

Modeling heat transfer of non-Newtonian nanofluids using hybrid ANN-Metaheuristic optimization algorithm

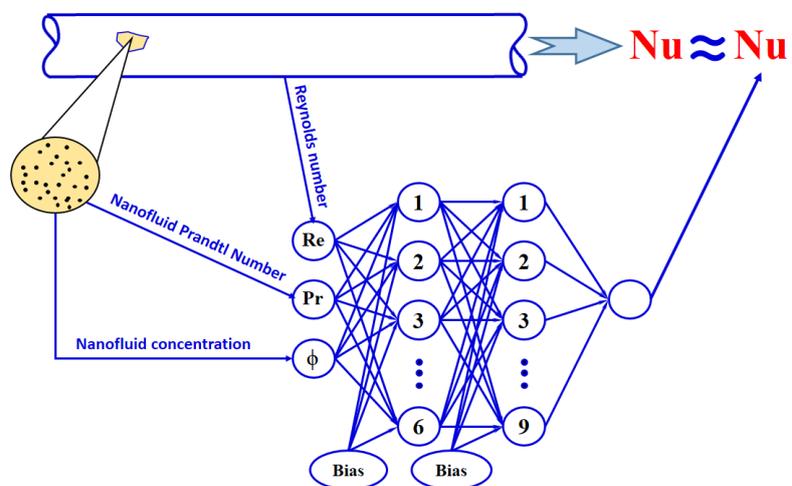
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HIGHLIGHTS

- Designing an ANN and optimized it by using a PSO algorithm to predict the Nusselt number of non-Newtonian nanofluids
- Assessment of the ability of an artificial neural network to predict convective heat transfer experimental data
- Comparison of ANN-PSO with existing correlation

GRAPHICAL ABSTRACT



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ABSTRACT

An optimal artificial neural network (ANN) has been developed to predict the Nusselt number of non-Newtonian nanofluids. The resulting ANN is a multi-layer perceptron with two hidden layers consisting of six and nine neurons, respectively. The tangent sigmoid transfer function is the best for both hidden layers and the linear transfer function is the best transfer function for the output layer. The network was trained by a particle swarm optimization (PSO) algorithm. Nanofluid concentration, Reynolds number, and Prandtl number are input for the ANN and the nanofluid Nusselt number is its output. There exists an excellent agreement between the ANN predicted values and experimental data. The average and maximum differences between experimental data and those predicted by ANN are about 0.8 and 5.6 %, respectively. It was also found that ANN predicts the Nusselt number of nanofluids more accurately than the previously proposed correlation.

1. Introduction

Heat transfer is the main challenge in modern systems with high heat fluxes such as nuclear power systems, high power lasers, space vehicles, and so on. Numerous heat transfer enhancement techniques have been proposed to overcome this challenge. Thermal characteristics of heat transfer fluids are major parameters affecting the performance of such equipment. Thus improvement of the thermal characteristics of heat transfer fluids can improve the performance of heat transfer systems. It is well known that dispersion of solid particles in fluids significantly enhances their thermal characteristics [1]. But problems concerning particles with large (milli- or micrometer) sizes, such as rapid settling, high erosion, clogging the channel with small dimensions and high pressure drop, have limited their use. Nanoparticles are uniformly suspended in base fluids to produce stable suspensions which do not have the mentioned problems. This new class of heat transfer fluids is called nanofluids [2]. Numerous studies have been carried out on thermophysical properties as well as the thermal and hydrodynamic behavior of nanofluids [3-10]. Results show that addition of nanoparticles enhances the thermal conductivity and convective heat transfer coefficient of the base fluid drastically. As new media for heat transfer, it is expected that nanofluids will create a revolution in heat transfer. A comprehensive investigation was conducted on thermal and hydrodynamic behavior of non-Newtonian nanofluids by Hojjat et al. [11-17]. Their results show that the thermal behavior of non-Newtonian nanofluids is superior to that of the base fluids. Before nanofluids can be used in practical applications we should increase our knowledge of principles governing the behavior of nanofluids. Results of most studies show that models and correlations of conventional heat transfer fluids do not predict thermophysical properties and thermal and hydrodynamic behavior of nanofluids well [3,9,18,19]. In other words, there exists no general model to predict the properties and behavior of nanofluids. Therefore, it is vital to find general models and correlations which can perfectly predict the properties and behavior of nanofluids.

