Received 2 May 2006
Revised 1 December 2006
Accepted 8 January 2007

Neural network methodology for heat transfer enhancement data

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Abstract

Purpose – The purpose of this paper is to study experimentally enhancement of heat transfer in a tube with axial swirling-flow promoters. The geometric features of flow geometry to improve heat transfer can be selected in order to yield the maximum opposite reduction in heat exchange flow irreversibility by using exergy-destruction method. The paper seeks to illustrate the use of neural network approach to analyze heat transfer enhancement data for further study in the scope of the experimental program.

Design/methodology/approach – For this purpose, 402 experimental measurements are collected. About 225 of those are used as training data for neural networks, the rest is used for testing. Then, these testing results of artificial neural network (ANN) and experimental data are compared. A formula for presenting exergy loses in a tubular heat exchanger is derived first and then the thermodynamic optimum instead of economic optimum is found by minimizing the exergy losses in the system.

Findings – Results from all configurations studied show that the heat transfer rate of the heated increases when the swirling-flow promoter is inserted. From the heat transfer improvement number defined, it is observed that about 100 percent increase in heat transfer rate and five times increase in the pressure drop can be achieved under the condition of constant flow for the single promoter which has three blades, its blade angle is 30° and its location is in the middle of the tube length.

Research limitations/implications – The back-propagation (BP) algorithm was selected as the neural network algorithm, which uses the generalized delta learning rule. The training time of BP algorithm is considerably long. However, the testing of our neural network is real-time.

Practical implications – The experimental setup is established to collect the experimental data. It consists of an entrance region, test region (heat exchanger and steam generator), and, flow measurement and control. Also, a software program of neural networks trained BP is written by using Pascal high-level languages.

Originality/value – An alternative and new approach is proposed in the paper to find optimum flow geometry for a pipe flow with an axial swirling-flow promoter inserts. It is too difficult to predict the response of a complex physical system that cannot be easily modeled mathematically. The result thus obtained compare well with experimental results, but the computational effort of the ANN and time required in the analysis is much faster as compared. These results show that the ANN can be used efficiently for prediction.

Keywords Heat transfer, Neural nets, Turbulent flow

Paper type Research paper

International Journal of Numerical Methods for Heat & Fluid Flow
Vol. 17 No. 8, 2007
pp. 788-798

0961-5539
DOI 10.1108/09615530710825774

Nomenclature

O_i = The output of unit i for multi-layer perceptron (MLP)
t_{pj} = Target values of MLP
w_{ij} = The weight of the connection from unit j to unit i of MLP
θ_j = The bias of unit
$f(x)$ = Transfer function used ANN structure
E_p = The mean squared error (MSE)
Δ_p = The generalized delta rule learning
ε = Learning rate
D = diameter of the pipe (m)
Cp = constant pressure specific heat for air (kJ/kgK)
f = friction factor, $\Delta P/(4L/D)(\rho U^2/2)$
I = irreversibility (W)
L = length of the pipe (m)
$\dot{m}$ = mass flow rate (kg/s)
Nu = Nusselt number based on the pipe diameter, hD/k
U = Mean velocity of air flowing inside the pipe (m/s)
P_1 = air pressure (abs) at the inlet of the pipe (kPa)
P_2 = air pressure (abs) at the exit of the pipe (kPa)
R = gas constant for air (kJ/kgK)
Re = Reynolds number based on pipe diameter, $4\dot{m}/\pi\mu D$
T_1 = bulk temperature of air at the inlet of the pipe (K)
T_2 = bulk temperature of air at the exit of the pipe (K)
T_o = ambient temperature (K)
T_w = wall temperature of the pipe (K)

Greek symbols

α = momentum coefficient
μ = dynamic viscosity of air (N.s/m^2)
ρ = density of air (kg/m^3)
Δ = difference

