Prediction of the Heat Transfer in an Air Cooler Equipped with Classic Twisted Tape Inserts using Artificial Neural Network (ANN)

A. Amiri, A. M. Karami, S. F. Seyedpour, and E. Rezaei

***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 classic twisted tape inserts. The effects of the twist ratio of classic inserts (Y) 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 0.457% and 0.478% were reached for the training and test data respectively. The results show that predicted values are very close to experimental values.**

***Index Terms*—Air cooled heat exchanger; classic twisted tape inserts; twist ratio; modeling; artificial neural network (ANN)**

Nomenclature

A heat transfer area (m^2)

Q heat transfer rate (W)

C_p specific heat capacity (kJ/kg·K)

D diameter of the smooth tube (m)

D_h hydraulic diameter (m)

h heat transfer coefficient ($W/m^2 \cdot K$)

K thermal conductivity (W/m·K)

m mass flow rate (kg/s)

Nu Nusselt number

P static pressure (Pa)

Pi axial distance of twist pitch (m)

I. 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. An experimental study was carried out on heat transfer in a round tube equipped with propeller type swirl generators by Eiamsa-ard et al. [8]. The effects of the blade angle, pitch ratio and number of blades on the Nusselt number, pressure loss and enhancement efficiency were also studied. Chang et al. [9], [10] studied the heat transfer enhancement in a tube fitted with serrated twisted tapes and broken twisted tapes. Shabanian et al. [11] Studied heat transfer enhancement in an air cooler equipped with different tube inserts. They showed that using the different tube inserts (butterfly, jagged and classic twisted tape inserts), increase the heat transfer from the air cooler. Also, they showed that by using the butterfly insert with an inclined angle of 90°, maximum heat transfer is obtained. Also, the results have 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 classic twisted tape inserts. The applied experimental data were obtained by Shabanian et al. [11].

II. Experimental Apparatuses

A schematic view of the experimental rig [11] is shown in Figure1a. 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 × 100 × 50 cm cubic channel [11]. 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

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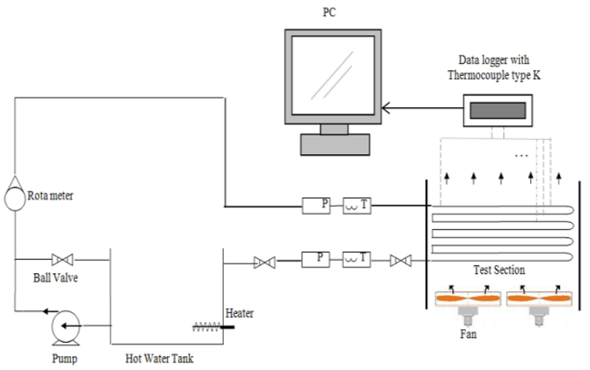
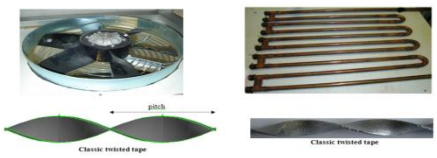
lit/hr to 400 lit/hr, which corresponds to Reynolds numbers from 4021 to 16118. The tube inlet and outlet water pressure and temperature are measured through two pressure transmitters and a copper-constantan thermocouple. Moreover, in order to determine the average Nusselt number, the temperatures at 20 different positions on the outer surface of the tube are measured. All twenty temperature sensing probes are connected to a data logger set [11]. In the experiments, the classic inserts are placed in the bent tube. Figure 1b shows the bent tube, fan and tube inserts used in the experiment. The tube applied here has 17 mm of inner diameter and 1mm thickness. The classic twisted tape inserts have 15mm width and 1mm thickness with four twist ratios as 1.76, 2.35, 2.94 and 3.53.



(a)



(b)

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

III. Data Reduction

If In order to express the experimental results in a more efficient way, the measured data are reduced using the following procedure [11]:

The heat transfer rate resulted from the hot fluid in the tubes is expressed as:

$$Q = mC_p(T_o - T_i) \tag{1}$$

On the other hand, the heat transfer rate to the air surrounded the tube is approximated by:

$$Q = hA(\bar{T}_w - T_b) \tag{2}$$

where,

$$T_b = (T_o + T_i)/2 \text{ and } \bar{T}_w = (\sum T_w)/20 \tag{3}$$

T_w is the local wall temperature and is measured at the outer wall surface of the tubes. The relations used in calculation of the average heat transfer coefficient and the average Nusselt number are as follows [11]:

$$h = mC_p(T_o - T_i)/A(\bar{T}_w - T_b) \tag{4}$$

$$Nu = hD_h / K \tag{5}$$

In addition, the Reynolds number is obtained according to the following equation:

$$\mathrm{Re} = UD_h / v \tag{6}$$

In the present work, the uncertainties of experimental measurements are determined based on ANSI/ASME [12]. The maximum uncertainties for *Nu* and *Re* are estimated at 7% and 5.2%, respectively.

