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RESEARCH ARTICLE

Thermal Conductivity Modeling of Aqueous CuO Nanofluids by Adaptive Neuro-Fuzzy Inference System (ANFIS) Using Experimental Data

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Abstract
In this article, thermal conductivity data of aqueous nanofluids of CuO have been modeled through one of the instruments of empirical data modeling. The input data of 5 different volume fractions of nanofluid obtained in four temperatures through experiments have been considered as network inputs. Also, triangular function, due to providing the best responses, has been used as membership function in ANFIS structure. The modeling results show that fuzzy networks are able to model thermal conductivity results of nanofluids with good precision. Regression coefficient of this modeling has been 0.99.

Keywords
nanofluids, fuzzy networks, thermal conductivity, ANFIS

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1 Introduction

Increase in energy cost in long time and growing need for energy have made scientists look for ways to conserve energy. One way for conserving energy in heat transfer field is to use operating fluids of heat transfer with better and more efficient transfer properties. Around 20 years ago, Choi [1] in his report proposed his solution for this problem by introducing suspensions called nanofluids. After scientists' familiarity with these fluids, a great deal of attention was drawn to them. When many researchers of heat transfer and mass field observed nanofluids potential in reducing energy consumption, they embarked on their researches on these new fluids and thousands of scientific articles in this field have been published so far.

These articles have different subjects such as nanofluids thermal conductivity [2-7], viscosity [8-11], heat transfer coefficient [12-18] and the other subjects about nanofluids.

In addition to experimental researches, a large number of analytical and numerical researches have been conducted on this field. Beyond this level, some researchers have begun studies on experimental data modeling. These researches are conducted with the purpose of nanofluids behavior modeling in thermophysical and hydrodynamic terms.

A report of the studies conducted to model nanofluids behavior is provided in Table 1.

In this article, thermal behavior of aqueous nanofluids containing CuO nanoparticles has been modeled by ANFIS network. The nanofluids were prepared through a two-step method and the thermal conductivity data were measured based on previous work [21, 22] in five volume fractions and four temperatures and the modeling results were compared with experimental data. It should be noted that in this article Sugeno method has been used for modeling the data through ANFIS network. Based on the author's knowledge, there are no similar studies in literature on modeling the thermal conductivity by Adaptive Neuro-Fuzzy Inference System (ANFIS).

Table 1 Research on modeling the properties of nanofluids

Author(s)	nanoparticle(s)	Characteristic	parameters	method
Yousefi et al. [19]	CuO, TiO_2, SiO_2 and Al_2O_3	viscosity	temperature volume fraction	diffusional neural network (DNN)
Zhao et al. [20]	CuO and Al_2O_3	viscosity	nanoparticle volume concentration, nanoparticle diameter, nanoparticle density and the viscosity of base fluid	**ANN with radial basis function**
Hemmat Esfe et al. [21]	ferromagnetic nanoparticles	thermal conductivity and dynamic viscosity	temperature, diameter of particles, and solid volume fraction	**artificial neural networks (ANN)**
Hemmat Esfe [22]	Al2O3	thermal conductivity	temperature and solid volume fraction	**artificial neural networks (ANN)**
Karimi and Yousefi [23]	Al_2O_3, CuO, Sb_2O_5 and ZnO	density	temperature and solid volume fraction	**ANN–GA**
Hojjat et al. [24]	γ-Al2O3, TiO2 and CuO	thermal conductivity	temperature, solid volume fraction and thermal conductivity of nanoparticles	**ANN**
Hemmat Esfe et al. [25]	MgO	thermal conductivity	temperature, solid volume fraction and particle diameter	**ANN**
Hemmat Esfe et al. [26]	Cu/TiO2 hybrid nanoparticle	thermal conductivity	temperature, solid volume fraction	**ANN**
Safikhani et al. [27]	Al_2O_3	nanofluid flow in flat tubes	heat transfer coefficient and friction factor	**CFD optimization using ANN-Genetic Algorithm**
Mehrabi et al. [28]	Al_2O_3	thermal conductivity	temperature, solid volume fraction and nanoparticle size	**FCM-based neuro-fuzzy inference system and genetic algorithm-polynomial neural network**

2 Adaptive Neuro-Fuzzy Inference System

Adaptive Neuro-Fuzzy Inference System or ANFIS is a category of adaptive networks functioning similar to a fuzzy inference system, introduced by Jang, which automatically produces a fuzzy rule base and membership functions [29].