Introduction

The engineering discipline of heat transfer, specifically deals with the analysis, design, and control of systems, and has a long history of development in response to the needs in a great variety of applications. It is widely recognized that the internal dynamics of heat and moisture transfer in an imperfectly mixed ventilated airspace have a fairly complex and spatially heterogeneous nature. It is a major challenge to control these heat and moisture transfer dynamics by using model-based control theory. However, before this can be applied, it is first required to have an appropriate dynamic model of the process to be controlled. Over the past decades, this has led to the development of sophisticated computational fluid dynamics (CFD) models which offer bright prospects as a design, and process optimization tool, but are too complex to be used for model-based control purposes. Towards the opposite end of data-based or statistical methods which allow to model the apparently complex nature of the heat and moisture transfer process in a dynamically simplified manner. Applications of these methods are quickly spreading areas of science and engineering especially for complex systems where more traditional methods have failed to be useful (Kawamura, 1977; Saad, 1998; Mahmud and Fraser, 2002). To investigate the mechanism of heat transfer augmentation, numerical computations of turbulent flow and heat transfer in a parallel plate channel, attached transversely with turbulence promoters at regular intervals on the lower surface, have been performed by using a simple turbulence model and the finite element method (Kimitoshi *et al.*, 2003). The optimum array geometries are determined based on comparison of the average surface Nusselt number (Nu).

The second law analysis of flow and heat transfer through a single tube and bundle of tubes for a periodic flow configuration and entropy generation profiles for various profiles are investigated (Haddad *et al.*, 2004; Luiz and Bejan, 2001). Second law characteristics of heat transfer and fluid flow due to forced convection of steady laminar flow of incompressible fluid inside channel with circular cross section and channel made of two parallel plates is analyzed by Mahmud and Fraser (2003). Analytical investigation of first and second law characteristics of fluid flow and heat transfer inside a channel having two parallel plates with finite gap between them for fully developed forced convection is analyzed by these authors. Two dimensional laminar forced convection in a sintered porous channel with inlet and outlet slots are numerically investigated by Hadim and North (2005) propose a length averaged *Nu* and friction factor correlations proposed. Theoretical and numerical analysis of second law for flow and heat transfer inside a rectangular duct is studied by Narusawa (2001) for non-circular duct.

Recently, the artificial neural network (ANN) and the other soft computing techniques have been shown to be particularly useful in heat transfer problems (Thibault and Grandjean, 1991; Jambunathan *et al.*, 1996; Pruvost *et al.*, 2001; Ayhan *et al.*, 2004). Especially, the ANN technique offers an alternative approach to the problem of flow geometry. It is a procedure that is usually used to predict the response of a complex physical system that cannot be easily modeled mathematically. The network is first trained by experimentally obtained input-output sets of data, after which, it can be used for prediction. The manufacturer can train a network using the experimental data; the constants or parameters of the trained network can then be transferred to the user who can calculate the performance of the heat exchanger under any other flow rate of channels with axial swirling-flow promoters.

Artificial neural network (ANNs)

ANN is an information processing system which information spreads parallel on. This system consists of processing elements connected by single-sided connections. The number of output signals is one, but it can be increased. ANN can determine its conditions and adjust itself to provide different responses by using inputs and desired outputs, which are given to the system. In practice, ANN depends on the identification and perception of information data in very different structure and form (Ozbay and Karlik, 2002).

Last decades, it has been shown that neural networks have the ability to solve various complex problems. On the other hand, multi-layered feed-forward networks have a better ability to learn the correspondence between input patterns and teaching values from many sample data by the error back-propagation (BP) algorithm (Ozbay and Karlik, 2002; Meric *et al.*, 1997; Karlık and Aydın, 2000; Ozyigit *et al.*, 2001). Therefore, in this paper, we used a three-layered feed forward neural network and trained it by error BP. The software of ANN can be written to employ BP in a supervised learning paradigm in which the generalized delta rule was used in adjusting the weight values (Ozbay and Karlik, 2002). The basic structure of ANN used in this study is shown in Figure 1. Here, the number of hidden nodes on the hidden layer must be the maximum of the number of input or output nodes. Otherwise, training error will be high. As the result of training and tests made, desired output for every input value is introduced to the system by realizing the learning rule which changes or adjusts the weights of the network connections depending on the input values or outputs of these inputs. The ANN adjusts itself gradually until realizing the input-output relation, which the generalized delta rule was used in adjusting the weight values. The output O_{ij} of each unit ij is defined by:

