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Predicting the viscosity of multi-walled carbon nanotubes/water nanofluid by developing an optimal artificial neural network based on experimental data☆

Masoud Afrand [a,*], Afshin Ahmadi Nadooshan [b], Mohsen Hassani [a], Hooman Yarmand [c], M. Dahari [d]

[a] Department of Mechanical Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Iran
[b] Faculty of Engineering, Shahrekord University, Shahrekord, Iran
[c] Department of Mechanical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia
[d] Department of Electrical Engineering, Faculty of Engineering, University of Malaya, 50603 Kuala Lumpur, Malaysia

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ABSTRACT

Regarding the viscosity of the fluids which is an imperative parameter for calculating the required pumping power and convective heat transfer, based on experimental data, an optimal artificial neural network was designed to predict the relative viscosity of multi-walled carbon nanotubes/water nanofluid. Solid volume fraction and temperature were used as input variables and relative viscosity was employed as output variable. Accurate and efficient artificial neural network was obtained by changing the number of neurons in the hidden layer. The dataset was divided into training and test sets which contained 80 and 20% of data points respectively. The results obtained from the optimal artificial neural network exhibited a maximum deviation margin of 0.28%. Eventually, the ANN outputs were compared with results obtained from the previous empirical correlation and experimental data. It was found that the optimal artificial neural network model is more accurate compared to the previous empirical correlation.

1. Introduction

Water is a common fluid for heat transfer applications such as heat exchangers, solar collectors, nuclear power industries, automobile radiators and so on. Water is inexpensive and non-toxic. The advantages of using water as a heat transfer fluid include high specific heat capacity, density, and availability. Despite all these advantages, this fluid has a low thermal conductivity. In order to improve the thermal conductivity of water, some researchers have proposed the dispersion of nanoparticles in liquids, which are called nanofluids [1–5]. Since dispersing the nanoparticles can lead to enhance the thermal conductivity of fluids, many researchers have focused on this topic [6–10]. These studies revealed that the thermal conductivity of nanofluids is higher than common fluids.

However, the viscosity of the fluids which is an imperative parameter for calculating the required pumping power and convective heat transfer is also affected by the dispersing nanoparticles in the base fluid. In this regard, many researchers have examined the viscosity of nanofluids, and reported that the viscosity of nanofluids is a function of temperature, concentration, size and shape of nanoparticles [11–19].

However, several experiments are needed to determine the viscosity of nanofluids at various temperatures and nanoparticles concentrations. For eschewing the costs of the experiments, which are expensive and time-consuming, artificial intelligence based on artificial neural network (ANN) model can be applied for prediction of the viscosity of nanofluids. Neural network unit processes datasets in the same way that the human brain does. ANN is made up of countless interconnected processing components which called neurons to work in parallel paths achieving a proper solution. An artificial neural network is implemented using an experimental data set, optimized network parameters, and appropriate training algorithms. Industrial applications usually provide large datasets which is an advantage of training an ANN model [20]. In fact, ANN model is an effective and applicable method for forecasting the relation between dependent and independent parameters which mathematical formulation is unavailable [21] or existed relationship has low precision [20,22]. Because of numerous applications of ANNs in various fields, many researchers applied different types of them to predict the thermophysical properties of nanofluids. Mention may be made of the research studies of Hojjat et al. [23], Longo et al. [24], Ariana et al. [25] and Hemmat Esfe et al. [26–30]. However, there are few studies for the viscosity of nanofluids employing soft computing methods. In this regard, Mehrabi et al. [31] recognized a model for predicting the effective viscosity of Al_2O_3, CuO, TiO_2 and SiO_2 water-based nanofluids by an FCM-ANFIS using experimental data. They

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* Corresponding author.
E-mail addresses: masoud.afrand@pmc.iaun.ac.ir, masoud_afrand@yahoo.com (M. Afrand).

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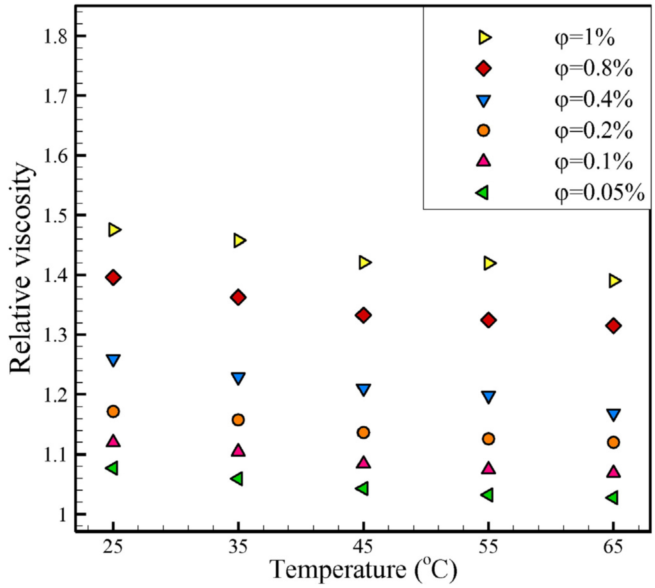

