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Rigorous models to optimise stripping gas rate in natural gas dehydration units

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HIGHLIGHTS

- Multilayer perceptron (MLP) neural network is used to estimate optimum gas stripping rate in natural gas dehydration units.
- Least squares support vector machine (LSSVM) algorithm is used to estimate optimum gas stripping rate.
- Both models have been developed and tested using 150 series of the data.
- The results of the rigorous models show excellent agreement with data.

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ABSTRACT

Natural gas is an extremely important source of energy. Demand for natural gas is likely to overtake other fossil fuels due to its availability, accessibility, versatility and smaller environmental footprint. Glycol dehydration is the most common and economic method of water removal from natural gas streams. The water content of the dehydrated gas depends primarily on the lean triethylene glycol (TEG) concentration. Injecting stripping gas into the reboiler is one of the most common methods for enhancement of the glycol concentration. In this article two intelligent approaches including multilayer perceptron (MLP) neural network and least squares support vector machine (LSSVM) algorithm are employed to predict optimum stripping gas flow rate in natural gas dehydration systems. Furthermore, a simple mathematical tool is presented for the application of interest. The results obtained from the presented MLP, LSSVM, and empirical models are found to be in excellent agreement with reported data in the literature with average absolute relative deviation percent (AARD%) being less than 0.01%.

1. Introduction

Dehydration is the process used to remove water from natural gas and is required to prevent formation of gas hydrates and condensation of free water in processing and transportation facilities and to meet a water content specification, as well as to avoid corrosion problem [1–6]. In gas dehydration operation water vapor (moisture) is removed from natural gas streams to meet sales specifications or other downstream gas processes such as gas liquid recovery. In particular, moisture level in natural gas must be maintained below a certain threshold so as to prevent hydrate formation and minimize corrosion in transmission pipelines [7,8]. Glycols are typically used for applications where dew point depressions of the order of 15–49 °C are required [9]. Diethylene glycol (DEG), triethylene glycol (TEG), and tetraethylene glycol (TREG) are used as liquid desiccants, but TEG is the most common for natural gas dehydration [10]. Liquid desiccant dehydration equipment is simple to operate and maintain [11,12].

There are several processes and principles for obtaining high triethylene glycol (TEG) purity in gas dehydration process. All approaches are based on the principle of lowering the effective partial pressure of water in the glycol reboiler's vapor space, and hence obtaining a higher glycol concentration at the same temperature [1]. Paymooni et al. [10], experimentally studied the effect of isooctane and toluene as liquid hydrocarbon solvents on TEG purity concentration of the outlet water. One of the most common choices for enhancement of the glycol concentration is injecting

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Nomenclature

ANN	artificial neural network
AARD%	average absolute relative deviation percent
CSA	Coupled Simulated Anneiling
GA	genetic algorithm
DEG	diethylene glycol
LSSVM	least squares support vector machine
MLP	multilayer perceptron
MSE	mean squared error
PSO	particle swarm optimization
SVM	support vector machine
TEG	triethylene glycol
TREG	tetraethylene glycol

Symbols

A^{η}	acceptance probability function
A_i	tuned parameter
B_i	tuned parameter
b	intercept of the linear regression in LSSVM
b_m	bias term
C	tuned parameter
D	tuned parameter
e_k	regression error for n training objects
f	function; activation function
$K(x, x_k)$	Kernel function
Q	gas flow rate, standard cubic meter per TEG cubic meter
Q_{LSSVM}	cost function
$\boldsymbol{r_m}$	linear combiner output
S	the set of all possible solutions
T	temperature, K
T_k^a	acceptance temperature
w	weight of regression
$\boldsymbol{w_{mi}}$	synaptic weights of the neuron
x	input
y	output
z_{norm}	normalized data
z	The data which should be normalized
$z_{\max}$	maximum of the original data
$z_{\min}$	minimum of the original data

Greek symbols

γ	relative weight of the regression errors summation compared to weight of regression
α_k	Lagrange multiplier
φ	feature map
σ^2	squared variance of the Gaussian function
ψ	coupling term
ρ	TEG concentration, weight fraction

the stripping gas into the regenerator. In some works presented by Moshfeghian [11–14], the effect of stripping gas rate on the regenerated lean TEG concentration for various operation conditions has been investigated by employing ProMax [15] as computer program.

The main objective of this communication is developing accurate and simple methods to estimate TEG purity as a function of reconcentrator (reboiler) temperature and stripping gas flow rate. This work discusses the capability of MLP network and LSSVM algorithm in calculating the TEG purity. To the best of author's knowledge, TEG purity modeling as function of the reboiler temperature and stripping gas flow rate has not been performed by utilizing the MLP and LSSVM techniques as well-proven intelligent algorithms. Furthermore, a new empirical predictive tool will be presented for the application of interest. The proposed mathematical correlation is exponential function which leads to well-behaved (smooth) equations enabling more accurate and non-oscillatory predictions and this is the distinct advantage of the proposed method.

2. MLP network

Artificial neural network (ANN), as parallel information processing systems, uses a number of input–output training arrangements from given data sets to find linear/nonlinear mathematical connections [16,17]. ANNs could be used for classification, pattern recognition, as well as prediction [18–24]. The constitutive units in ANN are known as "artificial neurons". Mathematically, the neuron $\boldsymbol{m}$ is defined as bellows:

$$r_m = \sum_{i=1}^{n}(w_{mi}x_i + b_m) \tag{1}$$

$$y_m = f(r_m) \tag{2}$$

where $\boldsymbol{x_1, x_2, \ldots, x_n}$ are the input signals; $\boldsymbol{w_{m1}, w_{m2}, \ldots, w_{mn}}$ are synaptic weights of the neuron; $\boldsymbol{r_m}$ is the linear combiner output; $\boldsymbol{b_m}$ is the bias term; $\boldsymbol{f}$ is the activation function; and $\boldsymbol{y_m}$ is the neuron's output signal.

MLPs are categorized as feed-forward neural networks and comprise input layer, hidden layer(s), and output layer. A typical three-layer MLP network has I input branching nodes, H neurons in the hidden layer, and O output neurons. The number of independent variables determine the number of input branching nodes of a MLP network. The number of neurons in the output layer is defined by the number of targets/dependent variables. The number of hidden neurons could be obtained by trial and error procedure [4,25,26]. Using weighted connections, each input node is linked to all the hidden neurons. Similarly, weighted connections exist between output layer nodes and hidden layer [22,27–29].

3. LSSVM algorithm

In 1995, the SVM as a supervised learning model was presented by Vapnik [30–32]. SVMs are studied extensively for regression analysis, function estimation, and classification [33–41]. Information about fundamentals of SVMs as well as discussion of various versions of available SVMs could be find elsewhere [31,42–48]. In the presented study, the well-known LSSVM approach is utilized for the TEG purity modeling.

Indeed, LSSVM is reformulation to standard SVM [44,45]. Contrary to the standard SVM, that employs quadratic programming techniques, LSSVM applies a set of linear equations for the simplicity involved. The rest of this section demonstrates the mathematical basis of LSSVM technique in brief.

The cost function of LSSVM model, Q_{LSSVM}, and regression weight, w, are defined by Eqs. (3) and (4), respectively [49,50].

$$Q_{LSSVM} = \frac{1}{2}w^T w + \gamma\sum_{k=1}^{n}e_k^2 \tag{3}$$

$$w = \sum_{k=1}^{n}\alpha_k x_k \tag{4}$$

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