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Artificial Neural Modeling of the Heat Transfer in an Air Cooled Heat Exchanger Equipped with Butterfly Inserts

A. Karami*[1], E. Rezaei[+], M. Rahimi[#] and M. Zanjani*

Abstract *– The present study is conducted in order to demonstrate the capability of the artificial neural network (ANN) in predicting the heat transfer in an air-cooled heat exchanger equipped with butterfly inserts. The effects of the inclined angle of the inserts (θ) and Reynolds number (Re) variation on average heat transfer in the air cooler are considered via this prediction. The training data for optimizing the ANN structure is based on available experimental data. The Levenberg-Marquardt back propagation algorithm is used for ANN training. The proposed ANN is developed using MATLAB functions. For the best ANN structure obtained in this investigation, the mean relative errors of 0.109% and 0.509%were reached for the training and test data respectively. The results show that predicted values are very close to experimental ones.*

Keywords – Air-cooled heat exchanger, artificial neural network (ANN), butterfly inserts, inclined angle, modeling.

1. INTRODUCTION

It is commonly known that the heat transfer rate of heat exchangers, especially for single-phase flows, can be improved through many enhancement techniques. In general, heat transfer enhancement (HTE) techniques can be divided into two categories: (1) active techniques which need an external power source and (2) passive techniques which do not need an external power source. Some examples of passive HTE methods include: insertion of twisted stripes and tapes [1], [2], insertion of coil wire and helical wire coil [3], [4] and mounting of turbulent decaying swirl flow devices [5], [6]. Despite the high pressure drop caused by an insert in embedded tubes, the use of tube inserts in heat exchangers has received a lot of attention during the last two decades [2], [7]. The increase in turbulence intensity and swirling flow may be the main reasons for HTE induced by tube inserts. Sivashanmugam and Suresh [8] studied the heat transfer and friction factor characteristics of circular tube fitted with full-length helical screw element of different twist ratio, and helical screw inserts with different spacer length. The aim of the paper was to investigate the effect of spacer length on heat transfer augmentation and friction factor, and the effect of twist ratio on heat transfer augmentation and friction factor. It was reported that heat transfer increases with the twist ratio and friction factor also increases with the twist ratio. Naphon [9] experimentally investigated the heat transfer characteristics and the pressure drop in the horizontal double pipes with twisted tape insert. The effects of relevant parameters on the heat transfer and pressure drop were considered in the paper. It was observed that the twisted tape insert has important effect on enhancing heat transfer rate. However, the pressure drop also increases. Sivashanmugam and Suresh [10] experimentally studied the heat transfer and friction factor characteristics of laminar flow through a circular tube fitted with helical screw-tape inserts. The main focus of the study was to investigate the effects of the Reynolds number and twist ratio of the inserts on heat transfer and friction factor characteristics of the tube. It was shown that the heat transfer increases with the twist ratio and friction factor also increases with the twist ratio. Chang *et al.* [11], [12] presented a comparison between the heat transfer and friction factor characteristics of smooth twisted tape with broken and serrated twisted tape inserts, based an experimental study. Sivashanmugam and Suresh [13] conducted an experimental study on the heat transfer and friction factor characteristics of turbulent flow through a circular tube fitted with helical screw-tape inserts. The effects of the Reynolds number and twist ratio of inserts were considered in this investigation. It was found that heat transfer and friction factor increase with the twist ratio. Murugesan *et al.* [14] investigated the effects of V-cut twisted tape inserts on heat transfer, friction factor and thermal performance factor characteristics in a circular tube. The experiments included the twist ratios (Y) and different combinations of depth (DR) and width ratios (WR). The results indicated that the average Nusselt number and average friction factor in the tube with V-cut twisted tape increase with the decreasing twist ratios (y), width ratios (WR) and increasing depth ratios (DR). Sivashanmugam and Suresh [15] studied the heat transfer and friction factor characteristics of circular tube fitted with full-length helical screw element of different twist ratio, and helical screw inserts with different spacer length. The effect of spacer length on heat transfer augmentation and friction factor, and the effect of twist ratio on heat transfer augmentation and friction factor were presented separately. It was reported that the heat transfer and friction factor increase with the