A typical ANFIS network is composed of connected nodes depending on parameters that are altered by learning rules reducing the error criteria. The most common learning technique is the gradient method, but Jang suggested hybrid learning rule that includes the least Square or LSE Estimator.

There are several different concepts related to ANFIS that will be explained below [29]:

NUMMFs is the number of membership functions per unit. In this study, 3 membership functions have been considered per unit. INPUTMF is the kind of membership function for each unit. In this research, triangular membership function has been used for all input membership functions.

OUTPUTMF is the type of output membership function. It can be linear or constant. The latter has been used as output membership function in this study.

Neuro-fuzzy systems have a lot in common with artificial neural networks. However, they also have some differences from each other. There are four major differences between them:

1. In a neuro-fuzzy system, nodes and links correspond to a certain component in the system. For instance, First Layer describes the antecedent MF.
2. A node is generally not completely connected to the nodes in a neighbouring layer.
3. Nodes in different layers of neuro-fuzzy system usually perform different tasks.
4. A neuro-fuzzy system usually has more layers than neural network.

In Fig. 1, the structure of ANFIS network with two inputs has been shown. For each input, there are three membership functions. This structure has 9 rules and 9 outputs.

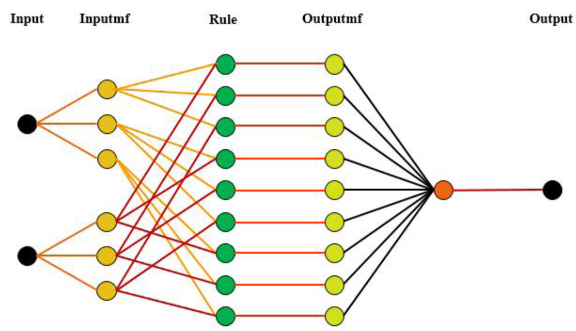

Fig. 1 ANFIS model structure

For a Sugeno type of fuzzy system having the rule base:

If x is A1 and y is B1, then $f_1 = p_1 x + q_1 y + r_1$

If x is A2 and y is B2, then $f_1 = p_2 x + q_2 y + r_2$

Let the membership functions of fuzzy sets A_i, B_i, i=1,2, be μ_{Ai}, μ_{Bi}.

In evaluating the rules, choose *product* for T-norm (logical *and*).

1. Evaluating the rule premises results in

$$w_i = \mu_{A_i}(x)\mu_{B_i}(y) \qquad i = 1,2 \tag{1}$$

2. Evaluating the implication and the rule consequences gives

$$f(x\cdot y) = \frac{w_1(x\cdot y)f_1(x\cdot y) + w_2(x\cdot y)f_2(x\cdot y)}{w_1(x\cdot y) + w_2(x\cdot y)} \tag{2}$$

Or leaving the arguments out

$$f(x\cdot y) = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} \tag{3}$$

This can be separated to phases by first defining

$$\bar{w}_i = \frac{w_i}{w_1 + w_2} \tag{4}$$

Then f can be written as

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{5}$$

All computations can be presented in a diagram form:

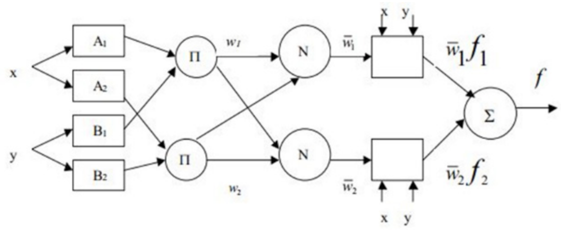

Fig. 2 Computation process of ANFIS

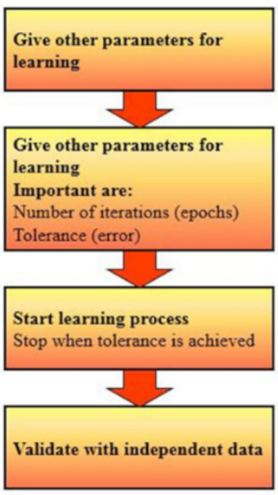

Fig. 3 Computational diagram of ANFIS

Basic flow diagram of computations in ANFIS

The diagrams used as membership functions in ANFIS network have been shown in Fig. 4. These functions have a determining role in weight values used in empirical data modeling.

