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PREDICTION OF HEAT TRANSFER CHARACTERISTICS FOR FORCED CONVECTION PIPE FLOW USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This paper investigates the ability of utilizing the artificial neural network (ANN) in calculating the forced convection characteristics coefficients from internal flow of air inside a pipe subjected to constant heat flux. The heat transfer characteristics such as Nusselt number (Nu), Stanton number (St) and friction factor (f) which are calculated using the empirical correlations have high deviation from that obtained from the experiments. So, the ANN method is proposed for predicting these characteristics coefficients more close to the experimental results. The training and testing data for optimizing the ANN structure are based on the experimental data obtained from the experiments performed on a forced convection apparatus. Three training algorithms for the training of the ANN were used and the presented ANN is implemented by using such MATLAB program. For the preferable ANN structure acquired in the current work, an acceptable mean square error was achieved for the training and test data, using the Trainlm algorithm. The results reveal that the estimated results are very close to the experimental data. Also, a new Graphical User Interface (GUI) is implemented for the application of ANN in the calculation of the attempted heat transfer parameters.

KEYWORDS*:* Pipe flow; Forced convection; Heat transfer characteristics; Neural networks; Graphical User Interface (GUI).

1. INTRODUCTION

Many heat transfer analysis is of significant practical interest because of a large number of heating and cooling processes associated with industrial applications. Equipment such as heat exchangers and boilers in power producing plants require the knowledge of surface temperature distribution within the geometries. Recently the Artificial Neural Networks (ANN) have been used in numerous engineering thermo-fluid applications. There are a lot of researches applied ANN to train many of heat transfer characteristics in order to achieve reasonable results. Jambunathan et al., 1996 used ANN to show one-dimensional transient heat conduction from measurements utilizing liquid crystal thermography. Neural systems were prepared to anticipate the heat transfer quantities at a point in a duct heated by a stream of hot air. Bittanti and Piroddi, 1997 used neural networks with a comprehensive smallest inconsistency control approach for heat exchanger uses. Diaz et al., 1999 conducted ANN to various problems of difficulty which involved conduction, convection, and the calculation of experimental data of cross-flow heat exchanger.

Chaobin and Eiji, 2008 employed ANN established on a lot of practical data to build a semi-prediction approach for flowing stream of supercritical carbon dioxide with a little quantity of entrained greasing oil in tubes. They proposed a procedure contains an input-output three-layer neural network with the tube diameter, Prandtl number, Reynolds number, heat flux, thermal conductivity and oil quantity as the input parameters and the heat transfer coefficient as the output parameter. Their practical data utilized reference to an extensive number of experimental conditions with various parameters such as tube diameter, heat flux, oil quantity, pressure and mass flux. They concluded that the heat transfer coefficient increases linearly with the mass flux, while an increase in the heat flux leads to only a slight increase in the heat transfer coefficient. Gerardo and Antonio, 2009 collected results for turbulent forced convection for the internal flow of binary mixtures in tubes. They used a completely associated back-propagation ANN to acquire the form of Nusselt number as a function of Reynolds and Prandtl numbers. Their obtainable results are divided into two subgroups to train and examine the neural network. They utilized interpolation abilities of ANN to estimate Nusselt number for numerous scopes of Prandtl and Reynolds numbers. These quantities are utilized to produce an overall heat transfer correlation that covers the endeavored scope of Reynolds in mix with a large Prandtl with uncertainty ±25%.

Ahmed, 2016 examined the effect of transfer functions and training algorithms using artificial neural networks (ANN) on experimental data for friction factors, entropy generation numbers, Nusselt numbers and irreversibility distribution ratios for nine different baffle plates embedded tubes. MATLAB code was utilized to find better network configuration by utilizing general multilayer feed-forward neural networks (MLFNN) with back proliferation (BP) learning algorithm with thirteen diverse training functions. Eighteen data tests were utilized in a sequence of simulations for every nine specimens of baffle embedded tube. His results demonstrate that the dependability of the ANN as a robust device for anticipating the behavior of transient forced convective heat transfer applications.

The aims of the present work are to build an ANN for predicting the heat transfer coefficients, Nu, St and f for turbulent internal flow in a pipe subjected to fixed heat flux at the external surface. These values of heat transfer coefficients which are calculated using the empirical correlations indicates a large deviation from the experimental results. So, the ANN method is proposed to predict values more close to the experimental results. The experimental data used for testing and training the ANN are obtained by using forced convection apparatus. Various values for Reynolds number and surface heat flux are taken for the experiments. The heat transfer coefficients Nu, St and f predicted by the ANN are compared with their values obtained from the empirical heat transfer correlations. Also, to make the proposed ANN easy to be used for users, the MATLAB graphical user interface is used.

2. EXPERIMENTAL SETUP

The experimental data attempted for training and validating the ANN is obtained by performing eighteen experiment test using forced convection apparatus which shown in Fig. 1. The apparatus gives the ability to examine the theory and related formula linked to forced convection in pipes. The measured data can be used to calculate heat transfer coefficients, the pipe friction factor and numerous non-dimensional sets involving Re, Nu and St.

The device constructed of an electrically driven centrifugal fan, which guides air over a control valve and releases through a U-shaped pipe. The fan speed kept fixed throughout. A British Standard orifice plate is held in this pipe to determine the air flow rate. This pipe is connected to a copper test pipe that discharges into the atmosphere. The examination pipe is electrically heated by a heating tape enveloped around the external pipe. The power input to the tape is changed by tuning of power control on the apparatus, the input levels are determined via a voltmeter and ammeter on the device panel. The examination pipe is insulated by fiberglass lagging. The test length, situated within the heated section of the test pipe, has pressure measuring tapping at each end, which is connected to manometers on the instrument panel measure fan discharge and the orifice pressure drop. A thermometer is existed to measure the air temperature at the inlet to the test pipe.