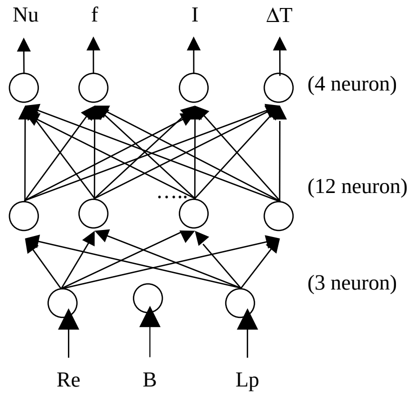


Figure 1. The structure of MLP for this study

$$O_{ij} = f(\text{net}_{ij}), \quad \text{net}_{ij} = \sum_i w_{ij} O_i + \theta_j \tag{1}$$

where, O_i is the output of unit i, and w_{ij} is the weight of the connection from unit j to unit i, θ_j is the bias of unit j, Σ is a summation of every unit ij whose output flows into unit j, and $f(x)$ is a monotonously increasing sigmoid function.

When the set of m-dimensional input patterns $\{i_p = (i_{p1}, i_{p2}, \ldots, i_{pm}); \quad p \in P\}$ where P denotes set of presented patterns, and their corresponding desired n-dimensional output patterns $\{t_p = (t_{p1}, t_{p2}, \ldots, t_{pm}); \quad p \in P\}$ are provided, the neural network is taught to output ideal patterns as follows. The squared error function E_p for a pattern p is defined by:

$$E_p = \frac{1}{2} \sum_{j \in \text{output layer}} (\mathrm{t}_{pj} - O_{pj})^2. \tag{2}$$

The purpose is to make $E = \Sigma_p E_p$ small enough by choosing appropriate w_{ji} and θ_j. To realize this purpose, a pattern $p \in P$ is chosen successively and randomly, and then w_{ji} and θ_j are changed by:

$$\Delta_p w_{ji} = -\varepsilon \left(\frac{\partial E_p}{\partial w_{ji}} \right) \tag{3}$$

$$\Delta_p \theta_j = -\varepsilon \left(\frac{\partial E_p}{\partial \theta_j} \right) \tag{4}$$

where, ε is a small positive constant, by calculating the right hand side of equations (3) and (4), it follows that:

$$\Delta_p w_{ji} = \varepsilon \delta_{pj} O_{pi} \tag{5}$$

$$\Delta_p \theta_j = \varepsilon \delta_{pj} \tag{6}$$

where:

$$\delta_{pj} = \begin{cases} f(\text{net}_j)(t_{pj} - O_{pj}) & \text{(when } j \text{ belongs } \textit{to} \text{ the output layer.)} \\ f'(\text{net}_j)\sum_k w_{kj}\delta_{pk} & \text{(otherwise)} \end{cases} \tag{7}$$

Note that k in the above summation represents every unit k whose output follows into unit j. In order to accelerate the computation, the momentum terms are added on equations (5) and (6).

$$\Delta_p w_{ji}(n+1) = \varepsilon\delta_{pj}O_{pi} + \alpha\Delta_p w_{ji}(n) \tag{8}$$

$$\Delta_p \theta_j(n+1) = \varepsilon\delta_{pj} + \alpha\Delta_p \theta_j(n) \tag{9}$$

where, n represents the number of learning cycles, and α is a small positive value. In this study, by the iteration the optimum α and ε constant values are found as $\alpha = 0.75$, $\varepsilon = 0.75$, respectively. It can be shown in Figure 1, the structure of multi-layer perceptron (MLP) is like 3:12:4, which means 3 neurons of input layer, 12 neurons of hidden layer, and 4 neurons of output layer. Optimum number of neuron of hidden layer was found trial depending on MSE using same iteration as it can be shown in Figure 2.

Thermodynamic irreversibility

There are many kinds of heat transfer augmentation techniques. Although these techniques are useful for heat transfer augmentation, the judgment their value depends on the evaluation method used. By stating that a method is "effective" usually means that it is:

- highly efficient; and
- not environmental destructive.

