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Robust model to predict the migration ratios of nanoparticles during the pool-boiling process of nanorefrigerants

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ABSTRACT

The migration features of nanoparticles between liquid phase and vapor phase during pool boiling of nanorefrigerants are highly significant properties, and deep knowledge of these properties under different conditions is necessary to evaluate how the distribution of nanoparticles impacts the cycle behavior of a refrigeration system. Due to the importance of the migration ratio, the prohibition of chlorofluorocarbon refrigerants like R113, and the cost, difficulty, and tediousness of experimental work, as well as the low integrity of the existing models, the implementation of a predictive model that is fast, robust, and reliable in this field of study is worthwhile and highly necessary. To this end, in this communication, seven important parameters were considered as the inputs to predict the migration ratio, and four models were developed: (1) multiple linear regression (MLR), (2) multilayer perceptron-artificial neural network (MLP-ANN), (3) adaptive neuro-fuzzy inference system (ANFIS), and (4) least-square support vector machine (LSSVM). The outcomes of this investigation indicated that the developed MLP-ANN approach has superior performance, compared to the others, based on the statistical values $R^2 = 0.99945799$, MSE = 0.0253, RMSE = 0.1591, and AARD = 1.3269. Meanwhile, by conducting a sensitivity analysis of the MLP-ANN model, it was concluded that nanoparticle size and heat flux are the most and least influential variables for migration.

1. Introduction

Nanofluids have attracted increasing attention in the recent years due to their important advantages, such as large thermal conductivity and other important properties related to heat transfer. Nanofluids, which belong to the class of nanotechnology, can be generated by mixing a base fluid and nanoparticles. Generally, the base fluid can be water, oils, refrigerants or other common liquids [1]. Utilization of nanoparticles in refrigerants, to form nanorefrigerants, can be used to solve many critical problems encountered by refrigerators and air conditioners, such as those related to performance and energy consumption [2,3]. In addition to such potential benefits, they are environmentally friendly and may be an interesting alternative to conventional refrigerants such as hydrofluorocarbon (HFC) to control greenhouse gases [4].

For a nanorefrigerant, the migration features of nanoparticles between the liquid phase and vapor phase during pool boiling play an important role, and deep knowledge of these features under different conditions is necessary to evaluate how the distribution of nanoparticles influences the cycle behavior of a refrigeration system. It is found that any changes in refrigerant type, nanoparticle size, nanoparticle type, mass fraction of lubricating oil, heat flux, and initial liquid-level height will result in a change in the migration of nanoparticles [5]; therefore, identifying the impact of such influential variables is at the core of investigating the effects of a nanorefrigerant on a system. Despite being an important property, a few scholars have studied the migration features of nanoparticles.

The first investigation was conducted by Ding et al. [6], by considering CuO nanoparticles, R113 refrigerant, and RB68EP lubricant oil to investigate the migration features of nanoparticles in nanorefrigerant and nanorefrigerant-oil mixture. The authors proposed a model to estimate migrated mass of nanoparticles. The model can be used to simulate the related experimental data in the range of 7.7–38.4%. To elucidate the effects of different parameters, such as nanoparticle type, nanoparticle size, refrigerant type, mass fraction of lubricating oil, heat flux and initial liquid-level height, on the migration features of nanoparticles, Peng et al. [5] carried out various experimental tests on nanofluids composed of Cu, Al, Al_2O_3, and CuO nanoparticles and R113, R141b and n-pentane refrigerants. However, it was found that, because of some limitations, Ding's model was not capable of forecasting migration features. To solve this issue, Peng et al. [7] developed a model that was able to predict 90% of the measured experimental data within an error band of ±20% and a mean deviation of 12.1%. In another study, Mahbubul et al. [8] conducted experiments to evaluate the influences of heat flux, initial liquid-level height, vessel size, insulation, and lubricating oil on the

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migration properties of TiO_2 nanoparticles during the pool boiling of R141b refrigerant.

A literature review indicates that there are two types of approaches to determining migration characteristics of nanoparticles: laboratory tests and the models of Ding et al. [6] and Peng et al. [7]. However, experimental works are time consuming, expensive, tedious, and difficult for engineers. Moreover, during experiments, great attention is needed to avoid negative influences in the test bench. Therefore, estimation of the behaviors of migration characteristics of nanoparticles is really helpful and essential to analyzing their performance, especially when CFC refrigerants such as R113 are used as the based fluid; thus, replacing experimental study with a robust and reliable model is optimal. However, a literature review highlights that because of the high number of influential parameters and the complex inter-relations among them, the present models may not be the best choices for such problems due to weak performance, since accurate estimation of this property is essential. Weak and unreliable approximations obtained using such methods in the prediction of this important property have prompted researchers to search for a new model to predict the parameters of nanorefrigerants.

In the past two decades, artificial-intelligence algorithms have been widely utilized by various scholars to solve nonlinear and complex problems in different research areas [9–12]. The advantages of such approaches, in comparison with conventional ones, are that they can model complex and nettlesome problems with high precision while decreasing the computational time. This claim has been proven by a variety of research studies published by experts in different research area [13–17].

