Simulation of Heat Exchanger Performance by Artificial Neural Networks

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The artificial neural network technique was applied to heat transfer through a series of problems of increasing complexity. For the simplest problem of one-dimensional heat conduction with linear activation function, it is possible to give physical meaning to the synaptic weights of the network. A network with sigmoid activation function was used for non-linear representation of convection problems where identification of the weights with physical variables was not possible. Two cases of convective heat transfer with one and two heat transfer coefficients and artificially generated data were examined. Finally, the method was applied to the analysis of data obtained in the laboratory for a single-row, fin-tube heat exchanger. It is shown that a better prediction with smaller scatter is obtained in comparison to a conventional power-law correlation for the heat transfer coefficients.

INTRODUCTION

In the design of thermal systems, predicting the heat transfer rate of heat exchangers under prescribed operating conditions is necessary. For a given device exchanging heat between two fluids, the heat transfer rate depends on the flow rates and the inlet temperatures of each fluid. Currently, most calculations are done on the basis of manufacturers' data for specific fluids that give the heat transfer rate as a function of the two flow rates and the two inlet temperatures. This is a four-variable function and difficult to represent completely. In principle the functional relation depends on the geometry of the heat exchanger, the materials with which it is made, the surface conditions, the fluids used, etc. The relationship completely characterizes the heat exchanger and is the information that must be transferred in some form from the manufacturer to the design engineer.

It would be advantageous to be able to compress the information contained in the heat transfer rate function so that it can later be accurately recovered. For instance, if the internal and external heat transfer coefficients are provided, the heat transfer for any flow rate, inlet temperature, or fluid can be easily determined. The situation is complicated by the fact that the heat transfer coefficients vary considerably with flow rates and fluid properties. Dimensional analysis can reduce the number of variables to the internal and external Nusselt (or Stanton) numbers as functions of the corresponding Reynolds and Prandtl numbers. If such correlations could be determined from experimental measurements, an acceptable procedure can be devised. In practice, without accurate tube wall temperature measurements, it is difficult to separate the experimentally determined overall thermal resistance into its internal and external components. Furthermore, property variations, especially the variation of liquid viscosity,
make any correlation obtained highly dependent on fluid temperatures. Procedures that take this variation into account, become very complex and potentially lose generality. In any case the user of the information, the system designer, is usually interested only in the heat transfer rate, and not in intermediate variables such as the heat transfer coefficients. For this purpose a straightforward interpolation of the original experimental data would probably be more useful, but would be inconvenient.

The artificial neural network (ANN) technique offers an alternative approach to the problem of information compression for heat exchangers. It is a procedure that is usually used for predicting the response of a 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 or inlet temperature conditions.

ANNs are an established technique; see, for example, Haykin (1994) for an account of the history and mathematical background. There have been a few applications to heat transfer problems. One is in the area of liquid crystal thermography to determine heat transfer coefficients (Jambunathan et al. 1996). The generalization capacity of the ANN has been used to design a finned heat exchanger (Lavric et al. 1994, Lavric et al. 1995). Huang and Nelson (1994) also applied this technique to determine the delay time for a HVAC plant to respond to control actions. Ding and Wong (1990) controlled a simulated hydronic system using an ANN. In a previous paper Díaz et al. (1996) applied ANNs to analyze experimental heat-exchanger data.

The goal of the present study is to represent heat exchangers using ANNs. The procedure used to set up and train the network is described first. Then a series of problems of increasing complexity are formulated to facilitate understanding. These problems are: one-dimensional conduction, convection with one heat transfer coefficient, convection with two heat transfer coefficients, and single-row plate-fin heat exchanger. Artificial data bases are generated for the first three problems. Finally, an experimental data base will be used for the fourth problem and the results of the ANN analysis presented.

