Artificial Neural Network Modeling of Heat Transfer in a Staggered Cross-flow Tube-type Heat Exchanger.

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ABSTRACT

This paper presents the application of Artificial Neural Network (ANN) in modeling the heat transfer coefficient of a staggered multi-row, multi-column, cross-flow, tube-type heat exchanger. Heat transfer data were obtained experimentally for air flowing over a bank of copper tubes arranged in staggered configuration with 5 rows and 4 columns at different air flow rates with throttle valve openings at 10 - 100%. The Reynolds number and the row number were used as input parameters, while the Nusselt number was used as output parameter in training and testing of the multi-layered, feed-forward, back-propagation neural networks. The network used in this study was designed using the MATLAB® Neural Network Toolbox.

The results show that the accuracy between the neural networks predictions and experimental values was achieved with mean absolute relative error (MRE) less than 1 and 4% for the training and testing data sets respectively, suggesting the reliability of the networks as a modeling tool for engineers in preliminary design of heat exchangers.

(Keywords: artificial neural network, ANN, heat transfer, staggered, cross-flow, heat exchanger)

INTRODUCTION

Heat transfer to and from a bank of tubes in cross flow is relevant to numerous heat exchanger applications, such as steam generator in a boiler or air cooling in the coil of an air conditioner (Kays and London, 1964). In these applications, one fluid moves over the tubes, while a second fluid at a different temperature passes through the tubes and hence, heat is exchanged between the fluids based on the convection heat transfer coefficient (McAdams, 1954). The tube rows of the bank are either arranged in staggered or aligned configuration in the direction of flow.

The flow conditions within the bank are dominated by boundary layer separation effects and by wake interactions, which in turn influence the convection heat transfer (Incropera and Dewih, 2002). Hence, the heat transfer coefficient associated with a tube is determined by its configuration and position of the bank. The heat transfer coefficient of a tube with staggered configuration is higher than that associated with of aligned. Also, for a given configuration, the heat transfer coefficient in the first row is lower than those associated with tubes of inner rows. In most configurations, however, heat transfer conditions stabilize, such that little change occurs in the convection coefficient for tube beyond the fourth or fifth row (Plint and Partners Ltd., 1981).

The modeling of these relationships has been the concern of many researchers. Generally, the average heat transfer coefficient for the entire tube bank is evaluated empirically based on the maximum fluid velocity. Different forms of empirical correlations have been proposed for airflow across tube bank with different geometry and configurations (McAdams, 1954; Zhukauskas, 1972). However, the applicability of these empirical models is limited to a confined range of flow conditions due to the complexity of the relationships. In this sense, therefore, artificial neural networks (ANNs) have been applied in modeling heat transfer phenomena of different heat exchanger applications because of providing better and more reasonable solutions (Islamoglu, 2003; Islamoglu and. Kurt, 2004). Pacheco-Vega et al. (2001a) and Pacheco-Vega et al., (2001b) used artificial neural networks to model the heat transfer of a fin-tube heat exchanger. Díaz et al. (2001) has applied artificial neural network technique to the simulation of the time-dependent behavior of a heat exchanger. Thibault et al. (1991) and Jambunathan et al. (1996) have applied neural network model for prediction of convective heat transfer. More recently, Varshney and Panigrahi (2005) developed a neural network based control for a heat exchanger in a closed flow air circuit. Fatona (2008) has investigated the feasibility of using back propagation neural network for prediction of flow and heat transfer characteristics of air flowing over bank of tubes.

