OPTIMAL NETWORK ARCHITECTURE FOR NUSSELT NUMBER AND FRICTION FACTOR

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Abstract

This present research uses artifical neural networks (ANNs) to determine Nusselt numbers and friction factors for nine different baffle plate inserted tubes. MATLAB toolbox was used to search better network configuration prediction by using commonly used multilayer feed-forward neural networks (MLFNN) with back propagation (BP) learning algorithm with five different training functions with adaptation learning function of mean square error and TANSIG transfer function. In this research, eighteen data samples were used in a series of runs for each nine samples of baffle-inserted tube. Up to 70% of the whole experimental data was used to train the models, 15 % was used to test the outputs and the remaining data points which were not used for training were used to evaluate the validity of the ANNs. The results show that the TRAINBR training function was the best model for predicting the target experimental outputs.

Keywords: Heat transfer, Nusselt number, friction factor, artifical neural network

Introduction

Artifical Neural Networks (ANNs) have been widely used for thermal analysis of heat exchangers during the last two decades. The applications of ANN for thermal analysis of heat exchangers are reviewed in detail (Mohanraj, Jayaraj and Muraleedharan, 2015). The various network architectures tested in (Zdaniuk, Chamra and Keith Walters, 2007) suggesting feed-forward network with log-sigmoid node functions in the first layer and a linear node function in the output layer to be the most advantageous architecture to use for prediction of helically-finned tube performance.

A feed forward ANN approach trained by Levenberg–Marquardt algorithm was developed to predict friction factor in the serpentine microchannels with rectangular cross section has been investigated experimentally (Rahimi, Hajialyani, Beigzadeh and Alsairafi, 2015) hybrid high order neural network and a feed forward neural network are developed and applied to find an optimized empirical correlation for prediction of dryout heat transfer. The values predicted by the models are compared with each other and also with the previous values of empirical correlation (Rostamifard, Fallahnezhad, Zaferanlouei, Setayeshi and Moradi, 2011).

ANN is applied for heat transfer analysis of shell-and-tube heat exchangers with segmental baffles or continuous helical baffles. Three heat exchangers were experimentally investigated. Limited experimental data was obtained for training and testing neural network configurations. The commonly used back propagation algorithm was used to train and test networks. Prediction of the outlet temperature differences in each side and overall heat

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transfer rates were performed. Different network configurations were also studied by the aid of searching a relatively better network for prediction (Xie, Wang, Zeng, and Luo, 2007). ANN is used 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 (Islamoglu and Kurt, 2004). The capabilities of an ANN approach for predicting the performance of a liquid desiccant dehumidifier in terms of the water condensation rate and dehumidifier effectiveness is proposed (Mohammad, Bin Mat, Sulaiman, Sopian, and Al-abidi, 2013). An application of ANNs to characterize thermo-hydraulic behavior of helical wire coil inserts inside tube. An experimental study was carried out to investigate the effects of four types of wire coil inserts on heat transfer enhancement and pressure drop. The performance of the ANN was found to be superior in comparison with corresponding power-law regressions (Jafari Nasr, Habibi Khalaj, and Mozaffari, 2010). This paper describes the selection of training function of an ANN for modeling the heat transfer prediction of horizontal tube immersed in gas–solid fluidized bed of large particles. The ANN modeling was developed to study the effect of fluidizing gas velocity on the average heat transfer coefficient between fluidizing bed and horizontal tube surface. The feed-forward network with back propagation structure implemented using Levenberg–Marquardt's learning rule in the neural network approach. Performances of five training functions implemented in training neural network for predicting the heat transfer coefficient (Kamble, Pangavhane, and Singh, 2015). Despite the fact that comprehensive studies were conducted on heat transfer applications in the literature, lack of sufficient research studies concerning the effectiveness and comparision of different ANN models considering transfer functions and training algorithms in the broader sense based on mean relative error (MRE) and correlation coefficient (R) for all data sets.