ANN ANALYSIS

An ANN, schematically shown in Figure 1, consists of a series of layers, each with a number of nodes. The first and last layers are the input and output layers, respectively. In a fully connected network, all nodes are connected to all nodes of the previous and following layers. The available data consist of $M_1$ runs. Of these $M_2$ will be used for training and $M_3$ for testing. Each run is a single experiment providing a number of values of the physical variables for that run.

All physical variables used by the ANN are normalized to confine them in the range $[0.15,0.85]$. The following notation is introduced: $(i,j)$ is the $j$th node in the $i$th layer, $x_{i,j}$ is its input, $y_{i,j}$ is its output, $\theta_{i,j}$ is its bias, and $w_{i,j}^{i-1,k}$ is the synaptic weight between nodes $(i-1,k)$ and $(i,j)$. The total number of layers, including input and output layers, is $n$, and the number of nodes in the $i$th layer is $m_i$. The input information is propagated forward through the network; $m_1$ values enter the network and $m_n$ leave. The relation between the output of node $(i-1,k)$ in one layer and the input of node $(i,j)$ in the following layer is

$$x_{i,j} = \theta_{i,j} + \sum_{k=1}^{m_{i-1}} w_{i,j}^{i-1,k} y_{i-1,k}$$  

(1)
Figure 1. Schematic of neural network

Furthermore, the relation between the input and output of the same node \((i,j)\) is \(y_{i,j} = g(x_{i,j})\) where \(g(x)\) is the sigmoidal activation function.

\[
g(x) = \frac{1}{1 + e^{-x}}
\]  

For the first layer the function \(g(x) = x\) is used.

Training of the network consists of changing the weights until the output values differ little from known target values. This is done here through a backpropagation method (Rumelhart et al., 1986; Thibault and Grandjean, 1991). First, the error is quantified at the output layer by

\[
\delta_{n,j} = (t_j - y_{n,j})y_{n,j}(1 - y_{n,j})
\]

where \(t_j\) is the target output for the node \((n,j)\). After calculation of the \(\delta_{n,j}\) we move back to the \((n-1)\)th layer. There is not a target output to compare with for this layer, so the error is defined for the nodes in this layer as

\[
\delta_{n-1,j} = y_{n-1,j}(1 - y_{n-1,j})\sum_{l=1}^{m} \delta_{n,l} w_{n-1,l,j}
\]

Having computed the errors for all the nodes of the \((n-1)\)th layer, \((n-2)\)th layer is evaluated using an expression similar to the above, and so forth all the way to the second. Next the change in the weights and the biases are computed using

\[
\Delta w_{i-1,k}^{j} = \lambda \delta_{i,j} y_{i-1,k}; \quad \Delta \theta_{i,j} = \lambda \delta_{i,j}
\]
where $\lambda$ is the learning rate that is used to scale down the degree of change made to the connections. The larger the learning rate, the faster the net will learn, but the chances of the ANN being unable to reach the desired output are also greater. For the current work a value of $\lambda = 0.4$ is chosen which appears to work well. At the end of one cycle of the backpropagation, using the corrections above, an updated set of values of the weights is obtained.

It is best if the training data contain the minimum and the maximum of the entire data base. The backpropagation algorithm is repeatedly applied to this set of training data until a certain criterion is reached. The percentage error between the heat rate predicted by the ANN, $Q_{ANN}$, and the one supplied by the training set of data, $Q$, is used. The relative heat flow is defined as $R_i = Q_i/Q_{ANN}$ for $i = 1, \ldots, M_1$, where $Q$ is the dimensional heat rate obtained experimentally or by means of a known relation, and $Q_{ANN}$ is the dimensional heat rate predicted by the ANN. The standard deviation of $R_i$ is

$$\sigma = \sqrt{\frac{\sum_{i=1}^{M_1} (R_i - \bar{R})^2}{M_1}}$$

where $\bar{R}$ is the average of $R_i$ over all the runs used for training.