The prediction performance of these developed neural networks models in different fields of engineering applications has demonstrated high generalization capability and robustness of technique in modeling of complex and non-linear heat transfer relationships in heat exchangers. The objective of this present study is to investigate the feasibility of applying artificial neural networks (ANNs) for modeling the convection heat transfer coefficient of air flowing over a staggered, multi-row, multi-column, cross-flow, tube-type heat exchanger

MATERIALS AND METHODS

Experimentation

The cross-flow heat exchanger apparatus (Model TE.93/A, Plint Engineers, England) was used for the purpose of data gathering. The experimental setup is shown in Figure 1. Air at ambient temperature (working fluid), driven by a centrifugal fan powered by a 1 hp electric motor at a constant speed of 2,500 rpm, is blown perpendicularly over a bank of cylindrical copper tubes arranged in staggered configuration of 5 rows and 4 columns inside the working section. The nominal dimensions of the working section and the configuration of the tube bank are shown in Figure 2. The air flow rate over the tubes is regulated by a throttle valve attached to the discharge end of the centrifugal fan. The nominal dimensions and properties of the copper tube are given in Table 1, while the properties of the working fluid are given in Table 2.

One of the copper tubes is heated to a maximum of about 90^0C with an electric heater and a K-type, 0.2 mm diameter thermocouple (DSS, AK28M Model) was imbedded at the centre of the tube was used to measure the temperature of the tube. The thermocouple voltage output is wired to digital multimeter (DSS, AK28M Model), which is connected Pentium® 4 laptop computer to record the measured temperature. The heated tube is then inserted into the spaces provided in the working section at middle points of each 4 row of the tube bank. At each row position, the rate cooling of the tube as indicated by a thermocouple embedded at its centre was recorded at the rate of 1 data per second by the computer for 10 different flow rates with throttle valve at 10, 20, 30, 40, 50, 60, 70 ,80, 90 and 100% openings. The air velocity over the tube bank at different openings was measured with a total head tube connected to an inclined water manometer.

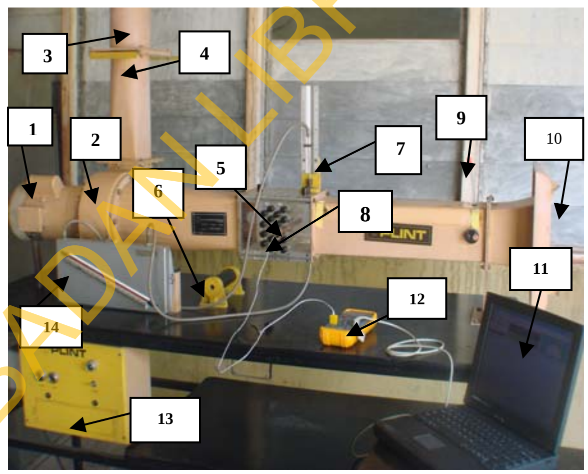

Figure 1: The Experimental Setup.

1: Electric motor, 2: Fan, 3. Air outlet, 4: Throttle opening, 5: Working section, 6: Electric heater, 7: Total head tube, 8: Test element, 9: Thermometer, 10: Air inlet, 11: Computer, 12: Digital multimeter, 13: Control panel, 14: Inclined manometer.

The Reynolds number (Re) of air flow is determined using the relation:

$$\mathrm{Re} = \frac{\rho V D}{\mu} \qquad \textbf{(1)}$$

where, ρ = density of air,
V = mean velocity of air
D = outside diameter of tube
μ = viscosity of air.

For the purpose of estimating the heat transfer coefficient, it is assumed that the whole of the heat lost from the tube is transferred to the air flowing past it.

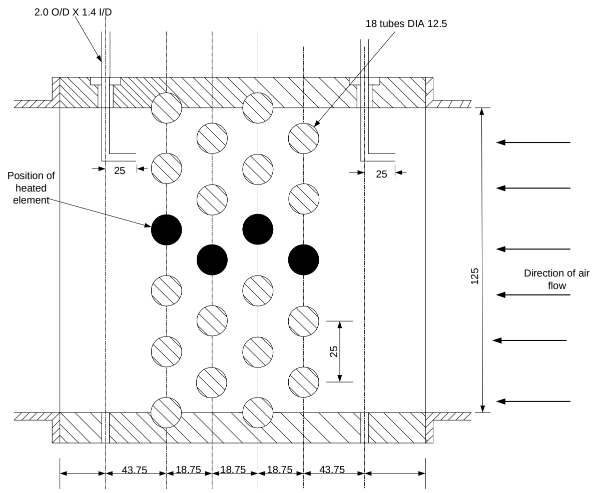

Figure 2: Nominal Dimensions of the Working Section with Staggered Tube Arrangement.

