Chemical and Process Engineering 2022, 43 (2), 159–163
DOI: 10.24425/cpe.2022.140818

Modeling and prediction of thermal conductivity ratio of metal-oxide based nano-fluids using artificial neural network and power law

Mohammad Hanief[1*], Qureshi Irfan[1], Malik Parvez[2]

[1]Mechanical Engineering Department, National Institute of Technology Srinagar, India
[2]Chemical Engineering Department, National Institute of Technology Srinagar, India

In this study, the thermal conductivity ratio model for metallic oxide based nano-fluids is proposed. The model was developed by considering the thermal conductivity as a function of particle concentration (percentage volume), temperature, particle size and thermal conductivity of the base fluid and nano-particles. The experimental results for Al_2O_3, CuO, ZnO, and TiO_2 particles dispersed in ethylene glycol, water and a combination of both were adopted from the literature. Artificial neural network (ANN) and power law models were developed and compared with the experimental data based on statistical methods. ANOVA was used to determine the relative importance of contributing factors, which revealed that the concentration of nano-particles in a fluid is the single most important contributing factor of the conductivity ratio.

Keywords: nano-fluids, thermal conductivity ratio, artificial neural network, regression, ANOVA

1. INTRODUCTION

The fluids such as engine oil, water and ethylene glycol are widely used fluids in different thermo-fluid systems, having low thermal conductivity. The thermal behaviour of nano-fluids prepared by mixing base fluid with nano particles was first studied by Choi and Eastman (1995). The study reported that the homogenized mixture of nano-particles at low volume fraction with conventional fluids such as ethylene glycol, glycerine, oil, and water remarkably increased the thermal performance. Nano-fluids have been thoroughly investigated and their importance has been studied by Sayes et al. (2006), Wang et al., (2006). These models depict the impact of nano-particles on the thermal conductivity of the combination. This prompted the advancement of new hypothetical models to assess the thermal conductivity of nano-liquids, which reveals the strong dependence of the two. Brownian motion was used by Koo and Clement (2004) to study the heat transfer enhancement by nano partcles.

* Corresponding author, e-mail: hanief@nitsri.net

Presented at the International Chemical Engineering Conference 2021 (ICHEEC): 100 Glorious Years of Chemical Engineering and Technology, held from September 16–19, 2021 at Dr B. R. Ambedkar National Institute of Technology, Jalandhar, Punjab, India.

Lately, neural networks (ANN) with broad limit and effortlessness were used in different mechanical and design fields. Thus ANN was used for predicting the thermo physical characteristics of nano-liquids by Mohanraj et al. (2012). Studies conducted on nano-fluids have shown that the thermal conductivity ratio (k_{nf}/k_{bf}) is effected by factors: concentration, temperature, size, nano-particle thermal conductivity, base fluid thermal conductivity, pH, shape factor and also the preparation technique of nano-fluid. Mathematically, it can be given by:

$$\frac{k_{nf}}{k_{bf}} = F\left(\text{Ø}, T, k_{bf}, k_p, D, S, \text{pH}\right) \tag{1}$$

Most of the models use only two characteristics of nano-fluids i.e., concentration of nano-particles and temperature of nano-fluid. Only few models have included particle size and thermal conductivity of base fluid. However, no equation or group of equations could be found in the literature which takes into account all the parameters affecting thermal conductivity, resulting in the deviation from the experimental results. This study aims to develop a model based on concentration, temperature, diameter, thermal conductivity of base fluid and nano-particles in bulk with minimum deviations from the true values. The main aim of this study is to provide a general approach for calculating the thermal conductivity ratio of metallic oxides based nano-fluids using ANN and power-law regression model. This study further aims to further evaluate the contribution percentage of each factor by ANOVA.

2. MODELLING METHODOLOGY

Thermal conductivity ratio being a nonlinear function of input factors, a power model is assumed, to take non linearity into account.

$$\frac{k_{nf}}{k_{bf}} = a \times \text{Ø}^b \times T^c \times k_p^d \times k_{bf}^e \times D^f \tag{2}$$

where k_p and k_{bf} are thermal conductivity of nano-particle, and base fluid in W/(m·K), Ø concentration (% volume), T is temperature in Kelvin, D is nano-particle diameter in nano-metres. The model parameters a, b, c, d, e, and f in Eq. (2) were estimated using least square method. In Eq. (3), C is the coefficient matrix

$$C = \left[A^T \quad A\right]^{-1}\left[A^T\right]\left[B\right] \tag{3}$$

Artificial neural is a kind of intelligence that has a capacity to learn without being expressly customized. It utilizes the presented information and draws inductions from the presented data. The general architecture of an ANN is shown in Fig. 1.