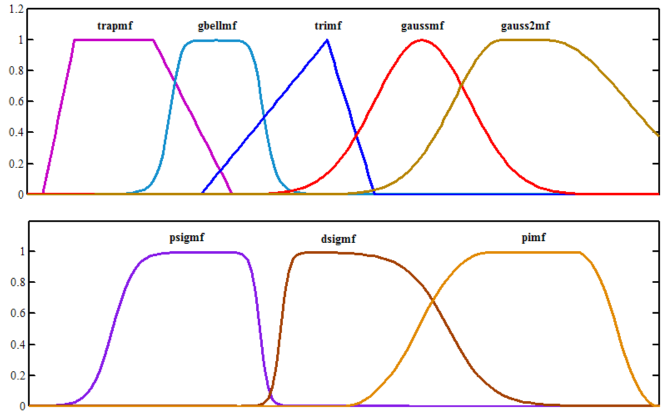

Fig. 4 Membership function gallery

In order to model the data by ANFIS, different membership functions have been used. A list of these membership functions as well as regression parameters has been provided in Table 2. The best response has been obtained from membership function of *trimf* or triangular membership function. In this table, MSE is Mean Squared Error, RMSE is square root of MSE, and STD is standard deviation of responses from empirical values.

Table 2 Regression parameters

membership function type	R (%)	MSE	RMSE	STD	Mean of Error
trimf	**99.28**	**1.2131e-4**	**0.0110**	**0.0113**	**4.5814e-7**
trapmf	81.68	0.0028	0.0529	0.0546	**2.2348e-7**
gbellmf	98.75	2.1122e-4	0.145	0.0149	**4.1561e-7**
gaussmf	99.00	1.6945e-4	0.130	0.0134	**1.3657e-7**
gauss2mf	98.24	2.9614e-4	0.0172	0.0177	**4.6802e-7**
pimf	80.86	0.0029	0.0528	0.0557	**2.2293e-7**
dsigmf	98.17	3.0792e-4	0.0175	0.0180	**3.6381e-7**
psigmf	98.17	3.0792e-4	0.0175	0.0180	**3.6382e-7**

After modeling the data, experimental values can be compared with output values of ANFIS modeling. This comparison has been shown in Fig. 5. As is observed in this figure, the model could estimate the experimental data with good precision. Therefore, we realize that ANFIS can be a proper tool for modeling nanofluids thermal conductivity.

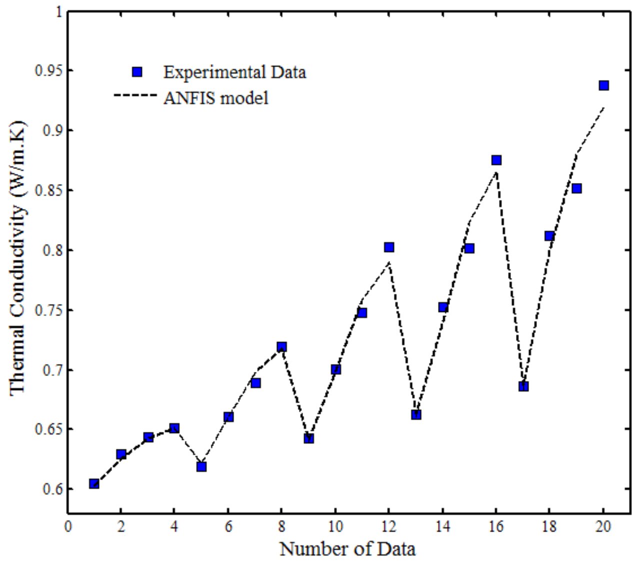

Fig. 5 Comparison between experimental data and ANFIS model

In Fig. 6, the histogram of modeling error has been shown. This diagram divides modeling error into five intervals and specifies the number of samples in each interval in vertical bars. If the modeling error is low, the number of samples in the interval close to zero is bigger. The curve in this diagram also shows that most of the data have an error close to zero.

