Designing an artificial neural network to predict thermal conductivity and dynamic viscosity of ferromagnetic nanofluid☆

Mohammad Hemmat Esfe [a,*], Seyfolah Saedodin [b], Nima Sina [a], Masoud Afrand [a,*], Sara Rostami [a]

[a] Department of Mechanical Engineering, Faculty of Engineering, Najafabad Branch, Islamic Azad University, Najafabad, Isfahan, Iran
[b] Faculty of Mechanical Engineering, Semnan University, Semnan, Iran

ARTICLE INFO

ABSTRACT

This paper focuses on designing an artificial neural network which can predict thermal conductivity and dynamic viscosity of ferromagnetic nanofluids from input experimental data including temperature, diameter of particles, and solid volume fraction. The experimental data were extracted and they were used as learning dataset to train the neural network. To find a proper architecture for network, an iteration method was used. Based on the results, there was no over-fitting in designed neural network and the neural network was able to track the data. ANN outputs showed that the maximum errors in predicting thermal conductivity and dynamic viscosity are 2% and 2.5%, respectively. Based on the ANN outputs, two sets of correlations for estimating the thermal conductivity and dynamic viscosity were presented. The comparisons between experimental data and the proposed correlations showed that the presented correlations were in an excellent agreement with experimental data.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

For many years, common fluids such as water, ethylene glycol, or oil have been used as the operating fluid in industry and engineering designs. The main problem is that the thermal conductivity of these fluids is small and thus the heat transfer rate is low. This is one of the limitations of this type of fluid that has led engineering design to have certain limitations. Recently, in order to increase the thermal conductivity of the fluid, nano-sized particles will be added to the fluid. In this way, the heat transfer of nanofluids within the enclosure and the influence of thermo-physical characteristics of nanofluids (such as thermal conductivity, thermal expansion coefficient, and dynamic viscosity) has been much studied [1–5].

In the last decade, several studies have been conducted on the thermal conductivity nanofluids. Wook Oh et al. [6] presented experimental data on the thermal conductivity enhancement in Al_2O_3 nanoparticle dispersed in DI water and EG as base fluids using the modified 3-omega (3ω) method. They showed that for DI water-based nanofluids, thermal conductivity incremental data agreed well with those of Wang et al. [7], which show higher increment compared to the results of Lee et al. [8] and Das et al. [9]. Also, they showed that EG-based nanofluids had relatively low thermal conductivity values compared with those of Lee et al. [8] and Wang et al. [7]. Experimental data on enhancement of thermal conductivity of ethylene glycol based silver nanofluids are reported

by Sharma et al. [10]. They illustrated thermal conductivity of silver nanofluids enhanced to 10%, 16%, and 18% as the amounts of silver particles in nanofluid were 1000, 5000, and 10,000 ppm, respectively. The effect of solid volume fraction of ethylene glycol based copper oxide fluids is investigated by Lee et al. [11]. Their experimental results demonstrated that these nanofluids, containing a small amount of nanoparticles, have significantly higher thermal conductivities than the same liquids without nanoparticles. In another study focusing on the solid concentration and shape of the nanoparticles, Xie et al. [12] studied silicon carbide nanoparticles into two spherical and cylindrical forms added to water and ethylene glycol. They observed that the thermal conductivity is further increased when nanoparticles are cylindrical. Although many researchers have not considered the effect of temperature on thermal conductivity, recent studies show that nanofluids temperature effect on the properties of nanofluids is very important. Das et al. [13] studied the behavior of CuO–water and Al_2O_3–water nanofluids with temperature. They concluded that with increasing temperature, the thermal conductivity of nanofluids increases. In another study, Karthik et al. [14] investigated the thermal conductivity of CuO–DI water nanofluids experimentally. Their study also showed that temperature has a significant influence on the thermal conductivity of nanofluids.

To access the thermophysical characteristics of nanofluids in different concentrations, particle diameters, and temperatures, we need to do several experiments which are time consuming and expensive. In recent decade, in order to avoid such costs, there has been an interest in using soft computing methods to predict the behavior of nanofluids which are known as neural networks, fuzzy logic, and genetic algorithms. Among these, artificial neural networks are good tools to solve complex

---

problems in different application with a considerable reduction in time and cost. However, there is a little reported work about modeling of thermal conductivity and viscosity of nanofluids using artificial neural network. In this regard, Mehrabi et al. [15] developed a model to predict the effective viscosity of nanofluids using an FCM-based adaptive neuro-fuzzy inference system (FCM-ANFIS) and a set of experimental data. They selected as the design parameters the size of the nanoparticles, volume concentration, and temperature to predict the effective viscosity of nanofluids. To model the viscosity, experimental data from literature were divided into two sets: a train and a test data set. The predicted viscosities were compared with experimental data for four nanofluids, which were Al_2O_3, CuO, TiO_2, and SiO_2, and with water as base fluid. The predicted results agreed with the experimental measurement.

