs

Hadi Rostami-Hosseinkhani [a,*], Feridun Esmaeilzadeh [b], Dariush Mowla [b]

[a] Department of Petroleum Engineering, Science and Research Branch, Islamic Azad University, Fars, Iran
[b] Chemical and Petroleum Engineering Department, School of Engineering, Shiraz University, Fars, Iran

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ABSTRACT

Dew-point pressure is a parameter that has a key role in development of gas condensate reservoirs. Dropping of reservoir pressure below the dew-point pressure results in a decrease in production because of near wellbore blockage. In addition, due to separation of liquids, the produced gas has fewer valuable components. This study tries to develop a dependable method based on machine learning to adequately predict this important parameter. The intelligent system used in this work is Radial Basis Function (RBF) network that is a very flexible tool for pattern recognition. This model was developed and tested using a total set of 562 experimental data point acquired from different retrograde gas condensate fluids covering a wide range of variables. To optimize the tuning parameters of the proposed model, genetic algorithm was incorporated. This study also presents a detailed comparison between the results predicted by the proposed RBF model and those of other universal empirical correlations and intelligent systems for estimation dew-point pressure. The results showed that the presented model is superior to the pervious classic correlations and also intelligent systems.

1. Introduction

Gas condensate reservoirs contain a significant resource of petroleum all around the world. The major gas condensate reservoirs include Shtokmanovskoye field in the Russian Barents Sea, Karachaganak field Kazakhstan, the North field in Qatar that becomes the South Pars field in Iran, and the Cupiagua field in Colombia. The choking happening near the wellbore can significantly reduce the productivity of the well (Fan et al., 1998). At the early stages of the gas condensate reservoirs production, the reservoir fluid is a single-phase gas that comprises mainly of methane and some other light hydrocarbons. However, it contains some heavy ends. As production goes on, the pressure tremendously decreases and the most severe condition happens near the wellbore of producing wells. At a certain pressure, which is called dew-point or saturation pressure, retrograde condensate starts to drop out of solution. In such a condition, the fluid separates to two phases of gas and liquid. Further decrease in pressure increases the volume of the liquid to a maximum amount and after that the liquid volume starts to decrease. The phase envelope of gas condensate reservoir obviously justifies this behavior (Fig. 1). The phase envelope of gas condensate reservoirs is smaller than the oil reservoir's ones and the critical points tend to be on the much more left side compared with oil reservoirs phase envelopes. The temperature of a gas condensate reservoir lies between the critical temperature and cricondentherm.

The liquid dropout develops an apparent skin (Blom et al., 2000; Calisgan et al., 2006; Elsharkawy, 2002; Nowroozi et al., 2009; Hashemi et al., 2006). Even in lean gas condensate wells by continual passing of fluid through the wellbore, high condensate saturation might develop (Boom et al., 1996). Several authors have reported large productivity losses due to condensate blockage (Afidick et al., 1994; Barnum et al., 1995; Smits et al., 2001; Fevang and Whitson, 1996). Thus, accurate determination of dew-point is of great importance. Several researchers have attempted to determine this feature either experimentally or theoretically. There have been several attempts to provide a general correlation to predict the dew-point of gas condensate reservoirs. At the first 1940s, Kurata and Katz (Kurata and Katz, 1942) developed a correlation to predict the critical features of volatile hydrocarbon mixtures. However, they neglected the effect of fluid composition. In 1942, Eilerts and Smith (Eilerts and Smith, 1942) related dew-point pressure to temperature, composition, gas oil ratio, and boiling point of the fluid. Olds et al. (Olds et al., 1949) developed a new

* Corresponding author. Tel.: +98 9177417691.
E-mail address: rostami.hadi2000@gmail.com (H. Rostami-Hosseinkhani).

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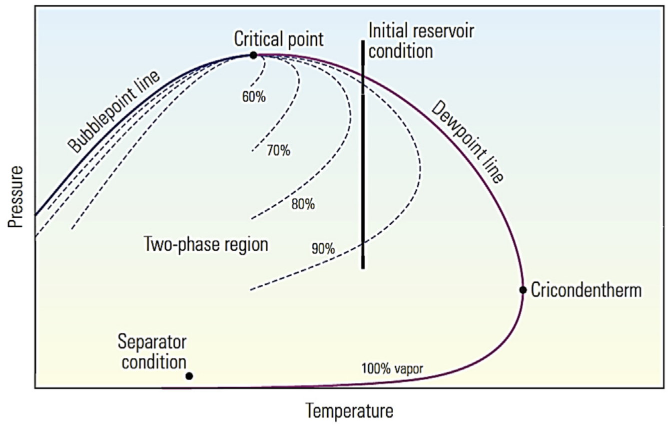

Fig. 1. A typical phase envelop of gas condensate fluid (Fan et al., 1998).

