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Thermal Conductivity of Cu-Zn Hybrid Newtonian Nanofluids: Experimental Data and Modeling using Neural Network

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Abstract

With the emerging trends in nanotechnology and development of biodegradable cutting fluids, the need for conventional mineral based oils have reduced. In this contest the, need for increasing the thermal conductivity of vegetable oils has raised the need to develop Hybrid nanoparticles. In the current work Cu-Zn hybrid nanoparticles with combinations (0:100, 75:25, 50:50, 25:75, and 100:0) were used to prepare nanofluids by dispersing them into vegetable oils. Thermal conductivity of the base fluid and nanofluids with various nanoparticle concentrations at different temperatures were measured experimentally. The results showed increase in thermal conductivity of nanofluids with increase in hybrid nanoparticle loading and with rise in temperature. Neural network models and data fit were proposed to represent the thermal conductivity as a function of the temperature, nanoparticle concentration, diameter of nanoparticle and the thermal conductivity of the nanoparticles and base fluids. The experimental data along with the input were tested for various types of models using existing theoretical models, Data fit software and ANN using Matlab nntool. In ANN regression models were also tested for various performance functions. These models were in good agreement with the experimental data. Regression model with data fit software predicted the outputs with 0.8889% confident levels and with ANN the predicted output has 0.999% confident levels. MSE performance function outperformed all models in training the data and with overall outputs.

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Keywords: Hybrid Nanoparticles; Vegetable oil; Newtonian fluid; Neural Network; Data Fit;

1. Introduction

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The concept of “Nanofluids” was introduced by Choi [1], describing it as a solid liquid composite obtained by suspending nanoparticles into traditional heat transport fluids to improve their heat transfer capabilities. Masuda et al. [2] and Lee et al. [3] found considerable increase in thermal conductivity when suspending Al_2O_3 and CuO nanoparticle in water and ethylene glycol. Furthermore, anomalous increase in thermal conductivity was found with dispersion of copper nanoparticles in ethylene glycol and oil by Eastman et al. [4] and Choi et al. [5]. A wide experimental investigation on increasing thermal conductivity of nanofluids had been carried out in the last ten years, including oxides, metallic, SCNT, MCNT and different basefluids.

The measurements show inconsistency due to difference in production of nanofluids, nanofluids characterisation and thermal conductivity measurement techniques. However a firm relationship is established from the experimental results between nanofluid thermal conductivity and following parameters: Nanoparticle volume fraction, size, shape, surfactants and additives [6 – 10]. With many parameters affecting thermal conductivity of nanofluids the traditional models available are not able to account all the differences. The classical Maxwell [11] equation is used for predicting thermal conductivity for micro-sized suspension, Bruggemans [12] equation is used for high volume fraction, whereas Hamilton [13] and crosser include effect of shape of nanoparticle. The Maxwell equation was modified by Yu and Choi [14] to include the effect of liquid layering and a model with sum of Maxwell and terms accounting Brownian motion was presented by Koo and Kleinsteuer [15]. All the equations available in literature are in efficient to account all the parameters affecting the thermal conductivity of nanofluids.

For solving complex problems in different areas in recent years, A Artificial Neural Network technique has been applied with substantial reduction in computational time. ANN technique has been used for analysis of refrigeration systems, fracture prediction in steel, thermal conductivity estimations of various materials and fluids, for finding convective heat transfer coefficients, dairy products and foodstuffs [16 – 20].

In this paper, the thermal conductivity of Cu-Zn hybrid nanofluids prepared with combinations (0:100, 75:25, 50:50, 25:75, and 100:0)/ vegetable oil is studied. The combined effect of all the combinations of Cu-Zn, the size factor, diameter of the particles, thermal conductivity, Volume fraction and basefluids are studied. An ANN model and data fit model is developed to predict the thermal conductivity of Cu-Zn hybrid nanofluid. Both the models will be compared with the theoretical models like the Hamilton and the Yu-Choi and the model with better results will be proposed.

2. Experimental data

Cu-Zn hybrid nanoparticles with combinations (0:100, 75:25, 50:50, 25:75, and 100:0) were used to prepare nanofluids by dispersing them into vegetable oils. The hybrid nanoparticle and Surfactant (SDS) were added in the required proportions in the basefluid and ultra-sonicated for 2 hrs. The nanofluids prepared after ultrasonication was brought to room temperature and the KS-1 sensor of the KD2 Pro (Decagon Device, Inc., USA) which is used for measuring the thermal conductivity of fluids was inserted and kept stationary for measurement, as even small vibrations can cause error in the measurement. The temperature rise in the nanofluid is measured and once the required temperature is reached, a maximum of 10 measurements were recorded for each volume concentrations and temperatures to make sure that the sample was at thermal equilibrium. Before starting the measurement with nanofluids, the instrument was calibrated with glycerol and found as 0.280 W/m K, which is very near to the literature value (0.285 W/m K). The thermal conductivity of nanofluids with 0%, 0.1%, 0.2%, 0.3%, 0.4% and 0.5% volume concentrations was measured in the temperatures ranging from 30 °C to 60 °C.

