Research Article

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Testing algorithm for heat transfer performance of nanofluid-filled heat pipe based on neural network

https://doi.org/10.1515/phys-2020-0170
received April 23, 2020; accepted June 29, 2020

Abstract: Traditional testing algorithm based on pattern matching is impossible to effectively analyze the heat transfer performance of heat pipes filled with different concentrations of nanofluids, so the testing algorithm for heat transfer performance of a nanofluidic heat pipe based on neural network is proposed. Nanofluids are obtained by weighing, preparing, stirring, standing and shaking using dichotomy. Based on this, the heat transfer performance analysis model of the nanofluidic heat pipe based on artificial neural network is constructed, which is applied to the analysis of heat transfer performance of nanofluidic heat pipes to achieve accurate analysis. The experimental results show that the proposed algorithm can effectively analyze the heat transfer performance of heat pipes under different concentrations of nanofluids, and the heat transfer performance of heat pipes is best when the volume fraction of nanofluids is 0.15%.

Keywords: neural network principle, nanofluid, heat pipe, heat transfer performance, testing, algorithm

1 Introduction

Nanofluid is a new type of heat transfer medium formed by adding nanoscale metal or metal oxide particles to liquid in a certain manner and proportion. Heat pipe is a heat transfer element with high thermal conductivity [1]. Its unique advantages and high thermal conductivity make the heat pipe widely used in many fields. However, for the traditional heat exchange tubes of pure working liquid, it has been difficult to achieve high performance cooling or heating requirements, and the emergence of nanofluids has brought new breakthroughs to this problem.

In recent years, with the emergence and development of nanofluids, this new type of heat transfer fluid has been used in various types of heat pipes to enhance the heat transfer performance. However, there are still some problems in practical applications, which need to be solved through more in-depth experimental research. The heat pipe has good isothermal performance, and the temperature distribution of each part of the heat pipe working under the optimal working conditions is uniform. When heat pipe is used to dry paper in the process of paper making, its good uniform thermal conductivity can be used to make the surface temperature of the paper uniform during the drying process, so as to ensure the final paper quality [2].

Conventional calender rolls for papermaking are made of cold iron forged steel. Compared with heat pipes, such metal materials have a lower thermal conductivity and a less uniform heat transfer. The hot tubular rolls, which are currently widely used, combine the heat transfer mechanism of induction heating and heat pipes to make the surface temperature distribution of the rolls even during operation [3]. In addition, it can also be used to heat cold water to reduce economic consumption. How to use this new type of heat transfer element more fully requires more in-depth analysis of heat pipe [4].

Foreign scholars have conducted extensive research on heat pipes filled with Ag–water nanofluids, and domestic scholars have carried out experimental research on small thermosiphons filled with coumarin (COU)–water nanoparticles, and also carried out boiling characteristics experiments on two-phase closed thermosiphon filled with carbon nanotube–water. Ma et al. studied heat transfer coefficients of nanofluids based on water and copper oxide particles in cylindrical channels; Li Q. M. et al. studied silica–water nanofluidic oscillating heat pipes; Do et al. studied aluminum oxide–water nanofluid-filled heat pipes; Gabriela H. and Angle H. conducted research on a ferric oxide–water nanofluid thermosiphon; Huang S. Y. et al. carried out a comparative study of zinc oxide–water,

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silica–water, alumina–water and titanium dioxide–water nanofluid thermosiphon; and Shafahi M. et al. used a two-dimensional mathematical model to simulate channel-type heat pipes and flat-plate heat pipes with Al_2O_3–water, CuO–water and titanium dioxide–water nanofluids [5]. Although many studies have shown that nanofluids can enhance heat transfer of heat pipe, it is necessary to continuously explore the real application of nanofluids in engineering practice.

In this paper, silica nano-sized particles with good chemical stability, dispersibility and suspension properties were used to prepare silica–water nanofluids and used as a working medium in heat pipes. Analysis of the heat transfer performance of silica–water nanofluidic heat pipes lays the foundation for the practical application of nanofluidic heat pipes.

2 Materials and methods

2.1 Preparation of nanofluids

Preparation is a critical step in the application of nanofluids, which directly affects the heat transfer performance of nanofluids [6]. At present, the preparation of nanofluids can be divided into a single-step method and a two-step method.

The one-step method refers to directly dispersing the particles in the base fluid while preparing the nanoparticles, and the preparation of the nanoparticles and the nanofluids is completed simultaneously. It is further divided into a vapor deposition method and a reduction method, which belong to the physical synthesis and chemical synthesis, respectively [7].

