Fuel 124 (2014) 241–257

Contents lists available at ScienceDirect

Fuel

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

Evolving predictive model to determine condensate-to-gas ratio in retrograded condensate gas reservoirs

Mohammad Ali Ahmadi [a,*], Mohammad Ebadi [b], Payam Soleimani Marghmaleki [c], Mohammad Mahboubi Fouladi [a]

[a] Department of Petroleum Engineering, Ahwaz Faculty of Petroleum Engineering, Petroleum University of Technology, Ahwaz, Iran
[b] Department of Petroleum Engineering, Islamic Azad University, Science and Research Branch, Tehran, Iran
[c] Department of Petroleum Engineering, Abadan Faculty of Petroleum Engineering, Petroleum University of Technology, Abadan, Iran

HIGHLIGHTS

- Implementation of low parameter approach to predict condensate-to-gas ratio in retrograde gas reservoirs.
- Performing different fuzzy approaches to estimate addressed target.
- Regression analysis for developing CGR correlation.
- Handling extensive condensate-to-gas ratio in retrograde gas reservoirs by new network approach.

ARTICLE INFO

Article history:
Received 8 October 2013
Received in revised form 22 January 2014
Accepted 23 January 2014
Available online 11 February 2014

Keywords:
Condensate gas
Dew point pressure
Condensate-to-gas ratio
Least square
Support vector machine

ABSTRACT

Added values to project economy from condensate sales and gas deliverability loss due to condensate blockage are the distinctive differences between gas condensate and dry gas reservoirs. To estimate the added value, one needs to obtain condensate to gas ratio (CGR); however, this needs special pressure–volume–temperature (PVT) experimental study and field tests. In the absence of experimental studies during early period of field exploration, techniques which correlate such a parameter would be of interest for engineers. In this work, the developed model inspired from a new intelligent scheme known as "least square support vector machine (LSSVM)" to monitor condensate gas ratio (CGR) in retrograde condensate gas reservoirs. The proposed approach is conducted to the laboratorial data from Iranian oil fields and reported in literature has been implemented to mature and test this approach. The generated results from the LSSVM model were compared to the addressed real data and generated results of conventional correlation and fuzzy logic models. Making judgements between the generated outcomes of our model and the another course of action proves that the least square support vector machine model estimate condensate gas ratio more accurately in comparison with the conventional applied approaches. It worth mentioning that, least square support vector machine do not have any conceptual errors like as over-fitting issue while artificial neural networks suffer from many local minima solutions. Outcomes of this research could couple with the commercial production softwares for condensate gas reservoirs for different goals such as production optimization and facilitate design.

1. Introduction

Retrograde gas condensate reservoirs modelling and characterization projects has always been one of the most minefield, demanding and paramount issues causing reservoir experts and engineers to spend too much time and energy to handle them carefully and effectively [1,2]. When the related meetings and discussions about retrograde gas condensate reservoirs characterization, as one of the most valuable kinds of petroleum reservoirs, are held, the importance of these kinds of topics emerges [3–5]. This is because of added values to project economy from condensate sales and gas deliverability loss as a result of condensate blockage [6]. In order to prevent any possible problems and defeat any probable obstacles, obtaining and estimating vital parameters of retrograde gas condensate reservoirs is enormously highlighted and also, a high level of accuracy is definitely required to conclude a global agreed interpretation about the performance of gas condensate reservoirs [7–11]. For instance, although measuring dew point pressure which behaves extremely nonlinear as

* Corresponding author. Tel.: +98 912 636 4936.
E-mail address: ahmadi6776@yahoo.com (M.A. Ahmadi).