The mimic diagram (see Fig. 2) on the front panel displays the locations of the thirteen thermocouples of type T; seven are attached to the test length, and six are located in the lagging wrapped around the test length. The output from any thermocouple may be chosen with a selector switch fitted to the instrument panel and measured with the electronic thermometer.

Fig. 1. Forced convection heat transfer apparatus.

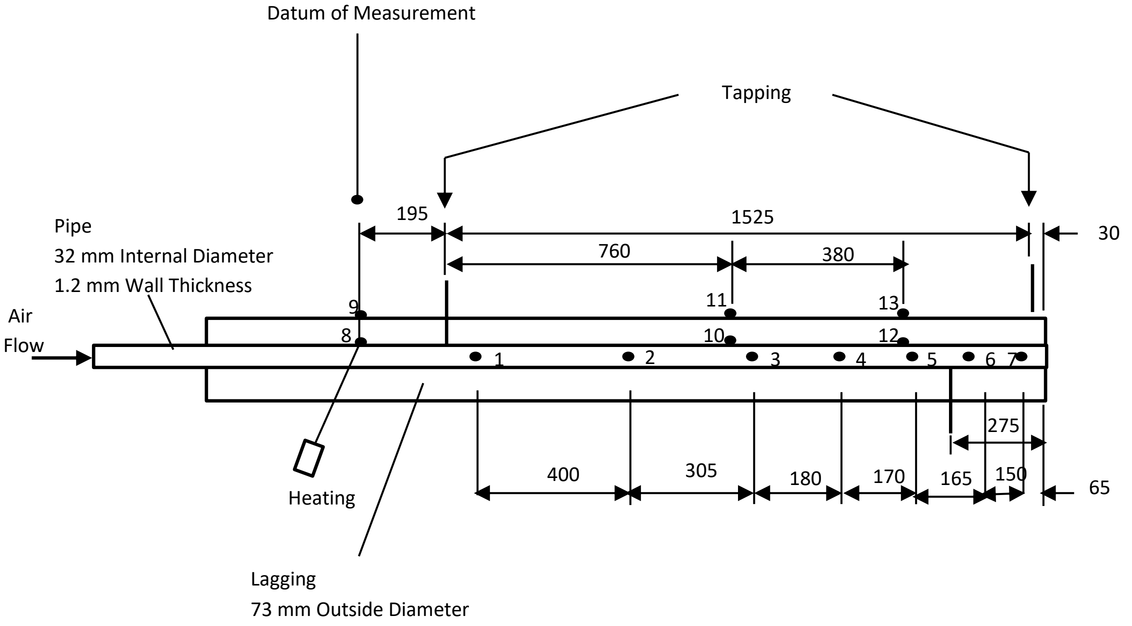

Fig. 2. Schematic for the locations of thermocouples (Dimensions in mm).

3. HEAT TRANSFER CALCULATIONS

In this section, the relations that used to predict the heat transfer parameters are mentioned. The air volume flow rate is calculated using the following equation:

$$Q_v = a\, C_d \sqrt{2gH_o} \tag{1}$$

The heat flux transferred to the air is given by the equation below:

$$q = \frac{Q_n}{A} \tag{2}$$

Where Q_n is the actual heat transfer rate to the air is given by:

$$Q_n = Q - Q_c \tag{3}$$

In which the total heat supplied to the heating tape (Q) is given by:

$$Q = IV \tag{4}$$

and the heat loss to the surrounding through the insulation layer (Q_c) is:

$$Q_c = \frac{2\pi L k \theta}{\ln\frac{r_o}{r_i}} \tag{5}$$

Where θ is the temperature difference through the insulation layer:

$$\theta = T_i - T_o \tag{6}$$

and,

$$T_i = \frac{(T_8 + T_{10} + T_{12})}{3} \tag{7}$$

$$T_o = \frac{(T_9 + T_{11} + T_{13})}{3} \tag{8}$$

The heat transfer coefficient is calculated from:

$$h = \frac{q}{(T_{w,m} - T_{b,m})} \tag{9}$$

where the mean wall temperature $T_{w,m}$ is given by:

$$T_{w,m} = \frac{(T_1 + T_2 + T_3 + T_4 + T_5 + T_6 + T_7)}{7} \tag{10}$$

and the mean bulk temperature of air $T_{b,m}$ is given by:

$$T_{b,m} = \frac{(T_{a1} + T_{a2})}{2} \tag{11}$$

It is possible to evaluate each of Nu, St and f by the following relations:

$$Nu = \frac{hD_i}{K_f} \tag{12}$$

$$St = \frac{h}{\rho_a U C_p} \tag{13}$$

$$f = \frac{2D_i\, g\, H_l}{4LU^2} \tag{14}$$

also, Nu, St and f can be calculated using the following empirical relations for turbulent flow (Holman, 1989):

$$\mathrm{Nu} = 0.023\mathrm{Re}^{0.8}\mathrm{Pr}^{0.4} \qquad 15$$

$$\mathrm{St} = 0.023\mathrm{Re}^{-0.2}\mathrm{Pr}^{-0.6} \qquad 16$$

$$\mathrm{f} = 0.046\mathrm{Re}^{-0.2} \qquad 17$$

Where Re and Pr are given by the following relations:

$$\mathrm{Re} = \frac{\rho U D_i}{\mu} \qquad 18$$

and,

$$\mathrm{Pr} = \frac{\mu C_p}{K_f} \qquad 19$$

The experimental values of Nu, St and f are calculated using Eqs. (12), (13) and (14) respectively which they are compared with their values that predicted by using ANN.

The experimental procedure was done by estimating the Reynolds number by adjusting the control valve at the fan inlet, and then the power input to the heating tape is estimated. After the steady state period is finished, the measurements of the temperatures along the test pipe length (T_1 to T_7), along the insulation layer (T_9 to T_{13}) and the temperature of the air inlet to test section and exit from it are recorded. Also, the pressure drop through the orifice plate (H_o), the test pipe length (H_l) and the fan pressure head are measured. Eighteen experiments are performed with various values for Reynolds number and the heat flux. The air properties for each experiment are calculated at the air mean temperature.