The two-step method refers to preparing the nanopowder first and then dispersing the nanoparticles in the base fluid by a suitable method to prepare the nanofluids, and the preparation of the nanoparticles and the nanofluids is completed step by step.

Although the one-step preparation of nanofluids has less agglomeration and high stability, it has higher requirements on working fluids and higher preparation costs. Therefore, as in this paper, most of the nanofluids are prepared in a two-step process with the following contents:

(1) Raw materials

The nanoparticles are purchased from Sigma-Aldrich (SiO_2, model number 637238-50G, with a particle size range of 10–12 nm and the deionized water matrix) [8].

(2) Required instruments are listed in Table 1.

(3) Process of preparation

The SiO_2/H_2O nanofluid is configured in a two-step process, as shown in Figure 1.

Take 0.1% by weight nanofluid as an example. The specific steps are as follows:

(1) Weigh 424.17 g of deionized water as the base fluid, and then weigh 0.43 g of SiO_2 nanoparticles into the base stream, disperse the nanoparticles in deionized water and put them on power agitator.
(2) After electrical stirring for 30 min, the suspension is shaken in an ultrasonic cleaner for 1 h.
(3) After repeating the first and the second steps several times, the suspension is shaken in an ultrasonic cleaner for 2 h and then centrifuged for 30 min, and the nanofluid configuration is completed [9].

2.2 Analysis model of heat transfer performance

Artificial neural network (ANN) is an algorithm that simulates the structure and function of biological neural networks and performs distributed parallel information processing [10]. The whole system consists of the following three parts: input layer, hidden layer and output layer, as shown in Figure 2. This method analyzes and summarizes the laws that exist between the two through

Table 1: List of equipment

Device name	Effect
Electronic balance	Nanoparticles and base fluids for accurately weighing certain qualities
Electric blender	The nanoparticles are added to the base fluid for mixing at the same time, thereby the electric agitator is added Uniform mixing of nanofluids
Ultrasonic cleaner	It is mainly divided into two parts: stainless steel cleaning cylinder installed in cleaning liquid. The ultrasonic generator. The principle is that nanofluids are uniformly dispersed under the action of ultrasonic wave, destroying the mutual attraction between nanoparticles, so as to produce suspended and stable nanofluids

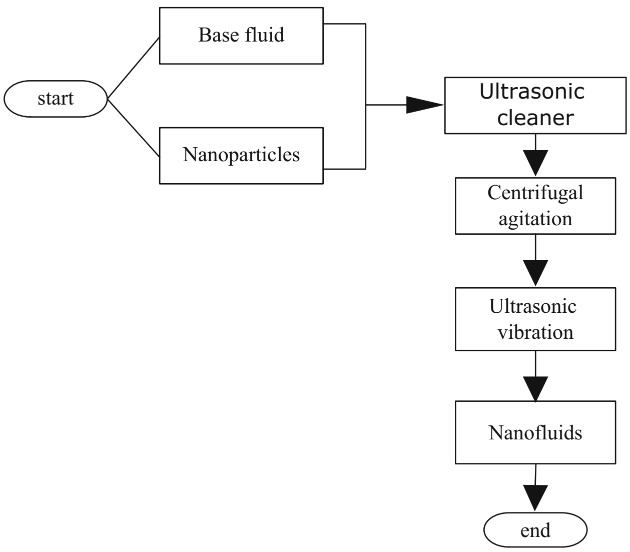

Figure 1: Preparation process of nanofluid.

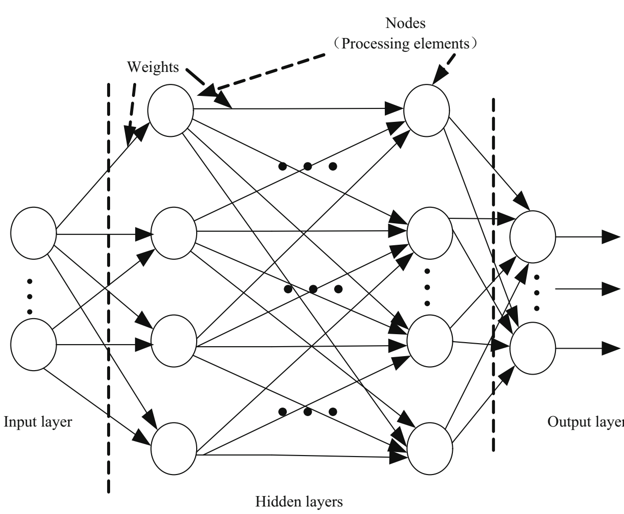

Figure 2: Structure diagram of typical ANN.

a batch of mutually corresponding input and output data [11]. According to the mastered rules, input new data to estimate the output. This process is applicable to the analysis and processing of multifactor effects with complex information, ambiguous background knowledge and unclear inference rules [12]. At present, ANNs have been widely used in many scientific fields.