Experimental procedure and data collection

Experimental setup

A schematic diagram of experimental setup used for the heat transfer analysis in this study for data gathering is presented in (Figure 1).

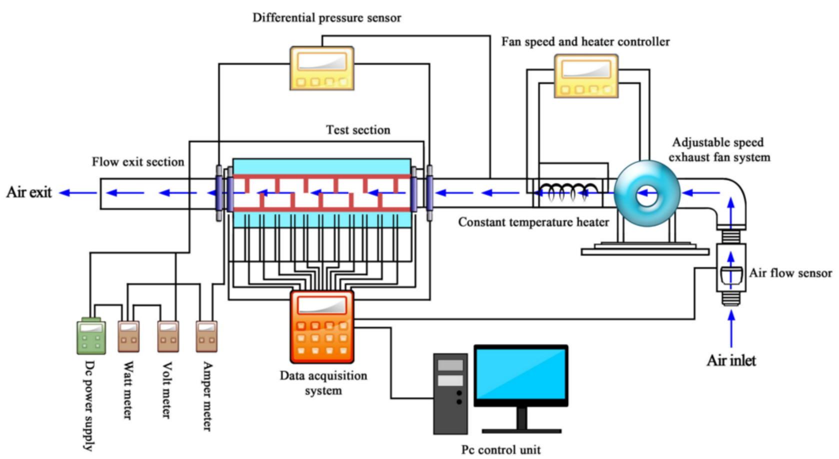

Figure 1: Schematic diagram of experimental setup

It consists of three parts flow entrance section; flow development section, test section and flow exit section. A detailed presentation of the experimental setup design, fabrication of experimental apparatus and data reduction are available in some of author's previous researche in detail (Tandiroglu, 2006). A total of nine samples of baffle inserted tubes having half circle geometry were investigated and the effect of thermal radiation for internal flow is ignored during the experiments due to low temperature difference between wall and baffle. Half circle baffles made of type AISI 304 L were set in tube which has an inner diameter of 31 mm and the thickness of 2 mm. In the experiments, at a specific air temperature, the air flow rate was fixed, then constant heat flux was induced to test section directly by means of PLC integrated DC power supply which could be regulated in the ranges of 0-60 V and 0-660 A. Data for all the measuring points were recorded and finally averaged over the elapsed time simultaneously by means of data online acqusition system till the system was allowed to approach the steady state. All these measurements along with the test runs were collected and displayed by a PC through the data acquisition system. The flow geometries and parameters investigated in this study were illustrated as follows and are shown in (Figure 2).

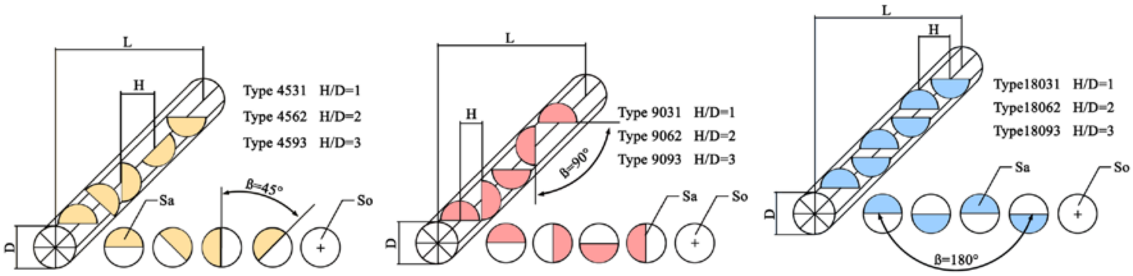

Figure 2: Schematics of half circle baffled tubes

The heat loss calibration tests were performed before taking measurements on the system for each type of baffle inserted tubes in the following manner. The time averaged wall temperature variations by time were recorded using data online acquisition system. When the steady state condition is established to insure that external thermal equilibrium can be achieved, heat loss calibration tests for different values of power supply are reported for a steady state case. It was found that the heat loss is directly proportional to the difference between the wall and ambient temperatures. The required constant of proportionality was taken from the previously determined heat loss calibrations. It was observed that the maximum heat loss did not exceed to %5 all through the test runs. More detailed explanation of the heat loss calibration technique was given by (Tandiroglu, 2006).