4. ANALYSIS OF UNCERTAINTIES

Many types of experimental errors may occur during the implementation of most experiments. These errors can be classified as systematic and random errors. The first type such as instrument errors (backlash, mounting, assembled, *etc*) cannot be avoided. However, other types of error which named random error or internal error may be reduced depending on many factors such as the experience of the expert. Human error, environmental error, sample representative error, reading error, ...*etc* are some of this kind of errors. In this study the main error that can be considered are the resolution error and thermocouple error which can be listed as in Table 1.

Table 1. Main sources of individual errors.

No. \ Item	Parameter	Type of error	Magnitude of error
1	Volt	resolution	± 5 V
2	Current	resolution	± 0.1 A
3	Ho	resolution	± 0.5 mm
4	H_l	resolution	± 0.5 mm
5	Inlet and outlet temperatures	Resolution & Thermocouple	± 0.5 °C ±0.03 °C
6	T_1 to T_{13}	Thermocouple	±0.03 °C

From Eq. (12) the standard error in Nusselt number (ΔNu) can be given as:

$$\Delta Nu = \pm\left[\left(\frac{\partial \mathrm{Nu}}{\partial \mathrm{h}}\Delta h\right)^2\right]^{1/2} \qquad 20$$

Where the above equation is considered by (Moffatt, 1988) and (Bolton, 1996). However, h is a function of such variables; therefore its error (Δh) can be written as:

$$\Delta \mathrm{h} = \pm\left[\left(\frac{\partial \mathrm{h}}{\partial \mathrm{q}}\Delta \mathrm{q}\right)^2 + \left(\frac{\partial \mathrm{h}}{\partial \mathrm{T_{w,m}}}\Delta \mathrm{T_{w,m}}\right)^2 + \left(\frac{\partial \mathrm{h}}{\partial \mathrm{T_{b,m}}}\Delta \mathrm{T_{b,m}}\right)^2\right]^{1/2} \qquad 21$$

Also, q,$T_{w,m}$ and $T_{b,m}$ are functions of another independent parameters as they given in Eqs. (2), (10) and (11) respectively. The errors in these factors can be derived as follows (Bolton, 1996):

$$\Delta q = \pm\left[\left(\frac{\partial q}{\partial Q_n}\Delta Q_n\right)^2\right]^{1/2} \qquad 22$$

For any dependent factor represented by a formula involves algebraic summation of an independent factor the standard error can be given as the root of summation of the square errors in these factors, see (Bolton, 1996). Therefore the error in $T_{w,m}$ and $T_{b,m}$ can be formulated as:

$$\Delta T_{w,m} = \pm\left(\Delta T_1{}^2 + \Delta T_2{}^2 + \Delta T_3{}^2 + \Delta T_4{}^2 + \Delta T_5{}^2 + \Delta T_6{}^2 + \Delta T_7{}^2\right)^{1/2} \qquad 23$$

$$\Delta T_{b,m} = \pm\left(\Delta \mathrm{T_{a1}}{}^2 + \Delta \mathrm{T_{a2}}{}^2\right)^{1/2} \qquad 24$$

Based on Eq. (3) the error in Q_n which named as (ΔQ_n) in Eq. (22) can be derived as:

$$\Delta \mathrm{Q_n} = \pm\left[\left(\frac{\partial \mathrm{Q_n}}{\partial \mathrm{Q}}\Delta \mathrm{Q}\right)^2 + \left(\frac{\partial \mathrm{Q_n}}{\partial \mathrm{Q_c}}\Delta \mathrm{Q_c}\right)^2\right]^{1/2} \qquad 25$$

From Eqs. (4) and (5), ΔQ and ΔQ_c can be calculated as follows :

$$\Delta \mathrm{Q} = \pm\left[\left(\frac{\partial \mathrm{Q}}{\partial \mathrm{V}}\Delta \mathrm{V}\right)^2 + \left(\frac{\partial \mathrm{Q}}{\partial \mathrm{I}}\Delta \mathrm{I}\right)^2\right]^{1/2} \qquad 26$$

$$\Delta Q_c = \pm\left[\left(\frac{\partial Q_c}{\partial\theta}\Delta\theta\right)^2\right]^{1/2} \quad 27$$

The error in temperature difference (Δθ) can be derived from Eq. (6) as follows:

$$\Delta\theta = \pm\left[\Delta T_i^{\,2} + \Delta T_o^{\,2}\right]^{1/2} \quad 28$$

And using Eqs. (7) and (8) ΔT_i and ΔT_o are:

$$\Delta T_i = \pm\left[\Delta T_8^{\,2} + \Delta T_{10}^{\,2} + \Delta T_{12}^{\,2}\right]^{1/2} \quad 29$$

$$\Delta T_o = \pm\left[\Delta T_9^{\,2} + \Delta T_{11}^{\,2} + \Delta T_{13}^{\,2}\right]^{1/2} \quad 30$$

St is a function of (h) and (U) therefore the error in St which will denoted as (ΔSt) and can be formulated from Eq. (13) as:

$$\Delta St = \pm\left[\left(\frac{\partial St}{\partial h}\Delta h\right)^2 + \left(\frac{\partial St}{\partial U}\Delta U\right)^2\right]^{1/2} \quad 31$$

Where (Δh) is given in Eq. (21), while (ΔU) can be derived from the formula ($U = Q_v/A_c$) as:

$$\Delta U = \pm\left[\left(\frac{\partial U}{\partial Q_v}\Delta Q_v\right)^2\right]^{1/2} \quad 32$$

Where ΔQ_v can be derived from Eq. (1) as follows:

$$\Delta Q_v = \pm\left[\left(\frac{\partial Q_v}{\partial H_o}\Delta H_o\right)^2\right]^{1/2} \quad 33$$