Through experiments and other means, there are a large number of complex input conditions and output targets [13], which is difficult to explain with the existing techniques and theories. ANN analysis is a better choice.

The operation mechanism of nanofluidic heat pipes involves heat exchange methods such as evaporation, condensation and convection. The internal flow is very complicated, and the heat transfer performance of heat pipes is more influential [14]. The current theoretical models have greatly simplified the operation of nano-heat pipes, and their calculation results are different from the actual situation. ANN has self-learning and adaptability, which can effectively approximate complex nonlinear relationships and solve uncertainties [15]. Analysis of the effects of multiple factors on the performance of nano-heat pipes provides assistance for the optimal design of nanofluidic heat pipes.

The establishment of an analysis model for the heat transfer performance of nanofluidic heat pipes based on ANN is divided into three steps as follows:

1. Determine model input and output parameters.
2. Design a neural network model, which includes determining the number of layers and the number of neurons in each layer, the transfer function of the model and the training learning algorithm [16].
3. Train the model and analyze the data [17].

2.2.1 Input and output parameters

According to the visual endurance fluidic heat pipe experiment, 306 sets of heat transfer performance test data with different inclination angle, pipe diameter (inner diameter), nanofluid concentration and heating power are set. The range of variation of each parameter is as follows: the inclination angle β is the angle between the axial direction of the straight pipe of the heat pipe and the y-axis direction, and the values are 0°, 30°, 60° and 90°, respectively. The tube diameters are 4.3 and 2.8 mm; the range of nanofluid concentration is 0–1%; and the range of heating power is 5–120 W. These parameters have different effects on the heat resistance of the heat pipe. When the β is 90°, the performance of the heat pipe is the best [18]. Due to the limitations of experimental conditions, there are only two parameters of inner-diameter, and the amount of data is small, which is not enough for fitting and regression. After the nanoparticles are added, the thermal resistance of the heat pipe at low heating power input is significantly reduced, but the addition of nanoparticles increases the viscosity of the working fluid, thereby increasing the flow resistance [19]. Therefore, the excessively large concentration of nanoparticles causes a decrease in heat transfer performance of the pulsating heat pipe. For the fixed-diameter heat pipe, the suitable nanofluid concentration can achieve better performance improvement. The heat transfer performance of the heat pipe has high dependence on the heating power. When the heating power is large, the heat transfer performance of the nanofluid and the conventional heat pipe tends to be consistent [20].

The nanofluid concentration and heating power are used as input to the performance optimization model. The thermal resistance represents the heat transfer performance of the heat pipe and is used as an output of the neural network. Sixty-three sets of discrete experimental data can be fitted [21] to provide the training database for the neural network model.

2.2.2 Neural network model

At present, there are few theories about the neural network structures. In practice, a variety of network structures are generally designed for training based on the complexity of the error and structure [22–27]. The following are some reference formulas for the neural network primary selection structure:

Kolmogorov formula:

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

Rogers–Jenkins formula:

$$N_t = 1 + N_h(J_i + J_o + 1)/J_o \tag{2}$$

Kalogirou formula:

$$N_h = \frac{1}{2}(J_i + J_o) + \sqrt{N_t}, \tag{3}$$

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 a single hidden layer; and N_t is the number of data groups required for training.

According to the aforementioned formula, the number of simulated neurons in the hidden layer is greater than 4, and the number set in this paper is about 25; 12 neural networks are selected for comparison, as shown in Table 2.

Since the input and output data are greater than zero, the logsig function is used as the transfer function of the neurons in the input layer and the hidden layer. The purelin function is used as the transfer function of the neurons in the hidden layer and the output layer.