Fig. 1. Relative viscosity versus temperature for various solid volume fractions.

assumed the size of the nanoparticles, nanoparticle concentration and temperature as design parameters. Their comparisons showed that the predicted results agreed with the experimental data. Karimi et al. [32] deigned an optimal ANN model based on genetic algorithm to predict the viscosity of nanofluids. They used the temperature and nanoparticle concentration as input variables. Their results revealed that optimal ANN model was in good agreement with experimental data. Lately, Hemmat Esfe et al. [33] designed an optimal ANN to predict both the thermal conductivity and dynamic viscosity of ferromagnetic. They used experimental data which include diameter of particles, temperature and concentration of nanoparticles as input variables. Their model outputs indicated that the ANN was able to predict the experimental data.

The study of the rheological behavior of the viscosity of nanofluids seemed necessary due to their numerous applications which include calculating the pumping power and convective heat transfer. On the other hand, artificial neural network models can be applied for prediction of the viscosity of nanofluids with less cost and time. Moreover, literature survey indicates that there is no reported work about the ANN modeling of viscosity of MWCNTs/water nanofluid. Hence, in the present study, for the first time, an optimal artificial neural network has been modeled to predict the relative viscosity of this nanofluid using a set of experimental data.

2. Methodology

2.1. Experimental data for the analysis

Thirty experimental data for the relative viscosity of multi-walled carbon nanotubes MWCNTs/water nanofluids were used for developing models. The experimental data were present in a solid volume fraction (φ) ranging from 0 to 1% and a temperature (T) ranging from 25 to 65 °C presented by Hemmat Esfe et al. [18] and shown in Fig. 1.

2.2. Development of artificial neural network model

Recently, since linear computing is unable to predict the nonlinear systems, the various ANN models has been used widely for determining relations between process parameters because of the significant advantages of high precision, low cost and time. As previously mentioned, the base of ANN is the human brain, which is a parallel processing network to determine the complex nonlinear relationships between independent and dependent variables [34].

There are three layers in an ANN model which called input, hidden, and output layers. Each layer consisted of some processing components, called neurons, as mentioned before. The ANN architecture gives the connections between the layers and neurons. The role of the hidden layers is to adjust input dataset to the new dataset of outputs. At first, specific weights considering randomly are assigned to inputs. This step is called as a training step of ANN. In the training step, the extracted errors from experiments and predicted values are returned to the beginning of networks where it makes all corrections to weights. This procedure is continued until the desired outcome was extracted. The number of neurons in the input and output layers is related to the number of input and output parameters. In this study, the transfer function of hidden layer was considered as Tan-Sigmoid, while Log-sigmoid

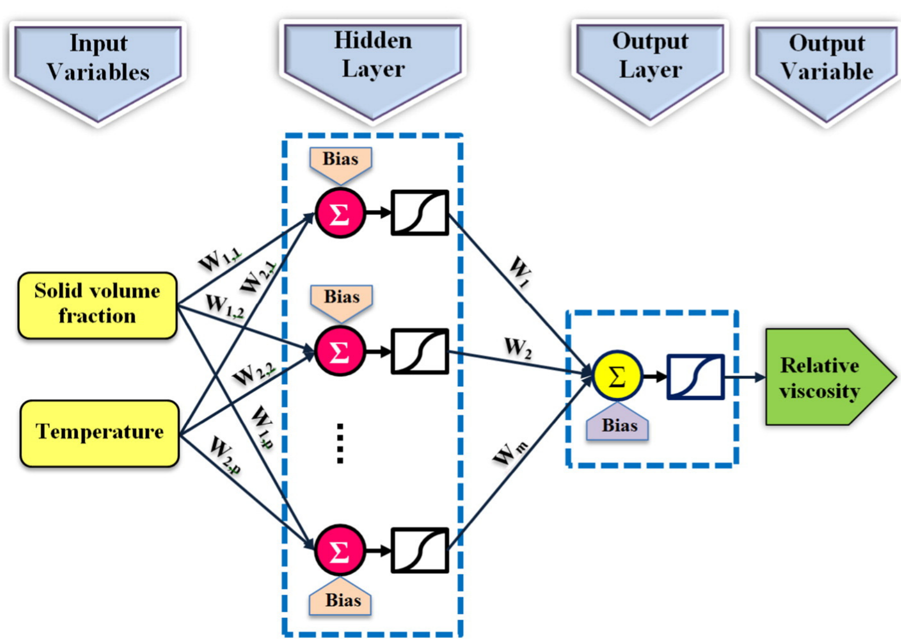

Fig. 2. Structure of the feed forward neural network ($W_{s,p}$ is the weight of *s*th elements in input vector to *p*th neurons and W_m is the weight of *m*th neurons to output).