3. Modelling Technique

Two types of models were used to represent the experimental data for the thermal conductivity of the nanofluids: the data fit model and artificial neural networks (ANN). The output data was obtained from experimental investigation. Datafit is a science and engineering tool that simplifies the tasks of plotting, regression analysis and statistical analysis. Datafit software allows user to enter data in the form of the independent variables and the dependent variables. Independent variables (X1, X2,….Xn) are the input values (Y) on which the output variables are dependent. After entering the data the regression is solved for non-linear with the pre-defined models available. Regression analysis is carried out for the available models and the model with better R^2 is selected here.

Table 1: Inputs ranges for training the Artificial Neural Network model

Parameters	Ranges
Volume Fraction (%)	0.1 - 0.5
Temperature (K)	303 - 333
Diameter of Nanoparticles (nm)	19 - 60
Ratio of Thermal Conductivity (Particle/Basefluid)	716.04 – 2469.13

The proposed ANN model was designed by software developed using the MATLAB Neural Network Toolbox. The input ranges for training the neural network are as given Table 1. The experimental data were grouped into training data and testing data. The interconnected group of each artificial neuron receives one or more data and sums them to produce an output. These sums are weights corresponding to the parameters of the model; this is passed through non-linear function known as activation function and in turn processed using connectionist approach to computation.

Neurons are organised into inputs, output and hidden layers which provide the predictions of the model for the variables of interest as shown in Fig. 1. In this study, 3 performance functions were considered in modelling ANN. The MSE function measures the average of the squares of the errors, SSE function measures performance according to sum of squared errors and MSEREG measures performance as the weight sum of two factors: the mean squared error and the mean squared weight and bias values. Single-layer architecture was chosen for ANN: input neurons are connected to a layer of N hidden neurons, which are connected to the output neurons. The number of input neurons for training the network were tested from 4 to 12 and found that with 10 neurons resulted better outcomes. The activation function is sigmoid for hidden neurons, and linear for output neurons. Data are first scaled so that each component of the input and output vectors has zero mean and unitary variance across the dataset, as to give to the inputs the same importance in the fitting procedure, independently from the magnitude of their values.

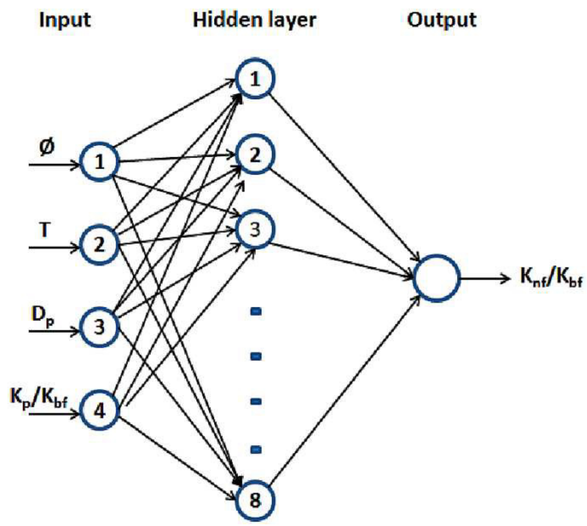


Fig. 1. ANN architecture selected as the predicting model for Effective Thermal conductivity

4. Results

The regression model was developed for the experimental data using datafit software and ANN using matlab nntool. Using the data fit software the regression model is tested for all the available models and the model which better agreement with the observed data is selected. Here the Fig. 2 shows the fit of the predicted model with the experimental data with R^2 value of 88.89. The model equation (1) and the co-efficient are given below.

$$Y = a * X1 + b * X2 + c * X3 + d * X4 + e \qquad R^2=0.8889 \tag{1}$$

a = 0.90764, b = 8.332644, c = -3.4252, d= -1.2743, e = -2.3317
X1 = Volume Fraction (%)
X2 = Temperature (K)
X3 = Diameter of Nanoparticles
X4 = ratio of Thermal conductivity of particle to Thermal conductivity of Basefluid
Y = Effective thermal conductivity= Thermal conductivity of nanofluid/Thermal conductivity of basefluid