Table 2: Neural network structure design

2-8-1	2-25-1	2-23-2-1	2-38-1	2-37-1-1	2-48-1
2-46-2-1	2-56-1	2-30-26-1	2-51-5-1	2-60-5-1	2-66-5-1

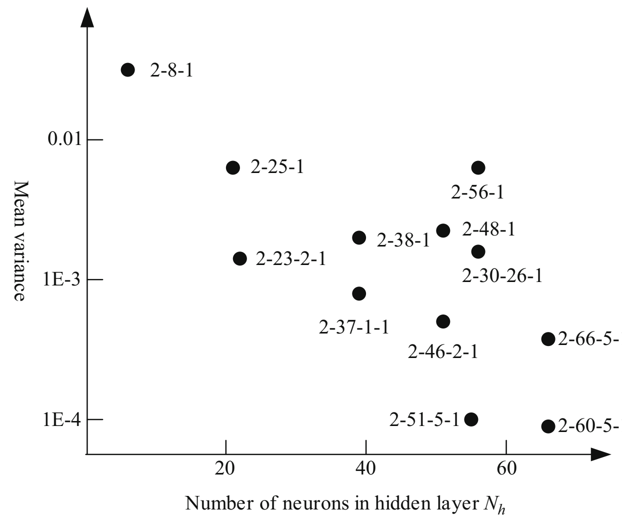

Figure 3: Convergence error of different network structure models.

The network structure with smaller average variance and shorter training time has better performance.

According to the experiment, it can be found that the increase of the trainings will reduce the error continuously, and the increase in N_h of the neuron number in the hidden layer will make the error convergence faster. When N_h is increased to a certain extent, the error convergence speed will be reduced due to the excessive occupancy of resources. The double hidden layer structure converges faster than the single layer structure. The number of second layer neurons in the double hidden layer structure is controlled to adjust the convergence of the error. Figure 3 shows the convergence error of different structural network models after 50,000 training sessions. 2-60-5-1 has the best structure, and the average variance after training for 50,000 times converges to 0.00010475.

2.2.3 Implementation of the model

The neural network structure 2-60-50-1 is selected and trained. The training target is set to averaging the variance to 0.0001. After training 97,744 times, the training target is reached and the average variance converges to 0.00009998.

When verifying the accuracy of the model, the data set that is not trained is compared to the predicted output data of the neural network. Among the 64 groups of data, the data with a maximum relative error between –18% and 18% have only three groups exceeding 10%. About 95% of the data is in the 10% error band, which indicates that the neural network model obtained by the training has good accuracy in predicting the thermal resistance of the heat pipe.

3 Results

3.1 Influence of nanofluid concentration on heat transfer performance of heat pipes

In order to verify the correctness of the performance test of the proposed algorithm, the heat transfer performance results analyzed by the algorithm are compared with the actual experimental results and are represented by Figures 4 and 5 respectively. The experiment is based on experimental material SiO_2 and the β is 90°.

It can be seen from the results in Figure 4 that, under different heating power inputs, the increase in the concentration of the nanofluid causes the heat transfer resistance of the heat pipe to rapidly decrease after the addition of SiO_2 nanoparticles. When the volume fraction of the nanofluid is about 0.15%, the value of the - thermal resistance is the smallest, and the heat transfer performance of the heat pipe is the best, and then the thermal resistance is continuously increased with the increase of the volume fraction. When it increases to about 0.6%, the heat transfer resistance tends to decrease; when the volume fraction reaches about 1.05%, the thermal resistance increases again.

Comparing Figures 4 and 5, it can be seen that the experimental results of thermal resistance change are in good agreement with the analysis results of the proposed algorithm, which indicates that the proposed algorithm can effectively analyze the influence of nanofluid concentration on heat transfer performance of heat pipe.

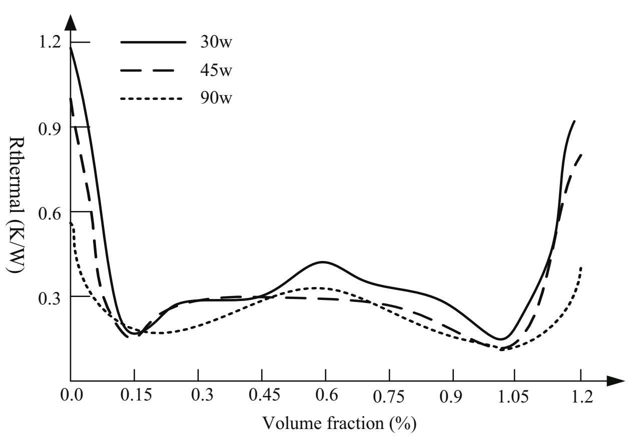

Figure 4: Actual results of heat transfer performance of nanofluid heat pipes at different concentrations.

