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Heat Transfer Analysis of Different Coolant in the Waist Tubes of a Radiator and Performance Prediction Based on Artificial Neural Network

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ABSTRACT

In this study, water, 0.05 Al_2O_3/water and 0.05 CuO/water nanofluids as a coolant in the waist tubes of a radiator are investigated numerically to evaluate their thermal and flow performance. Results are presented in terms of temperature distribution, heat transfer coefficient for different states. The results indicate that coolant has a significant impact on the heat transfer performance of the radiator, nanofluids increase the heat transfer coefficient. In addition, artificial neural network (ANN) was proposed for temperature difference between inlet and outlet of coolant prediction, ANN shows an extremely high prediction accuracy. The present study can help to understand the heat and flow behaviour of nanofluids in the waist tube.

1. INTRODUCTION

Radiator is one of the most important components of automobile engine cooling system, its role is to ensure that the engine works in the appropriate temperature range, avoiding overheating phenomenon. Its heat transfer performance directly affects the economy of the vehicle operation, reliability and the service life of engine parts. Fin-and-tube radiator are one of the mostly used in the automobiles. In this type of radiator, the heat transfer core is composed of a large number of Fins and tubes. As depicted in Figure 1, heat transfer between hot and cold fluids occurs via conduction through tube walls [1, 2].

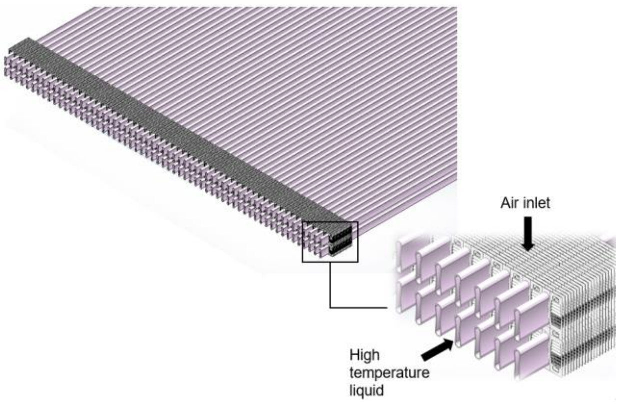

Figure 1. Fin-and-tube radiator core

With the rapid development of automobile industry, the requirements for heat transfer performance of radiators are becoming higher and higher. a significant research effort has been committed by modifying thermo-physical properties of working fluid.

1.1 Nanofluid as a coolant

At present, many studies conducted on nanofluid as a coolant to enhance the heat transfer performance in the radiator, which means that just one kind of solid particles was dispersed into base fluids to obtain the corresponding nanofluids. Hussein et al. [3] have simulated the effect of a nanofluid on the turbulence flow in a circular tube. Their results indicated that the addition of TiO_2 particles increase the heat transfer coefficient and friction coefficient. Elsebay et al. [4] performed a numerical study to examine the thermal performance of two nanofluids (Al_2O_3 /water and CuO/water) using flat tubes of an automobile radiator. The results demonstrated a significant enhancement the heat transfer rate of the automobile radiator. The increase in heat transfer coefficient reached 45 and 38% for Al_2O_3 /water and CuO, respectively compared to the values of the pure water. Zhang et al. [5] present study fabricated a hybrid Al_2O_3-CuO/water nanofluid and investigated its turbulent thermal and flow performance in a circular tube. Results reveal a relative enhancement of 2–35% in heat transfer performance of hybrid Nanofluid and pressure drop enlargement ranging from 1% to 12% under various flow rates.

1.2 ANN prediction

Artificial neural network (ANN) is a mathematical or computational model that mimics the structure and function of biological neural networks. ANN is mainly used for classification, prediction and cluster analysis of data. Its structure generally has input layer, hidden layer, output layer, Figure 2 shows the neural network structure that is adopted in this study.