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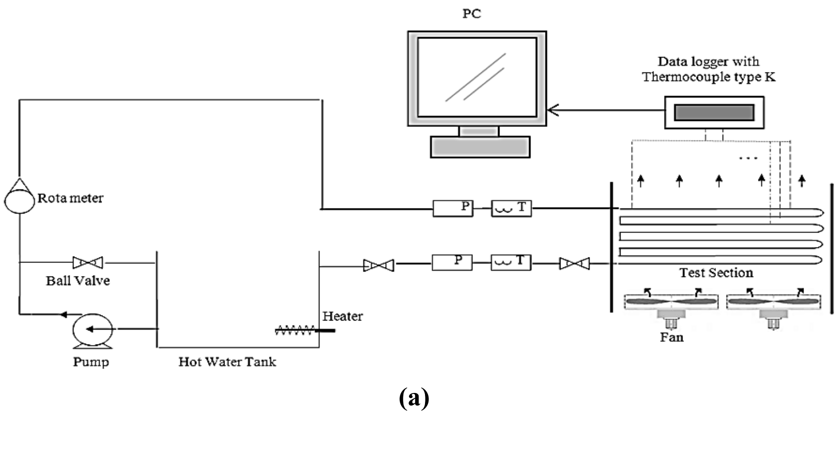
twist ratio. Moreover, the heat transfer for the helical twist decreases with increasing the spacer length. Rahimi *et al.* [16] numerically and experimentally investigated the heat transfer and friction factor characteristics of a tube equipped with modified twisted tape inserts. Four types of inserts including the classic, perforated, notched and jagged twisted tape inserts were employed in the experiments. The results indicated that the heat transfer and performance of the jagged insert are higher than other ones. Shabanian *et al.* [17] numerically and experimentally studied the heat transfer enhancement in an air cooler equipped with different tube inserts. It was observed that using the different tube inserts (butterfly, jagged and classic twisted tape inserts), increases the heat transfer from the air cooler. In addition, it was shown that by using the butterfly insert with an inclined angle of 90◦, maximum heat transfer is obtained. Also, the results revealed that the thermal performance factor decreases with the increase in Reynolds number, due to the more significant role of inserts in increasing the turbulence intensity at lower velocities.

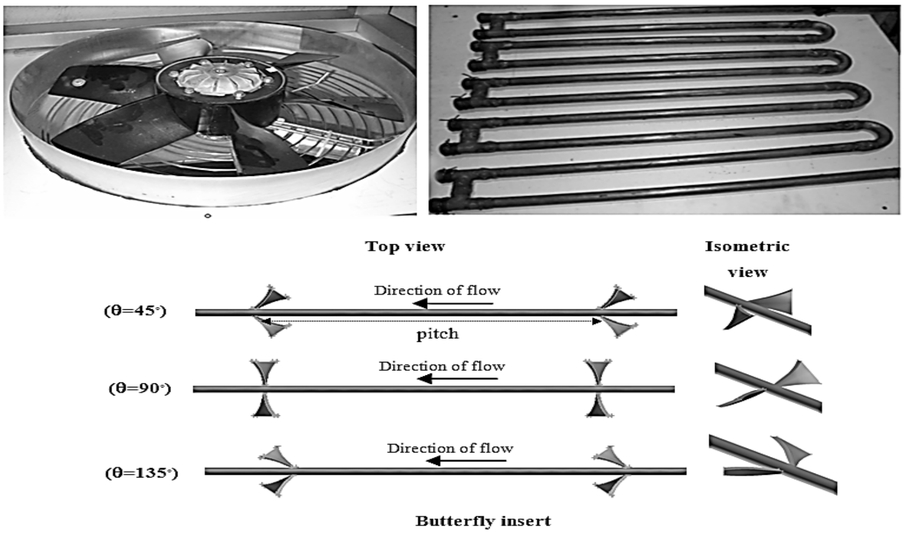
The current study is mainly focused on the modeling of the heat transfer in an air cooler equipped with butterfly inserts using an Artificial Neural Network (ANN). The applied experimental data to train and test the network were obtained by Shabanian *et al.* [17]. The ANN is presently one of the powerful tools widely used for modeling of various heat transfer processes. Sozen and Arcaklioglu [18] developed an ANN based model for the Exergy analysis of an ejector-absorption heat transformer. Pesteei and Mehrabi [19] Modeled the convection heat transfer of supercritical carbon dioxide in a vertical tube at low Reynolds numbers, using a neural network. Mohanraj *et al.* [20] demonstrated the capability of ANN approach in predicting the performance of a direct expansion solar assisted heat pump. Zdaniuk *et al.* [21] presented a neuro-based model for correlating heat transfer and friction in helically-finned tubes. Seyedan and Ching [22] applied ANN for the Sensitivity analysis of freestream turbulence parameters on stagnation region heat transfer using a neural network. Krzywanski and Nowak [23] adopted an ANN model to predict the heat transfer coefficient in the furnace of CFB boilers. Xie *et al.* [24] employed an ANN model to forecast the performance of laminar and turbulent heat transfer and fluid flow of heat exchangers having large tube-diameter and large tube-row by artificial neural networks.

