International Communications in Heat and Mass Transfer 86 (2017) 25–31

Contents lists available at ScienceDirect

International Communications in Heat and Mass Transfer

journal homepage: www.elsevier.com/locate/ichmt

Artificial neural network modeling of nanofluid flow in a microchannel heat sink using experimental data

Mohammad Mahdi Tafarroj[a], Omid Mahian[b,*], Alibakhsh Kasaeian[c], Kittipong Sakamatapan[d], Ahmet Selim Dalkilic[e], Somchai Wongwises[d,f,*]

[a] Department of Mechanical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran
[b] Renewable Energies, Magnetism and Nanotechnology Lab., Faculty of Science, Ferdowsi University of Mashhad, Mashhad, Iran
[c] Faculty of New Science & Technologies, University of Tehran, Tehran, Iran
[d] Fluid Mechanics, Thermal Engineering and Multiphase Flow Research Lab. (FUTURE), Department of Mechanical Engineering, Faculty of Engineering, King Mongkut's University of Technology Thonburi, Bangmod, Bangkok 10140, Thailand
[e] Heat and Thermodynamics Division, Department of Mechanical Engineering, Yildiz Technical University, Yildiz, Besiktas, Istanbul 34349, Turkey
[f] The Academy of Science, The Royal Institute of Thailand, Sanam Suea Pa, Dusit, Bangkok 10300, Thailand

ARTICLE INFO

Keywords:
Microchannel
Nanofluids
Nusselt number
Artificial neural network

ABSTRACT

The present paper deals with the artificial neural network modeling (ANN) of heat transfer coefficient and Nusselt number in TiO_2/water nanofluid flow in a microchannel heat sink. The microchannel comprises of 40 channels; each channel has a length of 4 cm, a width of 500 μm, and a height of 800 μm. In the ANN modeling of heat transfer coefficient and Nusselt number 23 and 72 datasets have been used, respectively. The experimental Nusselt number has been calculated based on three different thermal conductivity models, four volume fractions of 0, 0.5, 1, and 2%, two values of Reynolds number i.e. 400 and 1200 and three different heating rates including 50.6, 60.7, and 69.1 W. Therefore, the inputs that are introduced to the neural network are volume fraction of nanoparticles, Reynolds number, heating rate, and model number while the output of network is the Nusselt number. It is elucidated that an appropriately trained network can act as a good alternative for costly and time-consuming experiments on the nanofluid flow in microchannels. The average relative errors in the prediction of Nusselt number and heat transfer coefficients were 0.3% and 0.2%, respectively.

1. Introduction

Over the last decade, numerous studies both experimentally and numerically have been performed to appraise the nanofluids properties and their role in efficiency enhancement of energy systems (For example, refer to Refs. [1–10]). One of the challenges for assessing the nanofluid effect on the performance of thermal systems is difficulties in nanofluid preparation and relatively high expenses of production. One solution to save the time and reducing the expenses of experiments may be the implementation of soft computing methods such as Artificial Neural Network (ANN) to predict the efficiency of nanofluid-based thermal systems. Here, a brief review of some previous studies on modeling of nanofluid properties and applications using ANN is presented.

In 2009, Santra et al. [11] modeled natural convection of a non-Newtonian nanofluid (Cu/water) in a cavity using both CFD and ANN. A resilient-propagation (RPROP) algorithm was used for training the neural network. It was concluded that ANN could be more helpful than CFD from the time-saving viewpoint. Hojjat et al. [12] measured thermal conductivity of three different non-Newtonian nanofluids containing γ-Al_2O_3, TiO_2 and CuO nanoparticles and used ANN for modeling the experimental data. The inputs of ANN were temperature, nanoparticle volume fraction, and thermal conductivity of nanoparticles.

Balcilar et al. [13] used three different ANN approaches including multi-layer perceptron (MLP), generalized regression neural network (GRNN) and radial basis function (RBF) to model the pool boiling of TiO_2/water nanofluids. They found that ANN methods are able to predict the heat transfer coefficient with errors less than ± 5%. Yousefi et al. [14] estimated the relative viscosity of different nanosuspensions composed of various nanoparticles (i.e. CuO, SiO_2, Al_2O_3, TiO_2) and base liquids (i.e. water, ethanol, a mixture of propylene glycol and water, and a mixture of ethylene glycol and water) by designing a diffusional neural network. The modeling results were fitted with experimental data well. Esfe et al. [15] studied experimentally the thermal conductivity of ethylene glycol based nanofluids containing

* Corresponding authors.
E-mail addresses: omid.mahian@gmail.com (O. Mahian), somchai.won@kmutt.ac.th (S. Wongwises).