The following relation can be used to obtain margin of deviation of ANFIS output:

$$MOD(\%) = \frac{k_{exp} - k_{pred}}{k_{exp}} \times 100 \tag{6}$$

This equation yields the percentage of modeling error. The values obtained from this equation have been shown in Fig. 7. The maximum error for this modeling has been less than 4% that is considered an acceptable value for this modeling.

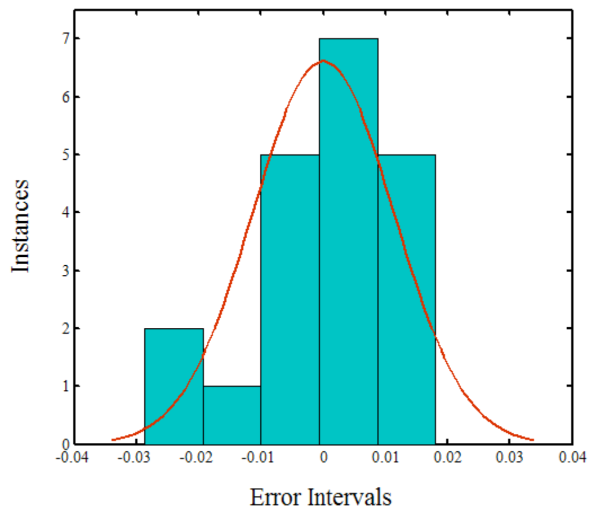

Fig. 6 Margin of deviation

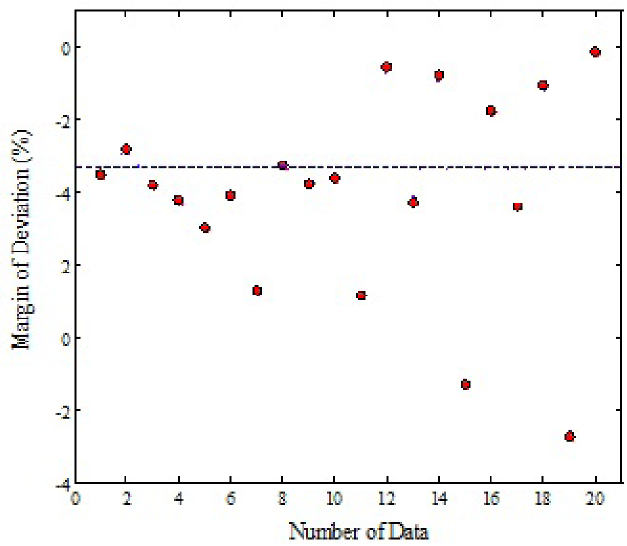

Fig. 7 Comparison between experimental data and ANFIS model

In Fig. 8, modeling results at different volume fractions of nanoparticles in nanofluids have been compared with experimental data. In this article, experimental data of 4 volume fractions of 0.04%, 0.08%, 0.12%, and 0.16% as well as base fluid have been used. It is seen in this figure that modeling the data could estimate the experimental data with good precision.

Considering the data in these diagrams reveals that increase in thermal conductivity of base fluid from 28 to 55°C has been just 7% and increased from 0.605 to 0.65 W/m.K while increase in thermal conductivity of nanofluids with volume fraction of 0.16% has been 38% and increased from 0.68 to 0.94 W/m.K.

The parameters of the nonlinear regression have been provided in Table 3:

Table 3 Parameters of the nonlinear regression

R	MSE	RMSE	mean of error
0.9918	1.4158e-4	0.0119	8.9000e-4

By considering the results provided in Table 3 and Fig. 6, we conclude that the conducted modeling has been very successful and these networks can be used for modeling more extensive data and for different properties of nanofluids. The closer R^2 value to 1 shows the better prediction of experimental data by the proposed model [30]. As can be seen from Table 3, R-squared is 0.9918.

3 Conclusions

The assessment of possibility of using adaptive neuro-fuzzy inference systems (ANFIS) for modeling experimental data of CuO nanofluids thermal conductivity was investigated in this article. For this purpose, a number of experimental data of thermal conductivity of CuO-water nanofluids are given to network as input and the modeling is conducted by determining the appropriate type of network structure and also membership function.