From Eq. (14) the standard error in friction factor (Δf) can be derived as:

$$\Delta f = \pm\left[\left(\frac{\partial f}{\partial H_l}\Delta H_l\right)^2 + \left(\frac{\partial f}{\partial U}\Delta U\right)^2\right]^{1/2} \quad 34$$

For the same parameter, if there is more than one source of error, then, the overall error can be calculated as (Bolton, 1996):

$$overall\ error = \pm\left[e_1^{\,2} + e_2^{\,2} + \cdots\right]^{1/2} \quad 35$$

Where (e_1, e_2,…..*etc*) are the individual error sources. By using Eq. (35), the error in the inlet and outlet temperature can be calculated in order to substitute them in the equations of standard error of the main factors. When using Eqs. (20) to (34) the error in Nu, St and f can be determined and listed as shown in Table 2.

Table 2. Uncertainties in the main factors.

Item / No.	Parameter	Magnitude of error
1	Nu	± 8.892
2	St	$\pm 2.83 \times 10^{-4}$
3	f	$\pm 1.146 \times 10^{-4}$

From these results, it can be concluded that the using of intelligent techniques to predict a new results in some heat applications is a very useful and safety; especially at the complicated cases. However, this fact is estimated from the variety of sources of error which associated with the implementation of the experiments as well as the high ranges of the magnitudes of these errors.

5. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network (ANN) has been developed at many steps from 1943 by McCulloch and Pitts until the conception of multi-layer Perceptorn which had appeared by the attempts of Werpos, 1974 and Rumelhart, 1986, see (Roland, 2001). It is one of the intelligent techniques that can treat the multi-input multi-output (mimo) applications. ANN can be trained with many algorithms such as Batch Gradient Descent (Traingd), Powell-Beale Restarts (Traincgb) and Levenberg-Marquardt (Trainlm) (Rojas, 1996). There are many factors that may affect the ability of ANN for prediction such as training algorithm, the number of hidden nodes and the number of hidden layers. In this study, the input layer consists of Re, Pr and Q. Where the output layer is consisting of Nu, St and f as shown in Fig. 3. Also, one hidden layer with thirteen nodes is used in this work.

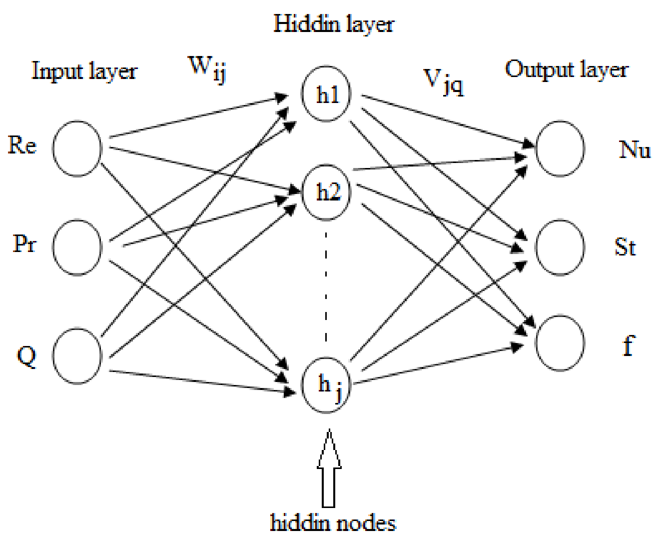

Fig. 3. Neural network structure.

6. RESULTS AND DISCUSSION

The Neural network which had been designed in this work was trained with some training algorithms. The results show that there is some difference in the regression (R) and mean square error (mse) that these algorithms have been produced. In Fig. 4 for Nu, Traingd algorithm was used and it can be noticed that there is some fitting between the ANN results and experimental results at points 2, 7 and 8. However, St results which are shown in Fig. 5 had appeared close in results at points 1, 2 and 9. The friction factor was not present acceptable regression at any point when using Traingd as seen in Fig. 6. These results can be described also by the mean square error (mse) in Fig. 7, which had high value (i.e., 0.1411) and a great amount of iteration (i.e., 500 epoch). Rather than that, the value of test regression (R=0.78871) represents another index for the weakness of this algorithm. In the other hand, when using more improved training algorithm (Traincgb) , the results of Nu, St and f which shown in Figs 8, 9 and 10 respectively, indicate high convergence between ANN results and experimental data except for some points. These results appear clearly in Fig. 11 and the small value of (mse) which equal to (0.0086331) represent a clear index. Also, the acceptable value of (R) (about 0.98615) show the high ability of this training algorithm for prediction. High fitting between the ANN and target can be achieved by using more effective training algorithm such as (Trainlm), illustrated in Figs. 12, 13 and 14. By hard testing and training of the network, test error and train error can be calculated as shown in Fig. 15. Very small value of (mse=8.7691$\times 10^{-8}$) as shown in this figure and very acceptable regression (about (1))) represent another indexes for the high efficiency of this training algorithm.

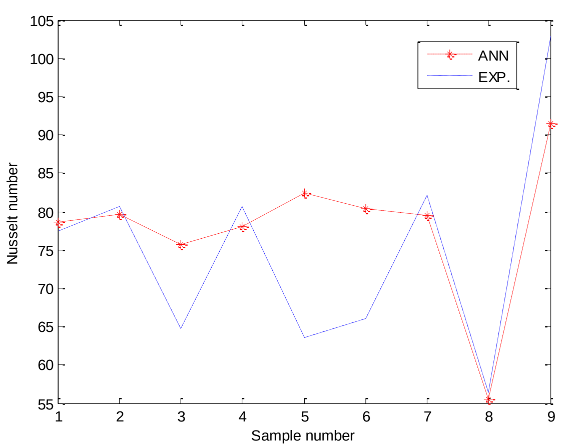

Fig. 4. Nusselt number predictions using Traingd algorithm.