In recent years, studies have proven that ANN models are a more adaptive and accurate method for the prediction for heat transfer related problems [6]. Wen et al. [7] proposed A novel genetic algorithm-optimized backpropagation artificial neural network for Nusselt number prediction. The developed ANN shows an extremely high prediction accuracy with a mean absolute relative deviation of 2.70%.

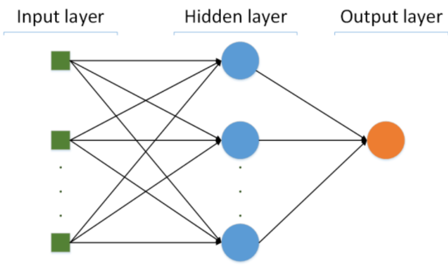

Figure 2. Schematic diagram of neural network structure

A MLP based ANN was developed by Pare and Ghosh [8] to estimate the thermal conductivity of metal oxide based nanofluids. The proposed ANN model was accurate to within 2% of the experimental dataset. Ahmadi et al. [9] proposed neural networks were used to predict pressure drop of CuO-based nanofluid in a car radiator. The outcomes indicated which a high accuracy in modeling and estimating the pressure drop of nanofluid flows in the studied.

In this study, CFD simulation was conducted and artificial neural network models were employed to predict heat transfer performance.

2. MATHEMATICAL MODELING

2.1 Geometry of the problem and basic settings of CFD simulation

A waist tube has a high surface to-cross- sectional flow area ratio, which enhances the heat transfer rate. The Figure 3. presents the radiator tube with waist section and a 600 mm length. The cooling fluid entered into the tube from one side and then leaved it from the other side of.

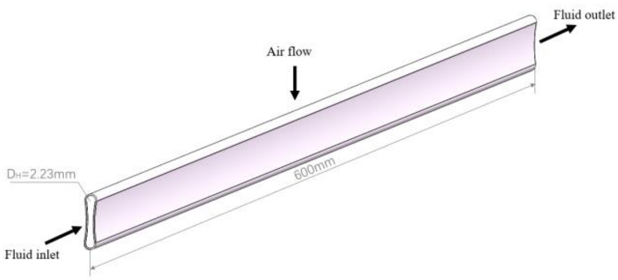

Figure 3. Simulated geometry.

The boundary conditions for the inlet and outlet were velocity inlet and pressure outlet respectively. According to formula (1), The Realizable k-ε model was selected to describe the turbulence in present study. Enhanced wall treatment approach was selected for the near-wall treatment and the grid of the wall boundary layer is encrypted. The commercial software of Fluent 19.2 was used to solve the governing equations, the Semi-Implicit Method for Pressure Linked Equations (SIMPLE) scheme was employed. When the CFD calculation converged, the required parameters of outlet fluid temperature, pressure and heat transfer coefficient could be obtained. Subsequently, the flow and thermal characteristics for water and hybrid nanofluids were calculated.

$$Re = \frac{\rho v D_H}{\mu} \tag{1}$$

where, ρ is fluid density(kg/m^3), v is inlet velocity(m/s), μ is fluid dynamic viscosity(kg/m.s), D_H is hydraulic diameter(m).

2.2 Governing equations

To simulate the current problem, The three conservation equations were presented as follows [10, 11]:

Continuity:

$$\frac{\partial}{\partial x_i}(\rho_n N_i) = 0 \tag{2}$$

where, N_i is a component of the velocity vector(m/s),

Momentum:

$$\frac{\partial}{\partial x_i}(\rho_n N_j N_i) = -\frac{\partial p}{\partial x_j} + \frac{\partial}{\partial x_i}\left(\mu_n\left(\frac{\partial U_j}{\partial x_i}\right)\right) \tag{3}$$

where, ρ_n is the density of nanofluid(kg/m^3), p is the pressure(pa), μ_n is nanofluid viscosity (kg/m.s)and $i, j \in \{1,2,3\}$.

Energy:

$$\frac{\partial}{\partial x_i}(\rho_n C_{pn} U_i T) = \frac{\partial}{\partial x_i}\left(K_n\left(\frac{\partial T}{\partial x_i}\right)\right) \tag{4}$$

where, C_{pn} is the specific heat of nanofluid (J/Kg.K), T is the flow temperature (K) and K_n is the nanofluid thermal conductivity (W/m.K).

