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Heat transfer analysis using ANNs with experimental data for air flowing in corrugated channels

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Abstract

The objective of this work is to use artificial neural networks (ANNs) for heat transfer analysis in corrugated channels. A data set evaluated experimentally is prepared for processing with the use of neural networks. Back propagation algorithm, the most common learning method for ANNs, was used in training and testing the network. To solve this algorithm a computer program using C++ has been developed. The accuracy between experimental and ANNs approach results was achieved with a mean absolute relative error less than 4%.

Keywords: Artificial neural network; Heat transfer and Corrugated channel

1. Introduction

Artificial neural networks (ANNs) have been used in many engineering applications because of providing better and more reasonable solutions [1,2]. Some examples are: analysis of thermosyphon solar water heaters, heat transfer data analysis, HVAC computations and prediction of critical heat flux [3]. Sreekanth et al. [4] for evaluation of surface heat transfer coefficient at the liquid–solid interface, Diaz et al. [5] for simulation of heat exchanger performance, Kalogirou [6] used ANNs for performance prediction of forced circulation type solar domestic water heating. Singh et al. modeled the entire flow field around an automobile using ANNs and Schreck et al. used ANNs models to predict the unsteady separated flow field on a wing [4]. Farshad et al. [7] for predicting temperature profiles in producing oil wells used an artificial neural network algorithm. Recently, Parcheco-Vega et al. [3,8] modeled the heat transfer phenomena in heat exchanger systems using neural network. In addition, same authors performed a simulation of the time-dependent behavior of a heat exchanger [9]. Boccaletti et al. [10], for simulation of gas turbine with a waste heat recovery section, Bechtler et al. [11], to model the steady-state performance of a vapor-compression liquid heat pump, and Sablani [12], for non-iterative calculation of heat transfer coefficient in fluid-particle systems, used ANNs. It should be understood from the literature review mentioned above that ANNs better serve to thermal analysis in engineering applications. However, the ANNs methods have not been used or tested for heat transfer analysis in corrugated channels yet. For this reason, the study was focused on the applicability of ANNs method for heat transfer analysis in corrugated channels, employed in the design of plate heat exchangers because of achieving enhanced heat transfer, and the best candidate for high heat flux applications.

2. Experimental details

A schematic diagram of the experimental apparatus used for the heat transfer analysis in this study for data gathering are presented in Fig. 1. A detailed

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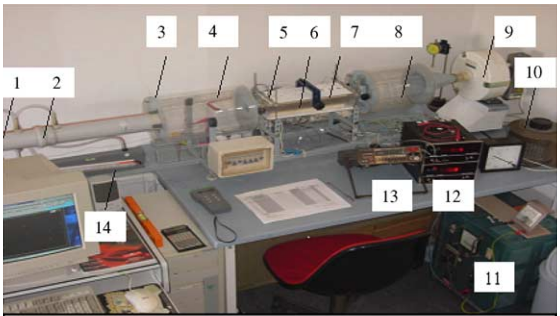
Nomenclature

a	corrugated height (from valley to peak)
a_i	actual value of the data
A_{cycle}	convection heat transfer area per cycle
D_h	hydraulic diameter
H	channel height
h	cycle-average fully developed heat transfer coefficient
k	thermal conductivity
L	length of the principal walls
n	the number of the data
Nu	cycle-average fully developed Nusselt number
p_i	predicted (output) value of the data
Q_{cycle}	heat added to fluid per cycle
Re	Reynold number
T_b	fluid bulk temperature
T_w	corrugated wall temperature
V	mean velocity
W	width of duct
θ	corrugation angle
ν	kinematics viscosity
Subscript	
fd	fully developed



1. Air inlet, 2. Orifice plate, 3. Upstream plenum, 4. Ice bath, 5. Insulation, 6. Electric heaters, 7. Test plates, 8. Downstream plenum, 9. Fan, 10. Auto transformer, 11. DC power suppy, 12. Scanner, 13. Multi meter, 14. Inclined manometer

Fig. 1. The experimental apparatus.

presentation of the design, fabrication of the experimental apparatus and evaluation method of the data are available in [13–16].