Recently, data driven models based on experimental data, such as artificial neural network, fuzzy logic, and evolutionary optimization algorithm (genetic algorithm, particle swarm optimization, etc.), have been used to

find general models for nanofluids behavior.

Rheological behavior of various nanofluids has been modelled by using an ANN [12,20-28]. Some investigators have used the ANN to predict the thermal conductivity of nanofluids [11,27-38]. Results reveal the high capability of ANN to predict nanofluids rheological behavior as well as thermal conductivity.

The effect of nanofluid on the cooling performance and pressure drop of a jacketed reactor has been experimentally investigated and modeled using an artificial neural network [39]. A multi-layer perceptron (MLP) neural network with one hidden layer containing ten neurons was used for convective heat transfer coefficient modeling and a MLP network with two hidden layers each contains six neurons was used for pressure drop. Both were trained by the Levenberg-Marquardt training algorithm. Reasonable agreement between experimental data and those predicted by ANNs is observed. Vaferi et al. [40] have proposed the best artificial neural network model for prediction of heat transfer coefficient of nanofluids in a circular tube subjected to various boundary conditions under different flow regimes. Results obtained from the ANN model have compared with some reliable correlations in the literature. They found that the performance of the proposed model was higher than other published works. Laminar convective heat transfer of Al_2O_3 -water nanofluids flowing inside various flat tubes was investigated numerically using CFD methods by Safikhani et al. [41]. Simulation was carried out based on a two-phase model. They calculated heat transfer coefficient and pressure drop of nanofluids. Resulted data were modeled by a grouped method of data handling (GMDH) type ANN. Finally, the obtained GMDH model was used for Pareto based multi-objective optimization of nanofluid parameters in horizontal flat tubes by a non-dominated genetic algorithm. The resulting Pareto solution contains significant design information on nanofluids parameters in flat tubes. Kalani et al. [42] assessed the capability of two artificial neural networks of a radial basis function artificial neural network (RBF-ANN), MLP-ANN, and an adaptive fuzzy inference system (ANFIS) in modeling the complex non-linear relation between input and output parameters of a photovoltaic thermal nanofluid based collector system. Their results indicate that all three models have the ability to predict the performance of the mentioned system. However, the accuracy of the ANFIS and RBF-

ANN is higher in estimation of electrical efficiency and fluid outlet temperature, respectively.

Since the convective heat transfer coefficient of nanofluids is the main parameter influencing the performance of heat transfer equipment and fewer investigations have carried out on modeling this important parameter, in the present study turbulent flow forced convective heat transfer of non-Newtonian nanofluids flowing through a circular tube under constant wall temperature boundary condition was modeled by an optimized artificial neural network. It receives the nanofluid volume fraction, Prandtl number, and Reynolds number as input variables and gives the Nusselt number of nanofluids as output. A particle swarm optimization algorithm was used to determine the best values of the ANN parameters instead of conventional gradient based training algorithms.

2. Experiments

Experimental data are obtained from results of the author's previous work [16]. This experiment is briefly reviewed below. Turbulent forced convective heat transfer of non-Newtonian nanofluids flowing through a double-pipe heat exchanger was experimentally investigated. Nanofluids flow in the inner tube. Hot water circulated through the annular section at very high flow rates so it is reasonable to consider the boundary condition as constant temperature [16].

2.1. Nanofluids preparation

Nanofluids under consideration were suspensions of γ -Al₂O₃ (25 nm), TiO₂ (10 nm), CuO (30-50 nm) nanoparticles in 0.5 wt% CMC solution. Since ultrasonic vibrations altered the rheological behavior of a CMC solution, nanoparticles were first dispersed in deionized water and sonicated to obtain uniform suspensions. An appropriate amount of high concentration CMC solution was added to the suspensions and well mixed by a mechanical mixer to achieve the desired nanofluids [16].