2.3 Thermophysical properties of nanofluid

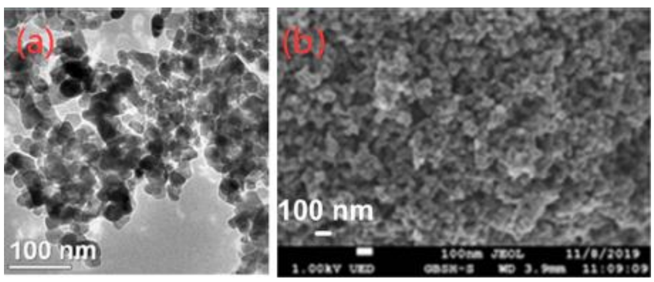

Figure 4. SEM images of nanoparticles [12]. (a) Al_2O_3, (b) CuO

Table 1. Thermal properties of nanoparticles and base fluid [13]

Material	specific heat [J/kg.K]	thermal conductivity [W/m.K]	Density [kg/m^3]	Viscosity [kg/m.s]
Water-fulid	4182	0.6	998.2	0.001003
Al_2O_3-water	3591.66	0.80348	1123.02	0.00061
CuO-water	3302.6	0.80198	1225.02	0.00061

The hybrid Al_2O_3-CuO/water nanofluid was fabricated through a two-step method. The Scanning Electron Microscope (SEM) images for these two kinds of nanoparticles are displayed in Figure 4. The properties used in this study are listed in Table 1.

The following correlations have been used to predict nanofluids thermal conductivity, viscosity, specific heat and density, respectively [14, 15].

$$K_n = \left[\frac{K_w+2K_w+2(K_m-2K_w)(1+\alpha)^3\varphi}{K_w+2K_w-2(K_m-2K_w)(1+\alpha)^3\varphi}\right]K_w \tag{5}$$

$$\mu_n = (1+7.3\varphi+123\varphi^2)\mu_w \tag{6}$$

$$C_{pn} = \frac{\varphi\rho_m C_{pm}+(1-\varphi)\rho_w C_{pw}}{\rho_n} \tag{7}$$

$$\rho_n = (1-\varphi)\rho_w + \varphi\rho_m \tag{8}$$

where, α is the ratio of the nanolayer thickness to the original particle radius (α=0.1), φ is the nanoparticles volume concentration and the subscripts "*n*", "*w*" and "m" refer to nanofluid, base fluid and particle, respectively. The properties used in this study are listed in Table 1.

2.4 Grid independence check

In order to verify that the number of grids will not affect the numerical simulation results, four different meshes were investigated and specific results are shown in Table 2. Considering the calculation accuracy and calculation time comprehensively, select 3792000 here as the number of grids for numerical simulation.

Table 2. Grid independence verification

Mesh	Element number	Pressure drops	T_p
Mesh1	1188972	328.5215	23249.72
Mesh2	1491000	328.5036	23366.15
Mesh3	3792000	328.3513	23670.95
Mesh4	3834874	328.3545	23671.17

2.5 Validation of model

Under the same working conditions, the experimental data are compared with simulation results, the maximum deviation is 10.75%, as shown in Figure 5. The results verify the reliability of the numerical simulation model used in this study.

