



Robust intelligent tool for estimating dew point pressure in retrograded condensate gas reservoirs: Application of particle swarm optimization

Mohammad Ali Ahmadi^{a,*}, Mohammad Ebadi^b, Arash Yazdanpanah^{c,*}

^a Department of Petroleum Engineering, Ahwaz Faculty of Petroleum Engineering, Petroleum University of Technology, Ahwaz, Iran

^b Department of Petroleum Engineering, Science and Research Branch, Islamic Azad University, Tehran, Iran

^c Iranian Offshore Oil Company (IOOC), Tehran, Iran

ARTICLE INFO

Article history:

Received 25 October 2013

Received in revised form

6 February 2014

Available online 4 June 2014

Keywords:

dew point pressure

swarm intelligence

fuzzy logic

condensate gas reservoirs

artificial intelligence

ABSTRACT

Liquid production from gas condensate reservoirs, which is an important economic and technical issue, depends on the thermodynamic conditions underlying the porous media. Accurately estimating the relevant parameters is an incentive for researchers to develop and propose a diversity of correlations; however, certain correlations are not sufficiently precise compared with correlations that are routinely applied to determine the dew point pressure (P_d). Due to numerous misunderstandings in P_d estimations, which are typically observed in upstream industries, great effort was expended herein to produce a high-performance method to monitor the P_d . The solution was produced by creating a hybrid of two effective and robust methods, the swarm intelligence and artificial neural network (ANN) models. The proposed model was extended using precise dew point pressure data reported in previous studies; moreover, based on these data, the evolved intelligent approach and conventional schemes were compared. The statistical results show a notable performance by the smart model in determining the dew point pressure of condensate gas reservoirs. Based on the reliable results, which are highly accurate and effective, it can logically be inferred that implementing the proposed approach, PSO-ANN, can aid in better understanding reservoir fluid behavior through reservoir simulation scenarios.

© 2014 Elsevier B.V. All rights reserved.

1. Introduction

Gas condensate reservoirs, which are one of the most valuable types of hydrocarbon sources with an ability to supplement high levels of energy, have become popular (Mohammadi et al., 2013; Mokhtari et al., 2013; Sadeghi Booghar and Masihi, 2010). Consequently, preparing effective, complete and multidisciplinary approaches to production using such reservoirs has practical, methodical and monetary significance. To develop vital and crucial plan for production using the aforementioned resources, demands for an exact, accurate and definite understanding of reservoir fluid properties have continuously been considered. In other words, PVT properties, for which even insignificant and infinitesimal mathematical errors in their estimation can result in severe problems for successive processes, are the most important pieces of information that can be determined from each step in reservoir simulations and development (Alavi et al., 2010; Mokhtari et al., 2013; Ursin, 2004; Yong et al., 2010).

A step referred to as “flow-in” is the starting point for reservoir pressure reduction, which leads to liquid drop formation in zones near the wellbore due to overtaking a pressure threshold referred to as *dew point pressure* (P_d) (Brown et al., 2009; Elsharkawy and Foda, 1998; Nasrifar et al., 2005). Dramatic reductions in the gas relative permeability and gas production rate are intense effects from the aforementioned drop formation (App and Burger, 2009; Chowdhury et al., 2008; Thomas et al., 2009). Accordingly, careful determination of the P_d is essential. Hence, great effort either via theoretical or laboratorial methods has been expended, and suggestions have been generated for measuring the P_d (Berning, 2012; Louli et al., 2012; Rahimpour et al., 2011; Nowroozi et al., 2009). Constant volume depletion (CVD) is an experimental process, which generates P_d from samples. These methodologies, the comprehensive steps for which have been fully determined in previous studies, routinely include technical hitches, such as price and slow speed, and their reliability is effected by external influences, such as human error (Luo et al., 2001; Shadizadeh et al., 2006; Shen et al., 2001; Zheng et al., 2000; Jalili et al., 2007).

Furthermore, certain mathematically inspired solutions and concepts, such as equation of states (EOS), and empirically

* Corresponding author. Tel.: +98 912 6364936.

E-mail addresses: ahmadi6776@yahoo.com (M.A. Ahmadi), ahmadi6776@yahoo.com (A. Yazdanpanah).

derived correlations have been presented that measure the critical PVT properties (Bonyadi and Esmailzadeh, 2007; Elsharkawy, 2002a, 2002b; Li et al., 2012). For instance, a formula mainly based on C7+ characterization, temperature and fluid composition was generated by Nemeth and Kennedy (1966) through multiple regressions and was supported by an extensive database to predict the P_d . The applicability of the formula is reliable under specific thermodynamic ranges (Nemeth and Kennedy, 1967). Additionally, researchers have attempted to model production from gas condensate reservoirs without using PVT data; this was exemplified in a study by Marruffo et al., who generated an approach for estimating the P_d and C7+ content in gas condensate reservoirs (Marruffo et al., 2001). In addition, the impact of impurities (mostly H_2S) on the P_d was studied by Carison and Cawston (Carlson and Cawston, 1996). Through total volume observations during the CCE test, a graphical model was proposed to predict the P_d through accurately determining the Z-factor. In sum, comparatively stress-free processing, ease of use and a general disregard of the temperature influence are the benefits and weaknesses of the experiential relationships (Nowroozi et al., 2009). Further, the reliance on primary derived data caused a decrease in appropriate EOS presentations upon application to new sites, and operators were required to calibrate the related parameters (Jalili et al., 2007).