Table 1: Dimensions and Properties of the Copper Tube.

Description	Quantity
External diameter of tube (d_1)	0.0125 m
Internal diameter of tube (d_2)	0.0115 m
Thickness of tube (t)	0.0005 m
Mass of tube (m)	0.0274 kg
Length of tube (l)	0.125 m
Effective length of tube (l_1)	0.1334 m
Surface area of tube (A)	0.004891m^2
Effective surface area of tube (A_1)	0.00522 m^2
Specific heat of copper (c)	308 J/kg ^{0}C

Table 2: Nominal Properties of the Air.

Description	Quantity
Ambient temperature (T_A)	302 ^{o}K
Barometric pressure (p_A)	99,325.19 N/m^2
Density at p_A and T_A	1.138 kg/m^3
Spec. heat at const. pres. (c_p)	1012 J/Kg ^{o}C
Viscosity (μ)	1.82E-05 kg/ms
Thermal conductivity (k)	0.0259 J/ms ^{0}C

It is also assumed that temperature gradient within the tube thickness is negligible, so that the thermocouple embedded at the centre in the inner diameter gives a true indication of the effective surface temperature of the tube. The rate of heat loss from tube to air is given by:

$$\dot{q} = hA_1(T - T_A) \qquad \textbf{(2)}$$

where, h = coefficient of heat transfer
$\dot{q}$ = rate of heat loss
A_1 = effective surface area of tube
T = temperature of tube
T_A = temperature of air.

In a period of time (dt) the temperature drop (dT) is given as:

$$-\dot{q}dt = mcdT \qquad \textbf{(3)}$$

where, m = mass of tube
c = specific heat of copper tube.

Combining Equations (2) and (3) and eliminating $\dot{q}$ gives the following:

$$\frac{-dT}{(T - T_A)} = \frac{hA_1}{mc}dt \qquad \textbf{(4)}$$

Integrating Equation (4) gives:

$$\log_e(T - T_A) - \log_e(T_0 - T_A) = -\frac{hA_1 t}{mc} \qquad \textbf{(5)}$$

where, T_0 = tube temperature at time (t) = 0.

The plot of $\log_e (T\text{-}T_A)$ against t yields a straight line of slope (M) as:

$$M = -\frac{hA_1}{mc} \qquad \textbf{(6)}$$

From which the heat transfer coefficient (h) is calculated as:

$$h = -\frac{A_1}{mc}M \qquad \textbf{(7)}$$

The fully developed Nusselt number (Nu) is evaluated by

$$Nu = \frac{hD}{k} \qquad \textbf{(8)}$$

where, k = thermal conductivity of air
D = outside diameter of tube.

The Nusselt numbers for different Reynolds numbers and row position numbers of the tube are given in Table 3.

Table 3: The Nusselt Number for Different Row and Reynolds Number.

Row No. (Rn)	Reynolds number (Re)									
	3,529	**4,555**	**6,442**	**7,890**	**10,186**	**13,666**	**16,425**	**18,222**	**19,857**	**20,875**
1	13.45	16.09	18.96	21.29	22.93	24.48	25.03	25.88	27.36	27.36
2	16.24	18.73	21.45	24.25	25.34	27.05	29.38	28.60	29.69	30.15
3	17.49	21.84	24.95	27.36	28.60	29.84	32.41	33.65	33.03	32.41
4	21.37	22.54	25.80	28.37	32.95	34.20	35.67	35.67	35.75	36.61

Design of neural network

Neural Network Toolbox for MATLAB® (Math Works, 2001) was used to design the neural network. The basic steps adopted in the design are as follows: experimentation and collection of data; analysis and pre-processing of data; design of the neural network; training and testing of the neural networks; simulation and prediction with the neural networks; and analysis and post-processing of predicted result.