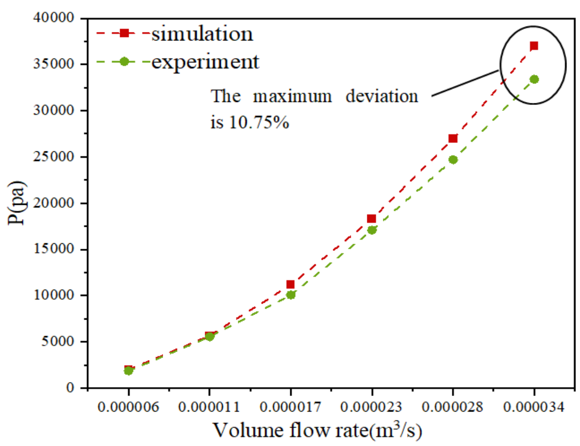

Figure 5. Model verification

3. ARTIFICIAL NEURAL NETWORK (ANN) MODEL

Since BP_ANN neural network has an extremely strong nonlinear mapping capability, Figure 6. presents a BP_ANN neural network used as a prediction model in this paper. The input layer has three nodes x_1 input for the inlet temperature, x_2 for the coolant inlet flow velocity, x_3 for the density of the coolant, and one node for the output layer, which predicts the temperature difference between the outlet and inlet coolant.

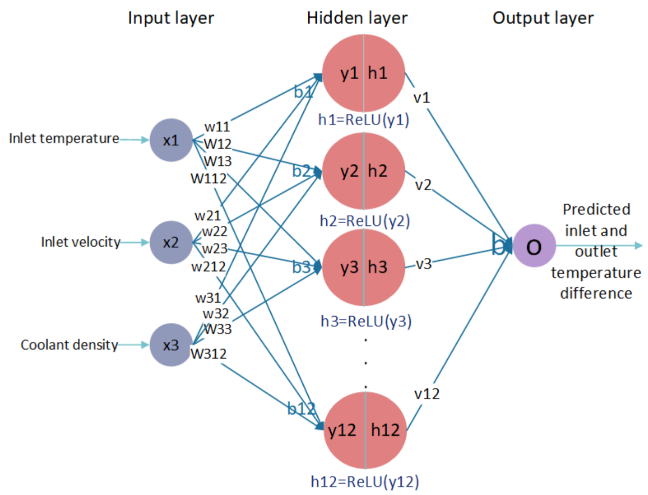

Figure 6. Neural network model for predicting inlet and outlet temperature difference

After data standardization, the data is input from the input layer, Suppose the k-th data sample input data is $x^k = [x_1^{(k)}, x_2^{(k)}, x_3^{(k)}]$, where, the subscript is the index of the input node of the input layer. Then in the forward propagation of this network, the y_i of the hidden layer is [16]:

$$y_i = [x_1^{(k)}, x_2^{(k)}, x_3^{(k)}] * \begin{bmatrix} w1,i \\ w2,i \\ w3,i \end{bmatrix} + b_i \tag{9}$$

where, $w_{1,i}$ is the weight of the first input node in the input layer corresponding to the *i*-th node in the hidden layer; y_i is the input of the *i*-th node of the hidden layer. b_i is the bias of the *i*-th node of the hidden layer.

The activation function of the hidden layer uses ReLU.

$$h_i = \mathrm{ReLU}(y_i) = \max(0, y_i) \tag{10}$$

During the forward propagation of the BP network, the output layer result o is:

$$o = [h_1, h_2, h_3, h_4 \cdots, h_{12}] * \begin{bmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \\ \vdots \\ v_{12} \end{bmatrix} + b \tag{11}$$

where, v_1 is the corresponding weight; b is the bias of the output layer; o is the temperature difference we predict.

During data training, there is an error between the predicted and true values, and the loss function used in this paper is MSE, which is calculated as follows:

$$E_{total} = \frac{1}{2}(t - o)^2 \quad (12)$$

where, t is the real value.

According to the chain rule, the updated value of each weight can be calculated. For example, after each training of bias b_i, it is modified as:

$$b_i = b_i - \eta \frac{\partial E_{total}}{\partial b_i} \quad (13)$$

where, η is the learning rate; $\frac{\partial E_{total}}{\partial b_i}$ is the gradient of E_{total} in the direction of b_i.

In this paper, there are 40 input data, after shuffling the data, 70% of the data are set as training set, 15% of the data are set as validation set and 15% of the data are set as test set. the learning rate is set to 0.001, the gradient descent algorithm is SGD, and the epoch is set to 50000.

