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ORIGINAL RESEARCH PAPER

Nanofluid Thermal Conductivity Prediction Model Based on Artificial Neural Network

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ABSTRACT: Heat transfer fluids have inherently low thermal conductivity that greatly limits the heat exchange efficiency. While the effectiveness of extending surfaces and redesigning heat exchange equipments to increase the heat transfer rate has reached a limit, many research activities have been carried out attempting to improve the thermal transport properties of the fluids by adding more thermally conductive solids into liquids. In this study, new model to predict nanofluid thermal conductivity based on Artificial Neural Network. A two-layer perceptron feedforward neural network and backpropagation Levenberg-Marquardt (BP-LM) training algorithm were used to predict the thermal conductivity of the nanofluid. To avoid the preprocess of network and investigate the final efficiency of it, 70% data are used for network training, while the remaining 30% data are used for network test and validation. Fe_2O_3 nanoparticles dispersed in waster/glycol liquid was used as working fluid in experiments. Volume fraction, temperature, nano particles and base fluid thermal conductivities are used as inputs to the network. The results show that ANN modeling is capable of predicting nanofluid thermal conductivity with good precision. The use of nanotechnology to enhance and improve the heat transfer fluid and the cost is exorbitant.It can play a major role in various industries, particularly industries that are involved in that heat.

KEYWORDS*: Nanofluid; Neural Network; Thermal Conductivity*

INTRODUCTION

Heat transfer plays an important role in numerous applications. For example, in vehicles, heat generated by the prime mover needs to be removed for proper operation. Similarly, electronic equipments dissipate heat, which requires a cooling system. Heating, ventilating, and air conditioning systems also include various heat transfer processes. Heat transfer is the key process in thermal power stations. In addition to these, many production processes include heat transfer in various forms; it might be the cooling of a machine tool, pasteurization of food, or the temperature adjustment for triggering a chemical process. In most of these applications, heat transfer is realized through some heat transfer devices; such as, heat exchangers, evaporators, condensers, and heat sinks. Increasing the heat transfer efficiency of these devices is desirable, because by increasing efficiency, the space occupied by the device can be minimized, which is important for applications with compactness requirements. Furthermore, in most of the heat transfer systems, the working fluid is circulated by a pump, and improvements in heat transfer efficiency can minimize the associated power consumption. There are several methods to improve the heat transfer efficiency. Some methods are utilizationof extended surfaces, application of vibration to the heat transfer surfaces, and usage of microchannels.

Heat transfer efficiency can also be improved by increasing the thermal conductivity of the working fluid. Commonly used heat transfer fluids such as water, ethylene glycol, and engine oil have relatively low thermal conductivities, when compared to the thermal conductivity of solids. High thermal conductivity of solids can be used to increase the thermal conductivity of a fluid by adding small solid particles to that fluid.

The feasibility of the usage of such suspensions of solid particles with sizes on the order of millimeters or micrometers was previously investigated by several researchers and significant drawbacks were observed.

These drawbacks are sedimentation of particles, clogging of channels and erosion in channel walls, which prevented the practical application of suspensions of solid particles in base fluids as advanced working fluids in heat transfer applications [1,2]. With the recent improvements in

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nanotechnology, the production of particles with sizes on the order of nanometers (nanoparticles) can be achieved with relative ease.

As a consequence, the idea of suspending these nanoparticles in a base liquid for improving thermal conductivity has been proposed recently [3,4]. Such suspension of nanoparticles in a base fluid is called a nanofluid. Due to their small size, nanoparticles fluidize a problem. It is even possible to use nanofluids in microchannels [5,6]. When it comes to the stability of the suspension, it was shown that sedimentation of particles can be prevented by utilizing proper dispersants.

Studies regarding the thermal conductivity of nanofluids showed that high enhancements of thermal conductivity can be achieved by using nanofluids. It is possible to obtain thermal conductivity enhancements larger than 20% at a particle volume fraction smaller than 5% [7]. Such enhancement values exceed the predictions of theoretical models developed for suspensions with larger particles. This is considered as an indication of the presence of additional thermal transport enhancement mechanisms of nanofluids. There are many experimental and theoretical studies in the literature regarding the thermal conductivity of nanofluids.

In thermal conductivity measurements of nanofluids, the transient hot-wire technique is the most commonly used easily inside the base fluid, and as a consequence, clogging of channels and erosion in channel walls are no longer method [8-12]. A modified transient hotwire method is required in the measurements, since nanofluids conduct electricity. The modification is made by insulating the wire. Some other methods such as steady-state parallel-plate technique, temperature oscillation technique, microhot strip method, and optical beam deflection technique have also been utilized by some researchers [13-15].

Due to lack of sophisticated theory to predict the effective thermal conductivity of nanofluid several researchers have proposed different correlations to predict the apparent thermal conductivity of two-phase mixture. The models proposed by Hamilton and Crosser (HC) [16], Wasp [17], Maxwell-Garnett [18], Bruggeman [19] and Wang et al. [20] to determine the effective thermal conductivity of nanofluid failed to predict it accurately. The experimental results show a much higher thermal conductivity of nanofluid than those predicted by these models. Yu and Choi [21] has proposed a renovated Maxwell model considering the liquid layer thickness, which is proved to be not realistic [22] and it fails to throw light on the temperature dependence of thermal conductivity. Kumar et al. [23] has proposed a model, where effective thermal conductivity is a function of both temperature and particle diameter.

Prasher et al. [24] have showed that the enhancement of effective thermal conductivity (keff) of nanofluid is mainly due to the localized Brownian movement of nanoparticles. They have also proposed a conduction-convection based model to find the keff of nanofluid. Patel et al. [25] has improved the model given in [23] by incorporating the effect of micro-convection due to particle movement. The effect of temperature is justified as Brownian motion increases with temperature, which causes additional convective effect. The above model is applicable for low concentration of solid volume fraction.

Also the model takes into account the effect of particle size through an increase in specific surface are of nanoparticles [26].

There involves an empirical constant ‘c’, to link the temperature dependence of effective thermal conductivity to the Brownian motion of the particles. This can be found by comparing the calculated value with experimental data, which comes in the order of 10^4. This empirical constant ‘c’ is adjustable and can be thought as a function of particle properties as well as size [25]. Recently, many theoretical studies were made and several mechanisms were proposed in order to explain the anomalous thermal conductivity enhancement obtained with nanofluids.

Most of these models suffer from considering all parameters affecting thermal conductivity.

In this study, we will try to prepare a new model based on a two-layer perceptron feedforward neural network and backpropagation Levenberg-Marquardt (BP-LM) training algorithm for Fe_2O_3- ethylene glycol and deionized water basednanofluid. To avoid the preprocess of network and investigate the final efficiency of it, 70% data are used for network training, while the remaining 30% data are used for network test and validation.In our model, volume fraction and temperature are used as input and thermal conductivity coefficient is used as output(target) parameter.

Nanofluid preparation method

Two-step method was used to prepare nanofluids. Commercial spherical-shaped Fe_2O_3 nanoparticles with diameter of 20 nm were selected as additives, and the mixture of ethylene glycol and deionized water with volume ratio of 45:55 was selected as a base fluid. In a typical procedure, adequate surfactant (sodium oleate) was dissolved into the mixture at first, and then the nanoparticles were gradually added into the base mixture fluid with violent stirring. Afterward, the suspensions were stirred using disperse mill (7,200 r/min) for 40 min. Nanofluids with different volume fractions (0.1-2%) were obtained by intensive ultrasonication for 45 min.

Measurement of Thermal Properties

The size of nanoparticles was observed by means of transmission electron microscope (TEM) (JEOL, JEM-2100F). The sample for TEM observation was prepared in a typical procedure. First, the nanoparticles were dispersed into the ethanol solution. Then, the mixture was ultrasonicated for 10 min to obtain stabilized suspension. Finally, the upper layer of the suspension was carefully selected to drop on a copper mesh.

The thermal conductivity of the nanofluids (knf) as a function of volume fraction of the nanofluids was measured using a transient short hot-wire method. Ethylene glycol was used to calibrate measurement apparatus. The thermal conductivity of ethylene glycol was measured threes times under a temperature at an interval of 5 min.

The instrument was capable of measuring thermal conductivity in the range of 0.02 to 2.00 W/(mK) . The uncertainty of measurements is estimated to be within ±1.0%.

ANN Model:

The ANNs have the potential of enhancing our knowledge of prediction issues. Artificial neural networks can be adopted in a variety of applications like prediction and optimization and prediction.

Performing non-linear, multidimensional interpolations between input and output parameters makes it possible to identify non-linear relationships that exist between input and output.

Generally, neural networks consist of neuron layers which perform calculations. A neuron layer includes the combination of the weights, the multiplication and summing operation, the bias b, the transfer function f, a net input vector ξ and an output vector a. The inputs vector is not involved in a layer. Each neuron in a particular layer is connected with all neurons in the next layer. The connection between neurons is characterized by the weight coefficients. The weight coefficient reflects the degree of importance of the given connection in the neural network. The first step to develop the neural network is to decide which training algorithm to use. The back-propagation network which is a powerful multilayer, feed-forward neural networks was employed in the present study because of allowing to network to adopt. This generalization property of back-propagation network makes them enable to train a network on a typical set of input/output pairs and obtain good results without training the network on all possible input/output pairs. Feed-forward networks often have one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple layers of neurons with nonlineartransfer functions allow the network to learn nonlinear and linear relationships between input and output vectors.

In this paper, experimental results are used to train artificial neural network (ANN) prediction model. The resulted data divided into training, validation and test subsets.

φ, k_{bf}, k_{nf}, T, d_{pnp} were used as input parameters to predict exergetic efficiency. One fourth of the data for the validation set, one fourth in the test set and one half of the training set were taken. To achieve acceptable predictions, several neural network architectures were tried, and a three-layer network, with tan-sigmoid transfer function in the hidden layers and a linear transfer function in the output layer was found to give better results than other architectures. Optimization procedure was used to determine the optimum number of neurons in the hidden layer. After normalizing data, the optimization process showed that network with 20 neuron numbers exhibits the best performance presenting acceptable R^2 values in the range of 1 to 30 neurons. Levenberg-Marquardt function of training was employed to combine the speed advantage of the Gauss–Newton algorithm and the stability of the steepest descent method. To avoid running into local optima instead of global optima, the network weights and biases reinitialized and the network retrained several times to provide the best solution. To reinitialize, the variable learning rate technique was employed to avoid local minima which allow the learning rate to change during the training process. An adaptive learning rate tries to keep the learning step size as large as possible whilst keeping learning stable. An adaptive learning rate needs some modifications in the training process. First, the initial network output and error are calculated. At each epoch new weights and biases are calculated using the current learning rate. New outputs and errors are then calculated.

RESULTS AND DISCUSSION

The XRD pattern in Figure 1 shows peaks at 30.272, 35.684, 43.34, 53.852, 57.4, and 63.011, which are corresponding to the diffraction peaks of Fe_2O_3 (JCPDS 25-1402), indicating that nanoparticles are single phase with tetragonal structure.

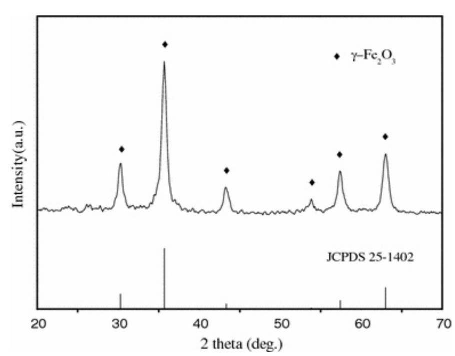


Fig. 1. XRD pattern of Fe_2O_3 nanoparticles

Figure 2 shows the TEM micrograph of Fe_2O_3 nanoparticles. The average size of nanoparticles is estimated to be about 20 nm.

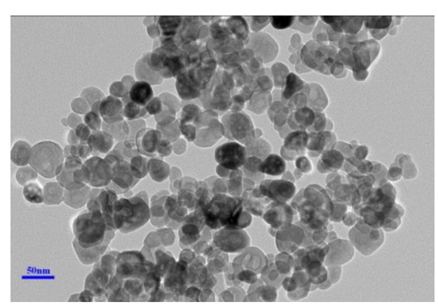


Fig. 2. TEM micrograph of the Fe_2O_3 nanoparticles

Figure 3 shows the particle size distributions in the magnetic nanofluids with and without surfactant, respectively.

From Figure 3, we can see that the average size is about 1,200 nm without surfactant (Figure 3a) and about 150 nm with surfactant (Figure 3b), respectively. When sodium oleate, a kind of organic salt, was dissolved into solution, the ionization of $C_{18}H_{33}O_2^-$ and Na^+ happens. One end of $C_{18}H_{33}O_2^-$ plunges into the solution, and another end was absorbed on the surface of nanoparticles.

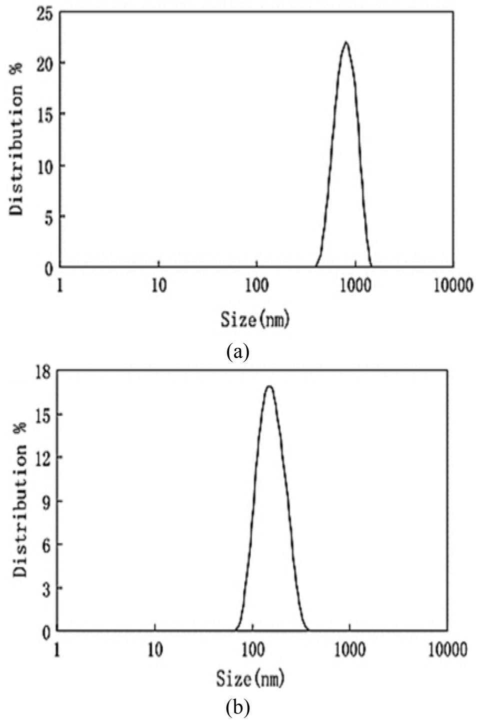


Fig. 3. Particle size distribution in the nanofluids a without dispersant b with dispersant

With the addition of dispersant in the base fluids, the suspensions can keep stability for a long time, while sedimentation happened immediately in the suspensions without surfactant. Sodium oleate is effective for improving the stability of Fe_2O_3 nanofluids. In the case of thermal conductivity in Table 1, the results show that increasing nanofluid concentration increases fluid thermal conductivity. In order to investigate the effect of solid volume fraction of the nanoparticles thoroughly, the percentage of enhancement of the relative thermal conductivity of the nanofluid at different solid concentrations and at the same temperatures with respect to the solid volume fraction of 0.1% has been presented in Table. 1. As can be seen, with the increase of solid concentration, the relative thermal conductivity with respect to the thermal conductivity of the nanofluid, with solid concentration of 0.1%, increases. This increase in the solid concentration of 2% in the temperatures of 20 and 50 °C is 14.24% and 26.71%, respectively. Furthermore, at the temperature of 50 °C, the percentage of enhancement increases from 5.22% in solid concentrations of 0.4%, to 26.71% in solid concentration of 2%.

Table 1
Effect of nanofluid concentration and temperature on thermal conductivity.

T(^{0}C) **φ (%)**	**20**	**25**	**30**	**35**	**40**	**45**	**50**
0.004	4.48	5.37	6.43	6.94	5.05	6.23	5.22
0.006	5.70	7.30	8.33	8.36	5.97	7.60	7.91
0.008	8.14	8.99	10.47	11.67	9.41	10.10	11.49
0.01	10.09	11.16	13.08	13.33	11.47	14.21	15.07
0.015	12.05	14.29	16.17	17.11	14.92	18.08	20.44

Figure 3 Particle size distribution in the nanofluids (a) without dispersant (b) with dispersant.

Figure 4 gives a comparison study of the predictions of this neural network with those of the experimental results for thermal conductivity. Although only a few sets in the input patterns were considered, it can be concluded that an ANN is able to predict the exergetic efficiency. This is mainly attributed to the ability of neural networks to find nonlinear functional patterns effectively.

To perform some analysis of the network response, the entire data set was put through the network (training, validation and test) and a linear regression between the network outputs and the corresponding targets were performed. The network outputs are plotted versus the targets as square in the figure 4.

The best linear fit is indicated by a dashed line. The perfect fit (output equal to the targets) is represented by the solid line. The output seemed to follow the target reasonably well and scattered in a straight line with an acceptable coefficient of determination (almost 0.95). As the figures show, it can be concluded that ANN model is able to predict the exergetic efficiency well which is due to the network capability to capture the nonlinear functional patterns effectively.

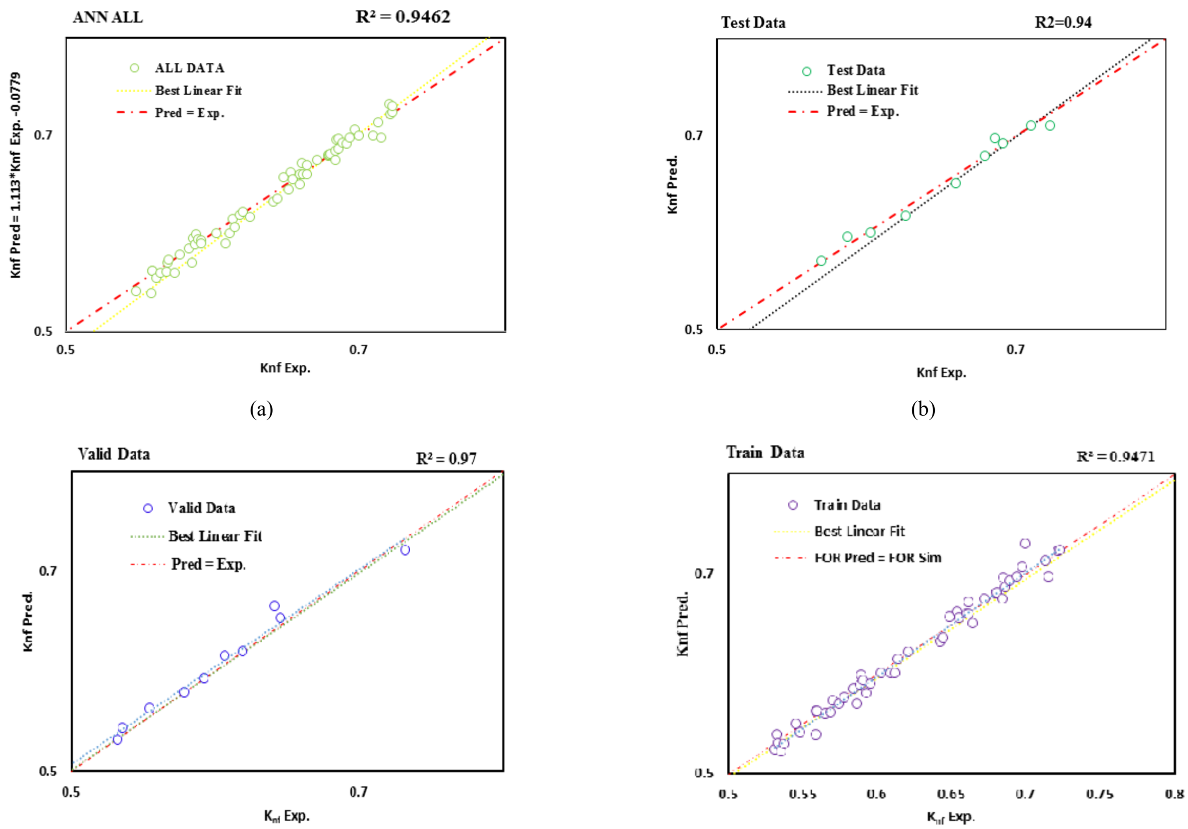
Figure 5 shows the residual plot. In a valid regression analysis, the residuals should be randomly distributed around zero, i.e. the scatter plot of the residuals should be disordered with no trend.

Conclusion

Nanofluids, i.e., well-dispersed (metallic) nanoparticles at low- volume fractions in liquids, may enhance the mixture's thermal conductivity, k_{nf}, over the base-fluid values.

Thus, they are potentially useful for advanced cooling of micro-systems. Focusing mainly on dilute suspensions of well-dispersed spherical nanoparticles in water and ethylene glycol, experimental observations was used to prepare an artificial neural network to predict nanofluid thermal conductivity.

The results show that ANN is capable of predicting nanofluid thermal conductivity with a high precision.



(a) (b)

(c) (d)

Fig.4 Comparing the Networks result with Experimental data

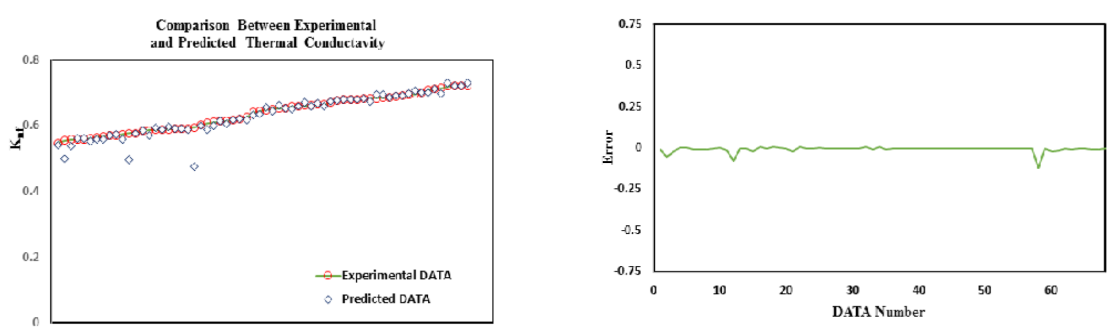


Fig.5 Residual Plots

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