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A neural network for predicting saturated liquid density using genetic algorithm for pure and mixed refrigerants

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ABSTRACT

In this study, a new approach for the auto-design of a neural network based on genetic algorithm (GA) has been used to predict saturated liquid density for 19 pure and 6 mixed refrigerants. The experimental data including Pitzer's acentric factor, reduced temperature and reduced saturated liquid density have been used to create a GA-ANN model. The results from the model are compared with the experimental data, Hankinson and Thomson and Riedel methods, and Spencer and Danner modification of Rackett methods. GA-ANN model is the best for the prediction of liquid density with an average of absolute percent deviation of 1.46 and 3.53 for 14 pure and 6 mixed refrigerants, respectively.

Réseau neuronal utilisé afin de prévoir la densité des frigorigènes purs et mélangés, à l'aide d'un algorithme génétique

Mots clés : Frigorigène ; Mélange ; Modélisation ; Calcul ; Densité ; Liquid

1. Introduction

The refrigeration process is lowering the temperature in an isolated sub system to some extent less than its surrounding temperature. Chemical industries are the main customers of refrigeration processes. In this respect, refrigeration cycles use refrigerant fluids. The design of economically acceptable low temperature refrigeration cycles requires accurate knowledge of the thermodynamic properties of refrigerants, i.e., liquid density, vapor density, enthalpy of vaporization and vapor pressure. Although there is a large body of experimental data on refrigerants in the literature, the amount of

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Nomenclature

AAPD	average of absolute percent deviation
CORGC	chain of rotator group contribution
EOS	equation of state
N	number of points
R^2	regression constant
r	linear correlation coefficient
T_r	reduced temperature
ρ	liquid density (mol/cm^3)
ω	Pitzer's acentric factor

experimental data is still incomplete and different data sets are usually inconsistent.

There are many equations of state for refrigerants and their mixtures in the literature. For the calculation of the saturated liquid density of refrigerants, 4 equations of state and 14 correlations have been examined and compared by Nasrifar and Moshfeghian (1999). They have recommended the Chain of Rotator Group Contribution (CORGC) equation of state (Pults et al., 1989) as the best among the equations of state and the fourth among 18 methods available for the calculation of saturated liquid density of refrigerants. Also, they have shown that Hankinson and Thomson correlation (Hankinson and Thomson, 1979) is the best among the correlations and Riedel correlation (Riedel, 1954) and modified Rackett correlation by Spencer and Danner (1972) are the second and the third.

Lugo et al. (2002) proposed a method to calculate some of the thermophysical properties of aqueous solutions which are used as secondary refrigerants. This method is based on the excess function approach for determining freezing points, densities, heat capacities, thermal conductivities and dynamic viscosities. Scalabrin et al. (2003) proposed a three-parameter density model based on corresponding states technique as a means of predicting the density of pure fluids and their mixtures. The studied fluids belong to two conformal families of the new refrigerant fluids' generation: the halogenated alkanes (HA) and the hydrofluoroethers (HFE). Sharafi and Boushehri (2005) extended the ISM (Song and Mason, 1989) equation of state based on statistical mechanical perturbation theory to liquid refrigerant mixtures by using correlations of Boushehri and Mason (1993). The equation of state was tested on 33 liquid mixtures from 12 refrigerants. Their results indicated that the liquid densities can be predicted to an error percentage of at the most 2.8 over a wide range of temperatures, 170–369 K.

Mafloon-Azad et al. (2005) examined an analytical equation of state for predicting density of some compressed liquid HCFC and HFC refrigerants. The input data for their equation of state were the liquid density and the heat of vaporization at the boiling point. They used a version of the ISM (Song and Mason, 1989) equation to predict the volumetric behavior of the six refrigerants. Goharshadi and Moosavi (2006) applied GMA (Goharshadi et al., 2005) EOS for predicting density of a limited liquid refrigerant mixtures. They concluded that GMA EOS provides a simple procedure for prediction of thermodynamic properties of liquid refrigerant mixtures especially for which the similar classes of refrigerants are mixed.

Eslami et al. (2006) developed their previous works (Eslami, 2000,2001; Eslami et al., 1999) on the equation of state for refrigerants to their mixtures. The temperature-dependent parameters of the equation of state have been calculated using their previous corresponding states correlation based on the normal boiling point temperature and the liquid density at the normal boiling point. They have applied a quadratic relation proposed by Nasrifar et al. (1999) for the normal boiling point constants to extend their previously proposed EOS to mixtures of refrigerants. Goharshadi and Moosavi (2007) calculated the density of 11 hydrochlorofluorocarbon (HCFC) and hydrofluorocarbon (HFC) refrigerants using Goharshadi–Morsali–Abbaspour equation of state (GMA EOS). Their results showed that GMA EOS is satisfactory enough for predicting liquid density. However, to use this EOS for a refrigerant, the six parameters must be known by fitting to experimental data. Also, they used GMA EOS to limited refrigerants.

Usually, the aforementioned correlations or equations of state require the critical constants in addition to some other adjustable parameters. The adjustment of these parameters is tedious and it is never certain that the best set of parameters has been obtained. The development of numerical tools, such as neural networks, able to represent, within the experimental uncertainties, and accurately predict, refrigerants' properties, reveals a promising approach to complete this task. Some attempts have been made for calculating thermodynamic properties of refrigerants using the artificial neural networks; as an instance, Chouai et al. (2002) used ANN for PVT representations of refrigerants from 240 to 340 K and up to 20 MPa. Results on three refrigerant compounds had been presented, namely, R134a, R32 and R134a. In their work, for both vapor and liquid phases, the neural models were devoted to the computation of the compressibility factor (Z), as a function of temperature and pressure. Then the derived properties such as enthalpy, entropy and heat capacity were calculated from Z as a function of temperature and pressure through numerical derivatives. In another study, Laugier and Richon (2003) repeated the work of Chouai et al. (2002) for six refrigerants. Sözen et al. (2007) developed an artificial neural network (ANN) for determining the thermodynamic properties – specific volume, enthalpy and entropy – of an alternative refrigerant (R508b) for both saturated liquid–vapor region and superheated vapor region. In their ANN, the back propagation learning algorithm with two different variants, namely scaled conjugate gradient (SCG) and Levenberg–Marqurdt (LM), and logistic sigmoid transfer function were used to determine the best approach. The most suitable algorithm with appropriate number of neurons in the hidden layer was found to be the LM algorithm. The results provided by the regression analysis give R^2 values in the range of 0.93–0.97 while they vary between 0.97 and 0.99 in the case where the ANN is employed for the same purpose.

In the past decade, ANNs have been used intensively in various fields. The major reason for this rapid growth and diverse application of neural networks is their ability to approximate virtually any function in a stable and efficient way. In spite of the wide range of applications, neural