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Prediction of a solid desiccant dehydrator performance using least squares support vector machines algorithm

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ABSTRACT

This study presents the potential of least squares support vector machines (LSSVM) modeling approaches to predict the moisture content of natural gas dried by calcium chloride dehydrator units. Genetic algorithm (GA) as population based stochastic search algorithms were applied to obtain the optimal LSSVM models parameters. The results revealed that the GA-LSSVM are capable of capturing the complex nonlinear relationship between the input and output variables. For the purpose of predicting water content of natural gas for freshly recharged conditions, the GA-LSSVM model yielded the mean absolute error (MAE) and coefficient of determination (R^2) values of 2.7898 and 0.9986; for the whole data set, while for the purpose of predicting water content of natural gas prior to recharging conditions, the GA-LSSVM models yielded the MAE and R^2 values of 1.1044 and 0.9995; for the whole data set. Proposed model provides fairly promising approach for predicting the approximate moisture content of natural gas dried by calcium chloride dehydrator units for both freshly recharged and just prior to recharging conditions.

1. Introduction

Calcium chloride ($CaCl_2$) dehydrator is the most widely used non-regenerative adsorption system in natural gas industry [1,2].

Fig. 1 shows how gas and liquids flow in the dehydrator. The dehydrator unit is designed to take advantage of the excellent desiccant properties of calcium chloride as a solid and in solution.

The lower or separator section is a gas–liquid separator which separates free liquids, hydrocarbons and water, from the inlet gas stream. The middle or tray section is the liquid absorption section where the brine removes most of the water in a series of trays. The upper or bed section contains the solid calcium chloride, which absorbs the final amount of water and furnishes the brine feed for the tray section [3-5].

Solid calcium chloride combines with water to form a brine solution. As water absorption continues, $CaCl_2$ is converted to successively higher states of hydration, eventually forming a $CaCl_2$ brine solution [5-7].

The relative simplicity of the concept and design of these units makes them ideal in offshore and periodically snowbound locations. Depending on operating conditions, a large number of calcium chloride units can be left unattended for up to six months [7].

As the need for natural gas increases, calcium chloride dehydration can contribute to make some gas wells more profitable to operate gas from remote or offshore wellheads, gas of a low flow rate, or gas which is high in sulfur content may benefit from this dehydration [7].

As long as pressure is sufficient, calcium chloride units function especially well at low flow rates. Further, the lower the flow rate, the longer a calcium chloride unit can function unattended between rechargings.

The main advantages of calcium chloride dehydrators are [6,7]:

- Energy efficient: no energy consuming equipment is part of the basic design of a calcium chloride dehydrator.
- Low labor costs: they can function up to six months unattended [7].
- Reduced fire risk: calcium chloride is not flammable [7].
- Competitive equipment costs: calcium chloride dehydrators usually cost much lower than glycol and other dehydrator units.

In view of the above mentioned issues, it is an essential need to develop accurate and simple methods to estimate water content of natural gas dried by calcium chloride dehydrator units [7].

Recently, Ahmadi and co-workers made huge amounts of attempts to apply different intelligent based method for figuring out the petroleum and chemical engineering challenging issues [8-19]. For example, Ahmadi et al. applied hybrid method to determine

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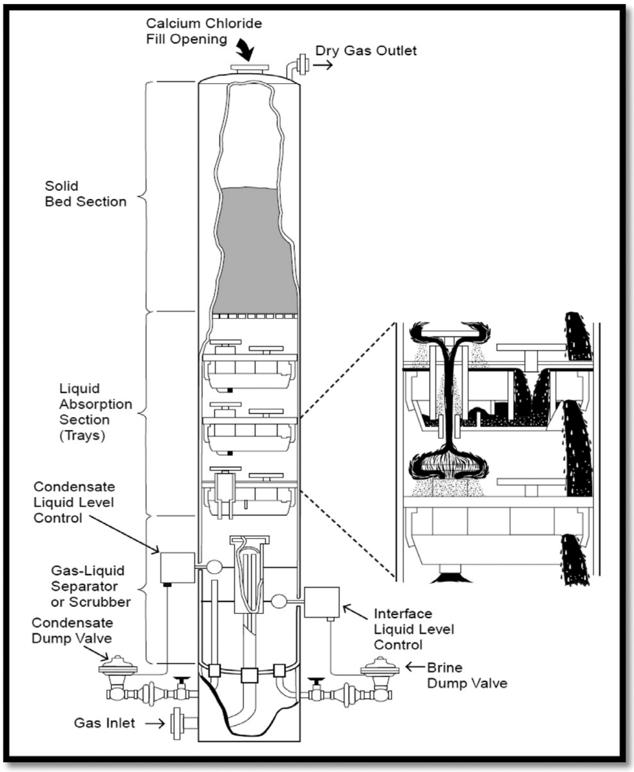

Fig. 1. A calcium chloride gas dehydration system (Reproduced with permission from reference [6]).

reservoir permeability with available conventional petrophysical logs [18]. Owing to this fact, throughout this communication enormous efforts have been put forth to facilitate prediction of water content of natural gas dried by calcium chloride dehydrator. To meet this crucial goal of this study, a robust and fast intelligent based approach has been utilized.

