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New tools predict monoethylene glycol injection rate for natural gas hydrate inhibition

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ABSTRACT

In the oil and gas production operations, hydrates deposition leads to serious problems including over pressuring, irreparable damages to production equipment, pipeline blockage, and finally resulting in production facilities shut down and even human life and the environment dangers. Hence, it is of great importance to forecast the hydrate formation conditions in order to overcome problems associated with deposition of hydrate. In this article, an effective, mathematical and predictive strategy, known as the least squares support vector machine, is employed to determine the hydrate forming conditions of sweet natural gases as well as the monoethylene glycol (MEG) flow-rate and desired depression of the gas hydrate formation temperature (DHFT). The outcome of this study reveals that the developed technique offers high predictive potential in precise estimation of this important characteristic in the gas industry. Beside the accuracy and reliability, the proposed model includes lower number of coefficients in contrast with conventional correlations/methods, implying an interesting feature to be added to the modeling simulation software packages in gas engineering.

1. Introduction

Hydrates formation causes serious problems in oil and gas production facilities and has also safety and environmental dangers (Bahadori, 2011; Christiansen, 2012; Ghiasi et al., 2013). Normally, high pressures, low temperatures and link between water molecules and guest gaseous molecules including nitrogen, hydrogen sulfide, carbon dioxide normal and isobutene, propane, ethane and specially methane can result in the hydrates deposition (Bahadori, 2011). Actually, hydrates are a subset clathrate compounds or inclusion compounds where a molecule of one substance is enclosed in a structure which is made from another substance molecules (Christiansen, 2012). Generally, natural gas hydrates deposit widely in a level of earth that is frozen all year round and marine sediments (Li et al., 2013).

Avoidance of the deposition of natural gas hydrates eliminates the possibility of condensed water formation (Ghiasi et al., 2013). Therefore, use of methods which lead to prevention of safety hazards and economic risks and in other words hydrate deposition seems reasonable. One of the most efficient and reliable ways to avoid hydrate formation is hydrate inhibitors injection as they decrease the temperature of hydrate deposition or/and hinder their formation. Chemicals, in particular alcohols including methanol, diethylene glycol (DEG) and monoethylene glycol (MEG), are the commonly utilized thermodynamic hydrate inhibitors in the oil and gas industries (Bahadori, 2011; Bahadori and Vuthaluru, 2010; Elgibaly and Elkamel, 1998). Methanol as a thermodynamic inhibitor shifts hydrate formation conditions by decreasing water activity (Ghiasi et al., 2013). However, a greater amount of methanol is vanished in the gaseous phase in comparison with glycols (Bahadori, 2011). Moreover, MEG is recommended instead of DEG for cases where the temperature is equal to −10 °C or lower because elevated viscosity is obtained at low temperatures (Bahadori, 2011).

To estimate hydrate deposition conditions, there are several

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techniques including laboratory measurements, empirical correlations, and using the Katz gravity chart (Holder et al., 1984; Sloan Jr and Koh, 2007). Among these methods, laboratory measurements are relatively expensive and time consuming to industrial necessities while dealing with hydrate deposition conditions (Bahadori, 2011). Consequently, empirical equations which are employed to forecast hydrate deposition conditions exhibit normally considerable error and also are occasionally very complicated that involve more computations. Bahadori (2011) proposed a simple-to-utilize empirical relationship to estimate hydrate deposition states for sweet natural gases. Furthermore, he developed correlations for estimating the MEG flow-rate and the required MEG (wt %) in the rich mixture for preferred depression of the temperature in which the gas hydrate formation occurs. However, these mathematical relationships require high adjustable parameters to calculate hydrate formation condition. Additionally, Katz gravity chart gives errors for compositions other than those applied to derive these charts. Introducing a reliable predictive model which does not need many adjustable parameters can be useful for prediction of hydrate formation condition.

Hence, this study introduces a two-adjustable parameters model on the basis of least squares supported vector machine (LSSVM) to determine the conditions which result in formation of gas hydrate formation. It also offers acceptable estimation of the desired depression of the gas hydrate formation temperature (DHFT) and the MEG flow-rate. In addition, the coupled simulated annealing (CSA) technique is employed to attain the optimal values of the predictive system parameters. A systematic statistical analysis including error and residual error calculation, and leverage approach is conducted to examine the performance and accuracy of the developed model (e.g., LSSVM).

