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Prediction of methanol loss in liquid hydrocarbon phase during natural gas hydrate inhibition using rigorous models

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ABSTRACT

Methanol is the most widely used natural gas hydrate inhibitor and it is only effective as a hydrate inhibitor in the aqueous phase. Methanol is not regenerated in natural gas inhibition process due to its intermittent application in most cases. However, a significant cost is associated with the process because of methanol loss while utilizing this inhibitor. In this work, several intelligent models along with a new mathematical correlation are presented in terms of methanol concentration in aqueous phase and temperature to precisely forecast the methanol loss in the saturated hydrocarbons phase. An excellent match was noticed between the calculated results and literature data.

1. Introduction

Hydrates formation in natural gas is considered as a serious concern in natural gas processing and production stages so that it may cause significant safety, environmental, and economic risks in the petroleum industries (Bahadori and Vuthaluru, 2009; Ghiasi, 2012; Ghiasi and Mohammadi, 2013; Tohidi et al., 1993; Bahadori, 2007, 2008; Haghighi et al., 2008; ØStergaard et al., 2000).

The most widely used chemical inhibitors to prevent gas hydrate formation in gas production and processing systems are methanol and glycols (Carroll, 2009; Sloan, 1998; Bahadori et al., 2008).

Methanol is a natural gas hydrate inhibitor with worldwide usage of several hundred million dollars per year (Bruinsma et al., 2004; Ghiasi et al., 2013; Lundstrøm et al., 2006, Chen et al., 1988). Methanol is usually cheaper than glycols to use as a natural gas hydrate inhibitor (GPSA, 2004).

To select a proper gas hydrate inhibitor, a number of important parameters such as physical characteristics, gas dehydration capacity, operating and capital expenses, corrosion inhibition, environmental aspects, and safety are generally involved (Bahadori et al., 2008). It seems clear that the potential related to regeneration, recovery and reinjection of used liquids/materials is a vital factor in the selection strategy.

In light of the above, it is an essential need to develop a reliable method for oil and gas practitioners (Arabloo et al.,2013, 2014). Prediction of inhibitor losses to the hydrocarbon liquid phase needs rigorous and accurate calculations (Bahadori et al., 2008).

The paper presents the formulation of such predictive tools in a classical manner. Indeed, several intelligent models along with a new mathematical correlation have been presented for estimating methanol loss.

To develop neural-based models, artificial neural networks (ANNs) including RBF-ANN and MLP-ANN have been employed. Another intelligent based model has been developed using special kind of SVMs namely LSSVM algorithm. The required data for modeling purposes have been gathered from GPSA engineering data book (GPSA, 2004). The accuracy and reliability of the proposed models have been evaluated by employing various statistical parameters.

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Table 1
Operating ranges of extracted data from GPSA.

Parameter	Min	Max
Temperature, K	233.6	323
Wt% methanol in water phase	20	70
Mol% methanol in condensate phase	0.099	2.474

2. Development of intelligent models

To construct MLP-ANN, RBF-ANN, and LSSVM models for predicting the loss of methanol in paraffinic hydrocarbons phase at various conditions, the required data points have been gathered from GPSA engineering data book (GPSA, 2004). Table 1 gives the operating ranges for temperature and methanol concentration in water phase as well as the methanol loss in liquid hydrocarbon phase.

Before developing MLP, RBF, and LSSVM models for estimating the methanol loss in hydrocarbon phase, the collected database was randomly separated into three subdata sets including training (70%), validation (15%), and test (15%) (Ghiasi et al., 2014b).

In this work, the mean squared error (MSE) between the outputs of the developed models and corresponding experimental values reported in the literature, as defined by Eq. (1), was considered as objective function during model computation (Ghiasi et al., 2014a, 2013; Nejatian et al., 2014; Shafiei et al., 2013; Zendehboudi et al., 2014).

$$MSE = \frac{1}{n}\sum_{j=1}^{n}(t_j - o_j)^2 \quad (1)$$

In equation (1), t, o, and n represent the actual response, predicted value, and number of data used in the study, respectively.