2. EXPERIMENTAL APPARATUS

A schematic view of the experimental rig [17] is shown in Figure 1a. The rig consists of two fans and a set of copper tubes. The set of tubes has three sections including a calming section, bent tube and outlet section. The fluid enters the calming section which has a length of 2 m to eliminate the entrance effect. The temperature and pressure are measured at the end of this section at the inlet of bent tube section. Then, the fluid passes through nine bends in the 6.5m length of bent tube and reaches the outlet section. The pressure and the temperature are measured at the outlet section. The 50 W fans with 1400 rpm rotation speed are placed at a 20cm distance beneath the bent tube and entire assembly is enclosed in a $60 \times 100 \times 50$ cm cubic channel [17]. Hot water from a 100 liter reservoir equipped with heaters enters the bent tube after passing through the rotameter with a 58°C temperature. Water volumetric flow rate varies from 100 lit/hr to 400 lit/hr, which corresponds to Reynolds numbers from 4021 to 16118. The tube inlet and outlet water pressure and temperature are measured through two pressure transmitters and a copper-constantan thermocouple. Moreover, in order to determine the average Nusselt number, the temperatures at 20 different positions on the outer surface of the tube are measured. All twenty temperature sensing probes are connected to a data logger set [17]. In the experiments, the butterfly insert, is placed in the bent tube. Figure 1b shows the bent tube, fan and tube inserts used in the experiment. The tube applied here has a 17mm of outer diameter and a 1mm thickness. The butterfly inserts are made from an aluminum sheet with a 0.5mm thickness and consist of a holding rod with a 1.9mm diameter. These inserts are used at three inclined angles of 45°, 90° and 135° between the butterfly piece and the rod with a 6cm pitch length. In the butterfly arrangement, pieces are placed on the rod to increase the flow turbulence intensity in the tube. Also the pieces on the rod are twisted slightly in order to reduce the blocking effect.



(a)



(b)

Fig. 1. (a) Schematic diagram of the experimental rig and (b) the used tools in the experiment.

3. METHOD OF MODELING

3.1 Computational Intelligence Model

The artificial neural networks (ANNs) are strong tools for the prediction and simulation in various engineering applications. In this study, the heat transfer in an air-cooled heat exchanger equipped with butterfly inserts, is adopted as a function of two variables namely the inclined angle of butterfly inserts (θ) and Reynolds number (Re). Therefore an ANN model as shown in Figure 2 is developed with the inclined angle (θ) ranging from 45° to 135° and Reynolds number (Re) from 4021 to 16118 as inputs and average Nusselt number (Nu) as desired output.

3.2 The ANN Advantages

The new techniques such as fuzzy logic (FL) [25], artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) consume less time for computation and offer better accuracy as compared to traditional techniques used for the modeling and prediction purposes. In addition, since the data used for developing the ANN, ANFIS [26] and etc is based on training data, therefore, we can test the validity of the proposed models with the test data. Since for developing a correlation, we basically use the total data, therefore it is not possible to carry on with validity business. It is useful mentioning that, among these new techniques, the ANN and ANFIS are widely used for the modeling and prediction purposes. In the current study, the ANN model is preferred due to following reasons:

a) The speed of training the ANN is more than that of the ANFIS.
b) Two outputs in the ANFIS, requires designing wo networks whereas in the ANN case, it is possible to consider more than one output with a single network.
c) Increasing the number of inputs, increases the time of ANFIS training whereas, the ANN training time is affected by the number of inputs but not that much.
d) Adding an extra input to the ANN, requires that an additional neuron with a simple relation (for example a linear or Tansig relation) to be added to the network, but in the ANFIS case by adding a similar input to the network, in fact one membership function having a nonlinear relationship should be added, which in turn increases the computations volume and subsequently, decreases the training speed of the network.

3.3 Feed Forward Artificial Neural Networks

In this study, the feed forward multi-layer perceptron (MLP) network is selected among the main neural network architectures used in engineering. The ANN is constructed as a massive connection model of simply designed computing unit, called "neuron". Figure 3 illustrates a simple model of -inputs single-output neuron. All the input signals are summed up as and the amplitude of the output signal is determined by the nonlinear activation function.