http://dx.doi.org/10.1016/j.fuel.2014.01.073
0016-2361/

a crucial attributes in these kinds of reservoirs is possible through running some traditional tests like Constant Mass Expansion (CME), researchers have usually preferred to utilize some offered methods either theoretical or combination of traditional laboratorial process and artificial intelligence [12–15] which are able to estimate efficiently this factor. Being still expensive and cumbersome, lack of ability to acquire a representative sample, having not enough samples to complete the analysis and inherent error of each experimental procedure are the most important reasons and setbacks that according to them, researchers would like to apply non laboratory methods. To evaluate the performance of retrograde gas condensate reservoirs a numerous number of approaches have been offered. Thomas et al. [16] to provide a deep insight into gas condensate reservoir in order to forecast the future of the target reservoir have implemented a technique gaining from appropriate characterization of the in situ fluids and relevant flow testing. The forthcoming performance prediction of the retrograde gas condensate reservoirs becomes important when designing and optimizing the wellhead equipment and facilities of the production unit draw both economically and technically attention [17–19]. In order to propose effectively the best and most compatible model, noticeable number of attempts has been made. Alavi et al. [20], achieved an acceptable convergence between calculated and observed data to generate production rate data, as a major parameter to design wellhead equipment, in a special case through tuning the Peng–Robison equation of state and some routine laboratory experiments. The incentive of made efforts is suggesting the most suitable design and solution to optimize the amount of the condensate production, mostly forms in a gas condensate reservoir and commonly around the wellbore when pressure declines below the dew point [21], as one of the most unlimited precious products of retrograde gas condensate reservoirs. In more details, some very exact laboratory procedures such as Constant Volume Depletion (CVD) and Constant Composition Expansion (CCE) can be referred to measure the amount of the produced condensate; however, some limitations like not having access to well equipped laboratories lead researchers and experts to use some conventional and modern models combined with artificial intelligence which have been recommended and presented to do predict the amount of produced condensate. Jokhio et al. [22] according to the Whitson and Fevang's model [23], which is based on relative permeability and pressure–volume–temperature (PVT) data, predicted liquid condensate production. They obtained the effective permeability as a function of pressure through using pressure transient methods. Next, the closest region to the wellbore as a source of condensate considered through applying some well testing models. In another case, Al-Farhan et al. [24] believed that the quality and quantity of the produced condensate is a strong function of surface operating pressure. As a result, they linked directly the amount of the produced condensate through paying attention to Condensate Gas Ratio (CGR). Initially, they take a three-stage separation process in which the pressure of the first and third stages is set by operator and the pressure of the second stage where the maximize liquid (condensate) yields is the variable. To optimize this process, they exploited a four layered Artificial Neural Network (ANN) with Back Propagation (BP) algorithm consisted of compositional ranges as inputs (13 neurons) and CGR, second-stage separator pressure and API as outputs (3 neurons). Furthermore, England [25] under special conditions derived a global polynomial correlation of CGR against temperature and pressure from a database of PVT data.

In this paper, an intelligent approach utilizing a new type of network modelling which known as the LSSVM approach is evolved and checked to serve as a rapid and inexpensive predictive model for CGR prediction in gas-condensate reservoirs. The proposed LSSVM model is developed implementing extensive actual CGR data. To depict the robustness, integrity and accuracy of the suggested LSSVM model, the obtained outcomes from the introduced approach are contrasted with the relevant actual CGR data. Outputs from this research reveal that the evolved approach can monitor the CGR with eye-catching level of precision. The established model could be served as a dependable approach for fast and inexpensive but rigorous prediction of CGR parameter in absence of appropriate experimental or/and real data, specifically through the primary steps of evolvement of gas-condensate reservoirs.

2. Methodology

2.1. Least square support vector machine (LSSVM)

Suykens and Vandewalle in 1999 developed the original least square support vector machine (LSSVM) based on first type of support vector machine (SVM). The prior idea of the least LSSVM is summarized to evolve rigorous, user friend and also avoiding over-fitting issue which could occur some times in original SVM and/or Artificial Neural Networks (ANNs). Before tackling the details of the LSSVM approach, a graphical illustration of the LSSVM depicted in Fig. 1 which presents the procedure of LSSVM regression algorithm. Consider given inputs Xi (Molecular Weight, Temperature and Pressure) and output Yi (Condensate-to-gas ratio) time series. Nonlinear function through least square support vector machine (LSSVM) can be expressed as follows [26–31]:

$$f(x) = w^T x + b \tag{1}$$

where f demonstrates the correlation between the condensate-to-gas ratio and molecular weight, temperature and pressure, w stands for them-dimensional weight vector, φ represents the planning function that maps x into the m-dimensional feature vector and b denote the bias term [26–31].

The regression issue can be obtained dedicated to the topological minimization phenomenon by mulling over the complicatedly of function a fitting error as follow [26–31]:

$$\text{Min } J(w, e) = \frac{1}{2} w w^T = \gamma \sum_{k=1}^{m} e_k^2 \tag{2}$$

While following restriction exist [26–31]:

$$y_k = w^T \varphi(x_k) + b + e_k, \quad k = 1, 2, \ldots, m \tag{3}$$

where γ is the margin parameter and e_k is the loose variable for x_k [26–31].

A way can be used to figure out the rout of the optimization problems given in Eq. (2) is changing the limited matter into an unlimited problem and defining the Lagrange multipliers α_i for determining the objective function as following as [26–31]:

$$L(w, b, e, \alpha) = J(w, e) - \sum_{k=1}^{m} \alpha_i \{ w^T \emptyset(x_k) + b + e_k - Y_k \} \tag{4}$$

Be dedicated by the Karush–Kuhn–Tucker (KKT), the optimal situations may be figured out by carrying the partial derivatives of Eq. (4) with respect to w, b, e and α, correspondingly as below [26–31]:

$$\left\{ \begin{array}{c} w = \sum_{k=1}^{m} \alpha_i \emptyset(x_i) \\ \sum_{k=1}^{m} \alpha_i = 0 \\ \alpha_i = \gamma e_i \\ W^t \emptyset(x_i) + b + e_i - Y_i = 0 \end{array} \right\} \tag{5}$$

Thus, the linear equations are figured out as below [26–31]:

$$\begin{bmatrix} 0 & -Y^T \\ Y & ZZ^T + 1/\gamma \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \tag{6}$$