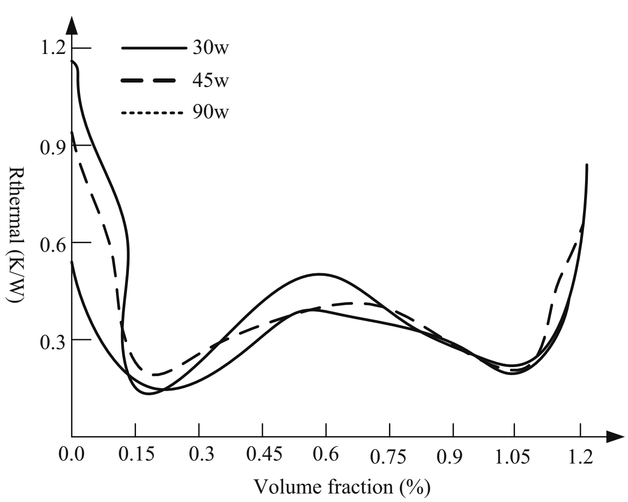

Figure 5: Results of heat transfer performance of nanofluid heat pipe at different concentrations analyzed by this method.

3.2 Influence of heating power and inclination on heat transfer performance

In the figures below, α is the angle between the arrangement of the straight tubes of the heat pipe and the x-axis direction.

It can be seen from Figure 6 that when α = 0° and β is between 30° and 90°, the operating temperatures of the different dip angle heat pipes are substantially the same under the same heating power input. At a certain heating

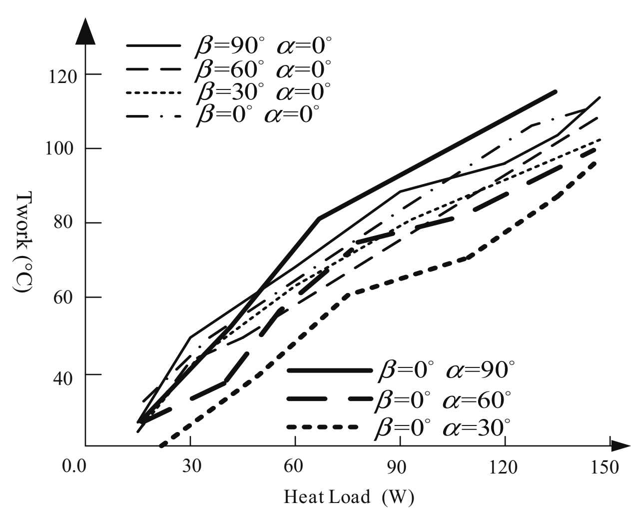

Figure 6: Variation of operating temperature of distilled water pulsating heat pipes with different inclination angles with heating power.

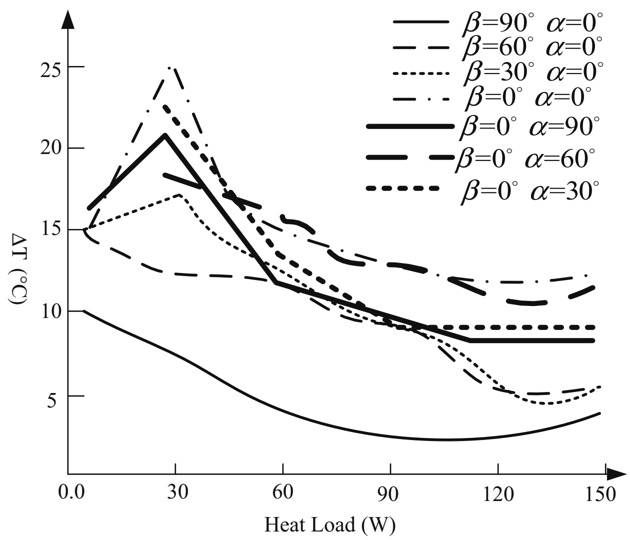

Figure 7: Variation of operating temperature difference with heating power for distilled water pulsating heat pipes with different inclination angles analyzed by the algorithm in this paper.

power input, the temperature is the highest, when $\alpha = 90°$ and $\beta = 0°$, the temperature is second when $\alpha = 30°$ and $\beta = 0°$; when $\beta = 30°$ and $\alpha = 0°$, the temperature is moderate.

Figure 7 shows the variation in the operating temperature difference of the distilled water heat pipe with the heating power under different dip angles. When the heating power is between 100 and 150 W, the operating temperature difference of the heat pipe changes little. The operating temperature difference of the heat pipe under each inclination can be roughly divided into three levels: when $\alpha = 0°$ and $\beta = 90°$, the working temperature difference is the largest, 4–5°C; when $\alpha = 0°$ or $\alpha = 30°$ and $\beta = 0°$, the working temperature difference is the largest, 11–12°C; the operating temperature difference of other dip heat pipes is 6–9°C.