Air from the laboratory room, the working fluid, was drawn through the systems by a downstream fan that was supplied the electrical power by the autotransformer to use it as variable speed. The mass rate of air through the systems were measured by the orifice plates. The DC power supply was the source of power for the plate type heaters, used for heating of the test section. Equal power input per unit heated length was established in the top and bottom walls. To prevent a temperature step between heater and principal walls, conducting compound which fills in the air spaces and to provide improved thermal contact was used. In order to measure the principal walls temperature distribution, equipped with six thermocouples the each walls, the thermocouples were installed in holes drilled from the rear face and centered of the walls. To measure the entering bulk temperature, thermocouple was positioned upstream of duct inlet. All thermocouples were K type, 0.2 mm diameter wire (Comark, AK28M code). The thermocouple voltage outputs were fed into an autoranging microvolt multimeter (Keithley, model 197).

Experiments were performed in the Reynolds number based on channel hydraulic diameter, range 1200–4000 for four corrugation angle of 20°, 30°, 40°, and 50°. Corrugated channels were fabricated from 10 mm thick copper plates, 50 mm wide and 278 mm long. The form of corrugation was accomplished by means of wire electrical discharge machining. A representative corrugated channel was shown in Fig. 2, geometric data for the tested channels were given in Table 1.

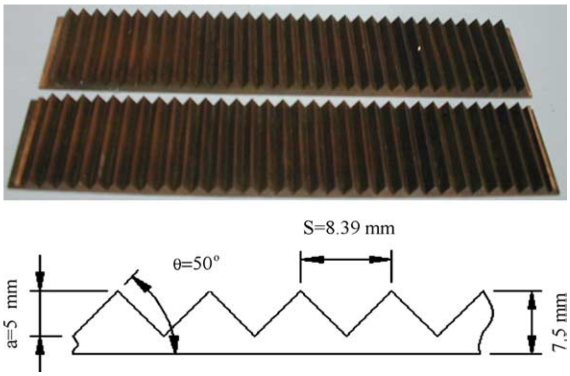


Fig. 2. A corrugated type channel.

Table 1
Geometric data for the tested channels

θ (°)	S (mm)	a (mm)
20	27.47	5.00
30	17.32	5.00
40	11.91	5.00
50	8.39	5.00

The goal of this experiment was the determination of fully developed Nusselt numbers for air flowing in corrugated channel. The Reynolds number, independent parameter based on the channel hydraulic diameter, is given by

$$Re = \frac{VD_h}{\nu}, \tag{1}$$

where (V) is the mean velocity, (D_h) the conventional hydraulic diameter, $\left(D_h = \frac{2HW}{H+W}\right)$, and ($\nu$) the kinematics viscosity. The term H is the channel height and W the duct width.

For a uniform heating condition the periodic flow employed in the present experiment, the wall temperatures at a succession of point separated from each other by an axial distance S lie on straight line. Similarly, the fluid bulk temperatures at the same set of axial points lie on a straight line whose slope is equal to that of the aforementioned wall temperature line and in periodic thermally developed regime, the cycle-average heat transfer coefficient is the same for all cycles [17].

The cycle-average full development heat transfer coefficients were evaluated from the measured temperatures and heat inputs. The displacement of the two lines yields the fully developed wall to bulk temperature difference. With heat added to fluid per cycle (Q_{cycle}) and the temperature difference of wall and fluid $(T_w - T_b)_{fd}$, cycle-average fully developed heat transfer coefficient (h) will be evaluated from the experimental data via the defining equation

$$h = \frac{Q_{cycle}}{(T_w - T_b)_{fd} A_{cycle}}. \tag{2}$$

The term A_{cycle} is convective heat transfer area per cycle. Then, fully developed Nusselt numbers (Nu) are evaluated by

$$Nu = \frac{hD_h}{k}, \tag{3}$$

where k is the thermal conductivity and D_h the hydraulic diameter.