Therefore, the choice of the evaluation method is important factor. For this reason, exergy analysis method is chosen for this experimental study. In this method, the impact of on augmentation technique on the irreversibility of a given heat exchanger tube can be evaluated by calculating the entropy generation rate in the "augmented" tube, and comparing it with the entropy generation in the "unaugmented" tube. This comparison is made by the irreversibility, I. According to the second law of thermodynamics, any natural process is irreversible and accompanied by the exergy loss. The higher the irreversibility the larger the exergy loss is. This indicates that the process is less perfect thermodynamically. In any heat-transfer process, there are two irreversible phenomena. One comes from irreversible heat transfer due to finite

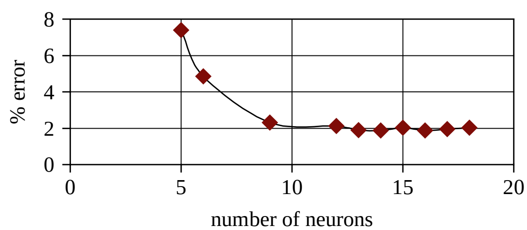


Figure 2.
Determination number of optimum neurons of hidden layer

temperature difference, and the other from flow friction. In a heat exchanger utilizing, a heat-transfer augmentation technique, such as axial swirling-flow promoting insert, the exergy loss or irreversibility from heat transfer across finite temperature difference is reduced while the exergy loss or irreversibility resulting from fluid friction increases. The accumulative effect in the form of net exergy loss from these two factors determinates the effectiveness of the augmentation technique. In this study, a formula presenting the irreversibility in a tubular heat exchanger is derived first for the constant temperature of the tube wall (100°C). Considering a constant *Cp* and density of air over the entire temperature range the exergy loses can be calculated as follows:

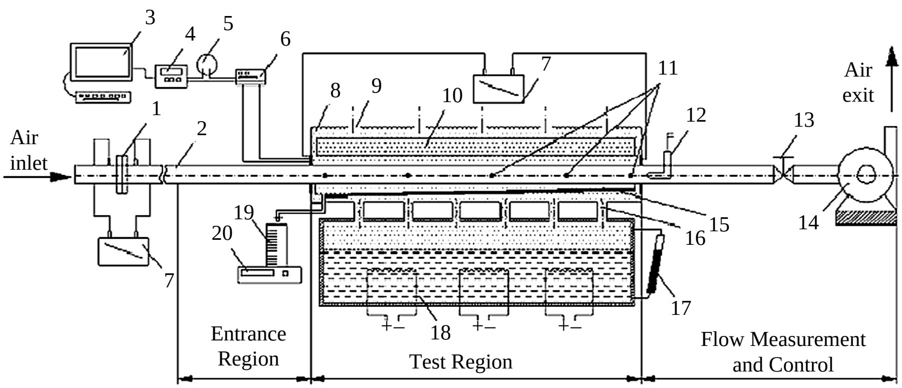
$$I = \dot{m} C p T_o \left[\ln \frac{T_2}{T_1} + \frac{T_2 - T_1}{T_w} \right] - \dot{m} R T_o \ln \frac{P_2}{P_1}. \tag{10}$$

Secondly, the geometric features of proposed augmentation technique are optimally selected in order to yield the maximum reduction in the heat exchanger tube irreversibility.

Comparison experimental and simulation methods

The main features of the experimental setup are shown schematically in a Figure 3. It consists of an entrance region, test region (heat exchanger and steam generator), and, flow measurement and control. The air stream was heated in the heat exchanger of the tube – in tube type with the inner tube heated by steam saturated at atmospheric pressure. Thus, the air stream was heated at the constant temperature of the tube wall. The experimental apparatus for air flow is operated in the suction mode. The ambient air was sucked through the orifice plate, the heat exchanger and mass flow rate control valve by the fan. Details are given in the reference (Ayhan-Saraç 2004).