Data reduction

The goal of this study is to determine Nusselt numbers, friction factor, entropy generation numbers and irreversibility distribution ratios of the baffle inserted tubes for fully developed turbulent flow by using ANNs. The independent parameters are Reynolds number and tube diameter. The Reynolds numbers based on the tube hydraulic diameter are given by,

$$\mathrm{Re} = \frac{\mathrm{uD}}{\mathrm{v}} \tag{1}$$

The average fully developed heat transfer coefficients are evaluated from the measured temperatures and heat inputs.

$$h = \frac{Q}{(T_w - T_b)A} \tag{2}$$

where A is convective heat transfer area. Then full developed Nusselt numbers are evaluated by using,

$$Nu = \frac{hD}{k} \tag{3}$$

It may be noted that for periodically fully developed flow, the pressure exibits periodicity character similar to those already ascribed to the temperature. The pressure at successive points lies on straight line as well as temperatures of the same set of points. With this, the friction factor is evaluated using Eq. (4).

$$f = \frac{-\frac{dP}{dX}}{\frac{1}{2}\rho u^2} \tag{4}$$

where $\frac{dP}{dX}$ is pressure gradient.

Experimental uncertainity analysis

The uncertainties of experimental quantities were computed by using the method presented (Kline and McClintock, 1953). The uncertainty calculation method used involves calculating derivatives of the desired variable with respect to individual experimental quantities and applying known uncertainties. The general equation presented by (Kline and McClintock, 1953). Showing the magnitude of the uncertainty in $R(uR)$ is

$$u_R = \pm\left[\left(\frac{\partial R}{\partial x_1}u_{x_1}\right)^2 + \left(\frac{\partial R}{\partial x_2}u_{x_2}\right)^2 + \cdots\left(\frac{\partial R}{\partial x_n}u_{x_n}\right)^2\right]^{\frac{1}{2}} \tag{5}$$

where $R = R(x_1, x_2, \ldots\ldots x_n)$ and x_n is the variable that affects the results of R.

The experimental results up to a Reynolds number of 20.000 were correlated with a standard deviation of 5% at most. Experimental uncertainties in the Reynolds number, friction factor, and Nusselt number were estimated by the above procedure described (Kline and McClintock, 1953). The mean uncertainties are $\pm$2.5% in the Reynolds number, $\pm$4% in the friction number. The highest uncertainties are $\pm$9% in the Nusselt number for the type 9031. Uncertainties in the Nusselt number range between $\pm$5% and 8% for 3.000$\leq Re \leq$20.000 at the type 18.093 and $\pm$8% and 10% 3.000$\leq Re \leq$20.000 at the type 9031, highest uncertainties being at the lowest Reynolds number (Tandiroglu, 2006).

Development of artificial neural network

ANN is a numerical model that simulates the human brain's biological neural network ability to learn and recognize complicated nonlinear functions. This learning ability makes the ANN more powerful than the parametric approaches. ANN usage in heat transfer applications is popular because of its functional approximation between the inputs and desired outputs. In this present study a MLFNN with BP learning algorithm (Tan, Ward, Wilcox and Payne, 2009) has been used. It is simple and high learning rates; therefore it is widely used to train the networks.

The ANN model was developed for the system with four independent parameters in the input layer (Reynold number, tube lenght to baffle spacing ratio, baffle orientation angles and pitch to diameter ratio), four parameters (time averaged values of Nusselt number and friction factor) and five neurons in hidden layer.