The network 4-5-5-1 (four layers with 4, 5, 5, and 1 nodes respectively) is analyzed as a typical configuration. The different starting conditions for the weights and biases were obtained in a random fashion. Figure 2 shows $\sigma$ as a function of the number of training cycles $N$. Each curve is for a different set of starting conditions. It is seen that the starting conditions do not make a significant difference after about 50,000 cycles, and that for $\sigma - N^{-1/2}$ for large $N$. It was assumed that a training period of 100,000 cycles was adequate. It is important to note that the final weights obtained after training are not unique and different starting values of the weights may lead to different outcomes.

The trained network was tested using weights and biases found from the training process with the test data. The evaluation consists of the agreement between $Q_{ANN}$ and $Q$ and the ratio of heat rates $R_i$ as a function of the run number $i$.

**ONE-DIMENSIONAL CONDUCTION**

This is a simple heat transfer problem that is chosen to illustrate the approach. The governing equation for one-dimensional conduction through a wall is

$$\dot{Q} = \frac{kA}{L} (T_1 - T_2)$$

(7)

For situations in which $kA/L$ is constant, function $\dot{Q}(T_1, T_2)$ from Equation (7) represents a plane in three-dimensional space.

Since the problem is linear, a linear activation function $g(x)$ is appropriate. For the simplest network of the form 2-1-1, the functional relation is

$$\dot{Q} = \theta_{3,1} + w_{2,1}^3 \theta_{2,1} + w_{2,1}^1 T_1 + w_{2,1}^2 T_2$$

(8)

Comparing Equations (7) and (8), established the following relations

$$\theta_{3,1} + w_{2,1}^3 \theta_{2,1} = 0; \quad w_{2,1}^3 \theta_{2,1}^2 = \frac{kA}{L}; \quad w_{2,1}^3 T_1 = \frac{kA}{L} T_1; \quad w_{2,1}^3 T_2 = \frac{kA}{L} T_2$$

(9)
the connect-ANN being ±0.4 is cho-

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(8)

Figure 2. Effect of different starting conditions on standard deviation
for configuration 4-5-5-1. For reference, straight line has slope of -1/2.

Different symbols correspond to different starting conditions.

The weights are not unique though there is a certain relationship between them. Furthermore, on taking, \( w_{2,1}^3 = 1 \) the weights \( w_{2,1}^1 \) and \( w_{2,1}^2 \) are related to the system parameter \( kA/L \).

An ANN with more nodes will yield similar results. For example, a 2-2-1 network with a linear activation function, the weights are nonunique and show physical significance for a special case. The degrees of freedom for the choice of system constants, however, increase with the size of the network. Indeed, the larger ANNs contain the smaller ones as special cases but, for this linear problem, do no better in representing the function \( Q(T_1, T_2) \).

The linear activation function is successful because \( Q(T_1, T_2) \) is a plane. Modification of the weights in such an ANN produce rotation and/or translation of the plane. The function \( Q(T_1, T_2) \) is not a plane if the conductivity is a function of temperature, and the activation function will not accurately represent the surface. For example, if the thermal conductivity is a linear function of the temperature, \( Q(T_1, T_2) \) is then a quadratic function. It was found that, even with quadratic activation functions, it is not possible to find physical meanings for the weights of the network. For nonlinear problems, the constants in the ANN do not have a physical meaning. For this reason, the sigmoid activation function, which works well with nonlinear problems was used.

CONVECTION WITH ONE HEAT TRANSFER COEFFICIENT

In the situation of forced convection due to flow in a duct with constant wall temperature, the heat transfer is controlled by the convection heat transfer coefficient between the fluid and the wall, \( h \). For the situation that \( h \) does not vary along the length of the duct, the heat flow is given by
\[ Q = \dot{m}c(T_{in} - T_{wall}) \left[ \exp\left( \frac{hP L}{\dot{m}c} \right) - 1 \right] \]  

(10)

For the situation in which only \( T_{in}, T_{wall}, \) and \( \dot{m} \) are varied and the other parameters being held constant, \( Q(T_{in}, T_{wall}, \dot{m}) \) is a curved surface in four-dimensional space.