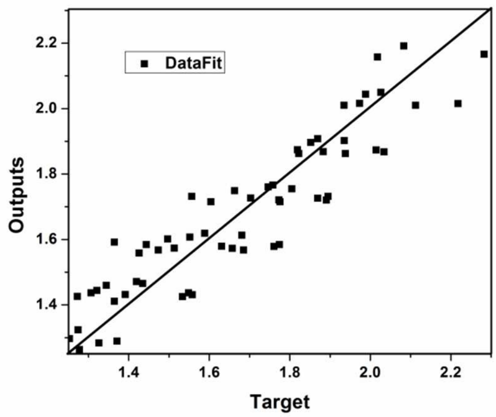
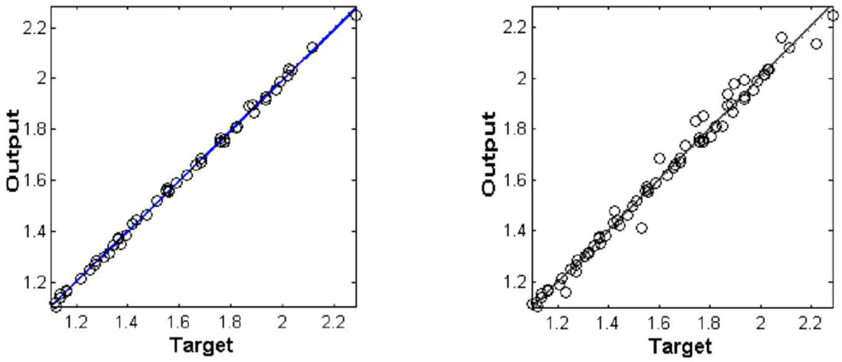


Fig. 2. Data Fit regression: Relationship between predicted results and experimental results

The relationship between measured (experimental) results and predicted results by using the ANN prediction model is shown in Figs. 3, 4 and 5. Figs. 3, 4 and 5 shows the regression analysis of the ANN model for the effective thermal conductivity values as shown in Table 2. Thus, the value of R^2 in the testing indicates that the network obtained explains at least 0.99% of the observed data. This situation supports the reliability of the proposed ANN model. The intermediate values were also obtained for thermal conductivity and were quite consistent with predicted and measured values.

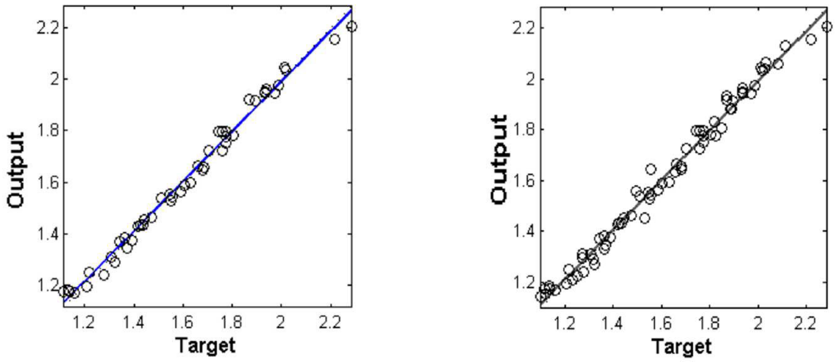
Table 2: Regression values of data with various Performance Functions

Performance Function	R^2 for Training	R^2 for all
MSE	0.99928	0.99379
MSEREG	0.99527	0.99378
SSE	0.996	0.98437



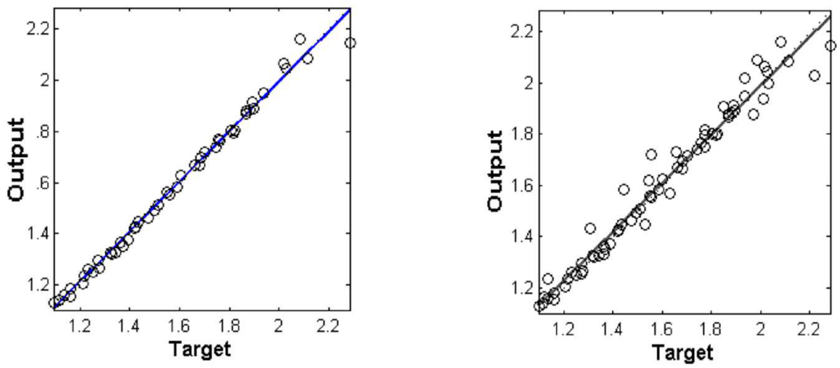
(a) (b)

Fig. 3. MSE Performance function (a) Training Regression (b) All Regression



(a) (b)

Fig. 4. MSEREG Performance function (a) Training Regression (b) All Regression



(a) (b)

