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Development of soft computing methods to predict moisture content of natural gases

Mohammad M. Ghiasi[a,*], Zohre Esmaeili-Jaghdan[b], Mohamad A. Halali[c], Moonyong Lee[d], Ali Abbas[e], Alireza Bahadori[f,**]

[a] National Iranian Gas Company (NIGC), South Pars Gas Complex (SPGC), Asaluyeh, Iran
[b] Gas Engineering Department, Petroleum Univeristy of Technology (PUT), Ahwaz, Iran
[c] Petroleum Engineering Department, Petroleum University of Technology (PUT), Ahwaz, Iran
[d] School of Chemical Engineering, Yeungnam University, 214-1 Dae-dong, Gyeongsan, Gyeongbuk 712-749, Republic of Korea
[e] School of Chemical and Biomolecular Engineering, The University of Sydney, Sydney, NSW, Australia
[f] Southern Cross University, School of Environment, Science and Engineering, Lismore, NSW 2480, Australia

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ABSTRACT

In this paper, several numerical models have been presented for predicting the water content of natural gases in equilibrium with liquid water. Machine learning approaches including multilayer perceptron (MLP) neural network, radial basis function (RBF) neural network, and least squares support vector machine (LSSVM) algorithm have been utilized for precise determination of water content of natural gases.
The presented models work for pressures up to 69 MPa and temperatures between 298.15 and 450.15 K as well as acid gas mole fractions up to 0.4. With accordance to the error analysis results it was found that the proposed LSSVM, RBF, and MLP models reproduce targets with the average absolute relative deviations (%AARD) being less than 2.8%, 4.1%, and 7.7%, respectively. Coefficients of determination values of the developed models are found to be greater than 0.99, illustrating good association of the predictions with corresponding reported data in the literature.

1. Introduction

Natural gas is very important and clean source of energy. In view of particular properties of water, calculating the natural gas water content is crucial for proper handling of natural gas production and processing operations [1]. Accurate prediction of natural gas water content leads to safe and economic design of natural gas equipment, gas processing facilities and pipelines [1–4].

Available methods for estimation of natural gas water content can be categorized in two main groups: thermodynamic approaches, and empirical correlations. By applying the Raoult's law to water, the simplest thermodynamic model known as ideal model is written as follows:

$$y_w = \frac{x_w P^{sat}}{P} \tag{1}$$

where y_w and x_w are mole fractions of water in vapor and liquid phase, respectively; P is absolute pressure of the system, and P^{sat} is water vapor pressure at system temperature. Based on this model Bukacek [5] and Mohammadi et al. [6] proposed separate correlations to estimate the water content of sweet natural gases. Bukacek [5] correlation is applicable at temperatures higher than 288.15 K [7,8], and proposed correlation of Mohammadi et al. [6] is developed in the temperature range of 273.15 K and 477.59 K and pressures up to 14.40 MPa.

More complicated thermodynamic models are based on fugacity uniformity of each component in all phases of the system. The methods of Erbar et al. [9], Li and Firoozabadi [10], Chapoy et al. [11], Zirrahi et al. [4], and Chapoy [12] are such models. The presented method by Chapoy [12], however, is derived by employing some assumptions. Hence, this method is a semi-empirical approach for predicting the natural gas water content. By using the equation of Chapoy [12], the water mole fraction in the gas phase is estimated as follows [1]:

$$y_w = \left(\frac{P^{sat}}{\varphi_w P}\right) \exp\left(\frac{\upsilon_w^L (P - P^{sat})}{RT}\right) \tag{2}$$

where υ_w^L is water molar volume, and φ_w is fugacity coefficient of water in the gas phase. υ_w^L and P^{sat} are estimated by the

Abbreviations: %AARD, average absolute relative deviation percent; ANN, artificial neural network; CSA, coupled simulating annealing; LSSVM, least squares support vector machine; MPE, mean percentage error; MSE, mean squared error; MLP, multilayer perceptron; RBF, radial basis function.

* Corresponding author. Tel.: +98 937 76 86 726.
** Corresponding author. Tel.: +61 2 6626 9412; fax: +61 2 6626 9857.
E-mail address: alireza.bahadori@scu.edu.au (A. Bahadori).