Figure 8 shows the heat transfer resistance of the distilled water heat pipe with different dip angles as analyzed by the algorithm in this paper. It can be seen from it that the thermal resistance decreases rapidly with the increase of the working temperature. When the working temperature is greater than 100°C, the heat transfer resistance is basically stable, between 0.03 and 0.08 K/W. The algorithm analysis shows that the heat transfer resistance of each dip heat pipe is arranged as follows: when $\alpha = 0°$, $\beta 90° < \beta 60° < \beta 30° < 0°$; when $\beta = 0°$, the influence of α on the thermal resistance of the heat pipe is extremely low. In summary, the algorithm can effectively analyze the influence of heating power and working inclination on the heat transfer performance of heat pipes.

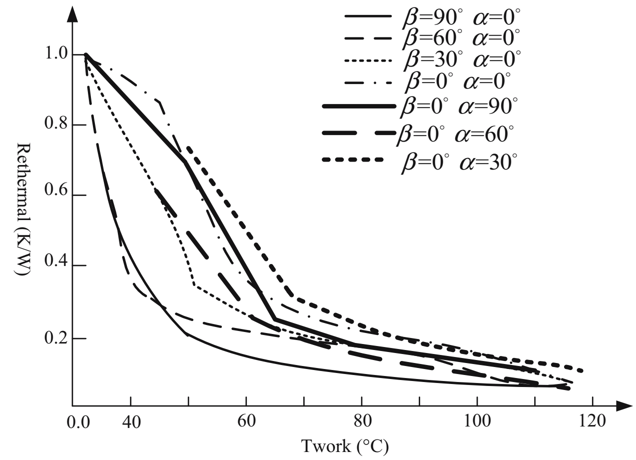

Figure 8: Variation of heat transfer resistance of distilled water pulsating heat pipes with different inclination angles with operating temperature analyzed by the algorithm in this paper.

3.3 Influence of nanofluid suspensibility on heat transfer performance

In order to verify the effectiveness of the proposed algorithm, the heat transfer resistance of the 0.3% wt SiO_2/H_2O nanofluidic heat pipe in the case of good suspension of the working fluid and 12 h after standing is analyzed. The results are shown in Figure 9.

As can be seen from the analysis of Figure 9, after the nanofluidic heat pipe is allowed to stand for a long time, the particles adhere to the wall or precipitate at the bottom. When the heat pipe is heated, the heat transfer performance is weakened due to the inability of the nanoparticles to be well suspended, and the adhesion and

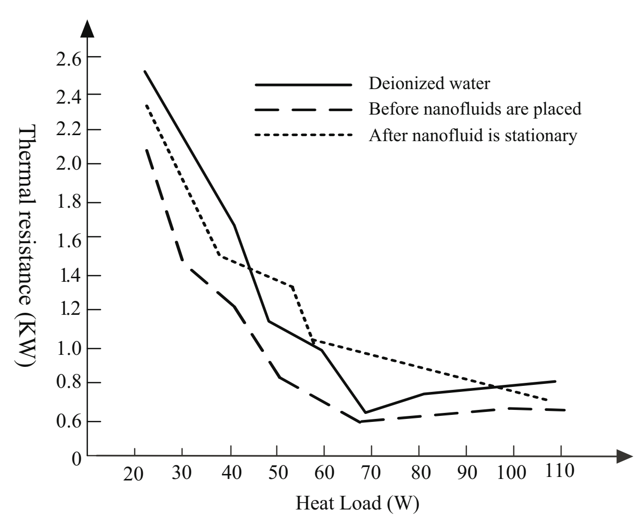

Figure 9: Comparison of heat transfer resistance between 0.3% wt SiO_2/H_2O nanofluids after static.

precipitation of the particles increase the wall frictional resistance. The increase of wall thermal resistance has deteriorating effect on the overall heat transfer performance; as the heating power increases, the working fluid in the heat pipe moves more frequently, which causes the particles to redisperse, and the thermal resistance gradually returns to the original level.

Figures 10 and 11 show the change in temperature of the heat pipe at the heating power of 50 W with time. It can be found that after a long period of standing, the starting temperature and time are both large at 50 W. The starting temperature differs by about 10°C, and the starting time differs by about 150 s. This is mainly because the precipitation increases the wall thermal resistance and resistance, and the heat pipe steam plug requires more time and energy to push the liquid plug movement. With the increase of power, the heat resistance of the heat pipe tends to be the same. The reason is that as the power increases, the working medium oscillation is significantly enhanced, and the precipitated nanoparticles are resuspended with the oscillation, thereby improving the heat transfer of the heat pipe.