IV. Method of Modeling

A. 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 classic twisted tape inserts, is adopted as a function of two variables namely the twist ratio of classic inserts (Y) and Reynolds number (Re). Therefore an ANN model as shown in Figure2 is developed with the twist ratio (Y) ranging from 1.76 to 3.53 and Reynolds number (Re) from 4021 to 16118 as inputs and average Nusselt number (Nu) as desired output.

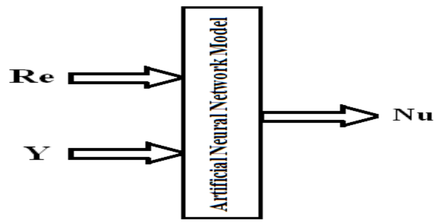


Fig. 2. A simplified overview of the proposed ANN model for heat transfer modeling

B. 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". Fig.3 illustrates a simple model of n -inputs single-output neuron. All the input signals are summed up as z and the amplitude of the output signal is determined by the nonlinear activation function $f(z)$.

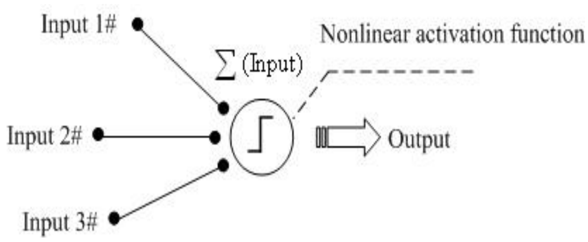


Fig. 3. Basic model of multi-inputs one-output neuron

The In this work, the modified sigmoid function $f(z)$ was used given as follow [13],

$$f(z) = \frac{1-e^{-kz}}{1+e^{-kz}} \tag{7}$$

In the limit of $k = \infty$, as the slope approaches the infinity, $f(z)$ behaves like a threshold function. Here, the sigmoid function was 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 [13], [14]. Here, a Multilayer Perceptron (MLP) type network is adopted with four layers, which has been used for various applications [13]-[17]. The architecture of the perceptron neural network is shown in Fig. 4.

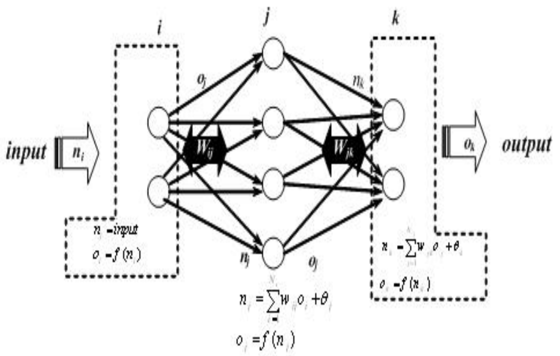


Fig. 4. Three layer multilayer perception consisting 'input', 'hidden' and 'output' layers

The For clear notation, the indices i, j and k will be use for the units corresponding to "input", "hidden" and "output" layers, respectively (see Figure4). 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 [15],

$$o_i = f(n_i) \quad ; \quad o_j = f(n_j) \quad ; \quad o_k = f(n_k) \tag{8}$$

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 [15]. The overall response of the present network is given as,

$$o_k = \sum_{j=1}^{N_j} w_{jk} f\left(\sum_{i=1}^{N_i} w_{ij} n_i + \theta_j\right) + \theta_k \tag{9}$$

where

$$n_j = \sum_{j=1}^{N_j} w_{ij} o_i + \theta_j \;,\quad n_j = \sum_{j=1}^{N_j} w_{jk} o_j + \theta_k$$

and

$$o_j = f(n_j) \tag{10}$$

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 [12]-[15],

$$MRE = \frac{1}{n} \times \sum_{i=1}^{n} \left| \frac{y_j - o_j}{y_j} \right| \tag{11}$$

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 [18] method with momentum term for the nonnegative energy function [13], [15]. 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.

V. MODELING RESULTS

Twenty eight experimental data are used to build up the ANN model, twenty one data (about 75% of the total data) are used for training and the rest seven data (about 25% of the total data) are used for testing the ANN model. The final

ANN architecture used in this study is described in table1. 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 the twist ratio (Y) for some arbitrary Reynolds numbers are shown in Fig. 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 1.709% and 0.948%, respectively. Also the mean relative errors for the training and test data are 0.457% and 0.478%, 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 can be observed in figure7, the heat transfer increases by decreasing the twist ratio. This behavior can be understood by the fact that, the swirl intensity increases by decreasing the twist ratio and therefore, increases the Nusselt number [11].