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Nomenclature

$b =$	bias term
$B =$	temperature dependent function
$b_i =$	constant
$C =$	temperature dependent function
$c_i =$	constant
$K(x_i, x_j) =$	kernel function
$L =$	Lagrangian
$P =$	pressure, MPa
$P^{sat} =$	water vapor pressure at system temperature
$I_N =$	$N \times N$ identity matrix
$w =$	weight vector
$1_v =$	$[1; \ldots; 1]$
$A^T =$	transpose of matrix A
$x_w =$	water mole fraction in liquid phase
$y_w =$	water mole fraction in vapor phase
$d =$	the polynomial degree
$n =$	number of data points
$T =$	temperature, K
$R =$	universal gas constant

Greek letters

$\varphi_w =$	fugacity coefficient of water in the gas phase
$\upsilon^L{}_w =$	water molar volume
$\Omega =$	kernel matrix
$\Phi =$	map from input space into feature space
$\gamma =$	regularization constant
$\alpha_i =$	Lagrange multipliers
$\sigma =$	width of kernel function

relationships introduced by Daubert and Danner [13] and McCain [14], respectively [1]. Chapoy [12] proposed the following equation to estimate φ_w:

$$\varphi_w = \exp(BP + CP^2) \tag{3}$$

where B and C are temperature dependent functions as below [1]:

$$B = b_1 + \frac{b_2}{T} \tag{4}$$

$$C = c_1 + \frac{c_2}{T} \tag{5}$$

where b_i and c_i are coefficients.

In addition to the thermodynamic and empirical methods, some charts have been provided in the literature [15] for estimation of natural gas water content. In many standards, McKetta and Wehe [15] chart is recommended for estimation of sweet natural gas water content [6]. This chart has been regenerated in many publications [7] like Gas Processors and Suppliers Association (GPSA) Engineering Book [16]. Since in most cases graphical based calculations need an interpolation, they are usually time consuming and tedious. Regarding this fact many authors such as Kobayashi et al. [17], Caroll et al. [7], and Bahadori et al. [18] tried to develop a correlation representing the curves plotted in the McKetta and Wehe [15] chart. Kobayashi et al. [17] correlation is quite intricate and is applicable for pressures up to 14 MPa.

Thus far, the estimation of natural gas moisture content by use of artificial neural networks has not been explored to a wide range. Although, there have been some attempts for estimating the water content of natural gases, for instance, Mohammadi and Richon [19] applied artificial neural network to predict the water content of natural gases based on 143 experimental data points. The model was acceptable for pressures up to 13.81 MPa. Shirvany et al. [20] made the same attempt for estimation of sour natural gas water content based on 136 experimental data points. The model was applicable for pressures up to 24.13 MPa.

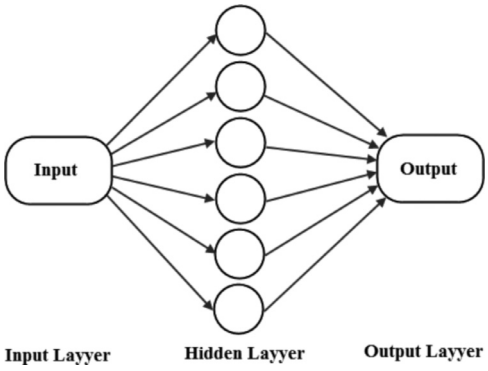

Fig. 1. Schematic representation of MLP neural network.

In this study, several intelligent models have been presented for the application of interest. To develop neural-based models, artificial neural networks (ANNs) including RBF-ANN and MLP-ANN have been employed. The two-parameter 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 [16].

2. Artificial neural networks

2.1. Multilayer perceptron networks

Multilayer perceptron (MLP) neural networks comprise of three various types of layers, including input layer, hidden layer(s), and output layer (Fig. 1). A single MLP might have one or more hidden layer. Each layer is composed of some neurons. The number of neurons in the input and output layers is corresponded to number of input and output data, respectively. The number of hidden layers and also neurons in them is optional and can be defined either intelligently or by trial and error to seize the best efficiency. Minimum square error (MSE) implies the performance of the proposed network. In such networks, the error is back propagated through the network and the weights and biases are optimized through some iteration called epochs. The number of epochs should be such that the network neither undertrain nor overtrain. In the former, the network does not have sufficient time to complete the learning process. In the latter, the network does not learn but memorizes. This results the inadequate capability of network in estimation of test data set [21].

2.2. Radial basis function networks

Both MLP and radial basis function (RBF) networks have identical applications but distinct internal calculation structures. The most prime advantage of RBF networks is simple design that it has just three layers. They have the ability of sound generalization, high tolerance of input noises and ability of online learning [22]. From the generalization point of view, RBF networks are capable of responding very well to patterns that were not applied for training [23].

RBF networks are neural networks on the basis of localized basis functions and iterative function approximation [24]. The RBF networks utilize supervise training technique and are a type of feed-forward neural networks [25]. The RBF network is a universal approximator, with a solid foundation in the conventional approximation theory [26]. RBF has a comparatively simpler structure than MLP which enjoys much faster training process. These features make RBF a favorite alternative to the MLP. The origin of RBF is in performing exact interpolation of a set of data points in a multidimensional space [27]. It is proved that RBF networks can be used by MLP networks with increased input dimensions [28]. The RBF architecture is analogous to