Neural network tool in the MATLAB R2011b version is used for ANN modelling of the system. In this study, multilayer feed-forward neural networks (MLFNN) with back propagation (BP) training and validation algorithms were applied for each of five different training functions given (Table 1).

Table 1: ANN training function descriptions used in for the study

Training function	Description
TRAINLM	Levenberg-Marquardt algorithm. Fastest training algorithm for networks of moderate size. Has memory reduction feature for use when the training set is large (Foresee and Hagan, 1997), (Hagan, and Menhaj, 1994).
TRAINRP	Resilient backpropagation. Simple batch mode training algorithm with fast convergence and minimal storage requirements (Riedmiller and Braun, 1993).
TRAINR	Random order incremental training w/learning functions. TRAINR trains a network with weight and bias learning rules with incremental updates after each presentation of an input. Inputs are presented in random order.
TRAINGD	Basic gradient descent. Slow response, can be used in incremental mode training.
TRAINGDM	Gradient descent with momentum. Generally faster than traingd. Can be used in incremental mode training.
TRAINGDA	Gradient descent with adaptive lr backpropagation. TRAINGDA is a network training function that updates weight and bias values according to gradient descent with adaptive learning rate.

Normalization of experimental data

It is desirable to normalize all the input and output data with the largest and smallest values of each of the data sets, since the variables of input and output data have different physical units and ranges. So, all of the input and output data were normalized between 0,1 and 0,9 due to restriction of sigmoid function (Nasr, Badrand Joun, 2003), (Sanjay, Jyothi and Chin, 2006), (Nasr, Badr, and Joun, 2003) using the below rearranged formula as follows:

$$\text{Normalized value} = 0{,}8 * \left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) + 0.1 \tag{6}$$

where the X is the measured value, while X_{min} and X_{max} values are the minimum and maximum values of found in the train set and also employed data for normalization are given shown (Table 2). TANSIG transfer function gives better results than logarithmic sigmoid function (LOGSIG) according to present investigation as mentioned (Dariush, Mehdi, Salman, Saeed, and Hassan, 2011).

Table 2: The range of employed data in the modelling

Variable	Range	
	Minimum	Maximum
f	0,01517	0,1835
Nu	52,87346	2712,383

TANSIG transfer function is being used as an activation function in the hidden layer of ANN (Vogl, Mangis, Rigler, Zink and Alkon, 1988) is given as

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \quad (7)$$

Results and discussion

MATLAB toolbox was used to search better network configuration prediction by using commonly used feed forward back propagation algorithm with five different training functions with adaptation learning function of MSE and TANSIG transfer function.

In this research, eighteen data samples were used in a series of runs for each nine samples of baffle-inserted tube. Reynold number, tube lenght to baffle spacing ratio, baffle orientation angle and pitch to diameter ratio were considered as input variables of ANNs and the time averaged values of Nusselt number and friction factor determined as the target data. Up to 70% of the whole experimental data was used to train the models, 15% was used to test the outputs and the remaining data points which were not used for training were used to evaluate the validity of the ANNs.

As mentioned above the ANN was trained using all possible five different training functions avaliable in MATLAB toolbox. TRAINLM training function has shown better performance as compared to other four training functions under the constant network parameters. The absolute fraction of variance values (R^2) and optimal number of hidden neurons for each training function were determined and tabulated in (Table 3).

Table 3: Absolute fraction of variance (R2) values for different training algorithms

Training algorithm	Number of optimal hidden neurons	R^2 Training
TRAINLM	10	0,99889
TRAINRP	6	0,99877
TRAINR	5	0,99823
TRAINGD	8	0,99792
TRAINGDM	7	0,99715