TABLE I: 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 neurons in the second hidden layer	8
Number of neurons in the output layer	1
Number of iterations	100
Activation function	Tansig (obtained by setting k=1 in equation7)
Training function	Levenberg-Marquardt back propagation

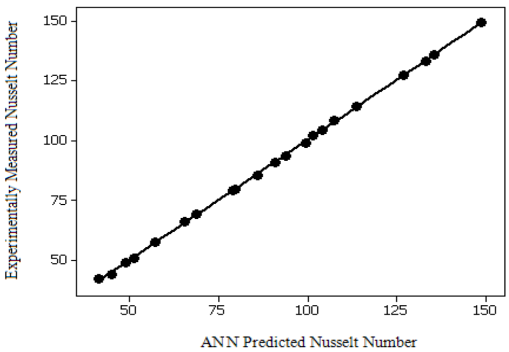


Fig. 5. The comparison between the experimental and predicted values of average nussle number using ANN for training data

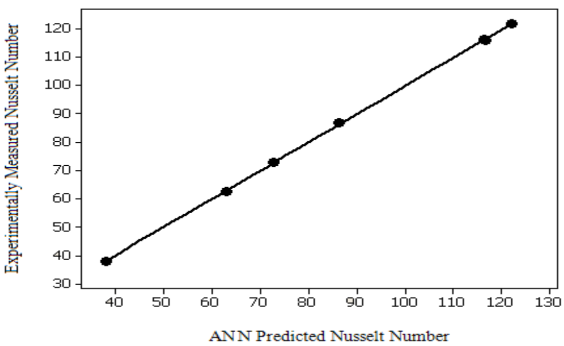
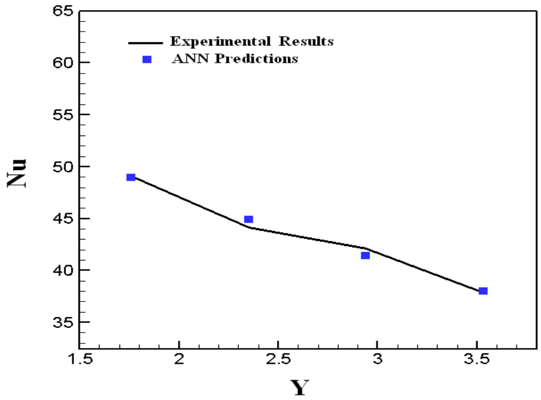


Fig. 6. The comparison between the experimental and predicted values of average nusselt number using ANN for testing data



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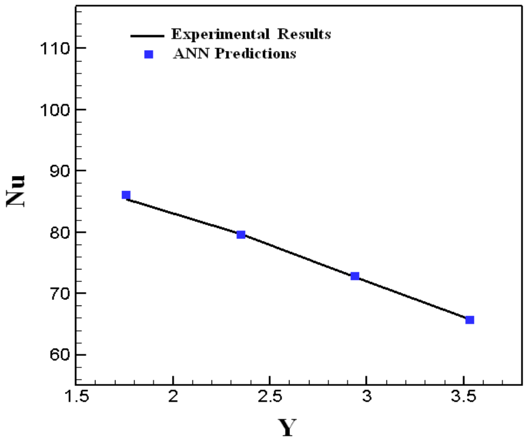

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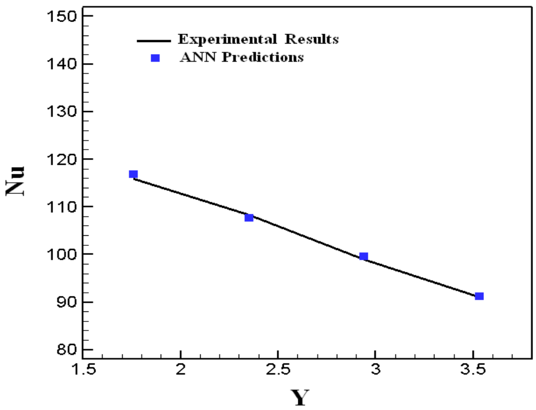

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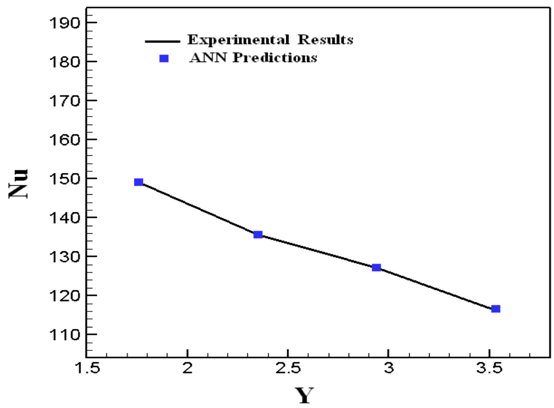

(d)

Fig. 7. Comparison between experimental and predicted values of average Nusselt number using ANN for a) Re=4021 b) Re=8059 c) Re=12097 d) Re=16118

VI. 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 classic twisted tape inserts. The comparison between experimental and predicted values of proposed ANN model showed that there is an 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.

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