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Evolving smart approach for determination dew point pressure through condensate gas reservoirs

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HIGHLIGHTS

- Evolving low parameter model to predict dew point pressure in retrograde gas reservoirs.
- Comparing effectiveness of the conventional models versus developed LSSVM model.
- Handling extensive dew point pressure data in retrograde gas reservoirs by new type of intelligent based model.

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ABSTRACT

To design gas condensate production planes with low uncertainty along with robust reservoir simulation, precise estimation or monitoring of dew point pressure play a crucial role. To handle successfully the addressed issue of condensate gas reservoirs, massive attentions have been performed previously but unfortunately fail to develop accurate approach for estimation dew point pressure. Dedicated to this fact, in current study enormous attempts have been put forth to proposed revolutionary method for determining dew point pressure in gas condensate reservoirs. To gain this end the new type of support vector machine method which evolved by Suykens and Vandewalle was utilized to generate robust approach to figure dew point pressure in condensate gas reservoir out. Also, lucrative and high precise dew point pressures reported in previous attentions were carried out to test and validate support vector machine approach. To serve better understanding of the proposed support vector machine approach, the conventional feed-forward artificial neural network and couple of genetic algorithm (GA) and fuzzy logic applied to the referred data banks and the gained solutions were contrasted with each other. According to the root mean square error (RMSE), correlation coefficient and average absolute relative deviation, the suggested support vector machine approach has acceptable reliability, integrity and robustness draw an analogy with the artificial neural network model and conventional methods. Thus, the proposed intelligent based way can be considered as an alternative model to monitor the dew point pressure of condensate gas reservoirs when the required real data are not accessible.

1. Introduction

Gas condensate reservoirs are generally known as one of the most precious types of hydrocarbon reservoirs having capability of supplementing a massive clean amount of energy [1–3]. As a result, providing efficient, multidisciplinary and detailed production plans for these reservoirs has its own technical and economic importance. To design crucial and vital schemes to exploit from these gas sources, requiring accurate, precise and specified knowledge about reservoir fluid properties has always been a matter of consideration. In other words, pressure–volume–temperature (PVT) properties, which even small errors in their estimations lead to be encountered with some serious difficulties in subsequent procedures, play the leading role in every aspect of these kinds of reservoirs simulations and developments [2,4–6].

After beginning the step named "Flow-In" in gas condensate reservoirs, continues reduction in reservoir pressure caused formation of liquid drops in zones vicinity of the wellbore as a direct consequence of crossing the reservoir pressure from a threshold, a pressure-type border called *dew point pressure* (*Pd*) [7–9]. The creation of referred drops gives rise to decline dramatically the gas relative permeability and also gas production rate [10–12]. As a result, exact determination of the *Pd* must be taken as a very important topic. Therefore, numerous numbers of theoretical or

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experimental methods have smartly been put forward to measure *Pd* [13–16].

The Constant Composition Expansion (CCE) and the Constant Volume Depletion (CVD) are known as laboratorial procedures which are capable of extracting the *Pd* factor from gathered samples. These methods which their detailed steps have fully been described in literatures are routinely concluded to have some difficulties such as their expensive and time-consuming processes and also their accuracies are highly infected by some external parameters like human errors [17–21].

Moreover, empirically derived equations and Equation of States (EOS) are mathematical inspired concepts for measurements of some critical PVT properties [22–24]. Through running a multiple regression and gaining from an extensive database, a correlation based on temperature, characterizations of C7+ and fluid compositions was developed by Nemeth and Kennedy to predict *Pd* working properly under specified thermo dynamical ranges [25]. Improvements in characterizations and production from gas condensate reservoirs without using PVT data were achieved by Marruffo et al. who proposed a model to predict Pd and C7+ contents of gas condensate reservoirs [26]. Also, the influence of non-hydrocarbon impurities, particularly H2S, on the Pd has been investigated by Carison and Cawston [27]. Potsch and Braeuer proposed a graphical model as strong function of *Z*-factor accurate reading to determine the *Pd* based on observations of total volume during running the CCE test [28]. To sum up, relatively easy to use and not normally considering the temperature behavior are respectively known as one of advantages and disadvantages of empirical correlations [16]. On the other hand, the noticeable level of dependency towards initial deriving data caused EOSs losing their appropriate performances in case of applying on new locations and channel operators towards calibrating again the related parameters [21].