The above evaluation results are compared with the evaluation results of the algorithm based on the pattern matching principle. The experts evaluate the nanofluid concentration, heating power, working inclination and nanofluid suspensibility. The results are shown in Table 3:

Analysis of the data in Table 3 shows that the performance of the algorithm is superior to the test algorithm based on the principle of pattern matching when using expert evaluation. The evaluation results show that the average scores of the algorithm in the aforementioned three aspects are 96.2, 94.7 and 94.5, respectively, which is far superior to the evaluation score of the traditional algorithm.

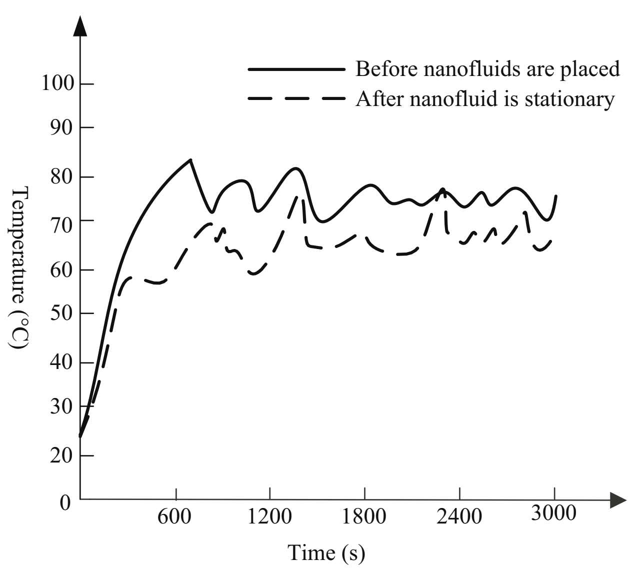

Figure 10: Average wall temperature of hot end at 50 W.

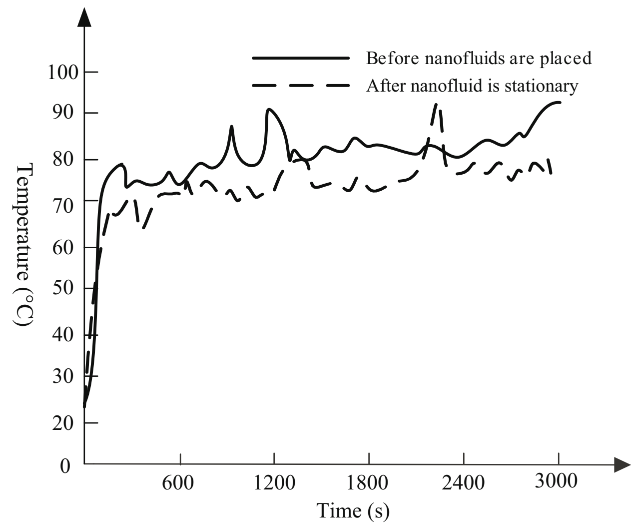

Figure 11: Wall temperature changes at two points at 50 W.

4 Discussion

4.1 Influence of nanofluid concentration on heat transfer performance of heat pipes

The addition of a small amount of nanoparticles causes the existence of the working medium in the tube and the change with the tube wall, which makes the heating section more likely to generate bubbles, improves the startup condition of the heat pipe, and reduces the thermal resistance of the heat pipe. When the volume fraction of the nanoparticles continues to increase, the viscosity of the nanofluid increases, increasing the resistance of the working fluid and the heat transfer resistance of the heat pipe tends to become larger. After the volume fraction is increased to a certain extent, the convective heat transfer coefficient between the working fluid and the pipe wall is significantly enhanced, so that the heat transfer heat resistance of the heat pipe tends to become smaller. As the volume fraction continues to increase, the thermal resistance increases significantly due to the faster viscosity increase.

Table 3: Two evaluation results of heat transfer performance of heat pipe (score)

Expert number	This paper's algorithm			Conventional test algorithm for heat transfer performance of nanofluid heat pipe based on pattern matching principle		
	Effect of nanofluid concentration on heat transfer performance of heat pipe	**Influence of heating power and working inclination on heat transfer performance of heat pipe**	**Effect of suspension of nanofluid on heat transfer performance of heat pipe**	**Effect of nanofluid concentration on heat transfer performance of heat pipe**	**Influence of heating power and working inclination on heat transfer performance of heat pipe**	**Effect of suspension of nanofluid on heat transfer performance of heat pipe**
1	96.5	95.5	96.5	65.2	60.2	67.5
2	98.4	94.5	93.6	74.1	64.7	65.7
3	96.5	92.5	95.8	65.2	65.4	61.8
4	93.2	95.4	94.7	65.6	67.3	67.3
5	95.3	95.7	94.9	75.2	65.2	65.6
6	96.5	92.2	95.3	75.6	64.5	65.2
7	95.7	98.4	96.5	71.5	75.3	74.7
8	98.4	94.7	97.6	64.2	75.2	64.8
9	95.5	95.7	97.2	73.2	74.5	68.8
10	96.1	95.8	95.6	74.2	74.2	64.5
11	96.7	91.8	94.6	75.1	74.5	71.7
12	95.8	94.9	93.2	70.2	71.2	67.2
Average score	96.2	94.7	94.5	70.7	69.4	67.1