The axial swirling-flow promoting insert is assembled inside the inner aluminum tube which is instated in the center of the rectangular shape (cross section is 250 × 250 mm) steam dome which is called as the heat exchanger. The test tube in the heat exchanger is



1 – Orifice plate
2 – Test tube
3 – Computer
4 – Digital microvolt meter
5 – Cold junction
6 – Selector switch
7 – Inclined manometer
8 – Steam dome
9 – Steam exits
10 – Roof
11 – Thermocouples
12 – Pitot tube
13 – Adjustable valve
14 – Fan
15 – Condensed collector try
16 – Steam channels
17 – Water level indicator
18 – Steam generator
19 – Condensed collector cup
20 – Balance machine

Figure 3. Schematic view of the experimental apparatus for the heat transfer study

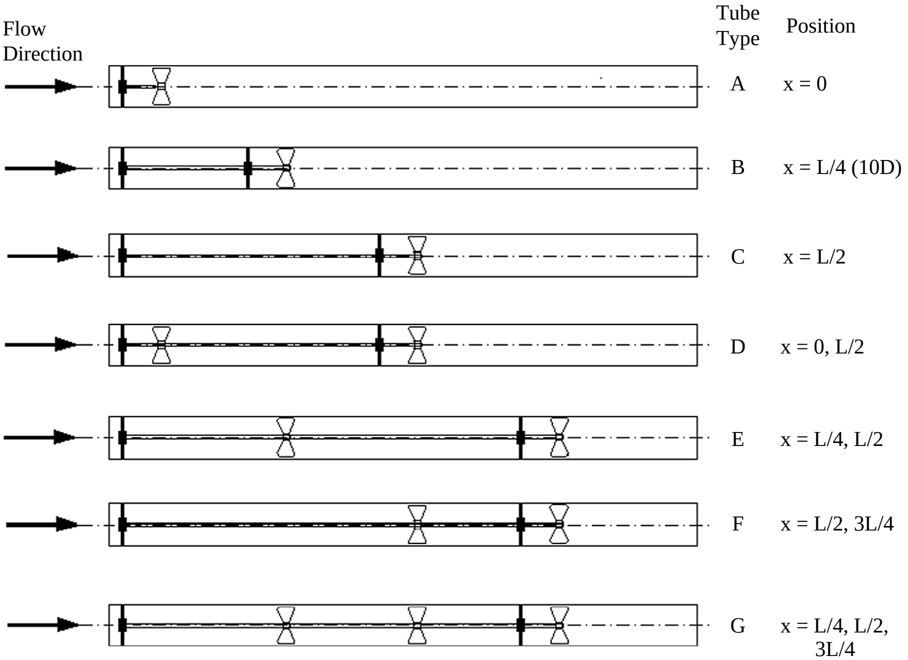


Figure 4.
Positions of the axial flow generators in the test tube

smooth aluminum pipe with 50 mm ID, and 2,000 mm length. Experimental investigations were performed by heating streams of air in the test tube with different geometries and positions furnished an axial swirling-flow promoter. The axial swirling-flow promoters are inserted in the test tube, which are shown in the Figure 4.

One example of the swirling-flow promoters which is produced for measuring the drag force can be shown in the Figure 5. A typical view of the decaying swirling-flow structure produced from the flow visualization apparatus for an axial swirling-flow promoter is shown in Figure 6. The distribution of the local temperature along the tube wall measured by a set of thermocouples ten uniformly spaced at a distance. These are compared with steam condensation temperature at an atmospheric air pressure. Both ends of the tube were isolated thermally from in let and outlet metal tubing by means of nylon connectors in order to eliminate heat loss in a longitudinal direction. The air stream temperatures at the inlet and at the final cross-section of the tube were measured by means of two sets

Figure 5.
The axial swirl flow generator with six blades and 45° of the blade angle

of thermocouples. Each set was made of four units with junctions located at radial positions, chosen so that the average of their indications was equal to the mean temperature of the air in each cross-section of the test tube. The pressure drop in the air stream was measured by a manometer connected with taps at the ends of the heat exchanger.

The heat transfer characteristics and flow structure in turbulent flow through the tube with swirling-flow promoting inserts have been investigated experimentally in the range of Reynolds number (*Re*) between 4,000 and 32,000. The enhanced tube friction factor f, and heat transfer indicator parameter the *Nu* depend on the number of the blades N_b, the blade angle β, number of the inserts N_{in}, the insert spacing length l_{sp}, and *Re*, among the other variables. The influence of the thickness of the blades, the surface micro roughness, and the diameter of the blades supporter is assumed to be in significant.