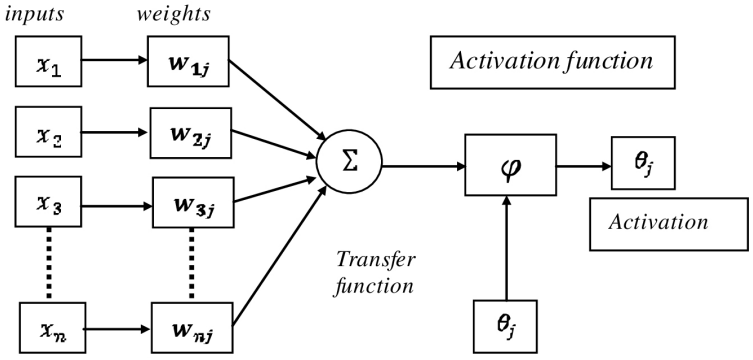

Fig. 1. Weighted synapses of ANN

The nature of ANN is exceptionally subject to the appropriate choice of information boundaries. The feed-back multilayer was applied to reproduce the output i.e. thermal conductivity. Multilayer perceptron neural network has various layers that include counterfeit neurons associated with the neighbours in the

network. Every unit has the capacity of getting, figuring, and sending information. In the initial phase of ANN, the information is acquainted with the network along with the ideal yield. At first, the inputs are set haphazardly and the backpropogation algorithm is used for calculations, to accomplish an agreeable degree of accuracy. The back spread calculation is a learning strategy that changes loads in ANN by proliferating weight changes backward from the yield to enter neurons. At the point when the acceptable degree of execution is accomplished, the preparation stops. At this stage, the organization utilizes these loads to settle on choices. The neural network MATLAB tool kit was used for ANN for modeling. A few autonomous runs having diverse introductory arbitrary loads were performed to achieve desired results.

3. RESULTS AND DISCUSSION

The power regression model and ANN network were developed to predict the thermal conductivity ratio of metallic oxide of nano-fluids. The data for the modelling was adopted from Chandrasekar et al. (2012), Kumar et al. (2018), Lee (2008), Lee et al. (2015), Putra et al. (2003), Sundar (2014), Wang et al. (2005), Yiamsawasd et al. (2012). ANN network was trained on a sample of 214 datasets, with each set containing 5 input parameters and one output. This procedure was carried out using ANN MATLAB toolbox using 150 data points for training and 32 each for testing and validation, thereby creating a neural network capable of predicting outputs. During the training phase ANN predicted the output values for each of these 214 sets of data inputs based on what the network had learned in the training phase. Further, the power-law model parameters were determined using the experimental data. The coefficients were calculated by adopting the same data used in the ANN training phase. The final regression equation is given as:

$$\frac{k_{nf}}{k_{bf}} = 03135 \times \text{Ø}^{00474} \times T^{02262} \times k_p^{00393} \times k_{bf}^{00815} \times D^{-00408} \tag{4}$$

Eq. (4) predicted the outputs by back testing the same inputs. The results of ANN and power law model were compared with the experimental data as shown in Fig. 2. MSE, MAE, MAPE, MAD were calculated