In this work, the sigmoid function $f(z)$ is used given as follow [27],

$$f(z) = \frac{1-e^{-kz}}{1+e^{-kz}} \tag{1}$$

In the limit of $k = \infty$, as the slope approaches the infinity, $f(z)$ behaves like a threshold function. Here, the sigmoid function is adopted with moderate slope so that the network can output continuous range of values from −1 to 1, which brings the differentiability of the network [27], [28]. Here, a Multilayer Perceptron (MLP) type network is adopted with three layers, which has been used for various applications [29]-[31]. The architecture of the perceptron neural network is shown in Figure 4.

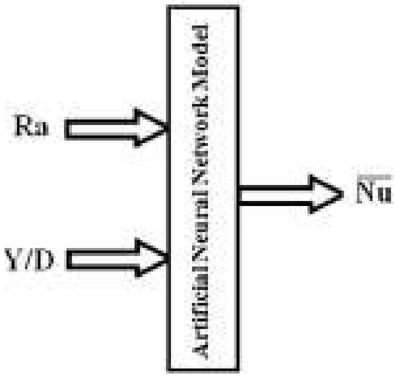


Fig. 2. A simplified overview of the proposed ANN model for heat transfer modeling.

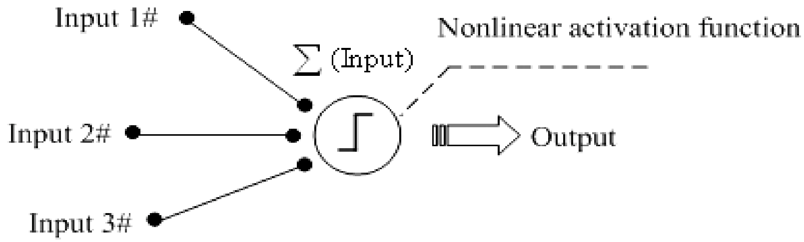


Fig. 3. Basic model of multi-inputs one-output neuron.

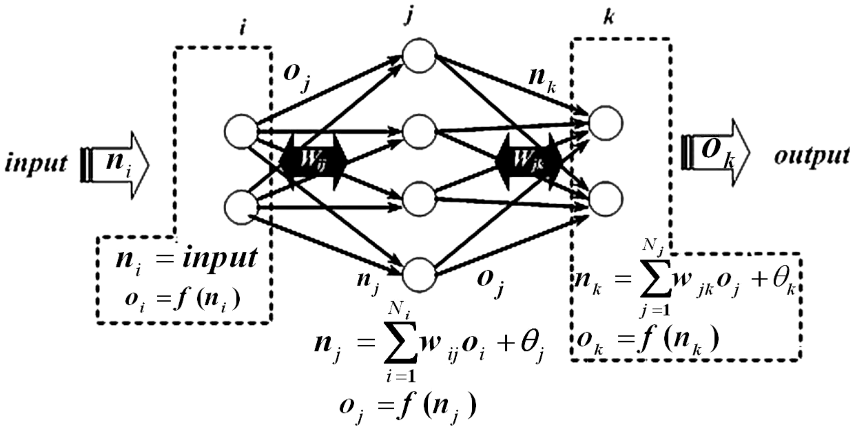


Fig. 4. Three layer multilayer perceptron consisting 'input', 'hidden' and 'output' layers.

For clear notation, the indices i , j and k will be used for the units corresponding to "input", "hidden" and "output" layers, respectively (see Figure 4). Note also that n_i and o_i are used to represent the input and output to the i^{th} neuron, respectively. Input-output properties of the neurons in each layer can be simply expressed in mathematical term as [29],

$$o_i = f(n_i) \quad ; \quad o_j = f(n_j) \quad ; \quad o_k = f(n_k) \tag{2}$$

Whereas inputs to the neurons are given as,

$$n_i = (inputsignaltotheANN) \ , \ n_j = \sum_{i=1}^{N_i} w_{ij} o_i + \theta_j$$

and $$n_k = \sum_{j=1}^{N_j} w_{jk} o_j + \theta_k$$

Here, N_i and N_j represent the numbers of the units belonging to "input" and "hidden" layers, while w_{ij} denotes the synaptic weight parameter which connects the neurons *i* and *j*. Threshold parameter (bias) with respect to the neuron *j* is represented by θ_j . We introduce the sigmoid function only in "hidden" layer to realize smooth and moderate response of the ANN and the linear function for the output layer. This architecture of ANN is a good function approximator. The overall response of the present network is given as,