Hence, great efforts have been made to propose more useful, exact and suitable methods. Soft computing approaches thanks to their abilities of dealing with non-linearity, uncertainty and ambiguity of supposed problems have drawn attentions of researchers to defeat obstacles of reservoir engineering problems like extracting PVT properties, ashphaltene precipitation, condensate-to-gas ratio, minimum miscible pressure (MMP) and reservoir permeability [29–36]. For instance, Akbari et al. implemented a certain type of an Artificial Neural Network (ANN) to predict *Pd* through taking a set of compositional and thermo dynamical factors as input [21]. Furthermore, Nowroozi et al. designed an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict *Pd* by regarding mostly compositional parameters [16]. In addition, The main goal of current study is execute new kind of reversed based solution approaches called "least square support vector machine (LSSVM)" to develop robust, lucrative and precise predictive correlation to forecast dew point pressure through gas condensate reservoirs. To beat successfully this referred hurdle, least square support vector machine (LSSVM) was carried out on the previous literature data bases. The integrity and performance of the proposed predictive approach in estimating experimental dew point pressure from the literature is described in details. Furthermore, to point out reliability of the (LSSVM) results, expensive experimental data from one of the northern Persian Gulf gas fields of Iran was implemented to draw an analogy and proves the intelligent approach versus well-known dew point pressure methods.

2. Least square support vector machine (LSSVM)

The least square SVM theorem was introduced and developed by Suykens and Vandewalle in 1999 dedicated to the presumption that the implemented data assortment $S=\{(x_1,y_1),\ldots,(x_n,y_n)\}$ that deal with a nonlinear function and decision function can be formulated as illustrated in Eq. (1). Through the addressed equation, w stands for the weight factor, φ denotes the nonlinear function which correlates the input space to a high-dimension characterization area and conducts linear regression while b represents the bias term [37–46]. Following expression was implemented as a cost function of the least square support vector machine (LSSVM) in calculation steps [37–46].

$$Q_{LSSVM}=\frac{1}{2}w^Tw+\gamma\sum_{k=1}^{N}e_k^2 \tag{1}$$

Relate to the following restriction [37–46]:

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

To figure out function estimation issue the structural risk minimization (SRM) approach is suggested and the optimization issue is implemented to mastermind the addressed R function while C represents the regularization constant and e_i stands for the training error [37–46].

$$R(\omega,e,b)=\frac{1}{2}||w||^2+\frac{1}{2}C\sum_{k=1}^{m}e_k^2 \tag{3}$$

To extract routs w and e, the Lagrange multiplier optimum programming approach is performed to solve Eq. (3); the addressed approach considers impartial and restriction parameters simultaneously. The mentioned Lagrange function L is formulated as following equation [37–46]:

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

Through above equation, α_i denotes the Lagrange multipliers that may be either positive or negative because LSSVM has equality restrictions. Owing to the Karush Kuhn–Tucher's (KKT) conditions, conditions for optimum goal are demonstrated in Eq. (3) [44–46].

$$\left\{\begin{array}{c}\partial_\omega L=\omega-\sum_{i=1}^{n}\alpha_i\varphi(x_i)=0\\ \partial_b L=\sum_{i=1}^{n}\alpha_i=0\\ \partial_{e_i}L=Ce_i-\alpha_i=0\\ \partial_{\alpha_i}L=w^T\varnothing(x_k)+b+e_k-y_k=0\end{array}\right\} \tag{5}$$

Therefore, the linear equations can be demonstrated below expression [44–46]:

$$\begin{bmatrix}0 & -1^T\\ 1 & \Omega+\frac{1}{\gamma}I_N\end{bmatrix}\begin{bmatrix}b\\ \alpha\end{bmatrix}=\begin{bmatrix}0\\ y\end{bmatrix} \tag{6}$$

While $y=(y_1,\ldots,y_n)^T$, $1_n=(1,\ldots,1)^T$, $\alpha=(\alpha_1;\ldots;\alpha_n)^T$ and $\Omega_{il}=\varphi(x_i)^T\varphi(x_l)$ for $i,l=1,\ldots,n$. Thanks to the Mercer's theorem, the resulting LS-SVM model for function approximation turns to the following equation [44–46]

$$f(x)=\sum_{k=1}^{N}\alpha_kK(x,x_k)+b \tag{7}$$

where α and b are the routs to Eq. (7) as below [44–46]:

$$b=\frac{1_n^T\left(\Omega+\frac{1}{\gamma}I_n\right)^{-1}y}{1_n^T\left(\Omega+\frac{1}{\gamma}I_n\right)^{-1}1_n} \tag{8}$$

$$\alpha=\left(\Omega+\frac{1}{\gamma}I_n\right)^{-1}(y-1_nb) \tag{9}$$

Eq. (10) may be executed as choice of nonlinear regression and utilize the Kernel function as below equation [37–46]: