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Prediction of Heat Transfer Characteristics of Nanofluids in Heat Pipes Based on Artificial Neural Network Model

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The objective of this study is to predict the heat transfer characteristics of nanofluids in heat pipes based on artificial neural network (ANN) theory. A visualized experiment for analyzing the heat transfer performance of heat pipes with nanofluid was constructed, and the effects of heating capacity, inclination angle, pipe diameter, nanofluid concentration and particle suspendability on the heat transfer characteristic of heat pipe were analysed. The heat transfer characteristics of nanofluids in heat pipes were contrasted with that of the heat pipe containing the base fluid only. This ANN model had been proven to be desirable in accuracy for predicting the heat transfer characteristics of heat pipe using nanofluid by comparing ANN model results with experimental results at the same operating conditions. This work provides an accurate modeling approach based on ANN for the research of heat transfer characteristics of nanofluids in heat pipes and solving phase change heat transfer problems related with complicated condition.

1. Introduction

A nanofluid is a fluid containing nanometre-sized particles. To prepare such a fluid, nanoparticles are added to a conventional heat exchange medium and subjected to some necessary treatments (Saleh et al., 2013). Compared with conventional heat transfer media and suspensions, nanofluids could significantly reduce the heat resistance and improve the heat transfer efficiency, due to high specific heat and strong heat exchange capacity (Yousefi et al., 2013). The extremely small size of nanoparticles helps to maintain the stability and uniformity of nanofluids, which reduces the wear on heat pipe walls and suppresses the chance of pipe blockage. Nanofluids have novel properties that make them potentially useful in many applications in heat transfer. It could be directly applied to heat pipe in precision equipment (Ghanbarpour et al., 2015).

Artificial neural network (ANN) is computing systems vaguely inspired the biological neural networks that constitute animal brains. It is a typical framework analysis technology for many different machine learning algorithms to work together and process complex data inputs. ANN provides a desirable solution to problems with multiple influencing factors. Before the analysis, the ANN needs to be trained with a large amount of data, so that the network establishes a stable mapping relationship between the input data and the output data. The ANN-based prediction has become increasingly popular with the continuous development of computer and programming technologies. Currently, much attention is paid to the application of the ANN in engineering, such as the ANN-based heat exchange model for heat pipe. The ANN-based prediction model can quantify the heat exchange rate and heating power of the heat pipe (Kavusi and Toghraie, 2017)

In this work, a visualized experiment for analyzing the heat transfer performance of heat pipes with nanofluid was constructed, and this ANN model was established to predict the heat transfer characteristics of heat pipe using nanofluid at the same operating conditions (Uddin and Hoque, 2018).

2. Experiment

A visualized experiment for analyzing the heat transfer performance of heat pipes with nanofluid was constructed. And the effects of inclination angle and inner diameter of the heat pipe, the mix proportion of the nanofluid, and the type of the nanofluid on the heat transfer performance of heat pipes were analysed. The heat pipes were all made of glass in this experiment. The inner diameters of these pipes were ∅3×0.85 mm and ∅2×0.85 mm. All the other dimensions of the pipes are the same. As shown in Figure 1, the experimental device consists of two elbows and four straight heat pipes. The total length of all heat pipes is 265 mm, and the spacing between different heat pipes is 20 mm.

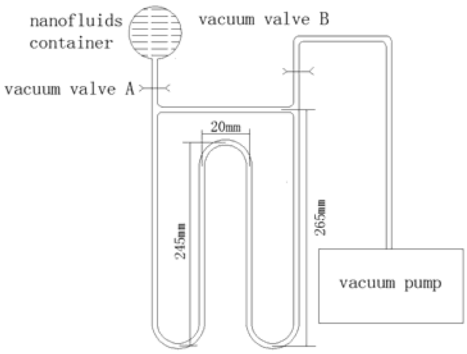

Figure 1: Experimental device

The tested nanofluids were prepared from two types nanoparticles: TiO_2 particles (10nm) and CuO particles (40nm). The TiO_2 particles were mixed with distilled water into solutions with volume concentrations C of 0.5%, 0.25% and 0.1%, respectively, while the CuO particles were also mixed with distilled water into solutions with volume concentration of 1%. Table 1 lists the inner diameters of the heat pipes and the working media of the experiment.

Table 1: Main parameters of the experiment

Inner diameter	Working medium
Φ3×0.85mm	Distilled water
Φ3×0.85mm	1%_10nm_TiO_2/H_2O nanofluid
Φ3×0.85mm	0.5%_10nm_TiO_2/H_2O nanofluid
Φ3×0.85mm	0.25%_10nm_TiO_2/H_2O nanofluid
Φ3×0.85mm	0.1%_10nm_TiO_2/H_2O nanofluid
Φ3×0.85mm	1%_40nm_CuO/H_2O nanofluid
Φ2×0.85mm	Distilled water
Φ2×0.85mm	1%_10nm_TiO_2/H_2O nanofluid

The previous studies have shown that the filling rate of nanofluid in heat pipes directly bears on the heat exchange performance of the pipe. The filling rate of nanofluid is positively correlated with the heat exchange efficiency of the heat pipe. Through contrastive experiments, it is learned that the heat exchange efficiency was relatively high when the filling rate stood at 55%, 60% and 68%, respectively. Hence, the filling rate is set to 55% in our research.

For the heat pipes with distilled water as the base solution, the heat resistance R minimized at 0.12 K/W under the inclination angle β=90° and working temperature T=130°C. The experiment reveals that the heat resistance R of the heat pipe with the solution medium of TiO_2/H_2O reached the minimum of 0.11 K/W under the water temperature T=110°C. The thermal conductivity K_{eff} of the heat pipes surpassed 5×10^3 W/(m·K), more than 10 times that of copper material. This means the glass heat pipes satisfy the heat exchange requirements.

In this work, the nanofluids were prepared by adding nanoparticles into the base solution of distilled water, and the effects of nanofluid concentration and particle suspendability on the heat exchange efficiency of the heat pipe were discussed.

(1) Before reaching the limit value, the heating efficiency of the fluid in the heat pipe is negatively correlated with the temperature in the heat pipe. With the decrease of heat resistance, the fluid medium temperature in the heat pipe fluctuated less violently and in shorter cycles.

(2) The inclination angle β had an extremely limited impact on the heat exchange coefficient of the heat pipe when it fell between 30° and 90°. When this angle approached zero, the fluid medium flowed slowly in the heat pipe, varied degrees of increase was observed for the working temperature, inside-outside temperature

difference and heat transfer resistance of the heat pipe, and the heat transfer efficiency of the fluid in the pipe plunged deeply.
(3) On the impact of the inner diameter, the inner diameter of the heat pipe is positively correlated with the working temperature in the pipe, when the nanofluid density remained the same; meanwhile, the inner diameter is negatively correlated with the fluctuation of the fluid medium temperature in the heat pipe.
(4) Compared with the heat pipe filled with distilled water, the heat pipes filled with nanofluids carry the following basic features:
(a) After standing for a while, the heat pipe filled with nanofluids suffered from different degrees of particle precipitation. The precipitated nanoparticles were restored to the suspended state through oscillation, creating bubbles of different diameters. As a result, the fluid medium can flow rapidly at a high heat transfer power after the heat pipe starts working. However, numerous disordered bubbles may appear inside the pipes if the flow rate is too fast.
(b) The heat pipes filled with nanofluids can work at a low heat transfer power. Compared with the heat pipe filled with distilled water, the heat pipes filled with nanofluids had a short start-up time, low heat transfer resistance, as well as slight and short-cycle temperature fluctuations.
(c) With the growing concentration of the nanofluid medium, the heat transfer efficiencies of the heat pipes increased by different degrees. However, when the concentration reached a certain value, the heat transfer efficiencies began to decrease. The optimal concentration is correlated with the inner diameter of the heat pipe. Under the same temperature conditions, the thermal resistances of the heat pipes filled with nanofluids were reduced by more than 40%.

3. ANN model

3.1 Model construction

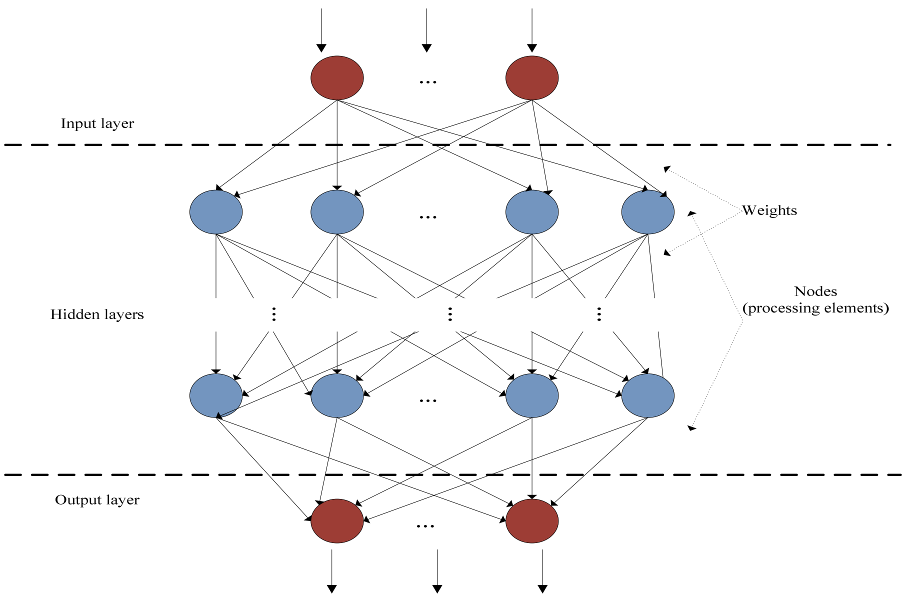

Figure 2: ANN structure

The ANN generally consists of a data input layer, an intermediate processing layer and a data output layer, as shown in Figure 2. Before formal application, the ANN should be trained repeatedly with paired input and output data, such that the network could learn the law of function mapping. Based on this law, the ANN could predict the output corresponding to new input data. Suitable for the analysis and reasoning of nonlinear problems, the ANN has been widely adopted for recognition and prediction of complex data with multiple influencing factors.
A total of 300 sets of experimental data were obtained from the above experiment. These data are about parameters like inclination angle of the heat pipe, the inner diameter of the heat pipe, the nanofluid concentration, and the heating power.
There are four possible values of the inclination angle (β=0°, 30°, 60° and 90°) and two possible inner diameters of the heat pipes (d= 4.3 mm and 2.8 mm). The nanofluid concentration varied between 0% and

1%, while the heating power ranged from 5 W to 120 W.

The above parameters had markedly different impacts on the heat transfer resistance. Among them, the inclination angle β exerted a greater influence over the heat transfer resistance of the heat pipe than the other parameters. The heat pipe achieved the best heat value at the inclination angle of 90°. Considering the experimental conditions, there were only two internal diameters for the heat pipes. The data amount was too small to perform nonlinear fitting and regression analysis.

After the nanoparticles were added to the solution, the heat value in the pipe decreased under a low heating power, but the solution became more viscous, pushing up the resistance of the fluid flow. Thus, the heat transfer ability of the pipe declined when a large volume of nanoparticles were added to the solution. For a heat pipe filled with nanofluid, the dosage of nanoparticles should be kept within a certain range to maintain a good heat transfer ability, when the inner diameter is fixed.

In this paper, the nanofluid concentration and heating power, as the optimal parameters of the heat pipe, are adopted as the input data of the ANN-based model, while the heat resistance, an indicator of the heat transfer ability of the pipe, is taken as the output. The ANN-based model was adopted to fit 60 sets of experimental data. The resulting continuous data were consistent with the experimental results. These data provide sufficient samples for the training of the model, which improves the accuracy and predication quality of the model.

In 63 out of the 300 sets of experimental data, the inclination angle β was 90° and d=4.3mm. The data were subjected to nonlinear fitting by the logistic function below:

$$y=\frac{A_1-A_2}{1+(x/x_0)^p}+A_2 \tag{1}$$

where A_1 is the initial data; A_2 is the actual value; x_0 is the intermediate value of the model; the exponent p=3. The residual was controlled within 0.01. The fitting results are illustrated in Figure 3.

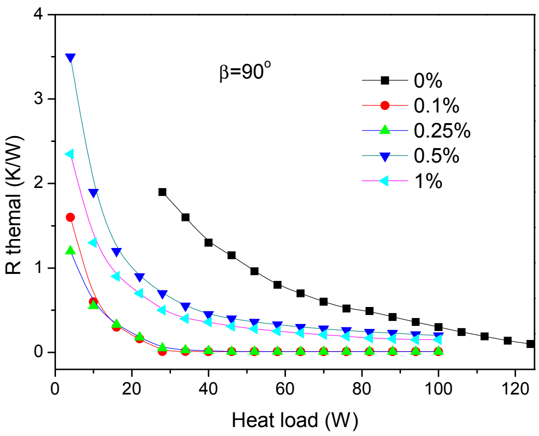

Figure 3: Fitting results

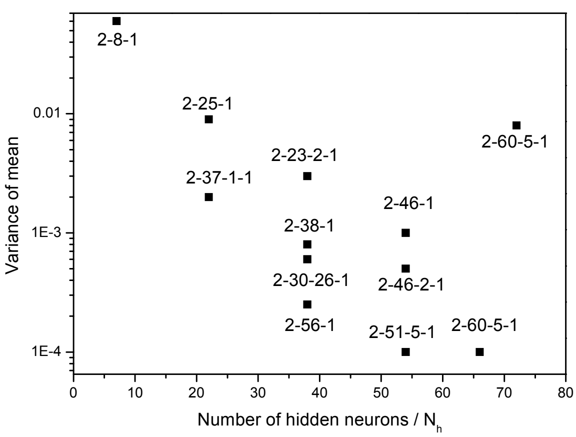

Figure 4: Convergence errors of different structural models

At present, there is still a lack of theoretical basis for ANN-based prediction models. In practice, several data training models should be designed to enhance the prediction accuracy. The trained models should be selected considering the errors and network complexities observed in the training process. The most popular selection equations for network structure are as follows:

Kolmogorov equation:

$$N_h=2J_i+1 \tag{2}$$

Rogers-Jenkins equations:

$$N_t=1+H_h(J_i+J_0+1) \tag{3}$$

Kalogirou equation:

$$N_h=\frac{1}{2}(J_i+J_0)+\sqrt{N_t} \tag{4}$$

where J_i is the number of input parameters; J_o is the number of output parameters; N_h is the number of neurons in the hidden layer; N_t is the amount of data for model training.
According to the above equations, it is learned that the hidden layer contains at least 4 neurons, and the value of N_h is about 25. Therefore, 12 different neural network structures are selected (Table 5.1).
Since the number of data inputs and that of data outputs of the model both surpassed zero, the logsig function was selected as the transfer function for neurons in the input and hidden layers, and the purelin function was adopted as the transfer function for neurons in the hidden and output layers. The error back-transfer algorithm was employed for model training.
It is observed that the model error gradually decreased through repeated trainings. The error convergence was greatly affected by the number of hidden layer neurons N_h. Figure 4 compares the convergence errors of different structural models after 50,000 trainings. It can be seen that the mean variance was 1.0475×10^{-4} after the trainings.

3.2 Accuracy verification

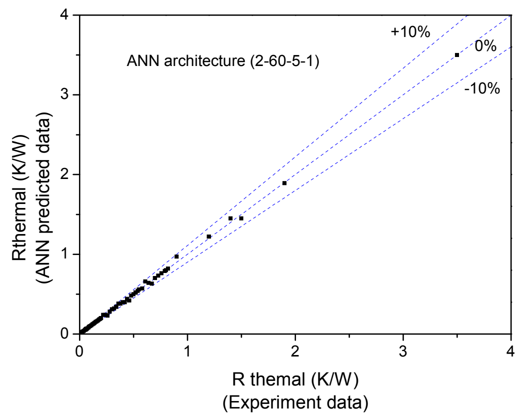

Figure 5: Comparison between the predicted data of the proposed model and those of an untrained model

Through the trainings, the 2-60-5-1 structure was selected for our ANN-based prediction model. With this structure, the averaged squared deviation δ converged at 9.998×10^{-5}, lower than the target value of 1×10^{-4}.
To verify the accuracy of our model, the prediction results of the model were contrasted with those of an untrained model. As shown in Figure 5, the 2-60-5-1 types model, i.e. the proposed ANN-based prediction model, had a maximum relative error of 18% in the 64 sets of verification data, realized a greater-than-10% error in more than 3 sets of data, and achieved a less-than-10% error in over 90% of the datasets. The results fully demonstrate the high accuracy of the ANN-based model in the prediction of heat resistance of the heat pipe, indicating that the model is suitable for the optimization of heat pipes filled with nanofluids.

3.3 Prediction results

Considering the major impacts of fluid concentration on heat exchange performance, the trained ANN-based model was applied to analyse the fluid added with nanoparticles. As shown in Figure 6, the addition of nanoparticles to the solution led to a rapid decline in the heat resistance of the heat pipe. When the volume fraction of the nanofluid surpassed 0.1%, the heat resistance of the heat pipe was at a high level. Further increase of the volume fraction brought corresponding growth in the heat resistance. After the volume fraction exceeded 0.5%, the heat resistance started to decline, but rose again after reaching 0.1%. These trends agree well with the experimental results.
In general, the fluid in the heat pipe flowed from the heating section to the cooling section. This trend was mainly driven by the temperature difference. Thus, the heat exchange in the heat pipe is mainly influenced by the fluid velocity and the heat exchange coefficient. When the heat exchange coefficient remains the same, faster fluid flow in the heat pipe can suppress the heat variation, lower the temperature difference between pipe ends and reduce the heat resistance.
The fluid velocity in the heat pipe is mainly affected by the fluid viscosity. With the growth in fluid viscosity, the six functional resistance values increase correspondingly. Under the same pressure difference, the fluid velocity is negatively correlated with the thermal resistance e in the heat pipe. Unlike traditional mixed fluids, nanofluids exhibited significant nonlinearities in concentration variation.
The nanofluid can significantly increase the heat exchange coefficient of the fluid in the pipe. More bubbles

may appear due to the nanoparticles in nanofluid. Besides improving the evaporation and condensation conditions in the pipe, much attention should be paid to enhance the turbulence features of the fluid considering the mutual collision effect between nanoparticles. In our experiment, the heat exchange coefficient of the heat pipes filled with 0.5%, 1% and 2.5% TiO_2 nanofluids increased by 5.6%, 13.2% and 13.5%, respectively, when the Reynolds number of the nano-media was Re=1700.
The relationship between heat resistance and nanofluid concentration in Figure 6 demonstrates that the addition of nanoparticles to the heat pipe changed the fluid state and collision against the wall of the heat pipe, creating more bubbles in the pipe. These bubbles can accelerate the fluid velocity, significantly reducing the thermal resistance in the heat pipe.

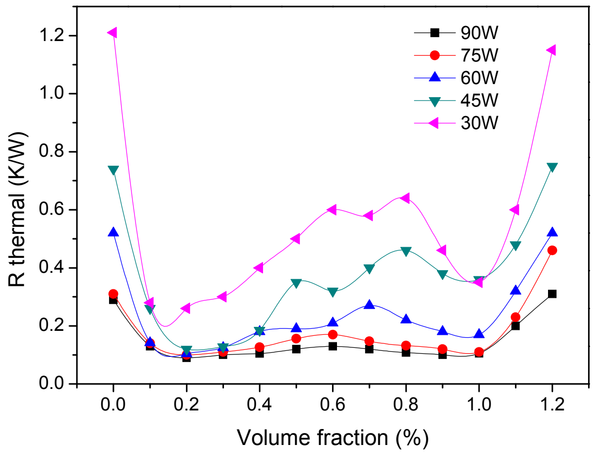

Figure 6: Relationship between heat resistance and nanofluid concentration

4. Conclusions

This paper discusses the effects of heating power, inclination angle and inner diameter of the heat pipe on the heat transfer performance of nanofluid in the heat pipes. The addition of nanoparticles could significantly improve the heat transfer performance of nanofluid, and the volume fraction of nanoparticles is positively correlated with the heat resistance of the heat pipe system.
A prediction model of heat transfer in heat pipes based on ANN model was constructed, and was applied to examine the interferences of nanofluid concentration and heating power in heat transfer performance in the heat pipe. The ANN model had been proven to be desirable in accuracy for predicting the heat transfer characteristics of heat pipe using nanofluid by comparing ANN model results with experimental results at the same operating conditions.
This work provides an accurate modeling approach based on ANN for the research of heat transfer characteristics of nanofluids in heat pipes and solving phase change heat transfer problems related with complicated condition.

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