A KD2 thermal property meter (Decagon Device Inc., USA) was used to measure the thermal conductivity of nanofluids. Rheological behavior of nanofluids was investigated using a rotational rheometer (HAAKE RV12). Results show that all nanofluids as well as the base fluid exhibit pseudoplastic behavior [12]. Other

physical properties were calculated at average bulk temperature according to the following equations [16]:

$$\rho_{nf} = \phi\rho_p + (1-\phi)\rho_{bf} \quad (1)$$

$$(\rho C_p)_{nf} = \phi(\rho C_p)_p + (1-\phi)(\rho C_p)_{bf} \quad (2)$$

Because of very low concentrations of the carboxy methyl cellulose, the physical properties of the base fluid are considered similar to those of pure water. Physical properties of nanoparticles are given in Table 1.

Table 1. Physical properties of the nanoparticles [43].

Nanoparticle	Density (kg/m ³)	CP (J/kgK)
γ -Al ₂ O ₃	3700	880
TiO ₂	3900	710
CuO	6350	535.6

2.2. Experimental procedure

A schematic diagram of the experimental set-up is shown in Figure 1 [16]. It is comprised of two loops. The first loop, including a container, a stainless steel gear pump, a bypass line, a flow meter, a cooler, several valves, and a test section, is related to nanofluids. The test section is a circular pipe with the length of 200 cm and inner diameter of 1 cm. The second cycle is related to hot water which is cooled in a double-pipe heat exchanger by the nanofluid. Six K-Type thermocouples mounted on the outer wall of the inner tube are used to measure the wall temperature. Two thermocouples are used to measure the inlet and outlet temperatures of the nanofluid. Details of experimental procedure and calculation of heat transfer coefficient and Nusselt number are explained in Ref. [16].

3. Particle swarm optimization

Particle swarm optimization is a population-based stochastic metaheuristic computational optimization algorithm inspired by bird flocking and fish schooling. PSO was first proposed by Kennedy and Eberhart in 1995 [44]. To implement PSO, first a population of particles is produced randomly on a D dimensional space of the problem. Every particle which can be a solution of the problem is characterized by its position, $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$ and velocity, $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$

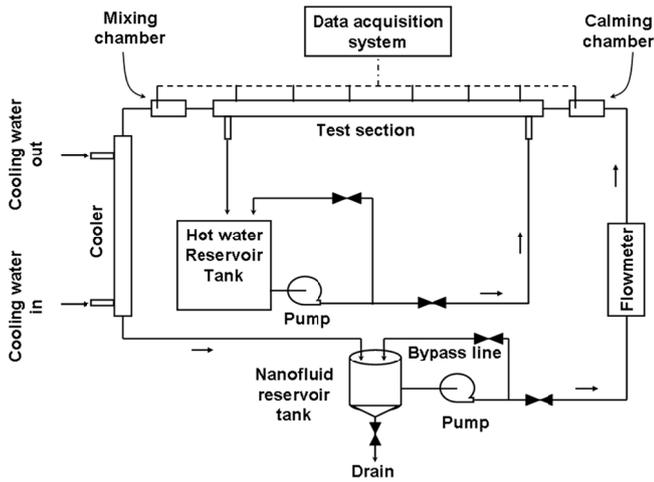


Fig. 1. Experimental setup of data results in [16].

vectors. For each particle the value of cost function is evaluated. The cost value of each particle is compared with its own best experience (local best) and the best experience of all other particles (global best). Each particle adjusts its velocity and position according to the following equations (Constriction coefficient):

$$v_{ij}(t+1) = \chi [v_{ij}(t) + \phi_1(x_{ij}^{lbest}(t) - x_{ij}(t)) + \phi_2(x_j^{gbest}(t) - x_{ij}(t))] \quad (3)$$

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \quad (4)$$

where:

$$\chi = \frac{2\kappa}{|2 - \phi - \sqrt{\phi(\phi - 4)}|} \quad (5)$$

with:

$$\phi = \phi_1 + \phi_2$$

$$\phi_1 = c_1 r_1$$

$$\phi_2 = c_2 r_2$$

Equation (5) is used under the constraints that $\phi \geq 4$ and $\kappa \in [0, 1]$.