Fig. 5. SSE Performance function (a) Training Regression (b) All Regression

The ANN model is compared with the data fit model and is as shown in Fig. 6. The ANN models shows good agreement with the experimental data and MSE in this case outperformed all the models in training the network and predicted the experimental data. The proposed ANN is compared with the standard theoretical model of Hamilton [13] and Yu-Choi [14].

$$\frac{k_{nf}}{k_{bf}} = \frac{\alpha + (n-1) - (n-1)(1-\alpha)\varphi}{\alpha + (n-1) + (1-\alpha)\varphi} \tag{2}$$

$$\frac{k_{nf}}{k_{bf}} = \frac{k_{pe} + 2k_{bf} + 2(k_{pe} - k_{bf})(1+\beta)^3 \varphi}{k_{pe} + 2_{bf} + (k_{pe} - k_{bf})(1+\beta)^3 \varphi} \tag{3}$$

k_{nf} = Thermal conductivity of Nanofluid, k_{bf} = Thermal conductivity of basefluid, k_{pe} = Thermal conductivity of equivalent nanoparticle when liquid layer is considered around nanoparticle, α = ratio of k_{np}/k_{bf}, $\beta = t/r_p$, t = nanolayer thickness, r_p = radius of particle, $\emptyset$ = volume fraction of particles.

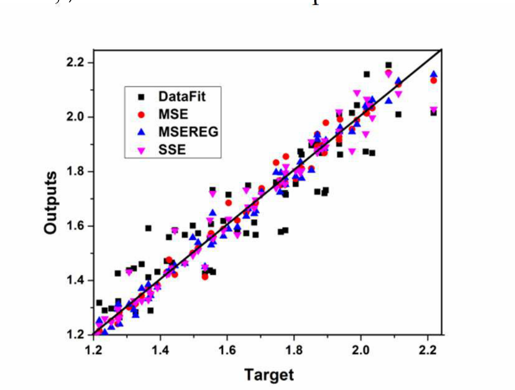
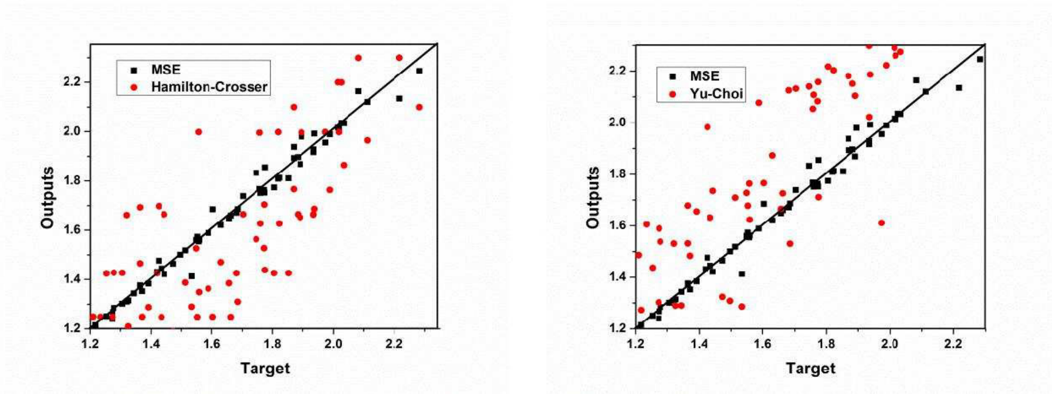


Fig. 6. Predicted outputs of Data fit, MSE, MSEREG and SSE Vs Target

Fig. 7 (a) and (b) shows the predicted output of the theoretical models, when compared with proposed ANN. The theoretical models either over predicted or under predicted the experimental data As a result of the study, it can be said that the well-trained ANN model can be used to optimize the effective thermal conductivity of hybrid Cu-Zn for all combinations (0:100, 75:25, 50:50, 25:75, and 100:0), at various temperatures, volume fractions, diameter of particles, thermal conductivity of nanoparticles and thermal conductivity of basefluids.



(a) (b)

Fig. 7. Comparison of predicted outputs (a) MSE Vs Hamilton-Crosser, (b) MSE Vs Yu-Choi

5. Conclusion

A relationship between the predicted values and experimental values were established by developing the regression models for the experimental data. The regression models were established using data fit software and

ANN using Matlab nntool box. Regression model with data fit software predicted the outputs with 0.8889% confident levels and with ANN the predicted output has 0.999% confident levels. The ANN regression model was tested for three performance function and the MSE performance trained the network better and the overall R^2 value was also better, when compared to other two performance functions. The output of this function is also compared with the theoretical models and showed better results. Thus MSE performance function is proposed for establishing the relationship between predicted and experimental data.

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