The results for the periodic fully developed Nusselt number used for the training and testing data are presented in Tables 2 and 3, respectively. Experimental uncertainty was estimated by the procedure described Kline and McClitock [18]. The mean uncertainties in the Nusselt numbers range between ±4% and 10% for $1200 \leqslant Re \leqslant 4000$, the highest uncertainties being at the lowest Reynolds number.

3. Artificial neural networks approach

ANNs consisting of very simple and highly interconnected processors called neuron are a computational structure inspired by biological neural systems. The processors are analogous to biological neurons in human brain. The neurons are connected to each other by weighted links over which signals can pass. Each neuron receives multiple inputs from other neurons in proportion to their connection weights and generates a single output which may be propagated to several other neurons [4].

Among the various kinds of ANNs that exits, the feed forward neural network has become the most popular in engineering applications [3], and it is the type of network used in this study. The network is somewhat simple in structure and easily analysed mathematically. The back propagation network is the first and most commonly used feed forward neural network because there exists a mathematically strict learning scheme to train the network and guarantee mapping between inputs and outputs. A typical feed forward architecture is

Table 2
Periodic fully developed Nusselt numbers selected for training the network

θ (°)	D_h (mm)	S (mm)	Re							
			1200	1600	2000	2400	2800	3200	3600	4000
20	1.9	27.47	11.83	11.15	11.14	11.68	11.92	14.42	15.50	16.40
30	1.9	17.32	12.35	14.29	16.87	18.84	–	–	–	–
	16.6	17.32	30.94	31.98	32.96	34.30	37.50	39.15	40.73	44.32
40	16.6	11.91	30.47	33.94	36.68	35.98	34.60	40.54	40.36	40.87
50	16.6	8.39	25.00	30.54	37.82	44.00	50.00	55.21	53.72	57.86

Table 3
The periodic fully developed Nusselt numbers selected for testing the network

θ (°)	D_h (mm)	S (mm)	Re							
			1200	1600	2000	2400	2800	3200	3600	4000
20	16.6	27.47	22.11	21.27	23.05	23.38	23.50	25.10	26.28	27.84

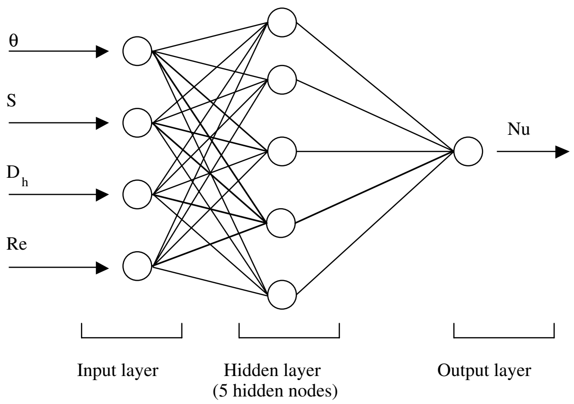


Fig. 3. Configuration on a 4-5-1 neural network for heat transfer analysis in corrugated channels.

schematically illustrated in Fig. 3. This configuration has one input layer, one hidden layer and one output layer. During the feed forward stage, a set of input data is supplied to the input nodes and the information is transferred forward through the network to the nodes in the output layer. The nodes perform non-linear input–output transformations by means of sigmoid activation function. The mathematical background, the procedures for training and testing the ANNs, and account of its history can be found in the text by Haykin [19]. Such non-linear mapping capability and the fact that the neurons are massively connected enable the ANNs to estimate any function without the need of an explicit mathematical model of the physical phenomenon. To train and test the neural networks, input data patterns and corresponding targets were required. In developing a ANNs model, the available data set (70–80% of the data [20]) is divided into two sets: the network was trained using the first data set, and then it was validated with the second data set [21]. The training process is carried out by comparing with the output of the network to the given data. The weights and biases are changed in order to minimize the error between the output values and the data for which the scheme used in this study is the back propagation algorithm. The configuration of the ANNs are set by selecting the number of hidden layer and the number of nodes in hidden layer, since the number nodes in the input and output layers are determined from physical variables.