The procedure is repeated until the stopping criterion is satisfied.

In the present study parameters were chosen as: $\phi = 4.1$, $\phi_1 = \phi_2 = 2.05$ and $\kappa = 1$.

4. Artificial Neural Network Design

ANN is a powerful tool inspired by the human nervous system and is capable of modelling complex functions. An ANN consists of an input, an output, and

one or more hidden layers. Information of source is propagated into the neural network through the input layer. The output layer gives the results of information processing. The number of hidden layers depends on the complexity of the problem, but in most cases it was found that one or two hidden layers are sufficient [11,45-48]. Each layer consists of a number of neurons, which are the basic structural components of neural networks. The numbers of neurons in the input and output layers are equal to the numbers of input variables and targets, respectively. Several methods have been used by investigators to determine the number of neurons in the hidden layers, but they only produce general guidelines [49-52]. The optimum number of neurons in the hidden layers is often determined by trial and errors. The neural network is trained with different numbers of hidden neurons and the best number of hidden neurons is determined according to the values of one or more evaluating statistical criteria such as mean square of errors (MSE), mean absolute error (MAE), coefficient of determination (R^2), and so on. This kind of neural networks is often called multi-layer perceptron (MLP) neural network. The output of each neuron is sent to all neurons of the next layer through weighted connections. In each neuron input values are added with a bias, and then an activation function is applied on the resulting value to yield the output as:

$$y_i = f(\sum_{j=1}^n w_{ij}x_j + b_i) \quad (6)$$

where y_i is the i^{th} neuron's output, x_j is the output of j^{th} neuron in the previous layer, w_{ij} is the weight, b_i is the bias of the i^{th} neuron, and f is the activation function. Weights are randomly selected at the beginning of the training process and then adjusted according to a training algorithm. Here the PSO algorithm is used as an alternative to traditional training algorithms such as Levenberg-Marquardt (LM), gradient descent (GD), and so on. The optimization algorithm minimizes the MSE as cost function.

Although not compulsory, input data are often normalized between 0 and 1 to avoid some numerical problems. This also causes the input data to be of the same order. The input dataset is divided into two parts: training data and test data. Training data are used to train the neural network according to the PSO algorithm. Test data are used to identify how well the ANN is trained.

The performance of ANNs may be assessed based on

some statistical criteria including mean squared error (MSE), maximum absolute relative deviation (Max ARD %), average absolute relative deviation (AARD %), and correlation coefficient (r), defined as:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_{i\text{exp}} - y_{i\text{cal}})^2 \quad (7)$$

$$\text{Max ARD \%} = \text{Max}_{i=1}^n \left(\left| \frac{y_{i\text{exp}} - y_{i\text{cal}}}{y_{i\text{exp}}} \right| \times 100 \right) \quad (8)$$

$$\text{AARD \%} = \frac{1}{n} \sum_{i=1}^n \left| \frac{y_{i\text{exp}} - y_{i\text{cal}}}{y_{i\text{exp}}} \right| \times 100 \quad (9)$$

$$r = \frac{\sum_{i=1}^n [(y_{i\text{exp}} - \bar{y}_{\text{exp}})(y_{i\text{cal}} - \bar{y}_{\text{cal}})]}{\sqrt{\sum_{i=1}^n (y_{i\text{exp}} - \bar{y}_{\text{exp}})^2 \sum_{i=1}^n (y_{i\text{cal}} - \bar{y}_{\text{cal}})^2}} \quad (10)$$

where $y_{i\text{exp}}$, $y_{i\text{cal}}$, \bar{y} , and n are experimental data, predicted data by ANN, mean value of data, and number of data points, respectively.

5. Artificial Neural Network Architecture

In the present study an optimal multi-layer perceptron neural network was designed to model the experimental data of turbulent flow of non-Newtonian nanofluids in a circular tube with constant wall temperature. Our previous experimental data are used to obtain the ANN model [16].