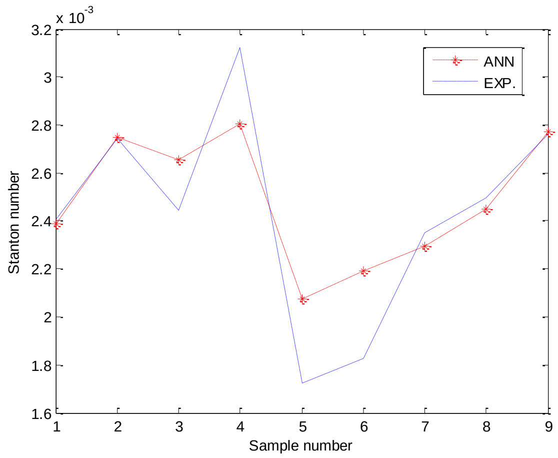

Fig. 5. Stanton number using Traingd algorithm.

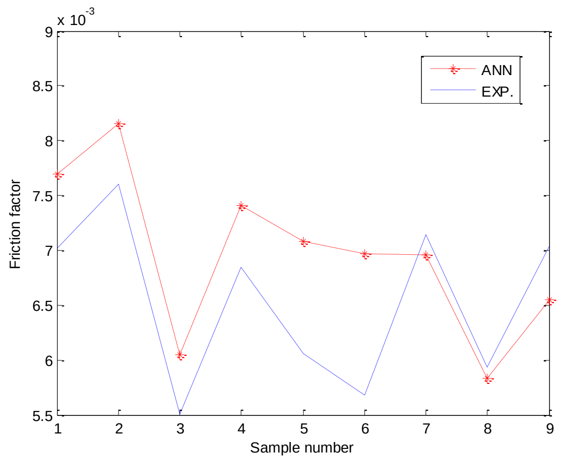

Fig. 6. Friction factor using Traingd algorithm.

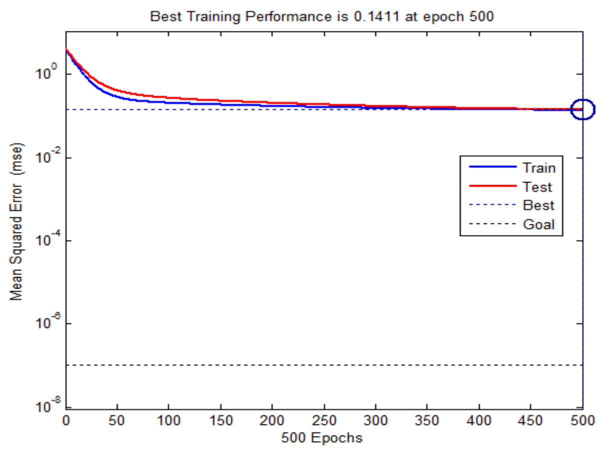

Fig. 7. Errors using Traingd training algorithm.

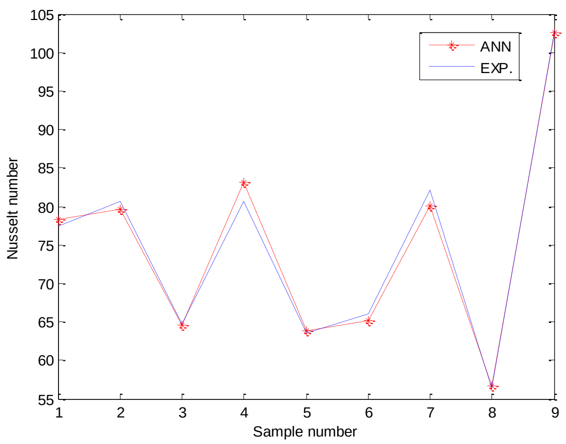

Fig. 8. Nusselt number predictions using Traincgb algorithm.

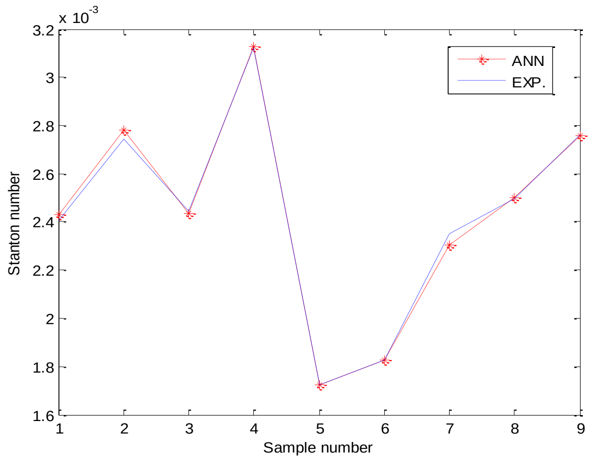

Fig. 9. Stanton number predictions using Traincgb algorithm.