The primary advantage of neural network methodology than conventional regression analysis is: free of linear supposition, have large degrees of freedom, and more effectively deal with non-linear functional forms [7].

The inputs were corrugation angle (θ), the axial length of cycle (S), hydraulic diameter (D_{h}) and Reynolds number (Re), and output was Nusselt number (Nu). Neural network requires that the range of the both input and output values should between 0.1 and 0.9 due to the restriction of sigmoid function. The data evaluated experimentally in this study are normalized in order to have the values. The formula used is the following:

$$\frac{\text{Actual value} - \text{Minimum}}{\text{Maximum} - \text{Minimum}} \times (\text{High} - \text{Low}) + \text{Low}, \quad (4)$$

where minimum is minimum data value, maximum is the maximum data value, high is the maximum normalized data value = 0.9, and low is the minimum normalized data value = 0.1 [22]. In order to decide the structure of neural network, the rate of error convergence was checked by changing the number of hidden layer and also by adjusting the learning rate and momentum rate. To facilitate the comparisons between predicted values for different network parameters (the learning and momentum rate, number of training cycles, and group of data set) and actual values, there is need for error evaluation. The mean relative error (MRE) is calculated according to following the expression:

$$\mathrm{MRE} = \frac{1}{n}\sum_{i=1}^{n}\frac{100|a_i - p_i|}{a_i}, \quad (5)$$

where a_i is the actual value, p_i the predicted (output) value and n the number of the data.

Once training is completed, predictions from a new set of data may be done using the already trained network. To solve the back propagation algorithm a computer program using C++ has been developed and all computations were performed with a personal computer.

Model sensitivity was examined for four different networks with 1, 5, 10, and 15 nodes in the hidden layer, respectively. The network with a 5 nodes hidden layer, both a learning rate and momentum coefficient of 0.6 was found to have the best performance. During the training period the developed ANNs model, had a 4-5-1 configuration and 194,443 training cycles fit well with a MRE less than 3% and less than 4% for the test/validation period, in agreement (<4%, mean absolute relative error) with those evaluated using experimental technique. Table 4 and Fig. 4 show that the error values

Table 4
Comparison of experimental and ANNs results for Nusselt numbers: testing results

Re	*Nu*, experimental	*Nu*, ANNs	RE (%)
1200	22.11	24.31	9.94
1600	21.27	23.41	10.08
2000	23.05	22.90	0.63
2400	23.38	22.89	2.10
2800	23.50	23.42	0.36
3200	25.11	24.48	2.51
3600	26.28	26.01	1.02
4000	27.84	27.91	0.25

MRE(%) = 3.36.

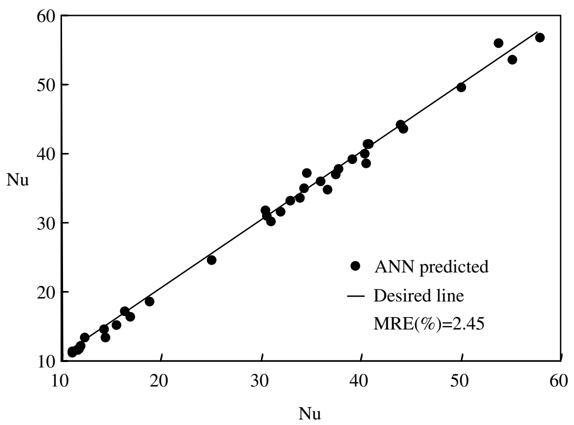


Fig. 4. Nusselt number from training result evaluated using ANNs.

are in the range 0–11%. The maximum relative errors were approximately 8.27% (from Fig. 4) and 10.08% (from Table 4, and the MREs were 2.45% and 3.36%), respectively.

4. Conclusion

In this study, ANNs model was developed for the analysis of heat transfer. Results indicate that the ANNs model can be trained to provide satisfactory estimations of Nusselt numbers for air flowing in corrugated channels. It should be advised that in preliminary engineering studies, the networks can be used an easy-to-use tool for engineers.

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