The optimum neural network architecture was determined by trial and error according to steps shown in Figure 2.

First experimental data were normalized between 0 and 1 according to equation (11):

$$X_{i,\text{norm}} = \frac{X_i - X_{i,\text{min}}}{X_{i,\text{max}} - X_{i,\text{min}}} \quad (11)$$

Then randomly divided into three parts: training data set (75%), validating data set (5%), and test data set (20%). The architecture of an ANN is normally determined by trial and error. First, the number of hidden layers and the number of neurons in each layer were set. Then the network was trained by a training algorithm. The activation functions of hidden and output layers were changed and the performance of ANN was assessed to specify the best activation functions. In

order to determine the best number of hidden neurons, the network was trained with different numbers of hidden neurons and its performance was evaluated. After that, the number of hidden layers was changed to determine the best number of hidden layers. Next, the best activation function of added hidden layers was also determined by trial and error. To evaluate the network repeatability each network trained 15 times. Finally, instead of using conventional training algorithms for training the ANN, the PSO algorithm is used to determine the best values of ANN parameters (weights and biases).

The ANN architecture shown in Figure 3 consists of two hidden layers of 6 and 9 neurons, respectively. The activation functions of both hidden layers are hyperbolic tangent sigmoid transfer function (tansig), and that of the output layer is a linear transfer function (purelin). MSE was chosen as the network performance function. It evaluates the ANN performance according to the mean of squared errors. ANN receives nanofluid concentration, Reynolds number, and Prandtl number as input parameters and gives the resulting Nusselt number as output.

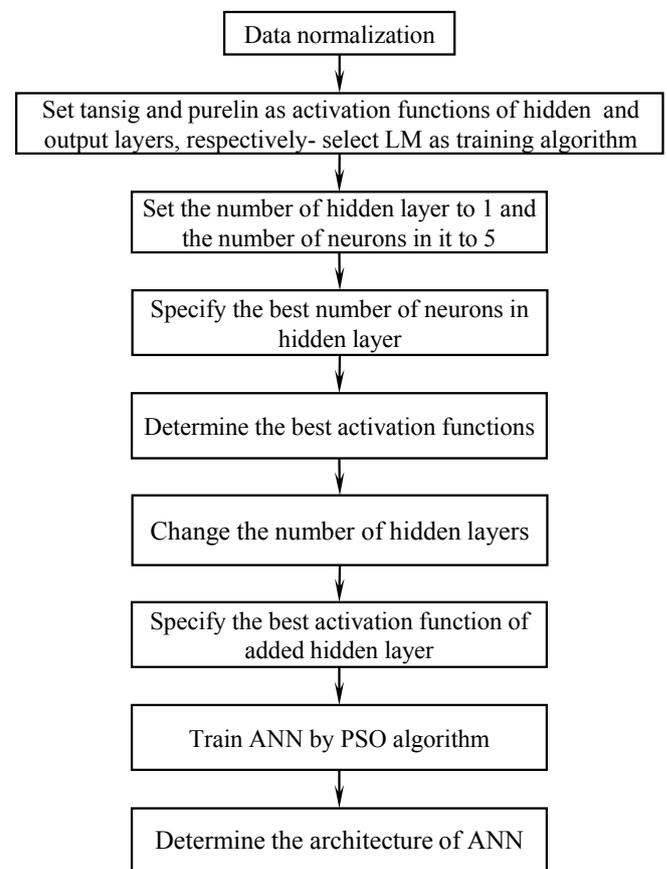


Fig. 2. Algorithm for optimization of ANN architecture.