The data collected during the experiment were used as input/output datasets for training and testing of the network, the Reynolds number and row position number were used input dataset, while the Nusselt number was used as the output dataset. Prior to the training of the network, the datasets ware normalized to values between –1 to +1 using the MATLAB® function 'premnmx'. The *i*th normalized dataset then becomes:

$$x_i = 2\frac{d_i - d_{\min}}{d_{\max} - d_{\min}} - 1 \quad \textbf{(9)}$$

Where, x_i = i^{th} normalized dataset

d_i = i^{th} raw dataset

d_{min} = minimum raw dataset.

d_{max} = maximum raw dataset

A standard back-propagation, multiplayer, feed-forward network was designed using the MATLAB® function 'newff'. The network work consists of three layers: input layer; hidden layer; and output layer. The number of neurons in the input and output layers are determined generally by the number of input and output parameters, which in case, are 2 and 1 respectively. The number of neurons in the hidden layer however is chosen arbitrarily based on experience. Different network configurations with 1 and 2 hidden layer with the number of neurons in each hidden layer was varied from 1 to 5 were investigated to determine the optimum network configuration that gives the best generalization capability. A typical network configuration with 2-5-5-1 is shown in Figure 3. The tan-sigmoid transfer function 'tansig' were used in the hidden layers, while linear transfer function 'purelin' was used in the output layer.

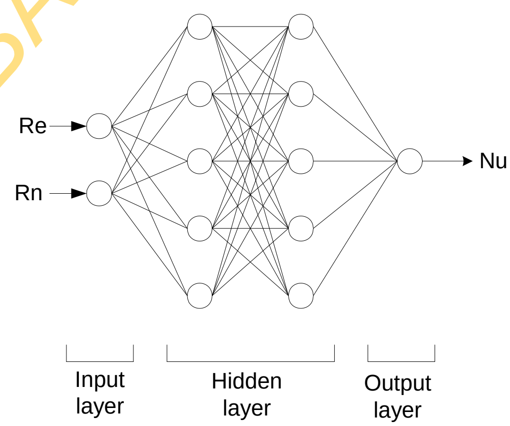

Figure 3: Network Configuration with 2-5-5-1 Neurons for Heat Transfer Prediction.

The network was trained using MATLAB® function 'train' with the 'weights' and 'biases' initialized to random values. Before the training the data set was divided randomly into training and test data set. Seventy-five percent of the data set was used as training set, while the remaining 25% was used in testing of the network. The Levenberg-Marquard training algorithm 'trainlm' was used in the training of the network. During the training the 'weights' and 'biases' of the network are adjusted so as to minimize the mean square error (MSE) between the experimental data and the predicted values.

The mean square error is computed as:

$$MSE = \frac{1}{Q}\sum_{k=1}^{Q} e(k)^2 = \frac{1}{Q}\sum_{k=1}^{Q}\left(t(k) - a(k)\right)^2 \quad \textbf{(10)}$$

where, Q = number of the dataset
e(k) = network error
t(k) = experimental value
a(k) = network predicted value

The target parameters for the termination of the training process were set at MSE<10^{-5} or when the number of iterations is equal 300. The prediction performance of the neural networks was evaluated based on the mean relative error (MRE) in percentage between the predicted and the experimental values according to the following expression:

$$MRE(\%) = \frac{1}{Q}\sum_{k=1}^{Q}\frac{t(k) - a(k)}{t(k)}100 \qquad \textbf{(11)}$$

where, Q = number of the dataset
t(k) = experimental value
a(k) = network predicted value.

RESULTS AND DISCUSSIONS

The network prediction performance for the different configurations with 1 and 2 hidden layers, with the number of neurons in each hidden layer varying from 1 to 5, were investigated. During the training process the 'weights' and 'biases' of the networks were adjusted so as to minimize the mean square error (MSE) between the experimental data and the ANNs predicted values. The results show that the network model with two hidden layer having 5 neurons in each layer (2-5-5-1) with a 20 training cycles and MSE of 1.49×10^{-5} was found to be the optimum network with the best performance.