$$o_k = f_k\left[\sum_{j=1}^{N_j} w_{jk} f_j(n_j) + \theta_k)\right] \tag{3}$$

Where, n_j is defined by Equation 2. ANN training is an optimization process in which an error function is minimized by adjusting the ANN parameters (weights and biases). When an input training pattern is introduced to the ANN, it calculates an output. Output is compared with the real output (experimental data) provided by the user. This difference is used by optimization technique to train the network. The error function to be minimized in our study is Mean Relative Error, *MRE*, and is given as follow,

$$MRE = \frac{1}{n} \times \sum_{i=1}^{n} \left| \frac{y_j - o_j}{y_j} \right| \quad (4)$$

Where, y_j is target data and o_j is the output of the neural networks. In our method the target data is the experimental data. The network is trained via the fast convergence gradient-descend back-propagation [31] method with momentum term for the nonnegative energy function [27], [29]. The back-propagation training algorithm is an iterative gradient algorithm, designed to minimize the mean relative error between the predicted output and the desired output (experimental data). The algorithm of training the network with back-propagation is summarized as follows:

i. Initialize the parameters: set all weights to small random values.
ii. Present input and output pairs: present a continuous valued input vector and specify the desired outputs. Usually the training sets are normalized to values between 0 and 1 during processing.
iii. Compute the output of each node in the hidden layer.
iv. Compute the output of each node in the output layer.
v. Compute the output layer error between the target and the observed data.
vi. Compute the hidden layer error.
vii. Adjust the weights and thresholds in the output layer.
viii. Adjust the weights and thresholds in hidden layer.

4. MODELING RESULTS

Twenty one values for the average Nusselt number from the experimental data obtained by Shabanian *et al.* [17] are used to build up the ANN model, fifteen data (about 70% of the total data) are used for training and the rest six data (about 30% of the total data) are used for testing the ANN model. The final ANN architecture used in this study is described in Table 1. Moreover, additional information related to the network parameters can be observed in this table. The training and testing results of the proposed ANN model are shown in Figures 5 and 6. The comparison between average Nusselt numbers obtained from the experiments and predicted ones by the ANN model, as a function of inclined angle (θ) for some arbitrary Reynolds numbers are shown in Figure 7. According to this figure and also the results shown in Figures 5 and 6, the maximum errors of the proposed ANN model in predicting the Nusselt number for the training and test data are 0.325% and 1.157%, respectively. Also the mean relative errors for the training and test data are 0.109% and 0.509%, respectively. Since, the error values are low, therefore, it can be concluded that there is good consistency between the experimental and predicted results for the training and test data sets. Hence, the ANN results can be applied to model the experiments precisely. As it can be observed from Figure 7, the tube fitted with butterfly insert with inclined of 90° has higher Nusselt number in comparison with other two inclined angles. This result may be explained by the generation of stronger turbulence intensity and more rapid mixing of flow created by this insert. More discussions on the physical significance of the obtained results can be found elsewhere [17].

Table 1. The optimum architecture and specifications of the proposed ANN model.

Neural network	MLP
Number of neurons in the input layer	2
Number of neurons in the first hidden layer	2
Number of the weight parameters in the first hidden layer	4
Number of the bias parameters in the first hidden layer	2
Number of neurons in the second hidden layer	6
Number of the weight parameters in the second hidden layer	24
Number of the bias parameters in the second hidden layer	6
Number of neurons in the output layer	1
Number of the weight parameters in the output layer	24
Number of the bias parameters in the output layer	1
Total number of weight parameters	52
Total number of bias parameters	9
Number of iterations	100
Activation function	Tansig (obtained by setting k=1 in Equation1)
Training function	Levenberg-Marquardt back propagation

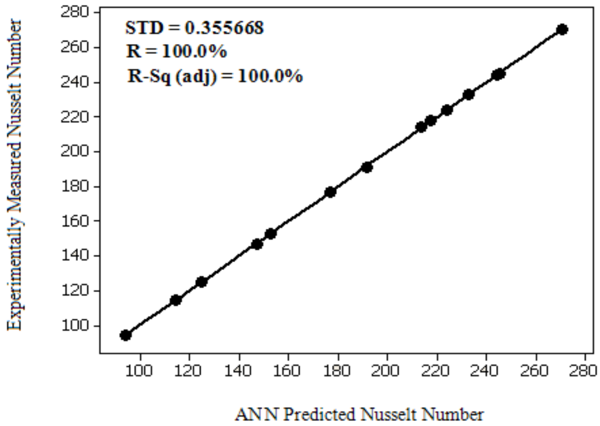


Fig. 5. The comparison between the experimental and predicted values of average Nusselt number using ANN for training data.