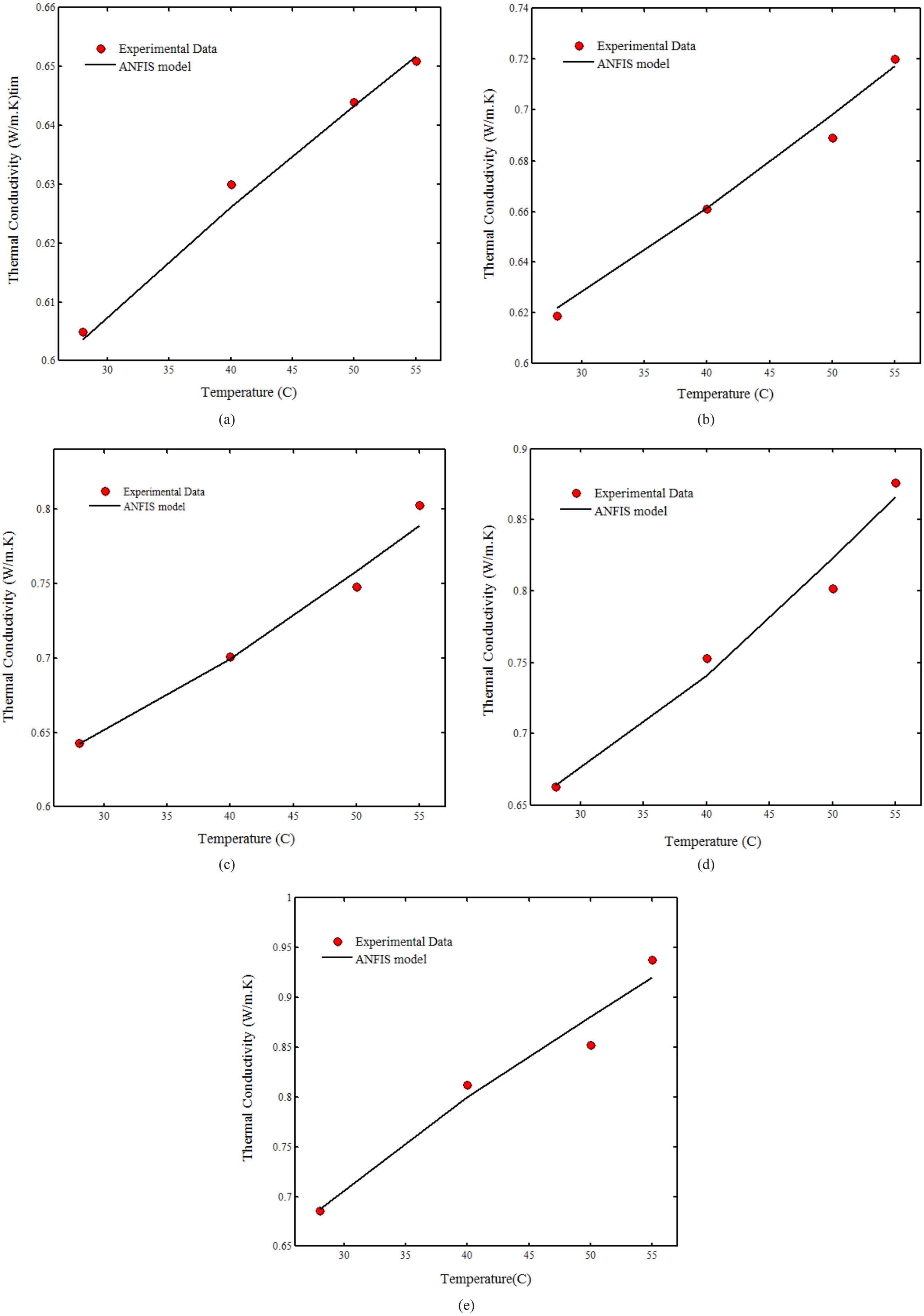

Fig. 8 Thermal conductivity versus temperature at different volume concentrations, A: base fluid, B: 0.04%, C: 0.08%, D: 0.12%, E: 0.16%

The results show that these networks can model with good precision. Therefore, these networks can also be introduced as an instrument for post-processing the nanofluids experimental data.

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