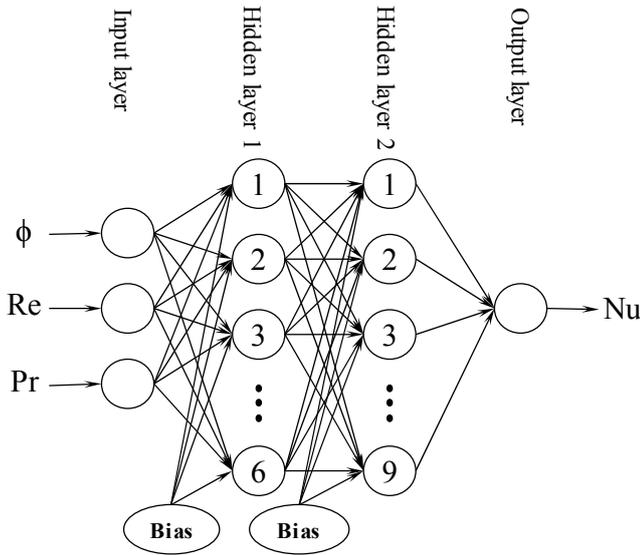


Fig. 3. Architecture of the ANN.

5. Results

Figure 4 shows the ANN predicted values of Nu in comparison with the experimental data. As can be seen, there exists very good agreement between the experimental data and corresponding values predicted by the ANN model. The values of statistical criteria, given in Table 2, suggest the accuracy of the proposed ANN.

Values predicted by the ANN model are compared with experimental data in Figure 5. Excellent agreement between the ANN model and experimental data is obvious. Max ARD % and AARD % of ANN are about 5.6 and 0.8%, respectively.

The following correlation has been proposed for the Nusselt number of non-Newtonian nanofluids [16]:

$$Nu = 0.00115 Re^{1.050} Pr^{0.693} (1 + \phi^{0.388}) \quad (12)$$

($2900 < Re < 8800$ and $39 < Pr < 71$)

In Table 3 the artificial neural network is compared with the above mentioned correlation. It is clear that the ANN predicts the Nu of nanofluids better than the correlation. Max ARD % and AARD % of ANN are

Table 2. Statistical criteria of the proposed ANN.

	Max ARD %	AARD %	r
Training data	1.37729	0.316967	0.9999
Test data	5.638172	2.357044	0.9880

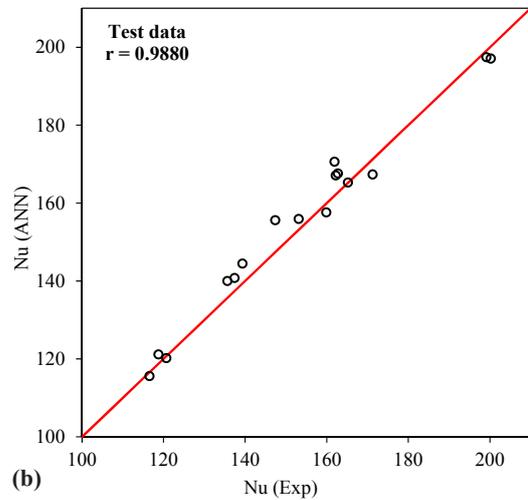
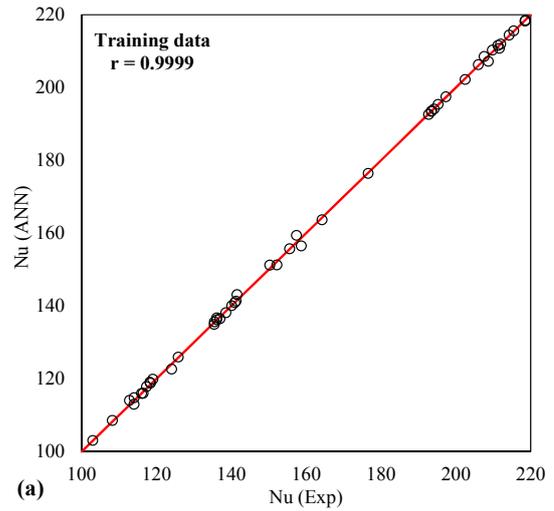


Fig. 4. ANN predicted Nu against experimental Nu in (a) training dataset and (b) test dataset.

almost half and one fifth of those of the correlation, respectively.

6. Conclusion

Nanofluids are a new class of heat transfer fluids that possess better thermal characteristics than the base fluids. Correlation of conventional heat transfer fluids cannot predict the behavior of nanofluids well. So finding new models for predicting the features of nanofluids is important. An artificial neural network has the ability of modeling nonlinear functions. In this

Table 3. Comparison of ANN and equation (12) for Nu of non-Newtonian nanofluid.