An artificial data base was generated using equation (10) and known heat transfer coefficients for duct flow. The heat transfer for laminar flow, in which \( Nu = 3.66 \), and for turbulent flow, \( Nu = 0.023 \, Re^{0.8}Pr^{0.4} \) were used; where \( Nu, Re, \) and \( Pr \) are the Nusselt, Reynolds, and Prandtl numbers, respectively. The critical Reynolds number for transition was taken to be 2300, the diameter of the duct was 0.05 m, and the fluid properties were those of air. Data were generated in the range \( 230 < Re < 23044 \). For laminar flow the training and testing data sets were \( M_1 = 142 \) and \( M_2 = 46 \), respectively, while for turbulent flow they were \( M_1 = 277 \) and \( M_2 = 91 \). The ANN was trained using artificial data and then the predictions of the trained network were compared with the analytical results. The results for laminar flow data alone are presented first, then for turbulent flow alone, and finally for both cases combined.

A configuration 3-5-5-1 was used for which the inputs were the mass flow rate, the inlet temperature, and the wall temperature and the output was the heat transfer rate. Figure 3 shows the relationship between \( Q_{ANN} \) and \( Q \) using two different networks trained for laminar and turbulent flow. It was found that the errors for laminar flow are in general, less than 2% with a maximum error of 6.8%. For turbulent flow, the results were very similar. The maximum error larger than 5.8%, and in general the error is less than 1.5%. Most of the larger errors were for runs in which the heat transfer rate was small, which makes the percentage error large. For both flow regimes combined, the errors were larger as shown in Figure 4. Large errors were observed for low values of the heat transfer rate, although good agreement was obtained for turbulent flow.

![Figure 3. Laminar (°) and turbulent flow (×) convection with one heat transfer coefficient. Straight line is \( Q_{ANN} = Q \)](image)
coefficients present, Nu and Prandtl number, the diameter in the tube was 142 and the ANN was trained with the inlet temperature and with a maximum error larger than 5 for runs in both flow regimes. For runs in the turbulent flow data yielded better heat transfer predictions.

**CONVECTION WITH TWO HEAT TRANSFER COEFFICIENTS**

The situation of forced convection in a duct with external fins and a known outside temperature was considered next. There are two heat transfer coefficients, one inside and another outside the duct. The data for training the ANN and testing its predictions were generated artificially. For the situation with water the in-tube and air the over-tube fluid, the heat transfer rate is a function of four variables: the two inlet temperatures \( T_{in}^w \) and \( T_{in}^a \), and the two mass flow rates, \( \dot{m}_w \) and \( \dot{m}_a \). For the case with the inner and outer heat transfer coefficients, \( h_i \) and \( h_o \), respectively, constant along the length of the heat exchanger tube, the heat flow is given by

\[
\dot{Q} = \dot{m}_w c_w (T_{in}^w - T_{in}^a) \left[ 1 - \exp\left(-\frac{UA_0}{\dot{m}_w c_w}\right) \right]
\]

where

\[
\frac{1}{UA_0} = \frac{1}{h_i A_i} + \frac{1}{\eta h_o A_o}
\]

Artificial data were generated using the inner and outer power-law correlations of Zhao (1995) for the same heat exchanger reported in the following section. These are

\[
\eta \text{Nu}_a = 0.1368 \text{Re}_a^{0.585} \text{Pr}_a^{1/3} \text{ for } 200 \leq \text{Re}_a \leq 700
\]
Figure 5. Two heat transfer coefficients. Straight line is \( \dot{Q}_{ANN} = \dot{Q} \)

\[
\begin{align*}
\text{Nu}_w &= 0.01854 \text{Re}_w^{0.752} \text{Pr}_w^{0.3} \quad \text{for} \quad 800 \leq \text{Re}_w \leq 4.5 \times 10^5 \\
\text{Re}_a &= \frac{V_a \delta}{v_a}; \quad \text{Re}_w = \frac{V_w D}{v_w}; \quad \text{Nu}_a = \frac{h_a \delta}{k_a}; \quad \text{Nu}_w = \frac{h_w D}{k_w}
\end{align*}
\] (14) (15)