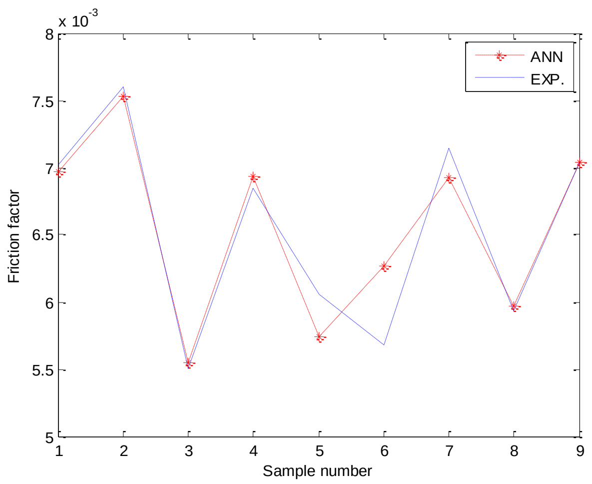

Fig. 10. Friction factor predictions using Traincgb algorithm

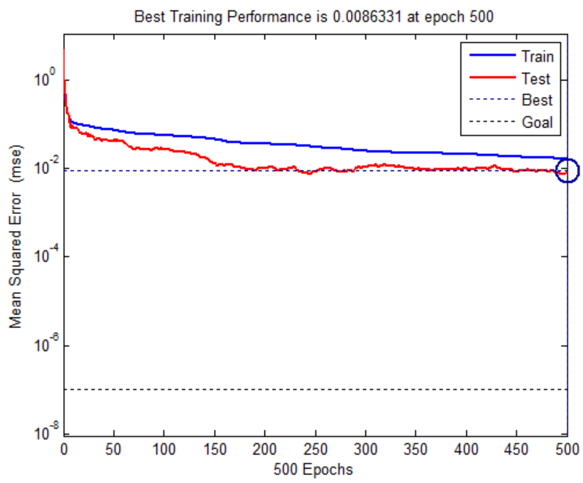

Fig. 11. Errors using Traincgb algorithm

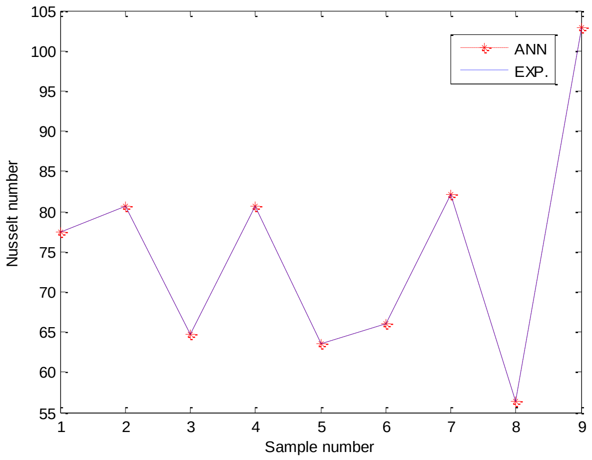

Fig. 12. Nusselt number predictions using Trainlm algorithm.

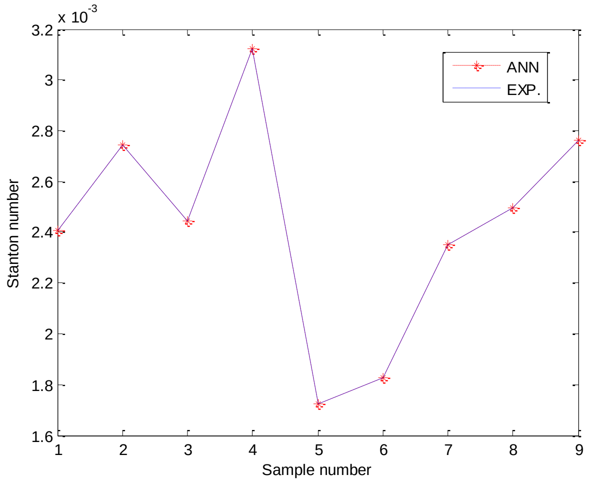

Fig. 13. Stanton number predictions using Trainlm algorithm.

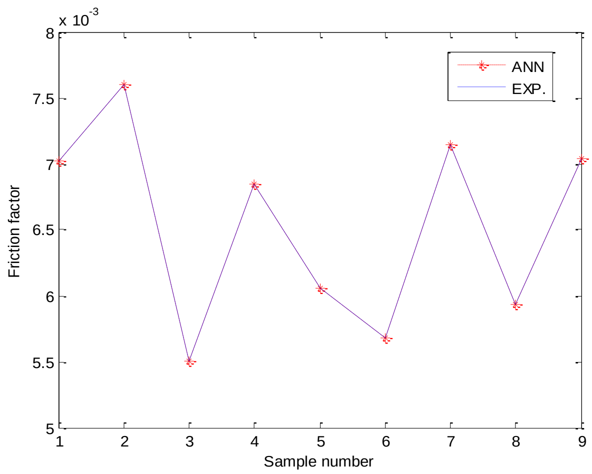

Fig. 14. Friction factor using Trainlm algorithm.

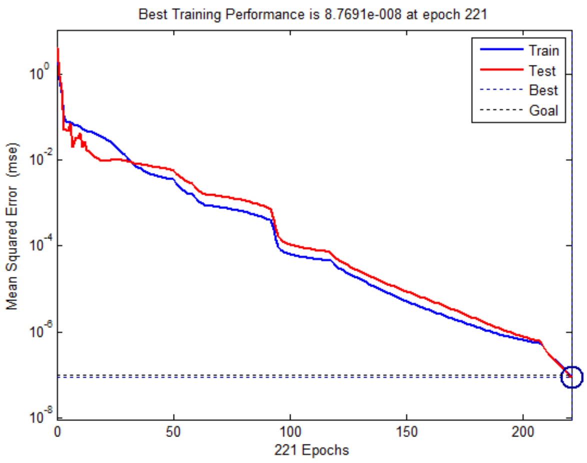

Fig. 15. Errors using Trainlm algorithm.

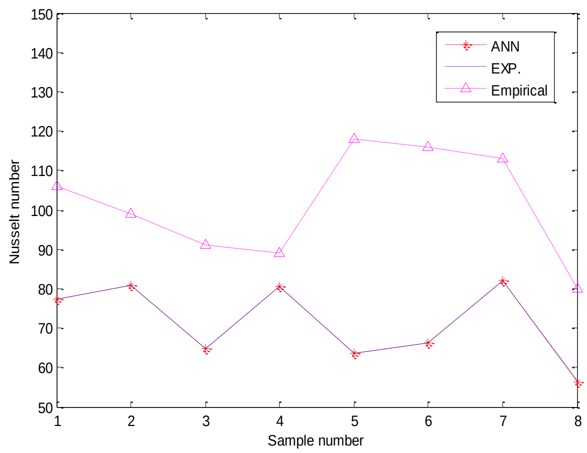

Fig. 16. Comparison of Nusselt number at three methods.