2. Data collection

The current study is targeted to obtain the hydrate formation conditions, desired DHFT, and flow rate of monoethylene glycol (MEG) with high precision. Therefore, wide ranges of data are collected from various sources. The required data are extracted from Katz gravity chart (Katz, 1945) to calculate pressure of the hydrate formation in this study. Consequently, hydrate-forming pressure data (Katz, 1945) is a function of molecular weight and temperature. Ranges and averages of the hydrate-forming pressure, molecular weight, and temperature are shown in Table 1. The desired temperature depression data (Moshfeghian and Taraf, 2008) is a function of pressure, MEG weight percent, molecular weight and feed gas temperature. Ranges and averages of these affecting parameters as well as depression temperature are provided in Table 2. As a result, the MEG flow-rate is strongly dependent on temperature, pressure, MEG (wt%), and molecular weight (Moshfeghian and Taraf, 2008). Ranges and averages of the flow-rate of MEG, pressure, temperature, molecular weight and MEG concentration are tabulated in Table 3. The compositions related to twelve feed gas streams used in this study are shown in Table 4.

3. Model development

3.1. Equations

According to the SVM model, the fundamental equation moving backward is given below (Suykens et al., 2002):

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

in which w^T introduces the vector of transposed output layer, b represents the bias, and the feature map is defined by $\varphi(x)$. The model input holds a dimension of N (number of data points) $\times$ n (number of input parameters). Furthermore, x is a vector of dimension n. To calculate w and b, the cost function should be minimized as expressed by Vapnik (Suykens et al., 2002):

$$Cost\ function = \frac{1}{2}w^T + c\sum_{k=1}^{N}(\xi_k - \xi_k^*) \tag{2}$$

To satisfy constraints:

$$\begin{cases} y_k - w^T\varphi(x_k) - b \le \varepsilon + \xi_k, & k = 1,2,\ldots,N \\ w^T\varphi(x_k) + b - y_k \le \varepsilon + \xi_k^*, & k = 1,2,\ldots,N \\ \xi_k, \xi_k^* \ge 0, & k = 1,2,\ldots,N \end{cases} \tag{3}$$

Here, ξ_k and ξ_k^* refer to the slack variables, the fixed accuracy of the function approximation is expressed by ε, N represents the number of data points, and kth data point input, and kth data point output are symbolized by x_k and y_k respectively. It is worth noting if a very low value is chosen for ε for the sake of accuracy, it may cause that a part of data are outside of the precision defined for ε. It implies that slack parameters are required to be employed in order to recognize the error margin. c in Equation (2) which holds a positive magnitude, is taken into account as a tuning parameter in the SVM approach to determine the deviation value, with respect to the desired ε. Considering the constraints, the following equations in the form of the Lagrangian are applied for minimizing the cost function (Suykens et al., 2002):

$$L(a,a^*) = -\frac{1}{2}\sum_{k,l=1}^{N}(a_k - a_k^*)(a_l - a_l^*)K(x_k,x_l) - \varepsilon\sum_{k=1}^{N}(a_k - a_k^*) + \sum_{k=1}^{N}y_k(a_k - a_k^*) \tag{4}$$

$$\sum_{k=1}^{N}(a_k - a_k^*) = 0, a_k, a_k^* \in [0,c] \tag{4a}$$

$$K(x_k,x_l) = \varphi(x_k)^T\varphi(x_l), \quad k = 1,2,\ldots,N \tag{4b}$$

where multipliers of Lagrangian are represented by a_k and a_k^*. After required rearrangement and simplification, the final form of the SVM model is obtained as follows:

$$f(x) = \sum_{k=1}^{N}(a_k - a_k^*)K(x,x_k) + b \tag{5}$$

The quadratic programming problem should be solved to attain a_k, a_k^* and b in Eq. (5). Hence, a least square form (LSSVM) of the SVM mathematical technique was presented by Suykens and Vandewalle (1999) to improve original version of the SVM approach. The advanced form of SVM, known as LSSVM, includes the equality constraints in points where the equality function does not exist for the SVM technique (Suykens and Vandewalle, 1999).

Table 1
Ranges and averages of the input/output data used for developing the hydrate pressure model.

Parameter	Min.	Avg.	Max.	Type
MW	16.06	21.78	29	Input
Temperature, K	278.93	294.32	298.91	Input
Hydrate formation pressure, kPa $\times 10^{+3}$	5.02584	17.08	49.64416	Output