The values of the properties were taken to be constant. The results obtained for the configuration 4-5-5-1, trained with \( M_1 = 160 \) and tested with \( M_2 = 38 \), are presented in Figure 5. The maximum error is 1.25%, but for most of the data the error is within ±0.7%. The average ratio of heat transfer rates is \( R = 1.00062 \) with a standard deviation of \( \sigma = 4.815 \times 10^{-3} \).

**SINGLE-ROW PLATE-FIN HEAT EXCHANGER**

In the examples reported, the training and testing data were generated artificially by means of smooth functions. One of the strengths of ANNs is that they are able to find characteristic patterns on a given set of data. This is exactly what is needed when dealing with experimental data in which there are measurement errors.

Experiments were conducted on a heat exchanger in a variable-speed wind tunnel facility, schematically shown in Figure 6. Hot water and room-temperature air were used as the in-tube and over-tube fluids, respectively. The motion of the air in the tunnel was due to a blower that is controlled by a variable speed drive. There was a honeycomb upstream and another downstream of the heat exchanger to straighten the flow. A PID-controlled electrical resistance heater raised the water temperature. The water flow rate was measured by a turbine flow meter. Type T thermocouples were used for sensing the air and water temperature. Because the inlet air is close to the room temperature, only one thermocouple was used for this purpose, while the average reading of five thermocouples is used for the outlet air temperature. A Pitot tube located upstream of the heat exchanger was connected to a differential pressure transducer to give the air flow rate. A computerized data acquisition system collected the experimental data. A nominal 457 mm by
The configuration 4-5-2-1-1 was chosen first. The input variables to the network were $\dot{m}_a$, $\dot{m}_w$, $T_{in}^a$, and $T_{in}^w$; the output is $\dot{Q}_{ANN}$. The performance of the trained network was evaluated by comparing the heat flow prediction with the data set aside for testing. The average value of $R_i$ is found to be $R = 1.00212$ with a standard deviation of $\sigma = 0.017$ and a maximum error of 7.88%. To examine the effect of network configuration, 14 different configurations using the same sets of data for training and testing were evaluated. The values of $R$ and the standard deviation $\sigma$ are shown in Table 1. The network configuration with $R$ closest to unity is 4-1-1-1, while
-5-5-1 is the one with smallest $\sigma$. Thus there are at least two different criteria for the selection of an optimal configuration, though in either case the error and the scatter are small. The configuration 4-1-1-1 has a much larger standard deviation with respect to the others so the configuration 4-5-1-1 was selected, which has a value of $R$ also very close to unity but with a smaller standard deviation. The performance of the 4-5-5-1 and 4-5-1-1 configurations are also compared in more detail. The values of $R_i$ for individual runs are shown in Figure 7. Although 5-1-1 has the second best $R$, there are some points in which the prediction differed from the experiment by more than 14%. The 4-5-5-1 network, on the other hand, has errors confined to less than 3.7%. It was observed that no matter how many layers the network has, the prediction
has a large standard deviation if all hidden layers contained just one node. For all but the three configurations of hidden layers with just one node, the different configurations overpredict the heat transfer rates with an average error of only 0.33%.

The effect of the normalization used for the variables was also studied. For the network 4-5-5-1, which has the smallest standard deviation, a computation using a different normalization range of [0.05,0.95] was run. The number of cycles used was the same as before, i.e. $N = 100,000$. The results showed that $R = 1.00063$ and $\sigma = 0.016$, which can be compared to the values in Table 1. There was only a 6.6% difference in $\sigma$ due to changing the normalization range.