An accurate and efficient artificial neural network based on genetic algorithm (GA) for predicting of nanofluids viscosity was developed by Karimi et al. [16]. They used genetic algorithm (GA) for optimizing the neural network parameters. Temperature and nanoparticle volume fraction were used as input data. The obtained results demonstrated that the GA-NN model was in good agreement with the experimental data. Papari et al. [17] used the neural network method to predict the thermal conductivity of different nanofluids, including single-walled carbon nanotubes in epoxy and polymethylmethacrylate and also multi-walled carbon nanotubes suspended in oil, decene, water, ethylene glycol. The comparisons between predicted and experimental data showed good agreement. Thermal conductivity modeling of γ-Al_2O_3, TiO_2, and CuO nanoparticles in a 0.5 wt% of carboxymethyl cellulose (CMC) aqueous solution using a three-layer feed-forward neural network is exhibited by Hojjat et al. [18]. They proposed neural network models to report the thermal conductivity as a function of the volume fraction of nanoparticles, temperature, and the thermal conductivity of the nanoparticles. Proposed models were in good agreement with the experimental values. Longo et al. [19] presented two neural network models for predicting the thermal conductivity of Al_2O_3–water and TiO_2–water nanofluids by considering the temperature, volume fraction, nanoparticle diameter, and particle thermal conductivity as the input variables. Both models revealed that reasonable predicted data are in good agreement with the experimental data; but the 4-input model showed better performance. Recently, Hemmat Esfe et al. [20] modeled the thermal conductivity of MgO/EG nanofluids using experimental data and artificial neural network. Feedforward multilayer perceptron neural network was used to predict the thermal conductivity of the MgO/EG nanofluid. They considered the volume fraction, particle size, and temperature as the input data. The predicted results are in good agreement with the measured data.

Literature survey reveals that there is not any reported work about modeling of thermal conductivity and dynamic viscosity of Fe/EG nanofluids using artificial neural network (ANN). Therefore, in this work, ANN is designed using obtained experimental thermal conductivity and dynamic viscosity values of Fe/EG nanofluids depending on the different temperatures, diameters of particles, and volume fractions.

2. Architecture of artificial neural network

In complicated systems with several effective input parameters, artificial neural network (ANN) can predict output data. ANN is inspired from the human brain in order to process data and information. It includes integrated process units called neurons that can process input data. The multi-layer perceptron neural network includes input layer, hidden layer, and output layer. In this article, the ANN is used for modeling the behavior of Fe-EG nanofluid. The thermal conductivity and viscosity of Fe-EG nanofluid is modeled by ANN. The number of input parameters is three, which includes temperature (T), diameter of particles (d_p), and volume fraction (ϕ). Output values are the thermal conductivity (k) and dynamic viscosity (μ).

The basic unit of neural network is the neuron. In each neuron, the sum of input values are weighted and added with a parameter called
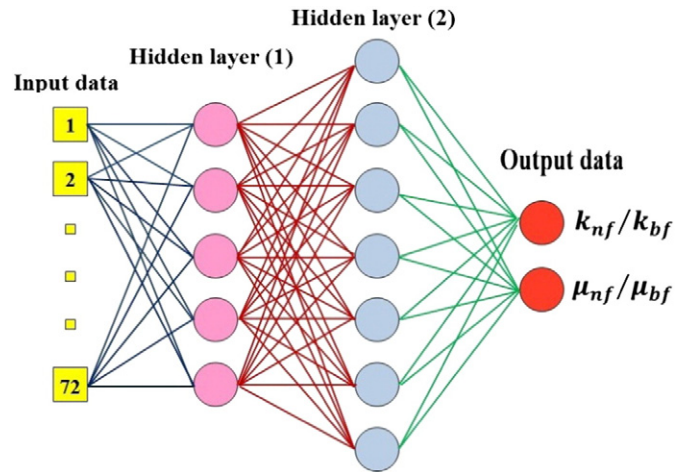

Fig. 1. Structure of the neural network.

bias, and the sum is passed through a function which is called transfer function or activation function (see Fig. 1). The transfer function calculates the output of a neuron from its input. Some ANN includes several layers. Each layer includes several neurons and performs a simple process on data. In this ANN, the input dataset is divided into 3 sets randomly: train data, validation data, and test data. 70% of data set is regarded as train data. 15% of dataset is regarded as validation, and 15% of data is regarded for test data. During training process, the weight and biases of each neuron is generated. Validation data are used during training and it tunes parameters of classifier and defines stopping criteria also it prevents the network from over-fitting. Over-fitting occurs when the error on the training dataset reaches a very small value, but when new data are imported to the ANN, the new error is not small. It means that the ANN has memorized only the training examples, but the network is not able to generalize and predict new input values correctly. The test dataset shows how good the ANN is trained. In this simulation, the ANN includes two hidden layer and an output layer.

Feedforward multilayer perceptron neural network is used to predict the thermal conductivity enhancement and dynamic viscosity of the Fe/EG nanofluid. The first hidden layer includes seven neurons with tan-sigmoid transfer function (Eq. (1)). The second layer includes 5 neurons with the same previous transfer function.

$$n_j = \frac{2}{1 + e^{2Z}} - 1 \tag{1}$$

Where n_j is the output of the jth neuron and z is given by

$$z = \sum_{i=1}^{r} w_{ij} p_i + b_j \tag{2}$$

Where w_{ij} are the weights of connections from the i-th neurons in the previous layer to the j-th neurons, p_i denotes the output from the i-th neuron, b refers to the bias parameter, and r represents the number of neurons in the previous layer.

Finally, the output layer should have only two neurons because the number of outputs is two. The designed transfer function for output layer is linear. The number of input data is 72, which is extracted from experimental results. The selected learning algorithm is Levenberg Marquardt. In this network, during learning process, maximum number of iteration is 1000, maximum number of fail in validation check is 20, and the performance of network is mean square error (MSE). The value of MSE is calculated from Eq. (3).

$$MSE = \frac{\sum_{i=1}^{n} (t_i - a_i)^2}{n} \tag{3}$$