Method	Max ARD %	AARD %
ANN	5.64	0.83
Proposed correlation [16]	10.4	3.82

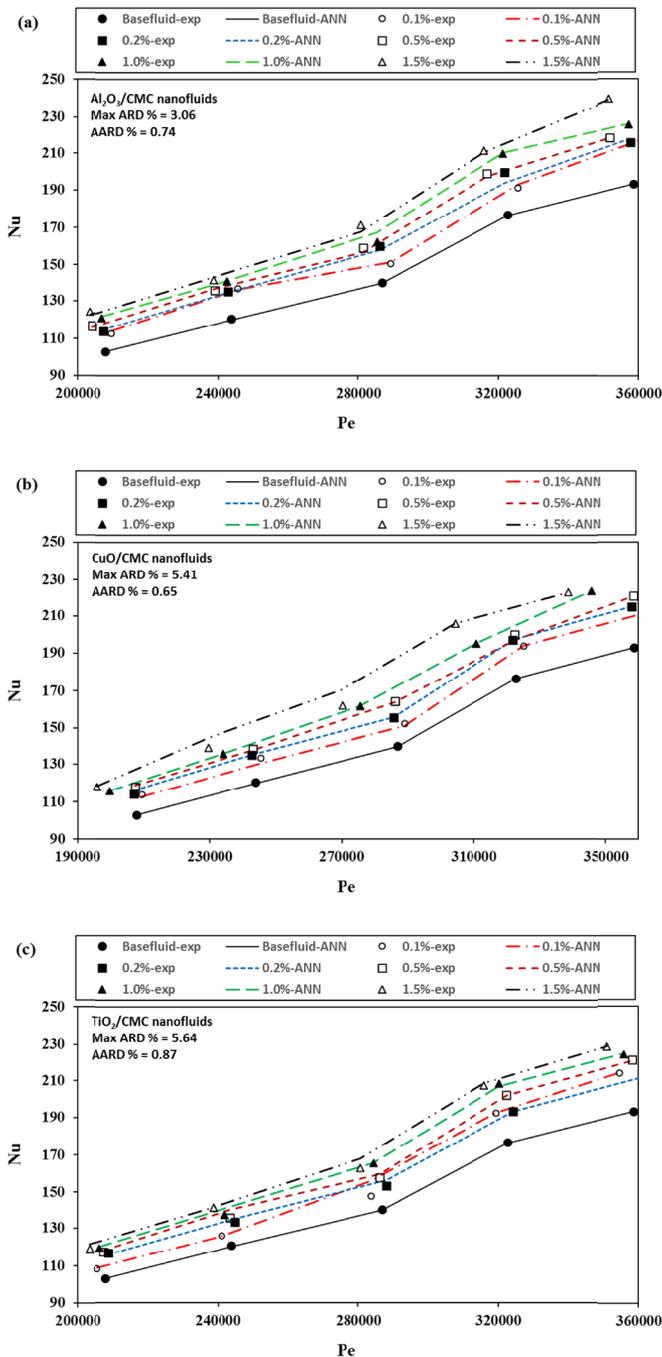


Fig. 5. Comparison between experimental data [16] and values predicted by the ANN (a) $\text{Al}_2\text{O}_3/\text{CMC}$, (b) CuO/CMC and (c) TiO_2/CMC nanofluids.

investigation an artificial neural network was designed and optimized by PSO algorithm to predict the Nusselt number of non-Newtonian nanofluids flowing through a circular tube subjected to constant wall temperature in a turbulent regime. The developed network consists of two hidden layers with six and nine neurons, respectively. Max ARD % and AARD % between the ANN predicted values and experimental data are 5.64 and 0.83, respectively; this indicates the excellent predictive ability of the ANN. Results also show that the

ANN is better than the previously proposed correlation. The maximum and average absolute relative deviations of the ANN are almost half and one fifth of the values predicted by the correlation in the literature.

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