correlation to predict the dew-point pressure in both graphical and tabular form using samples obtained from primary separator of a well in the Paloma field. Investigating the effects of intermediate molecular components, the authors concluded that these fractions have a prominent effect on the dew-point pressure. Reamer and Sage (Reamer and Sage, 1950) tried to extend the existing correlations to greater ranges of gas-oil ratios. They stated that because of complex relations between composition and dew-point pressure, it is not practical to develop a universal correlation to predict this parameter. Two years later, Organick and Golding (Organick and Golding, 1952) developed a correlation in form of working charge to predict the dew-point pressure of gas condensate fluids. In 1967, Nemeth and Kennedy (Nemeth and Kennedy, 1967) attempted to develop a mathematical relationship between dew-point pressure and temperature, composition, and characteristics of the C_{7+} fraction of the hydrocarbon fluid. For this aim, they used multiple-variable regression analysis. The proposed correlation has some coefficients and resulted in an average deviation of 7.4%. About thirty years later, Crogh (Crogh, 1996) tried to modify the Nemeth and Kennedy (Nemeth and Kennedy, 1967) correlation. Humoud and Al-Marhoun (Humoud and Al-Marhoun, 2001) proposed a correlation to predict dew-point pressure using available field data form Middle East region. Elsharkawy (Elsharkawy, 2002) proposed a mathematical correlation between dew-point of the gas condensate reservoirs and composition of the hydrocarbon fluid, temperature, and molecular weight and specific gravity of the heptane-plus components. In 2003, Gonzalez et al. (González et al., 2003) constructed a multilayer perceptron artificial neural network to predict the dew-point pressure. The reservoir temperature, hydrocarbon and non-hydrocarbon composition, molecular weight, and specific gravity of the C_{7+} were used as the input of the developed network. An alternative to predict the dew-point pressure is the use of equation of state (EOS). Despite several proposed EOSs, none can accurately predict the dew-point pressure of the complex hydrocarbons such as volatile oils and gas condensates, especially in the retrograde region (Sarkar et al., 1991).

The complexity of non-linear behavior of involved parameters indicates that development of a universal correlation to predict dew-point pressure of gas condensate is an illusion. The best tool to deal with this challenge is intelligent system. The use of intelligent systems in petroleum engineering is well developed in literature (Gharbi and Elsharkawy, 1997; Elsharkawy, 1998; Al-Shammasi, 1999; Al-Marhoun and Osman, 2002; Gharbi et al., 1999; Goda et al., 2003). The aim of this study is to develop an accurate and reliable intelligent system based on radial basis function networks (RBFN) to predict the dew-point pressure.

2. Radial basis function networks

Artificial Neural Networks (ANNs) are flexible tools that can learn from experience and improve their performance (Santos et al., 2013). Using ANNs, it is possible to manipulate a large amount of data and generalize the results. ANNs consist of artificial neurons as processing units, which are distributed in layers. Two popular and well-known ANNs with the same application but different internal structures are multilayer perceptron (MLP) networks and radial basis function (RBF) networks. Despite of MLPs, RBFs have a structure with only three layers. This kind of networks responses very well to the data, which were not introduced to the network in training process. In other words, they are capable of good generalization (Santos et al., 2013; Hao et al., 2011). The other advantages of RBFNs are high tolerance of input noises and online learning (Santos et al., 2013). However, RBF networks can be implemented using MLP with some changes (Wilamowski and Jaeger, 1996). The schematic representation of RBF networks is presented in Fig. 2. These networks are comprised of three different layers namely input, output, and a hidden layer. Each node in the hidden layer uses an RBF as a nonlinear activation function. As it is evident, the RBF network's structure is sort of similar to that of MLP networks. Despite MLP networks in which there can be several hidden layers, RBF contains only one hidden layer, thus, it has a fixed structure. Thus, RBF networks are simpler than MLP ones. This feature generally results in much faster training in RBF networks. The other point is different classification methods. In MLP, the data clusters are separated by hyper surfaces, while in RBF networks, hyper spheres separate them (Hao et al., 2011).

RBFNs are feed-forward neural networks and uses supervised training (Karri, 1999). Exact interpolation in a multidimensional space is the origin of the RBF (Powell, 1987).

The formulation of the RBFN is as follows:

$$y_i(x) = \sum_{k=1}^{J_2} w_{ki}\phi(\|x - c_k\|) \tag{1}$$

For $i = 1,\ldots,J_3$, where $y_i(x)$ is the ith output of the network, c_k is prototype of center of the kth hidden unit, w_{ki} is the connection weight from the kth hidden unit to the ith output unit, and $\|\cdot\|$ denotes the Euclidean norm. The RBF $\phi(\cdot)$ is typically selected as the Gaussian function (Du and Swamy, 2006).

The matrix form of Equation (1) is:

$$Y = W^T\Phi \tag{2}$$

In which $W = [w_1,\ldots,w_{J_3}]$ is a $J_2 \times J_3$ weight matrix, $w_i = (\omega_{1i},\ldots,\omega_{J_2 i})^T$, $\Phi = [\phi_1,\ldots,\phi_N]$ is a $J_2 \times N$ matrix,

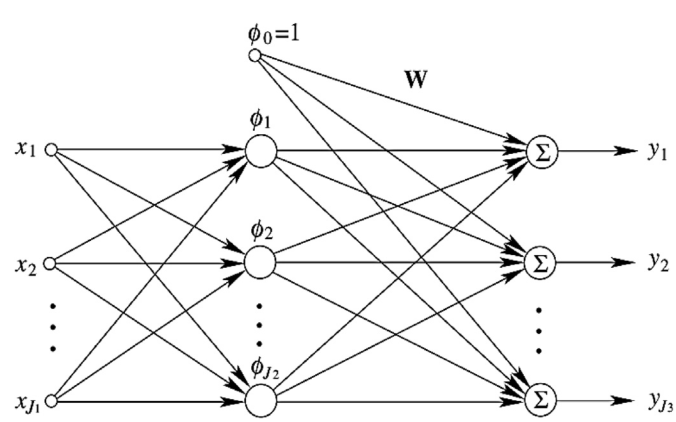

Fig. 2. The architecture of radial basis function network (Hao et al., 2011).