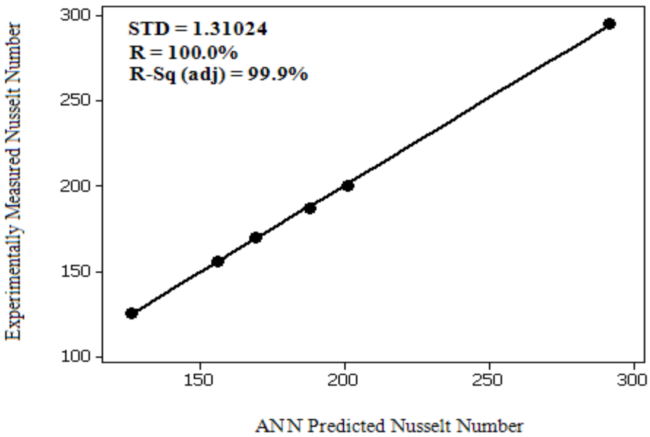


Fig. 6. The comparison between the experimental and predicted values of average Nusselt number using ANN for testing data.

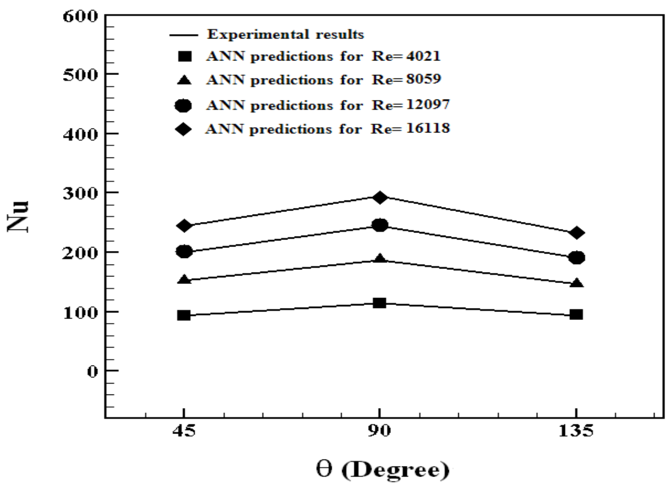


Fig. 7. Comparison between experimental and predicted values of average Nusselt number using ANN for different Reynolds numbers.

6. CONCLUSIONS

In this paper, an artificial neural network (ANN) was employed in order to model and predict the heat transfer in an air-cooled heat exchanger equipped with butterfly inserts. The comparison between experimental and predicted values of proposed ANN model showed that there is excellent consistency between the predicted heat transfer and the experimental results with least error. This means that the proposed ANN model is a reliable flexible mathematical structure for the modeling and prediction of results due to its high accuracy and therefore, it can be used to simulate the experiments precisely.

NOMENCLATURE

A	Heat transfer area (m^2)
Q	Heat transfer rate (W), $Q = mC_p(T_o - T_i)$
Q'	Heat transfer rate to the air surrounded the tube (W), $Q' = hA(\overline{T}_w - T_b)$
C_p	Specific heat capacity (kJ/kg·K)
D	Diameter of the smooth tube (m)
D_h	Hydraulic diameter (m)
h	Heat transfer coefficient ($W/m^2 \cdot K$), $h = mC_p(T_o - T_i)/A(\overline{T}_w - T_b)$ by setting $Q = Q'$
k	Thermal conductivity (W/m·K)
m	Mass flow rate (kg/s)
Nu	Nusselt number, $Nu = hD_h / K$
P	Static pressure (Pa)
R-Sq	R-squared
R-Sq(adj)	Adjusted R-squared
Re	Reynolds number, $\mathrm{Re} = UD_h / v$
STD	Standard deviation
T_b	Bulk temperature (K), $T_b = (T_o + T_i)/2$
T_i	Inner wall surface (K)
T_o	Outer wall surface (K)
T_w	Local wall temperature measured at the outer wall surface of the tubes (K)
$\overline{T}_w$	Average wall temperature (K), $\overline{T}_w = (\sum T_w)/20$
U	Mean velocity (m/s)

Greek Letters

v	Kinematic viscosity (m^2/s)
θ	Inclined angle

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