http://dx.doi.org/10.1016/j.icheatmasstransfer.2017.05.020

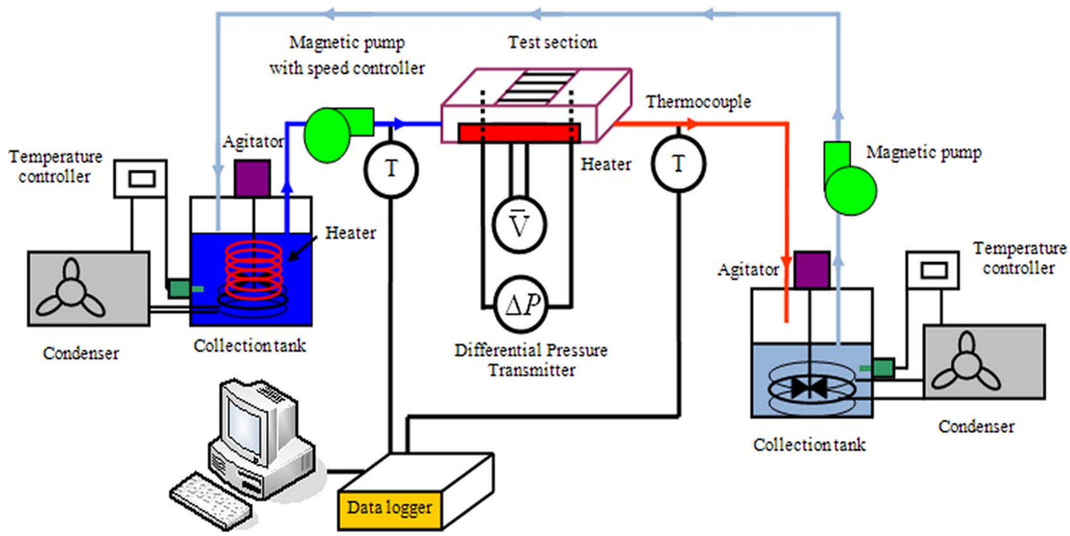

Fig. 1. Schematic of the experimental set-up [From Nitiapiruk et al. [30], with permission from Elsevier].

MgO particles with four different sizes including 20, 40, 50, and 60 nm where temperature changes between 25 and 55 °C, and concentration varies between 0 and 5%. Next, a neural network was trained to model the measured data of thermal conductivity by introducing volume fraction, nanoparticle dimension, and temperature as inputs of the network.

Bahiraei and Mashaei [16] first presented a three dimensional CFD model for Al_2O_3/water nanofluid flow in a canal with discrete heat sources and then using the simulation data they extended an artificial neural network to predict the heat transfer coefficient and pressure drop in the channel.

Esfe et al. [17] measured thermal conductivity of COOH-functionalized MWCNTs/water nanosuspensions and then implemented MLP technique to model the data. Temperature (between 25 and 55 °C) and nanofluid concentration (up to 1%) were the inputs of trained network. The results of modeling were in good agreement with experimental data.

Afrand et al. [18] used 48 experimental data obtained for viscosity of MWCNTs-SiO_2/AE40 nanolubricants to develop a correlation. Next, they designed an optimal ANN based on the derived correlation. The comparisons between outputs of the correlation and the optimized ANN revealed that the deviation margin of ANN results from experimental data is just 1.5% while the deviation margin reaches 4% in the case of correlation. Abdollahi and Shams [19] studied the nanofluid flow in a channel equipped to vortex generator numerically. They utilized neural network along with multi-objective genetic algorithm and CFD modeling to obtain the optimal nanofluid concentration, and position and shape of vortex generator in the channel. Ziaei-Rad et al. [20] solved numerically the nanofluid flow over a horizontal permeable stretching sheet under magnetohydrodynamic(MHD) flow by converting governing equations from partial differential to ordinary differential form. Effects of different parameters including suction/injection, nanofluid concentration, viscous dissipation and MHD parameter on the values of skin friction factor and Nusselt number have been evaluated. Next, using a multilayer neural network approach a model with excellent accuracy was presented to predict the Nusselt number and friction factor where the average difference between results of numerical solution and neural network model was less than 0.4%. Kalani et al. [21] used adaptive neuro fuzzy inference system (ANFIS) model and two different neural networks including RBF and MLP to predict the outlet temperature and electrical efficiency of a photovoltaic thermal (PVT) system using Zinc Oxide/water nanofluid. Particle Swarm Optimization (PSO) procedure was implemented to optimize the structure of the three models. It was found that ANFIS and RBF can estimate the desired outputs with a higher accuracy. To save the space, other related papers on modeling of nanofluid flow using the neural network are not reviewed here; as other instances, interested readers can refer to Refs. [22–28].

The above literature review reveals that most of the studies on neural network modeling of nanofluids have been conducted on thermophysical properties and not enough attention has been paid to use ANN for modeling of nanofluid flow in industrial thermal systems such as microchannel heat sinks. There is a conference paper released in 2008 that reports the application of ANN for modeling of Cu/water nanofluid flow in a microchannel heat sink. However, the modeling was done based on the results of an analytical analysis and not experimental data [29].

Based on the best knowledge of the authors, there is no study on neural network modeling of nanofluid flow in microchannel heat sinks using measured data, despite the high importance of microchannels in cooling of electronic devices. The present paper aims to extend a neural network to predict the Nusselt number and heat transfer coefficients due to nanofluid flow in a microchannel heat sink. The experimental data used in the present modeling have been extracted from our previous experimental work on the flow of TiO_2/water nanofluid in a microchannel heat sink composed of 40 channels [30]. It should be mentioned that the experiments on the microchannel heat sink were performed under real conditions in which domestic computers operate.

2. Experiments

A complete description of experimental set- up and procedure has been given in Ref. [30], but here a summary of the experimental study is represented. Fig. 1 depicts a schematic of the experimental set-up. The test section comprises of a microchannel heat sink with 40 channels and a heater in the bottom. Each channel has a length of 4 cm, a width of 500 μm, and a height of 800 μm. The heat was applied to the microchannel heat sink at three different rates including 50.6, 60.7, and 69.1 W. Water-based nanofluids containing TiO_2 nanoparticles at concentrations of 0.5, 1, and 2% have been prepared, and the results were compared with water. Experiments were performed under laminar regime of nanofluid flow. Nusselt number and heat transfer coefficients were estimated based on measured temperatures and heating rate. Nusselt number is related to heat transfer coefficients through thermal conductivity. For estimation of Nusselt number, three different thermal conductivity models have been used as follows:

Model 1: Maxwell equation is used to calculate thermal