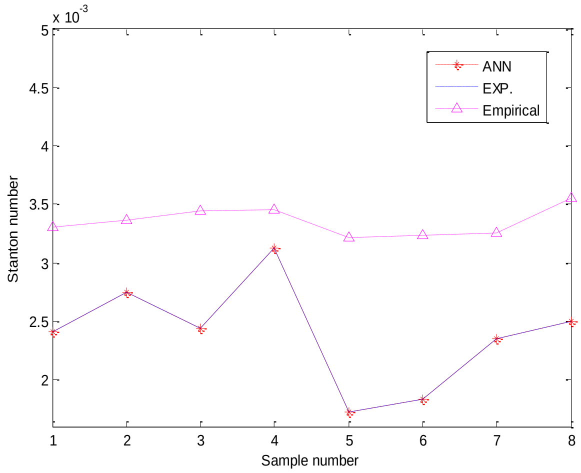

Fig. 17. Comparison of Stanton number at three methods.

In order to explain the high ability of ANN in the field of prediction, such comparison against empirical results has been implemented as shown in Figs. 16, 17 and 18. The empirical results have a great range of error while ANN results had appeared quite fit with the experimental data. This efficiency in prediction has been reached in the test of Nu and St were the empirical results had higher magnitudes than others. Also, f that calculated with empirical relation (i.e., Eq. (17)) has lower magnitudes than ANN and experimental results, see Fig. 18. Optimum nonlinear relations have been formulated for best fitting of the experimental data. As shown in Fig. 19, it can be noticed that Nu results obtained from the correlation have a great difference than that of experiments. This fact has also proved by the high magnitude of standard error (9.23) and low value of the correlation factor (7.83×10^{-1}). Although that all the data have been used in the correlation program, the results of St and f illustrated in Figs. 20 and 21 respectively reveal the great deviation from the experimental results. The great amount of error had appeared because of the complexity of the model. Also, high fluctuation of output variables which associated with many input variables may produce high values of uncertainties. For this reason, ANN has been used to obtain multi-input multi-output structure which appears very acceptable results as shown in Table 3.

Table 3. Error and Correlation factor.

Outputs \ Test factor	Error		Correlation factor	
	Best fit	**ANN**	**Best fit**	**ANN**
Nu	9.23	8.7691×10^{-8}	0.78	1
St	2.83×10^{-4}	8.7691×10^{-8}	0.68	1
f	9.79×10^{-4}	8.7691×10^{-8}	0.27	1

The use of ANN can reduce the number of experiments which then can reduce the required power and also the erratic condition can be investigated. Some comparisons have been implemented in order to explain the powerful of ANN against empirical (emp) relations as compared with the experimental data. These results were presents for Nu, St and f as shown in Tables 4, 5 and 6 respectively, where it can be concluded how the ANN can predict precise results with small percentage of error especially at complex heat transfer problems. Also, in this work, a new Graphical Usage Interface (GUI) named ANN-Heat parameters calculation had been constructed with three inputs (i.e. Re, Pr and Q). These inputs are received by relations depend on best trained ANN and produce three outputs Nu, St and f (see Fig. 22).

Table 4. A comparison of absolute error in (Nu) at different methods.

Nu		
Exp.vs.ANN	Exp.vs.emp	ANN.vs.emp
0.006157424	28.5471000000	28.5532574243
0.001358131	18.2768999999	18.2782581316
0.000106911	26.2260200000	26.2259130885
0.000021350	8.36513999999	8.36516135037
0.014384559	54.4855500000	54.4999345592
0.014515652	49.9094199999	49.8949043474
0.023074865	30.8857399999	30.9088148651
0.000098816	23.5647299999	23.5648288161

Table 5. A comparison of absolute error in (St) at different methods.

St		
Exp.vs.ANN$\times 10^{-6}$	Exp.vs.emp	ANN.vs.emp
0.20289916617	0.00090099200	0.0009007891
0.03807893144	0.00062325500	0.0006232169
0.00386091232	0.00099796000	0.0009979638
0.00370309769	0.00033476900	0.0003347727
0.47544645030	0.00149474000	0.0014942645
0.47932358165	0.00140215900	0.0014026383
0.75651406161	0.00090159400	0.0009008374
0.00371102404	0.00105783000	0.0010578262

Table 6. A comparison of absolute error in (f) at different methods.

f		
Exp.vs.ANN$\times 10^{-7}$	Exp.vs.emp	ANN.vs.emp
0.066153210	0.001633936	0.0016339426
0.290296906	0.002111671	0.0021116419
0.004717140	0.000093101	0.0000931005
0.090940783	0.001212297	0.0012122879
0.115654798	0.000808321	0.0008083325
0.466124264	0.000411829	0.0004117823
0.624972617	0.001841161	0.0018412234
0.009478575	0.000150416	0.0001504150

For more confidence, the new GUI is compared with results obtained from M-file program of ANN where an adequate fitting had appeared as shown in Table 7. The test of GUI was implemented for a sample numbered (4) in Table 7 where the outputs are much closed to each other.

Table 7. Results of M-file for heat parameters calculations.

