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### A computational intelligence scheme for prediction equilibrium water dew point of natural gas in TEG dehydration systems



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### HIGHLIGHTS

- Particle swarm optimization (PSO) is used to estimate the water dew point of natural gas in equilibrium with TEG.
- The model has been developed and tested using 70 series of the data.
- Back-propagation (BP) algorithm is used to estimate the water dew point of natural gas in equilibrium with TEG.
- PSO-ANN accomplishes more reliable outputs compared with BP-ANN in terms of statistical criteria.

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### ABSTRACT

Raw natural gases are frequently saturated with water during production operations. It is crucial to remove water from natural gas using dehydration process in order to eliminate safety concerns as well as for economic reasons. Triethylene glycol (TEG) dehydration units are the most common type of natural gas dehydration. Making an assessment of a TEG system takes in first ascertaining the minimum TEG concentration needed to fulfill the water content and dew point specifications of the pipeline system. A flexible and reliable method in modeling such a process is of the essence from gas engineering view point and the current contribution is an attempt in this respect. Artificial neural networks (ANNs) trained with particle swarm optimization (PSO) and back-propagation algorithm (BP) were employed to estimate the equilibrium water dew point of a natural gas stream with a TEG solution at different TEG concentrations and temperatures. PSO and BP were used to optimize the weights and biases of networks. The models were made based upon literature database covering VLE data for TEG-water system for contactor temperatures between 10 °C and 80 °C and TEG concentrations ranging from 90.00 to 99.999 wt%. Results showed PSO-ANN accomplishes more reliable outputs compared with BP-ANN in terms of statistical

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### 1. Introduction

All natural gas streams contain significant amounts of water vapor as they exit from oil and gas reservoirs. Water vapor in natural gas can make several operational problems during the processing and transmission of natural gas such as line plugging due to formation of gas hydrates, reduction of line capacity due to formation of free water (liquid), corrosion, and the decrease of natural gas heating value.

Various techniques can be executed to dehydrate natural gas. Among these gas dehydration methods, glycol absorption processes, in which glycol is considered as liquid desiccant (absorption liquid), is the most common dehydration process used in the gas industry since it approximate the features that fulfill the commercial application criteria.

In a typical TEG system, shown in Fig. 1, water-free TEG (lean or dry TEG) enters at the top of the TEG contactor where it is flow countercurrent with wet natural gas stream flowing up the tower. Elimination of water from natural gas via TEG is based on physical absorption.

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Nomenclature  Acronyms		$\frac{grad}{r_1, r_2}$	the gradient of the performance function random number
ANN	artificial neural network	SH	hidden neuron's net input signal
TEG	triethylene glycol	$T_d$	equilibrium water dew point temperature
VLE	Vapor–Liquid Equilibrium	T	contactor temperatures
BP	back-propagation	$v_i$	velocity of ith particle
MEG	monoethylene glycol	$v_i \ \mathbf{w}^H$	Weight between input and hidden layer
FFNN	feed-forward neural network	$x_i$	position of ith particle
GA	genetic algorithm	$\chi_g$	gbest value
ICA	imperialist competitive algorithm		pbest value of particle <i>i</i>
MSE	mean square error	$X_{i,p}$ $Y^{pre}$	predicted output
PA	pruning algorithm	$Y^{exp}$	actual output
DEG	diethylene glycol	$O^H$	output of the hidden neuron
TREG	tetraethylene glycol		
PSO	particle swarm optimization		
	hybrid genetic algorithm and particle swarm optimiza-	Greek symbols	
110/11 50	tion	$\varphi$	activation function
$R^2$	correlation coefficient	$\omega$	inertia weight
MLP	multilayer perceptron	α	learning rate
TST	Twu-Sim-Tassone		
SPSO	stochastic particle swarm optimization		
UPSO	unified particle swarm optimization	Subscri	1
0130	difficult particle swarm optimization	1	particle i
Symbols used		j input j	
symbols b <sup>H</sup>	bias associated with hidden neurons		(7) kth iteration
b <sup>O</sup>		m	number of neuron in the input layer
	bias associated with output neuron	Z	zth experimental data
c <sub>1</sub> , c <sub>2</sub> wt%	trust parameters		
wt% °C	weight percent	Superscripts	
-	centigrade degree	n	iteration number
kPa	kilopascals	max	maximum
psia v	pounds per square inch absolute	min	minimum
K	number of input training data	pre	predicted
A	input signal (vector)	ехр	experimental
W	vector of weights and biases		

In TEG system, specification of the minimum concentration of TEG to fulfill the water dew point of exit gas has always been operationally important. Indeed, the one single change that can be made in a TEG system, which will produce the largest effect on dew point depression, is the degree of TEG concentration (purity). To that end, it is needed to have a liquid-vapor equilibrium relation/model for water-TEG system.

Several equilibrium correlations [1–7] for estimation the equilibrium water dew point of natural gas with a TEG dehydration system can be found in the literature. Generally, the correlations presented by Worley [4], Rosman [5] and Parrish et al. [1] work satisfactorily and are suitable for most TEG system designs. However, according to the literature [8], previously published correlations are unable to estimate precisely the equilibrium water concentration above TEG solutions throughout the vapor phase.

Parrish et al. [1] and Won [7] generated correlations in which equilibrium concentrations of water throughout the vapor phase have been ascertained at 100% TEG (unlimited dilution). Moreover, the other approaches employ data extrapolations at lower concentrations to predict equilibrium throughout the unlimited dilution area [8]. The effect of pressure on TEG-water equilibrium is small up to about 13,800 kPa (2000 psia) [1].

Recently, Bahadori and Vuthaluru [9] proposed a simple correlation for the prompt prediction of equilibrium water dew point of a natural gas stream with a TEG solution in terms of TEG concentrations and contactor temperatures. In addition, Twu et al. [10] employed the Twu–Sim–Tassone (TST) equation of state (EOS) [11] to specify the water–TEG system phase behavior. Furthermore, they presented an approach for employing the TST EOS

to determine water content and water dew point throughout natural gas systems. Although, these methods (i.e. TST equation of state and simple correlation) have good predictive capability, applications of presented methods are typically limited to the system which they have been adapted for. As a matter of fact, aforementioned schemes need tunable parameters which should be adjusted based upon experimental data points. Without experimental data points and adjusted parameters, aforementioned models are totally not reliable. In such circumstances, it is preferable to develop and employed general models competent to predict phase behaviors of such systems. Among the various predictive methods, artificial neural network (ANN) is one of the competent methods enjoy great flexibility and capable to explain multiple mechanisms of action [12]. ANNs are computational schemes, either hardware or software which imitates the computational abilities of the human brain by using numbers of interconnected artificial neurons. The inimitability of ANN lies in its ability to acquire and create interrelationships between dependent and independent variables without any prior knowledge or any assumptions of the form of the relationship made in advance [13].

In the last two decades, ANNs have become one of the most successful and widely applied techniques in many fields, including chemistry, biology, materials science, engineering, etc. Especially, in the field of modeling of Vapor–Liquid Equilibrium (VLE) ANNs have successful track records [14–24].

Implications of artificial intelligent based approaches in various complicated engineering aspects have got a noticeable attentions through recent years such as application back propagation (BP)-

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