Different studies have been conducted on the use of artificial-intelligence algorithms to estimate different properties of nanofluids. For example, estimation of the thermal conductivities of alumina-water nanofluids using a fuzzy C-means clustering-based adaptive neuro-fuzzy inference system (FCM-ANFIS) a genetic-algorithm polynomial neural network (GA-PNN) was carried out by Mehrabi et al. [18]. In 2013, Mehrabi et al. [19] proposed another FCM-based adaptive neuro-fuzzy inference-system model for the prediction of the viscosities of nanofluids by collecting experimental data from the literature regarding Al_2O_3, CuO, TiO_2, and SiO_2. Finally, it was concluded that the developed model greatly outperformed the other considered models. In 2014, Vaferi et al. [20] estimated the convective heat-transfer coefficients of nanofluids flowing through circular tubes. In this paper, the authors collected experimental data from the literature to develop and compare different types of artificial neural networks and conventional correlations. The comparison showed the higher precision and effectiveness of applying a multilayer-perceptron neural-network approach as a sufficient model for the prediction problem, compared to other models. In 2015, Esfe et al. [21] used an artificial neural network to estimate the thermal conductivities of Al_2O_3-water nanofluids. The model was developed and compared with a correlation to demonstrate its accuracy. Recently, another multilayer-perceptron artificial neural-network approach was developed to estimate the viscosities of nanofluids by Heidari et al. [22]. Actual data were taken from the literature and the approach has been preferred for its accuracy and ease of use. Sharifpur et al. [23] used a hybrid neural network based on the group method of data handling to estimate effective viscosity of Al_2O_3-glycerol nanofluids. More recently, Adio et al. [24] developed FCM-ANFIS and GA-PNN models to predict effective viscosity of MgO-ethylene glycol nanofluids. The results of all the modeling techniques indicated good agreement with the experimental data.

Reviewing the relevant literature indicates the possibility of applying artificial-intelligence methods for the estimation of different properties of nanofluids. On the other hand, to the best of our knowledge, there are no reports on a powerful tool for predicting the migration ratio of nanoparticles (ζ). Therefore, further investigations are strongly needed to develop and present a proper predictive tool to overcome this scientific gap. Thus, the objective of this paper is to develop a rigorous modeling approach using multiple linear regression (MLR), multilayer-perceptron artificial neural network (MLP-ANN), adaptive neuro-fuzzy inference system (ANFIS), and least-square support vector machine (LSSVM) to calculate accurately the migration ratio of nanoparticles. For this purpose, the nanoparticle molecular mass (M_n), nanoparticle size (D_p), refrigerant molecular mass (M_r), mass fraction of lubricating oil (X_o), initial nanoparticle concentration (φ_n), heat flux (q), and initial liquid-level height (L) were considered as the models inputs. A comparison between the values predicted using the developed models and the corresponding actual data is carried out and their effectiveness are evaluated utilizing various statistical and graphical error tests. Moreover, a sensitivity analysis is conducted to determine the influence of each parameter on the output.

2. Theoretical background

2.1. Multiple linear regression (MLR)

MLR, which is a well-known statistical method, was first presented by Francis Galton in the 19th century. This approach models the relationship between two or more input variables and one output variable by fitting a linear equation to the observed data as follows.

$$\gamma = \alpha_0 + \alpha_1 \chi_1 + \alpha_2 \chi_2 + \alpha_3 \chi_3 + \ldots + \alpha_n \chi_n \tag{1}$$

In this equation, γ is the output variable, α_i ($i = 0, 1, 2, 3, \ldots, n$) are the regression coefficients, and χ_i ($i = 1, 2, 3, \ldots, n$) are the input variables.

2.2. Multilayer-perceptron artificial neural network (MLP-ANN)

ANNs are mathematical approaches inspired by the functioning of the human brain that are used to model fairly complex and nonlinear problems. Ahmadi et al. [25] mentioned that the multilayer-perceptron (MLP) neural network is among the most popular ANNs and has been widely utilized in several engineering fields to solve related regression problems using defined input vectors. A correctly designed MLP utilizing a proper learning algorithm, along with a number of hidden layers and their neurons, has the ability to precisely connect input variables to the corresponding output(s) without applying any assumptions. An input layer, an output layer, and hidden layer(s), which carry out the processing step, are used to create the MLP-ANN. Each layer is composed of simple processing elements called neurons, which are connected to one another in a parallel structure [26]. The numbers of input and output variables determine the numbers of neurons in the input and output layers. However, there is no proven method for selecting of the number and sizes of hidden layers. These numbers directly depend on the complexity of the problem, the numbers of training and testing data points, and the noise in the considered data sets. In this case, a

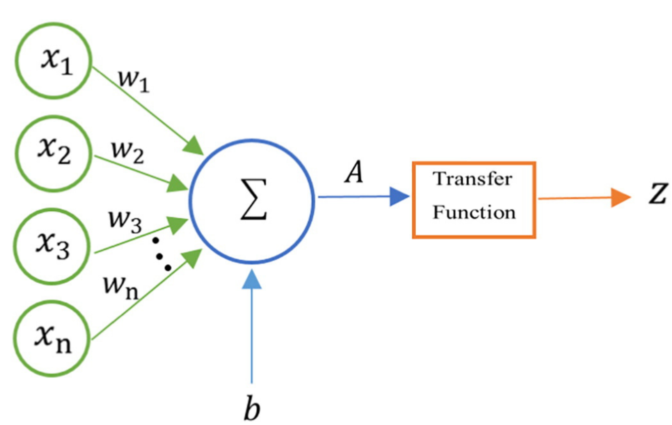

Fig. 1. A model of the ANN neuron.