Five different ANN training models have been compared by mean square error (MSE), mean relative error (MRE) and absolute fraction of variance (R^2) mathematically expressed as following equations:

$$MRE = \frac{1}{n}\sum_{i=1}^{n}\frac{100*|a_i - t_i|}{|t_i|} \tag{8}$$

$$MSE = \frac{1}{n}(a_i - t_i)^2 \tag{9}$$

$$R^2 = 1 - \left[\frac{\sum_{i=1}^{n}(a_i - t_i)^2}{\sum_{i=1}^{n}(t_i)^2}\right] \tag{10}$$

where a_i is the actual (experimental) value, t_i is the predicted (output) value and n is the number of the data. The networks were trained for all five different training functions under same network parameters. The training was continued till the least value of MSE at a definite value of epochs attained for all five different training functions seperately. The use of the MSE is an excellent numerical criterion for evaluating the performance of a prediction tool. Table 4 shows the results for the MRE, MSE and R^2 values for different training algorithms. After analysing all the results, TRAINLM training function has shown best performance as compared to other four training functions for predicting the target experimental outputs which has the least MSE value.

Table 4: MRE, MSE and R^2 values for different training algorithms

Training algorithm	MRE	MSE	R^2
TRAINLM	0,996613818	0,88701807	0,997701323
TRAINRP	0,996825454	0,887394837	0,996842496
TRAINR	0,997248727	0,88814861	0,996243534
TRAINGD	0,998306910	0,890034442	0,995245664
TRAINGDM	0,998306910	0,890034442	0,994048880

All of the evaluations clearly show that; the coefficient of determination values R^2 for best training function TRAINLM has achieved unity for all outputs. The results show that the optimal neural network configuration TRAINLM training function is successful in predicting the solution of transient forced convective heat transfer problems to determine friction factor, Nusselt number and entropy generation number.

Conclusions

In the present study, artifical neural network methodology has been successfully applied on transient forced convective heat transfer to determine the time averaged values of Nusselt number, friction factor, entropy generation number and irreversibility distribution ratio. Alternative five configurations of feed forward back propogation to determine optimal training function by using commonly used MLFNN with BP learning function with five different training functions with adaptation learning function of mean square error and TANSIG transfer function. The highlights of the work are the use of an actual experimental data set to develop an optimal ANN configuration between five different ANN configurations. It is obvious that all of the the training functions are in good agreement with the experimental data set but TRAINLM training function is the best training function for prediction of output layer parameters.

Almost perfect accuracy between the TRAINLM neural network training function predictions and experimental data was achieved with mean relative error (MRE) of 0,996613818 % for data sets, which suggests the reliability of the ANNs as a strong tool for predicting the performance of transient forced convective heat transfer applications.

Nomenclature			
A	crossectional area (m^2)	R	coefficient of correlation
$\frac{\mathrm{dP}}{\mathrm{dX}}$	pressure gradient, $\left(\frac{\mathrm{N}}{\mathrm{m}^3}\right)$	R^2	coefficient of determination
D	tube inlet diameter, (m)	Re	Reynolds number
h	heat transfer coefficient, $(\frac{\mathrm{W}}{\mathrm{m}^2\mathrm{K}})$	u	velocity, $(\frac{m}{s})$
H	baffle spacing or pitch, (m)		
$\mathrm{H/D}$	ratio of pitch to tube inlet diameter	**Greek symbols**	
f	dimensionless pressure drop	ρ	density, $(\frac{\mathrm{kg}}{\mathrm{m}^3})$
k	thermal conductivity, $(\frac{\mathrm{W}}{\mathrm{mK}})$	v	kinematic viscosity, $(\frac{\mathrm{m}^2}{\mathrm{s}})$
L	tube length, (m)		
Nu	Nusselt number	**Subscripts**	
Q	heat transferred to fluid, (J)	b	bulk
S	cross sectional area, (m^2)	m	mean
T	temperature, (K)	o	smooth pipe
X	measured value	w	wall

Abbreviations

ANN	artifical neural network
BP	back propagation
DC	direct current
LOGSIG	logarithmic sigmoid
MLFNN	multilayer feed-forward neural network
SE	mean square error
MRE	mean relative error
PLC	programmable logic controller
TANSIG	tangent sigmoid

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