4. RESULTS AND DISCUSSION

When the CFD calculation converged, the required parameters of outlet fluid temperature, pressure and heat transfer coefficient could be obtained. Subsequently, the flow and thermal characteristics for water and hybrid nanofluids were calculated.

4.1 Temperature analysis of different coolants

As shown in Figure 7, under the same working conditions, the temperature of liquid water in the tube is the highest, while that of CuO/water is the lowest. The results indicate that coolant has a significant impact on the heat transfer performance of the radiator, compared with liquid water, nanofluid has stronger heat transfer ability.

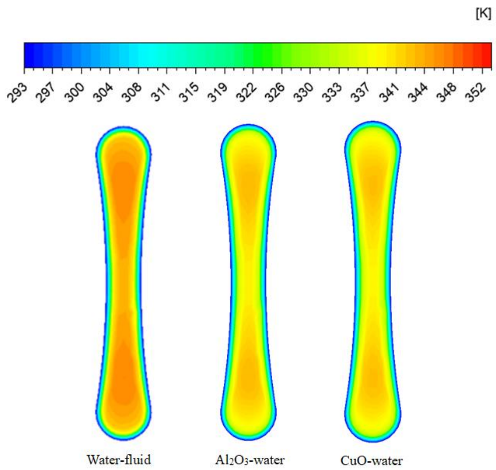

Figure 7. Contour of temperature in the same section

4.2 Analysis of inlet and outlet temperature difference and heat transfer coefficient

Under the same working conditions, the greater the temperature difference between the inlet and outlet, the better the heat dissipation effect. It can be seen that CuO/water has the best heat dissipation performance from Figure 8.

As shown in Figure 9, the heat transfer coefficient of three different cooling media increases with the increase of the volume flow rate. Under the same volume flow rate, the maximum heat transfer coefficient is CuO/water, and the minimum is water, the result indicates that the nanofluid as a coolant in the waist tube strengthens the heat transfer.

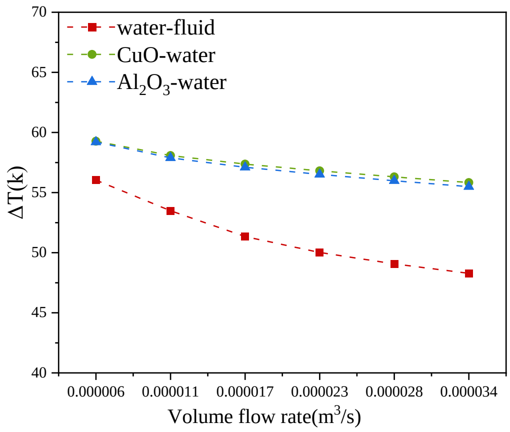

Figure 8. Temperature difference between the inlet and outlet at different volume flow rate

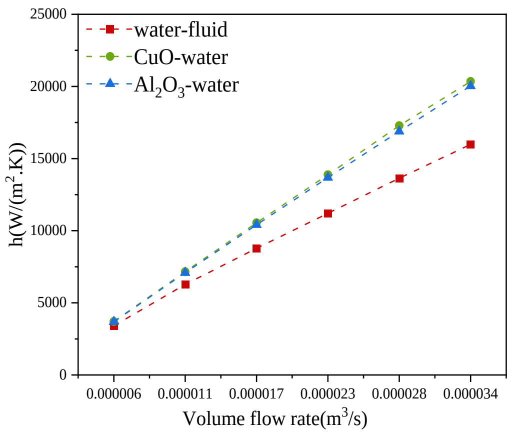

Figure 9. Heat transfer coefficient at different volume flow rate

4.3 ANN prediction results

In this paper, the modeling coefficient which is used to evaluate the fitting degree of the model is:

$$R^2 = 1 - \frac{SSE}{SST} \quad (14)$$

where, SSE is the sum of squares of errors; SST is the sum of squares of the total.