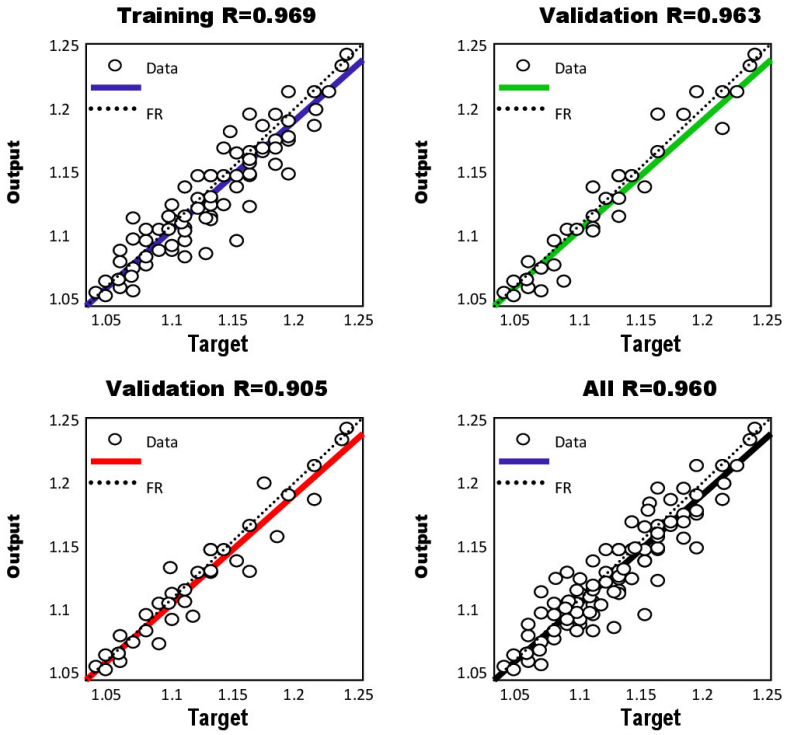

Fig. 2. Correlation coefficient for ANN model

as deviations from experimental values. Fig. 3 shows 21 randomly selected outputs as predicted by ANN. In order to check the validity of both ANN and regression models, the models were used to predict outputs from a sample of 17 data sets of inputs which were not used in the training phase, these data sets were specifically kept for predicting purposes. The performance of the current models was compared with statistical performance parameters of existing models in literature. A comparison between experimental and model values is depicted in Fig. 3. This study was carried out on a significance level of 95%. The contribution of concentration (% volume), temperature, size, k (base fluid) and k (metal) factors to thermal conductivity ratio was found to be 77.10%, 10.26%, 10.05%, 0.00% and 1.51% respectively. The single most dominant factor affecting thermal conductivity ratio is concentration (%volume). At the same time thermal conductivity of base fluid is found to have no bearing on overall results.

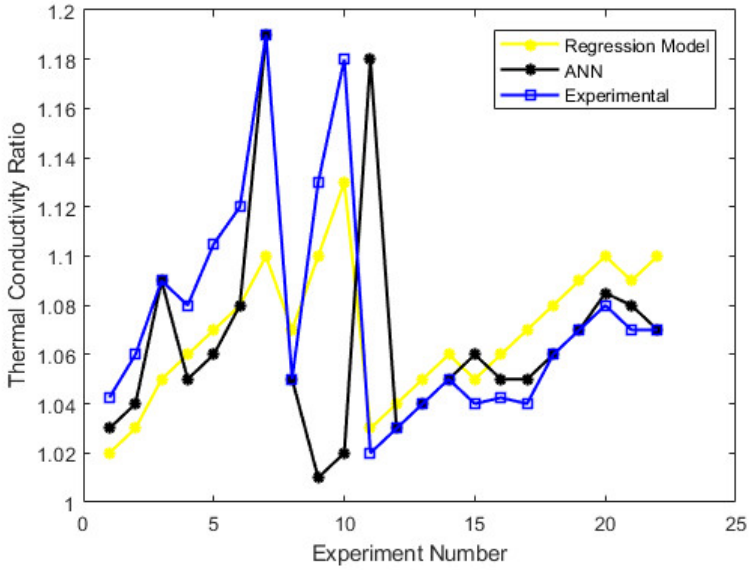

Fig. 3. Experimental vs. predicted values of thermal conductivity ratio

4. CONCLUSION

ANN and power-law were used to predict the thermal conductivity ratio of metallic oxide. Nano–fluids with reasonable degrees of accuracy as suggested by the statistical parameter MAPE being as low as 0.9% for ANN and 2.1% for the power-law model were found during the training phase and MAD being 0.010365 and 0.0239 respectively. During the testing phase, the deviations increased considerably with MAPE being 3.45% for ANN and 4.01% for the regression model and MAD being 0.028828 and 0.02391 respectively. At the same time, TS (tracking signal) during testing was found to be 0.1045 for ANN and 0.033411 for the regression model which suggests a negative bias implying the predicted values are lower than experimental values. During the testing phase, the TS in case of ANN is 2.83 which makes the signal significant and implies a larger negative bias. The predictions in general are lower than experimental values. In other cases, as $TS = 5.75$ (> 3.75). This suggests persistent underprediction which makes the model unreliable to an extent. At the same time, MAE during both training and testing for ANN (7%, 9%) and the power-law model (15%, 19%) is quite large. This becomes quite considerable because the thermal conductivity ratio rarely exceeds 30% so a maximum error of 19% cannot be ignored. The performance characteristics were also compared with other studies, which revealed an interesting observation. The present models performed as well as other models and even better on some parameters like MAD. This is important because the present models are applicable to a wider range of nano-fluids, whereas existing models were limited to at most two types of nano-particles dispersed in a single base fluid. Finally, nano-particle concentration was found to have the largest influence on the thermal conductivity ratio.