Thermal performance and fluid flow characteristics of the test tubes are presented empirical correlations. Correlations of the friction factor and heat transfer for these tubes were developed by Ayhan-Saraç (2004). These correlations are based on experimental data for all enhancement types. Since, data base covered wide range of enhancement variables, the correlations are applicable to practically all tubes considered by designers.

In this study, seven different types of tubes are used. In order to test the effects of promoter spacing and the influence of promoter geometries and their number on heat transfer and their flow characteristics. These are:

- straight tube;
- four blades for three kinds of swirling angle with single unit, double and triple unit arrangements; and
- six blades for three kinds of swirling angle with single unit, double and triple unit arrangements.

Experiments were performed for turbulent flows in the range of *Re* between 4,000 and 32,000, and Prandtl number of 0.7. The convective heat transfer coefficients and pressure drops provided by experimental studies and artificially generated data were examined. Finally, the geometric features of the proposed flow geometry to improve heat transfer can be selected in order to yield the maximum opposite reduction in heat exchange flow irreversibility by using exergy destruction method. The optimum array geometries are determined based on comparison of the average surface *Nu*. The experimental results for the different design constraints show that optimum axial swirling-flow promoter blades number is 4, its blade angle is 30° the insert spacing length is 1,000 mm. It is shown in the Figure 4, as the type C. Table I explains comparing results between neural networks and experimental for a swirling flow promoters with six blades (its blades angles are 15, 30, 45, and 60°), and three units.

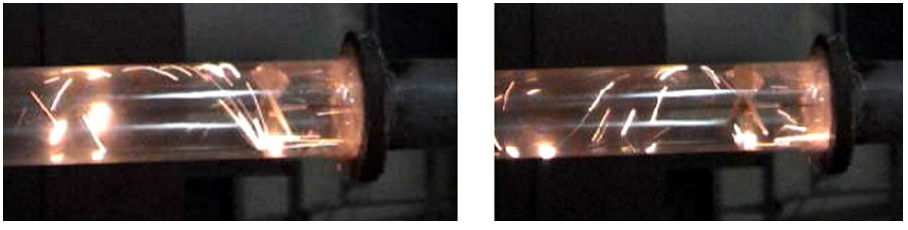


Figure 6.
Swirling flow visualization (the axial swirl flow generator and swirling flow structures)

Table I.
The comparison results between neural networks and experimental for a swirling-flow promoters with six blades and three units

For Lp/2 and Lp3/4 β	Re	Nu EXP	Nu ANN	Friction factor EXP	Friction factor ANN	Irreversible EXP	Irreversible ANN	Logarithmic tem. diff EXP	Logarithmic tem. diff ANN
15°	2,474.76	1,625.94	1,686.6	0.093900	0.105512	0.078750	0.080836	0.679457	0.680166
	5,864.86	2,913.72	3,192.885	0.060593	0.061502	0.199900	0.216209	0.733171	0.723376
	9,595.6	4,651.08	4,645.635	0.059827	0.060171	0.332150	0.339709	0.744300	0.756743
	18,853.34	7,201.2	7,204.825	0.062921	0.061262	0.679900	0.726849	0.830357	0.835301
30°	2,261.6	1,390.08	1,393.35	0.038740	0.037027	0.076100	0.075654	0.710186	0.710786
	4,811.74	2,399.88	2,405.22	0.030220	0.032362	0.152000	0.156088	0.766071	0.755153
	9,729.66	3,605.4	3,659.11	0.027033	0.025115	0.339800	0.345256	0.814943	0.809628
	19,064.4	5,915.76	5,844.42	0.024233	0.023222	0.600450	0.608193	0.899114	0.888936
45°	2,751	1,348.08	1,284.645	0.027040	0.027451	0.070700	0.071609	0.768229	0.780612
	7,252.06	2,659.08	2,658.54	0.017260	0.017272	0.222100	0.225224	0.799814	0.812192
	12,216.66	4,050.6	3,959.355	0.016333	0.016363	0.378550	0.403047	0.850729	0.860259
	19,067.06	5,283.84	4,966.33	0.014480	0.015821	0.677250	0.652528	0.896700	0.914020
60°	3,603.6	1,426.8	1,428.85	0.011920	0.011778	0.096500	0.094391	0.837857	0.830680
	5,965.14	2,004.42	1,908.6	0.009060	0.010253	0.159400	0.160936	0.852468	0.842902
	9,448.94	3,205.32	3,229.265	0.007287	0.007682	0.255400	0.261866	0.825514	0.823758
	11,718	3,783.6	3,742.92	0.006573	0.006141	0.345100	0.345410	0.954157	0.951717