4.2 Influence of heating power and inclination on heat transfer performance

According to the research of the algorithm in this paper, when $\alpha = 0°$ and $\beta = 90°$, a long steam plug will be formed in the heating section of the heat pipe. Since no liquid is returned to the heating section, it is prone to dry out, and in most cases the heat pipe cannot be successfully started. When $\beta \geq 5°$, there is liquid confluence on the tube wall and the heat tube can start normally. By adjusting α, the working fluid can realize the one-way flow in the pipe about 5°, so that the heat pipe obtains better temperature uniformity, smaller temperature fluctuation range and period.

4.3 Effect of levitation on heat transfer performance

The study also shows that the thermal resistance of the nanofluid increases after standing, and the working temperature of the hot end increases. With the strengthening of the working fluid oscillation, the precipitated nanoparticles will resuspend and improve the heat transfer of the heat pipe. As the heating power increases, its thermal resistance will decrease, but the overall trend is more gradual than before standing. The temperature fluctuation of the nanofluid after standing is smaller than that of the nanofluid before standing at the same power inputs.

In response to the research content of this paper, the following suggestions are given:

(1) Optimize the heat transfer performance of the nanofluidic heat pipe by selecting the appropriate concentration. The nanoparticle improves the heat transfer property of the base fluid and also increases its viscosity and the flow resistance of the working fluid, which is disadvantageous for reducing the heat resistance of the heat pipe. Therefore, when using nanofluids to improve heat transfer performance of heat pipes, it is necessary to control their concentration.

(2) The methods of seeking to reduce the adhesion of nanoparticles to the tube wall need to be paid attention, since the nanoparticles will form the precipitate in the heat pipe and form the adhesion layer on the inner wall of the heating section, which will block the heat exchange passage of the micro heat exchange device.

(3) Continue to carry out research on the structure of the pulsating heat pipe, the formulation of the nanofluid and the filling rate.

5 Conclusions

The proposed testing algorithm for heat transfer performance of a nanofluidic heat pipe based on the neural network analyzes the effect of nanofluidic concentration and heating power on heat pipe performance. As long as a small volume (0.1–0.3%) of nanoparticles is added to the heat pipe, the heat pipe performance can be improved. When the volume fraction of the nanoparticles is too large, the heat transfer performance of the heat pipe is lowered. The ANN has the characteristics of strong nonlinear adaptability; the trained neural network model has higher prediction accuracy; and it can obtain information other than experimental data, which is suitable for occasions with large experimental data and complex parameter relationships. The experimental results show that the proposed algorithm can accurately analyze the heat transfer performance of nanofluidic heat pipes from multiple angles.

In recent years, with the emergence and development of nanofluids, researchers have applied this new kind of heat transfer medium to all kinds of heat pipes to enhance the heat transfer performance of heat pipes and achieved some research results, but there are still some problems in practical application that need to be solved through further experimental research. For this paper, although a variety of different nanofluids are used as heat pipe working fluid, the thermal conductivity of each nanofluid heat pipe is tested and the strengthening effect of nanofluids is preliminarily analyzed, there are still many deficiencies in the experiment. The strengthening mechanism of nanofluids to heat pipe is very complex, which involves a lot of heat transfer knowledge. In this paper, the strengthening mechanism is simply analyzed. The heat pipe has good equal humidity performance, and the temperature distribution of each part of the heat pipe is uniform under the best working conditions. When the heat pipe is used to dry the paper in the paper making process, it can make the surface temperature of the paper even and ensure the final quality of the paper. The excellent heat transfer capability of heat pipe makes its application in the papermaking process have a broad prospect. How to use this new type of heat transfer element more fully in the papermaking industry still needs more in-depth analysis and discussion on heat pipe and papermaking process.

Acknowledgements: This work was supported by the National Natural Science Foundation of Jiangsu Province (No. SBK2020042624) and the general projects of National

Science Research in Universities of Jiangsu Province (No. 19KJB560024).

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