2.1. Development of MLP model

In the case of MLP modeling, a network with the structure having one hidden layer has been chosen (Ghiasi et al., 2014a,b; Zendehboudi et al., 2014). The back-propagation (BP) algorithm has been utilized to adjust the values of the MLP network weights. The hidden layer utilizes log-sigmoid transfer function that could be represent as below:

$$f(x) = \frac{1}{1+\exp(-x)} \quad (2)$$

The output layer has a linear transfer function.

2.2. Development of RBF model

Like MLP network, the radial basis artificial neural network model was trained using BP technique to minimize the MSE with two parameters (wt% methanol in water phase, temperature) as input and the desired output (methanol loss in hydrocarbon phase).

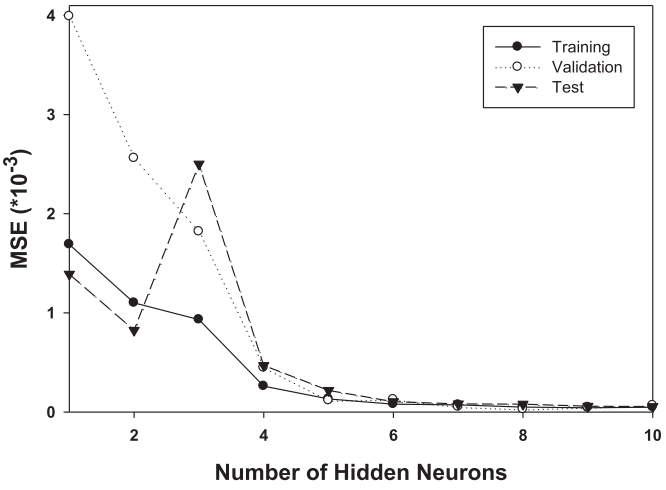

Fig. 1. Performance evaluation of various MLP-ANN structures based on MSE.

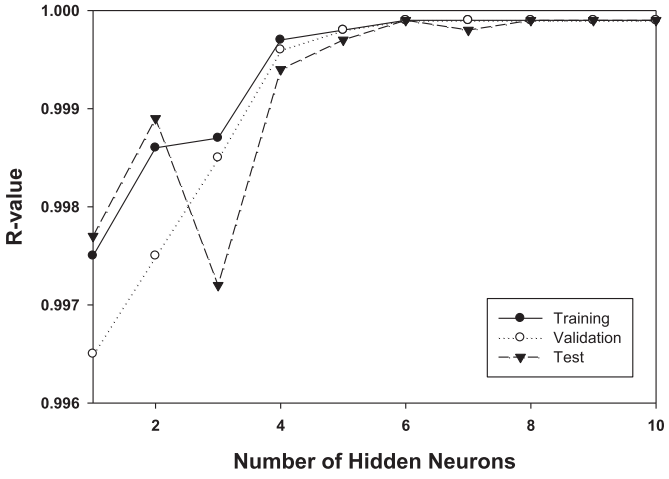

Fig. 2. Correlation analysis between MLP network outputs and the corresponding targets.

Developed network comprises of two layers. The first layer has radial basis transfer functions with the maximum number of 200 neurons. The second layer has a linear transfer function. More details on mathematical background and calculation procedure can be found elsewhere (Talebi et al., 2014; Tatar et al., 2013).

2.3. Development of LSSVM model

During the computation, the widely used kernel function, i.e radial basis function (RBF), has been implemented. To find the optimum values of γ and σ^2 as optimized parameters of the

Table 2
Tuned coefficients used in Eq. (5) for estimating methanol loss in condensate phase.

Coeff.	Value	Coeff.	Value	Coeff.	Value
A_1	0.13547738747779	B_1	−221.223543293036	C_1	1.2470211953134
A_2	−6.86863826756525E-04	B_2	3353.39690340339	C_2	25.8544642039717
A_3	1.27631535057017E-06	B_3	−102226.521767392	C_3	−6.13644682366637E-03
				D	−8.06631815292666