Once the network has been trained for a given heat exchanger, as by the manufacturer, the information can be transferred to the user as a set of weights and biases. For example, the data are put in columnar form for the configuration 4-2-1 and presented in Tables 2 and 3. A computer code that will read this data file and be able to predict the performance of the device for any other flow rate or inlet temperature within the range tested could easily be written.

### Table 2. Values of the Weights for Configuration 4-2-1

<table>
<thead>
<tr>
<th>$i$</th>
<th>$j$</th>
<th>$k$</th>
<th>$l$</th>
<th>$w_{i,j}^{k,l}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>1</td>
<td>-8.744</td>
</tr>
<tr>
<td>1</td>
<td>1</td>
<td>2</td>
<td>2</td>
<td>0.401</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>1.321</td>
</tr>
<tr>
<td>1</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1.120</td>
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<tr>
<td>1</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>0.772</td>
</tr>
<tr>
<td>1</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>1.356</td>
</tr>
<tr>
<td>1</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>-0.303</td>
</tr>
<tr>
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<td>4</td>
<td>2</td>
<td>2</td>
<td>-0.223</td>
</tr>
<tr>
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<td>1</td>
<td>3</td>
<td>1</td>
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<tr>
<td>2</td>
<td>2</td>
<td>3</td>
<td>1</td>
<td>8.576</td>
</tr>
</tbody>
</table>

### Table 3. Values of the Biases for Configuration 4-2-1

<table>
<thead>
<tr>
<th>$i$</th>
<th>$j$</th>
<th>$\theta_{ij}$</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
<tr>
<td>2</td>
<td>2</td>
<td>-2.474</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>-1.848</td>
</tr>
</tbody>
</table>

**DISCUSSION AND CONCLUSIONS**

The problem of prediction of heat-exchanger performance is one of transfer of manufacturer's test data to a designer in suitably compact form so as to be accurate enough for calculations. There are many ways in which this can be done. At one extreme, the information can be contained in two fundamental heat transfer correlations, one for the inside and another for the outside. Another extreme is to transfer the entire test data for interpolation. The technique using ANNs lies somewhere in the middle of these two approaches. The technique has the accuracy comparable to the latter while the information being transferred consists only of the synaptic weights and nodal biases of the trained network. A comparison between the ANN prediction $Q_{ANN}$, and that from the correlations $Q_{cor}$, is shown in Figure 8. The network is seen to give better predictions with a smaller scatter. The correlation was specifically developed from experimental data for this heat exchanger and the methodology used is given by Zhao (1995).
Figure 8. Comparison of ANN and correlation predictions; correlations (*); ANN (+)

(Straight line is \( \dot{Q}_{ANN} = \dot{Q} \) and \( \dot{Q}_{cor} = \dot{Q} \); dotted lines represent ±10% deviations.)

The results of tests with artificial data for both one and two heat transfer coefficients indicated that the ANNs predict heat flow accurately and just as well as Equations (10) and (11). These equations assume that the heat transfer coefficient is constant along the length of the heat exchanger tubes. There are several reasons why the assumption does not hold for an actual heat exchanger. There are hydrodynamic and thermal entrance regions, secondary flows in the tube bends, complex vortex structures in the neighborhood of the tube-fin junctions, heat conduction along tube walls, natural convection within the tubes and between fins, temperature dependence of fluid properties like the viscosity. There are far too many nondimensional fluid, flow, thermal and geometrical parameters in the problem for existing correlations to be accurate. The relationships between the Nusselt, Reynolds, and Prandtl numbers only oversimplifies the problem so that the resulting predictions have a large uncertainty that are not due to measurement error but to information compaction through correlations.

Correlations in terms of Reynolds and Prandtl numbers have the advantage that predictions can be made for fluids other than those used in the original experiments. The price for this is a lack of precision in the predictions. One reason is that any correlation chosen, e.g., power-laws may not accurately represent the actual phenomena due to the use of limited number of parameters. Another is the uncertainty due to the property variations with temperature that must be considered twice, once when obtaining the correlations from experimental data and next when using them for predictions for a particular application. This is an important source of error especially when the fluids used for the former are different from the latter.