Generally speaking, the closer R^2 is to 1, the higher the fitting degree of the model. Figure 10 shows the difference between the predicted temperature difference and the real temperature difference on the validation data set. The graphs show that the predicted values are very close to the true values.

Figure 11 shows the goodness of fit between the real value and the predicted value on the validation data set. The results show an extremely high fit.

Figure 12 shows the difference between the predicted temperature difference and the real temperature difference on the test data set.

Figure 13 shows the goodness of fit between the real value and the predicted value on the test data set. The results show that the fit of the model is also good on the test data set.

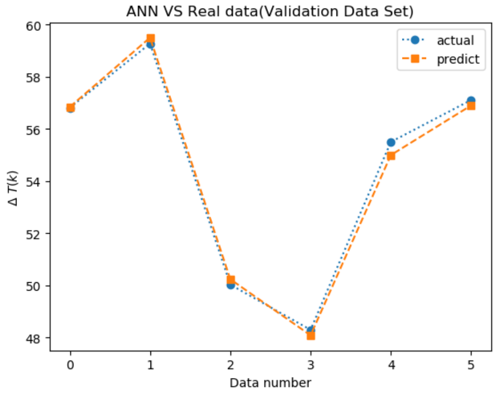

Figure 10. Comparison of ANN modeling results with real data on validation data set

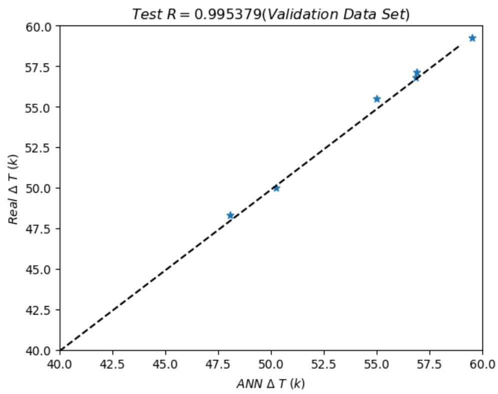

Figure 11. Fitting degree of ANN model on validation data set

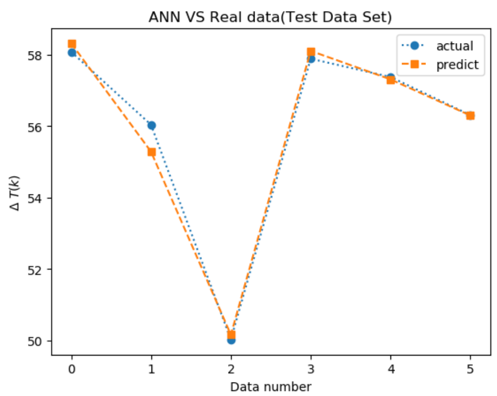

Figure 12. Comparison of ANN modeling results with real data on test data set

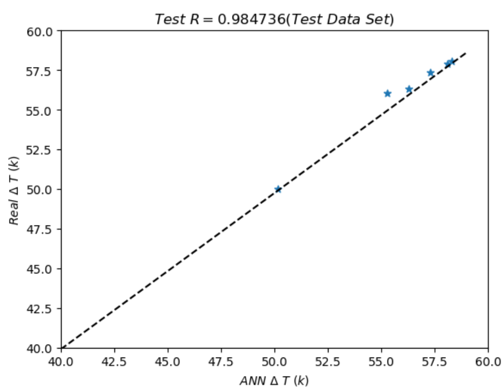

Figure 13. Fitting degree of ANN model on test data set

5. CONCLUSION

In this paper, the flow characteristics and heat transfer performance in a waist tubes of a radiator have been investigated numerically with three distinct working fluids: water and two water based nanofluids (Al_2O_3/water and CuO/water). Artificial neural network (ANN) was proposed for temperature difference between inlet and outlet of coolant prediction. The following conclusions are made:

1. Coolant has a significant impact on the heat transfer performance of the radiator, Al_2O_3/water and CuO/water can enhance the heat transfer rate of the automobile radiator.
2. ANN shows an extremely high prediction accuracy.

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