REFERENCES

Chandrasekar M., Suresh S., Senthilkumar T., 2012. Mechanisms proposed through experimental investigations on thermo-physical properties and forced convective heat transfer characteristics of various nano-fluids – A review. *Renewable Sustainable Energy Rev.*, 16, 3917–3938. DOI: 10.1016/j.rser.2012.03.013.

Choi S., Eastman J.A., 1995. Enhancing thermal conductivity of fluids with nano-particles. *1995 International mechanical engineering congress and exhibition*. San Francisco, CA, United States, 12–17 November 1995, 99–105.

Koo J., Clement K., 2004. A new thermal conductivity model for nano-fluids. *J. Nanopart. Res.*, 6, 577–588. DOI: 10.1007/s11051-004-3170-5.

Kumar N., Sonawane S.S., Sonawani S.H., 2018. Experimental study of thermal conductivity, heat transfer and friction factorof Al_2O_3 based nano-fluids. *Int. Commun. Heat Mass Transfer*, 90, 1–10. DOI: 10.1016/j.icheatmass transfer.2017.10.001.

Lee J.-H., Hwang K.S., Jang S.P., Lee B.H., Kim J.H., Choi S.U.S., Choi C.J., 2008. Effective viscosities and thermal conductivities of aqueous nano-fluids containing low volume concentration (percentage volume) of Al_2O_3 nano-particles. *Int. J. Heat Mass Transfer*, 51, 2651–2656. DOI: 10.1016/j.ijheatmasstransfer.2007.10.026.

Lee J., Lee H., Baik Y.-J., Koo J., 2015. Quantitative analyses of factors affecting thermal conductivity of nano fluids using an improves transient hot-wire method apparatus. *Int. J. Heat Mass Transfer*, 89, 116–123. DOI: 10.1016/j.ijheatmasstransfer.2015.05.064.

Mohanraj M., Jayaraj S., Muraleedharan C., 2012. Applications of artificial neural networks for refrigeration, air-conditioning and heat pump systems – A review. *Renewable Sustainable Energy Rev.*, 16, 1340–1358. DOI: 10.1016/j.rser.2011.10.015.

Putra N., Roetzel W., Das S.K., 2003. Natural convection of nano-fluids. *Heat Mass Transfer*, 39, 775–784. DOI: 10.1007/s00231-002-0382-z.

Sayes C.M., Liang F., Hudson J.L., Mendez J., Guo W., Beach J.M., Moore V.C., Doyle C.D., West J.L., Billups W.E., Ausman K.D., Colvin V.L., 2006. Functionalization density dependence of single-walled carbon nano-tubes cytotoxicity in vitro. *Toxicol. Lett.*, 161, 135–142. DOI: 10.1016/j.toxlet.2005.08.011.

Sundar L.S., 2014. Thermal conductivity and viscosity of stabilized ethylene glycol and water mixture Al_2O_3 nanofluids for heat transfer applications: An experimental study. *Int. Commun. Heat Mass Transfer*, 56, 86–95. DOI: 10.1016/j.icheatmasstransfer.2014.06.009.

Wang X.-Q., Mujumdar A.S., Yap C., 2006. Thermal characteristics of tree-shaped microchannel nets for cooling of a rectangular heat sink. *Int. J. Therm. Sci.*, 45, 1103–1112. DOI: 10.1016/j.ijthermalsci.2006.01.010.

Wang X., Xu X., Choi S.U.S., 2005. Thermal conductivity of nanoparticles – fluid mixture. *J. Thermophys. Heat Transfer*, 13, 474–480. DOI: 10.2514/2.6486.

Yiamsawasd T., Dalkilic A.S., Wongwises S., 2012. Measurement of the thermal conductivity of titania and alumina nano-fluids. *Thermochim. Acta*, 545, 48–56. DOI: 10.1016/j.tca.2012.06.026.

Received 16 February 2022
Received in revised form 22March 2022
Accepted 6 April 2022