To the best of authors' knowledge, no work has been published on the subject of predicting the water content of dehydrated natural gas by calcium chloride using least squares support vector machines and genetic algorithm.

This paper discusses the formulation of such a method in a systematic manner to show the accuracy and usefulness of such models.

2. Theory

2.1. Least squares support vector machines and genetic algorithm

Vapnik and co-workers developed a very nice framework or methodology called support vector machine (SVM) at AT&T Bell Laboratories in 1995 [8,9,13,20], with combining the advantages of ANNs (handling large amount of highly nonlinear data) and nonlinear regression (high generalization) lead to high generalization ability and the sparseness of the solution [8,9,13,21].

It is a powerful computational intelligence approach which is based on recent advances in statistical machine learning theory. SVM is basically applicable to both classification and regression problems [8,9,13,20]. SVM model can be computationally difficult because it requires the solution of quadratic programming (QP) [8,9,13,22].

Suykens and co-workers [8,9,13,23] proposed a modified version of SVM called least square support vector machine (LSSVM), leading to solving a set of linear equations that is easier to use/solve than QP problems, while most of the important advantages of SVM are retained [8,9,13,21]. The formulation of LSSVM is briefly introduced as follows.

Consider a given training set of N data points $\{x_k, y_k\}_{k=1}^{N}$ where $x_k \in \mathcal{R}^n$ is the input vector at the training point k, and $y_k \in \mathcal{R}$ is corresponding output value. According to the standard LSSVM theory of Suykens [8,9,13,23], the unknown nonlinear function can be approximated by

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

where $K(x, x_k)$ is the kernel function meeting the Mercer condition [8,9,13,23], parameters $\alpha_k \in \mathcal{R}\,(k = 1, 2, \ldots, N)$ and b can be acquired by dint of following equation [8,9,13]:

$$\begin{bmatrix} 0 & 1_\upsilon^T \\ 1_\upsilon & \Omega + \gamma^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{2}$$

where $y = [y_1 \ldots y_N]^T$, $1_v = [1 \ldots 1]^T$, $\alpha = [\alpha_1 \ldots \alpha_N]^T$, I is an identity matrix and Ω is a $N \times N$ *kernel matrix*; $\Omega_{kl} = \varphi(x_k)^T.\varphi(x_l) = K(x_k, x_l) \forall\, k, l = 1, \ldots, N$. Three typical choices for the kernel function are:

$$K(x, x_k) = x_k^T x \; (Linear\ kernel) \tag{3}$$

$$K(x, x_k) = \left(\tau + x_k^T x\right)^d \; (Polynomial\ kernel\ of\ degree\ d) \tag{4}$$

$$K(x, x_k) = \exp\left(-x - \frac{{x_k}^2}{\sigma^2}\right) \; (Radial\ basis\ function\ RBF\ kernel) \tag{5}$$

In the case of applying RBF kernel function, the generalization performance and efficiency of the LSSVM is directly affected by two adjustable parameters embedded in the algorithm including regularization parameter (γ) and RBF kernel parameter (σ^2). As stated by Ahmadi et al. [8,9,13,24], application of non-population based optimization methods are not appropriate choice in such circumstances, owing to the high nonlinearity of the SVM method. In this respect, genetic algorithm (GA) as a popular and respected population-based optimization algorithm was applied to determine these two parameters.

GA is a population-based stochastic general search method which is based on the mechanism of natural selection and natural genetics [8,9,13,25,26]. It proceeds in an iterative manner by generating new populations of chromosomes (representing candidate solutions to a problem) from the former ones. It should be noted that each chromosome consists of genes; indeed each chromosome contains the solution in the form of genes.

At each step, the GA selects chromosomes haphazardly from the current population to be parents and uses them to generate the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. The GA uses three main types of operators at each step to create the next generation from the current population including selection, crossover and mutation [8,9,13,27].

The details of GA algorithm have been well-presented in the literatures [8,9,13,19,28,29]. Also the theory of LSSVM has been described clearly elsewhere [8,9,13,30].

3. Methodology

GA-LSSVM was performed by Genetic Algorithm Toolbox of MATLAB R2009a and LSSVM Lab 1.8 free toolbox was used for optimizing hyper parameters of LSSVM. The robust LSSVM model was intended for prediction of approximate water content of natural gas dried by calcium chloride dehydrator units for both freshly recharged and just prior to recharging condition as a function of pressure and temperature. To achieve a high level of performance with LSSVM model, some parameters have to be decided, including the regularization parameter γ and the kernel parameter corresponding to the kernel type [31,32].