The minimization in MSE during the training process of the optimum network is shown in Figure 4 for the training and testing data sets. The prediction performances of the network using the training and testing data sets are shown in Figure 5 and Table 4 respectively.

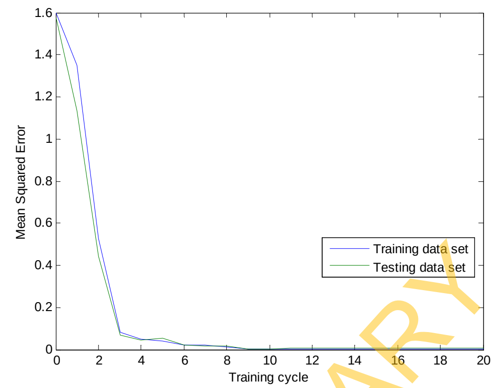

Figure 4: Reduction in MSE During the Training Process for the Network with 2-5-5-1 Configuration.

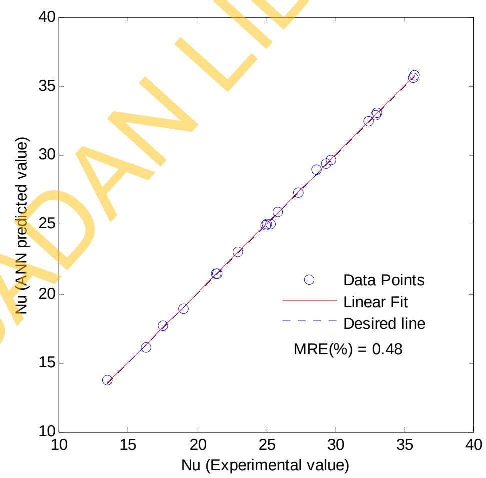

Figure 5: Comparison Between the Experimental Data and the Neural Network Predictions for Training Dataset.

Table 4: Comparison Between the Experimental Data and the Neural Network Predictions for Testing Dataset.

Rn	Re	Nu, Experimental	Nu, ANNs	RE (%)
1	4555	16.09	15.74	2.20
1	13666	24.48	23.40	4.43
1	20875	27.36	27.61	0.92
2	7890	24.25	23.16	4.51
2	18222	28.60	29.88	4.48
3	4555	21.84	20.48	6.24
3	13666	29.84	30.36	1.74
3	20875	32.41	33.04	1.94
4	7890	28.37	29.40	3.64
4	18222	35.67	36.25	1.63

MRE (%) = 3.17.

Figure 5 and Table 4 show that the network has MREs of 0.48 and 3.17% for the training and testing data sets respectively. The maximum relative errors were approximately 1.91% (from Fig. 5) and 6.24% (from Table 4). respectively.

CONCLUSION

In this paper, ANNs model has been developed for the prediction of the convection heat transfer coefficient of air flowing over a staggered, multi-row, multi-column, cross-flow, copper tube-type heat exchanger. The model has high prediction performance with mean relative error (MRE) less than 1% for the training data set and less than 4% for the testing data sets respectively. The ANNs model can therefore be used as a modeling tool for preliminary design of heat exchangers.

NOMENCLATURE

D	outside diameter of element (m)
d	inside diameter of element (m)
l	length of element (m)
l_1	effective length of element (m)
A	surface area of element (m^2)
A_1	effective surface area of element (m^2)
m	mass of element (kg)
c	specific heat of copper element (J/kg ^{0}C)
p_A	barometric pressure (N/m^2)
T_A	temperature of air (^{o}K)
V	mean velocity past element (m/s)
ρ	density of air (kg/m^3)
c_p	specific heat of air at const. pres. (J/Kg ^{o}C)
μ	viscosity of air (kg/ms)
k	thermal conductivity of air (J/ms ^{0}C)
T	temperature of element (^{o}K)
M	slope of cooling curve
$\dot{q}$	rate of heat transfer to air (J/s)
h	coefficient of heat transfer (J/m^2s ^{0}K)
Nu	Nusselt Number
Re	Reynolds Number
Rn	row position number of the test element

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