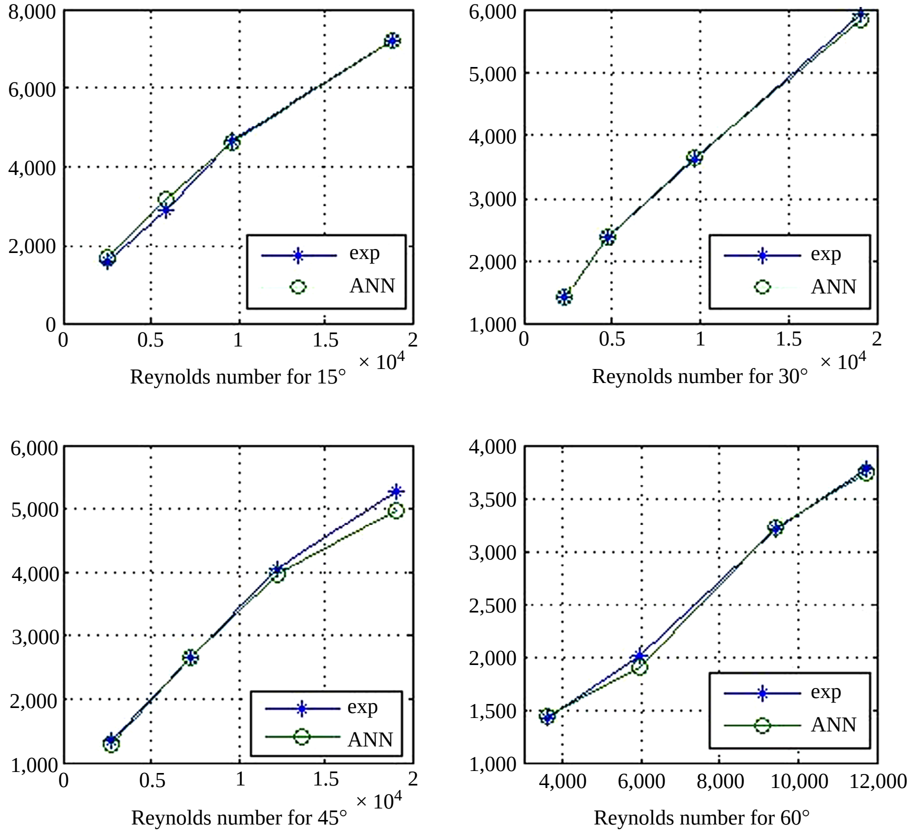


Figure 7.
Comparative results of Nusselt numbers using experimental and ANN methods

Figure 7 shows comparative results of *Nu* between experimental and ANN according to *Re* and blade angles for 15, 30, 45, and 60°, respectively. As it can be shown in Figure 7, ANN method is very good alternative to solve optimum flow geometry of pipes.

Conclusions

This study presents a new application of ANN methods to find optimum flow geometry for a pipe flow with an axial swirling-flow promoter inserts. This kind of research on heat transfer and fluid flow characteristics take long time. The ANN method is more useful to solve this problem easily. If the results compare with experimental data, the prediction of results is supported. Also, ANN can be useful to produce new values for proposed flow geometries. So, ANN application on heat transfer and fluid-flow characteristics for these kinds of flow geometry is more successful. Moreover, this new approach can be used successfully on new flow geometries with heat transfer for future applications.

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