Coefficient \ Case	1	2	3	4
Nu	77.4456	82.1018	56.4343	102.8179
St	0.0024	0.0024	0.0025	0.0028
f	0.007	0.0071	0.0059	0.007

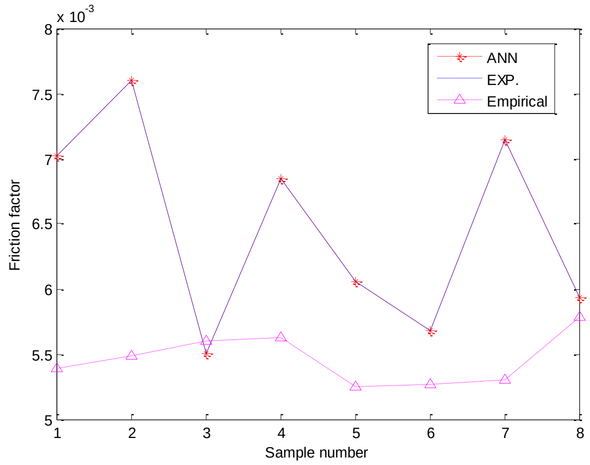

Fig. 18. Comparison of friction factor at three methods.

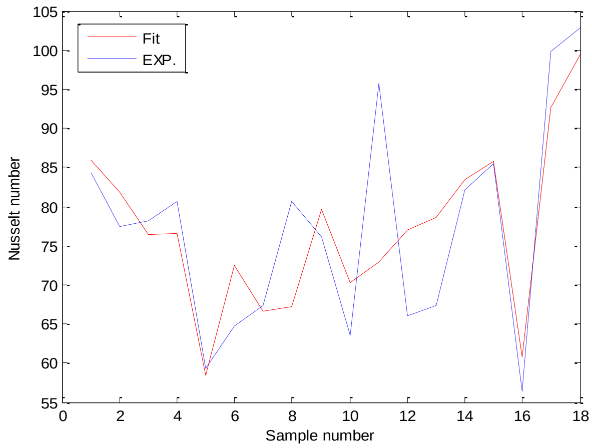

Fig. 19. Comparison of Nusselt number (correlation vs. experimental results).

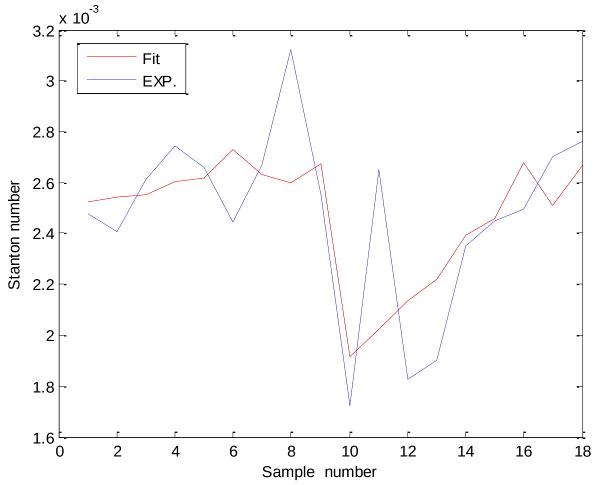

Fig. 20. Comparison of Stanton number (correlation vs. experimental results).

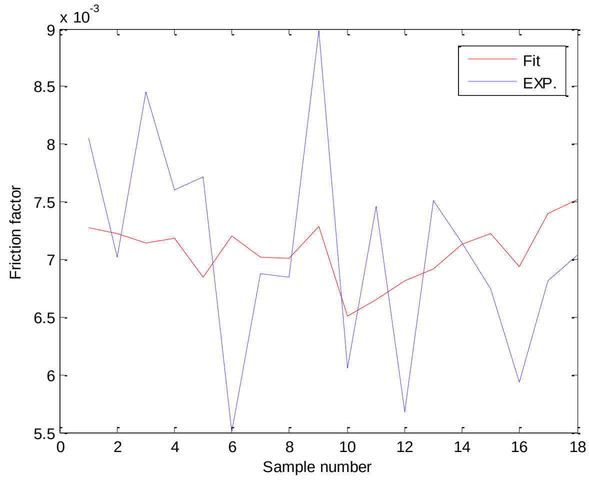

Fig. 21. Comparison of friction factor (correlation vs. experimental results).

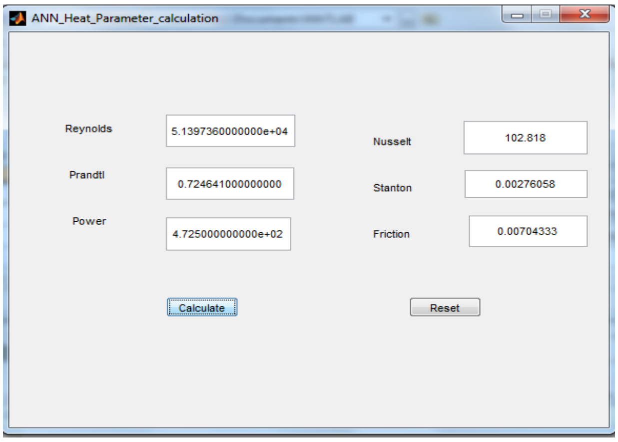

Fig. 22. Graphical Usage Interface for ANN-Heat parameters calculation.

7. CONCLUSIONS

The ANN can be used effectively for the predictions of the heat transfer characteristics and its results are better than that obtained from the heat transfer correlations. However, there are many factors which affect with a great percentage in the magnitude of the correlation factor (R) and the mean square error (mse) such as the best estimating of training algorithm and number of hidden layers and nodes of ANN structure. Also, learning rate and number of training sample can lead the efficiency of ANN to high levels. In this study, eighteen experiments were divided into nine training samples and as that testing which is enough to cover a wide range of required inputs and outputs in order to predict any value lied in this area of data. This ability is very important in the prediction of heat transfer coefficients for turbulent internal forced convection flow in pipes because it can reduce the time and cost as well as the effort. Such best fitting relations have been obtained with help of Curve Expert software in order to explain the power of ANN at the prediction procedure. Also, such analysis on uncertainties has been implemented in this study and the main derivations of the standard error formula of effective parameters were done. The magnitude of errors represents a useful index for using ANN in this research. A very powerful GUI had been proposed in this study which allows to evaluate several important factors in heat transfer applications such as Nu, St and f based on a previous trained artificial neural network.

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