Thus, studies have yielded more beneficial, careful and appropriate approaches. Due to their inherent capacity for managing non-linearity, vagueness and uncertainty, scientists have used soft computing methods to overcome reservoir engineering problems, such as extracting PVT properties (Farasat et al., 2013; Zendehboudi et al., 2012). For example, Akbari et al. applied a certain type of artificial neural network (ANN) to calculate the P_d using a group of thermodynamic and compositional features as the input (Jalili et al., 2007). Likewise, Nowroozi et al. constructed an adaptive neuro-fuzzy inference system (ANFIS) to predict the P_d by primarily considering compositional factors (Nowroozi et al.,

2009). Similarly, Kaydani et al. (2013) proposed a conventional type of back-propagation artificial neural network to predict the P_d of lean retrograde gas condensate reservoirs.

For modern optimizing algorithms, it is valuable to refer to research by Rostami and Khakassr (2012), who proposed a model to predict the P_d through coupling Gaussian processes and particle swarm optimization methods. Moreover, this research was proposed as an easy-to-use, robust and sharp model for predicting dew point pressure (P_d) in retrograded gas condensate reservoirs. Thus, a hybrid composed of swarm intelligence and neural network as well as fuzzy logic (FL) coupled with genetic algorithm (GA)-fuzzy logic (FL) as robust artificial intelligent models was utilized to address the problems considered by this research. Thus, massive dew point pressure data banks extracted from previous studies (Ahmadi and Ebadi, 2014; Al-Dhamen, 2010) were used in the aforementioned approaches for testing and validation. To confirm the capability and reliability of the evolved PSO-ANN approach, conventional correlations were used to estimate crude oil saturation pressure. The results for both intelligent and conventional correlations are shown in detail in the sections below. Additionally, descriptions of the models addressed herein are expanded in the following sections.

2. Methodology

2.1. Artificial Neural Network (ANN)

Artificial neural networks compose a bio-inspired approach, the initial pattern for which was determined from studying common human brain processes, that can numerically and inversely correlate relationships between input and output for each system due its distinct mathematical structure. The data are then technically implemented to train the network, and the network is used to estimate imprecise and vague data (Bain, 1873; James,

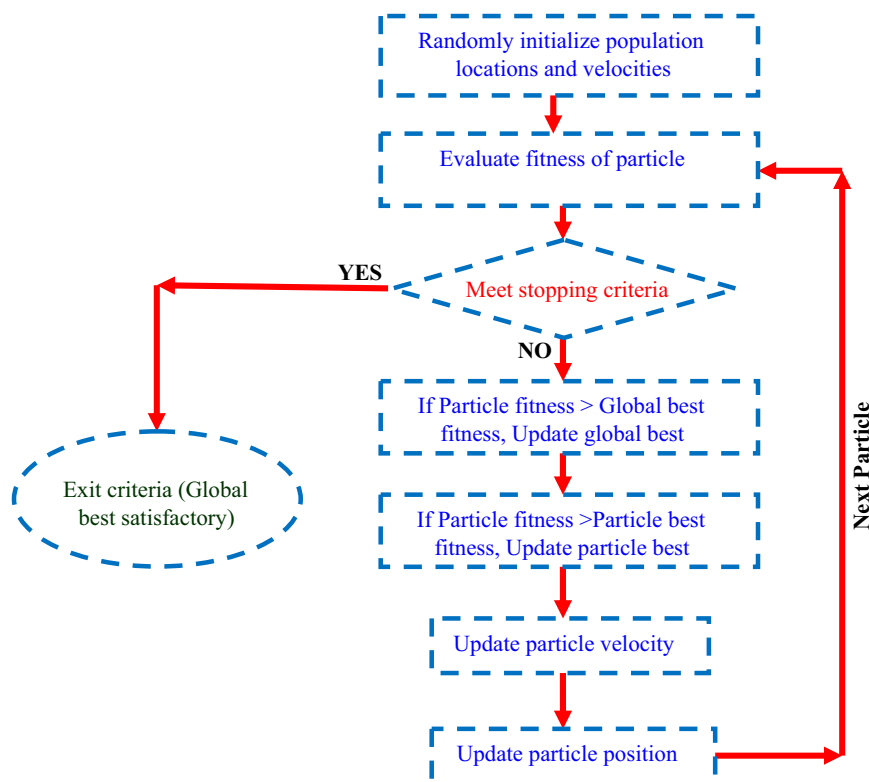


Fig. 1. Flow chart for the particle swarm optimization process (Ahmadi and Shadizadeh, 2012; Zendehboudi et al., 2012, 2013a, 2013b).

Download English Version:

<https://daneshyari.com/en/article/1754901>

Download Persian Version:

<https://daneshyari.com/article/1754901>

[Daneshyari.com](https://daneshyari.com)