Under these circumstances, the ANN approach is an attractive alternative that has been shown to be satisfactory for heat exchangers using data both artificially generated and for experimentally obtained from a compact heat exchanger. The errors in prediction using a trained ANN are comparable to measurement errors. The precision is much better than from simplified correlations and is comparable to a direct transfer of the entire test data.

The usefulness of the ANN approach is that it basically allows prediction of the behavior of a given heat exchanger without need for an accurate mathematical model of the details of the pro-
cess. With processes involved that cannot be modeled exactly using first principles, the ANN is an effective means for the transfer of information from the manufacturers’ laboratory to the design engineer who would like to use test data for application. All that would have to be transferred are the weights and biases corresponding to a particular heat exchanger. The designer simply reads these values into his or her own network and is quickly in a position to make accurate predictions of the thermal behavior of the heat exchanger.

ACKNOWLEDGMENTS

We gratefully acknowledge the support of Mr. D.K. Dorini of BRDG-TNDR for this and related projects in the Hydronics Laboratory. G.D. also thanks the Organization of American States for a PRA Fellowship.

NOMENCLATURE

\( A \) \text{ transverse area for conduction, m}^2

\( A_i, A_0 \) \text{ inner and outer heat transfer areas, m}^2

\( D \) \text{ tube inner diameter, m}

\( c \) \text{ specific heat, J/(kg·K)}

\((i,j)\) \text{ jth node of i th layer}

\( g(x) \) \text{ activation function}

\( h \) \text{ heat transfer coefficient, W/(m}^2\cdot\text{K)}

\( k \) \text{ thermal conduction coefficient, W/(m}·\text{K)}

\( L \) \text{ length of duct, m}

\( m \) \text{ mass flow rate, kg/s}

\( m_i \) \text{ number of nodes in i th layer}

\( M \) \text{ total number of runs}

\( M_1 \) \text{ number of training runs}

\( M_2 \) \text{ number of test runs}

\( n \) \text{ total number of ANN layers}

\( N \) \text{ total number of cycles for training}

\( Nu \) \text{ Nusselt number}

\( P \) \text{ perimeter of duct, m}

\( Pr \) \text{ Prandtl number}

\( Q \) \text{ heat transfer rate between fluids, W}

\( Q_{ANN} \) \text{ heat transfer rate predicted by ANN, W}

\( Q_{cor} \) \text{ heat transfer rate predicted by power-law correlations, W}

\( R_i \) \text{ average of } R_i \text{ over all test runs}

\( Re \) \text{ Reynolds number}

\( T_i \) \text{ known target output at node } (n,j)

\( T \) \text{ temperature, °C}

\( T_{ref} \) \text{ reference temperature, °C}

\( U \) \text{ overall heat transfer coefficient, W/(m}^2\cdot\text{K)}

\( \dot{V} \) \text{ average velocity of fluid, m/s}

\( w_{i,j} \) \text{ synapt weight between nodes } (i,j) \text{ and } (k,l)

\( x_{i,j} \) \text{ input to node } (i,j)

\( y_{i,j} \) \text{ output from node } (i,j)

\( \delta_{i,j} \) \text{ error for node } (i,j)

\( \eta \) \text{ fin efficiency}

\( \lambda \) \text{ learning rate}

\( \nu \) \text{ kinematic viscosity of fluid, m}^2\text{/s}

\( \theta_{i,j} \) \text{ bias of node } (i,j)

\( \sigma \) \text{ standard deviation over all runs}

Subscripts and Superscripts

\( a \) \text{ air side}

\( i \) \text{ inlet}

\( o \) \text{ outlet}

\( w \) \text{ water side}

\( \text{wall} \) \text{ wall}

REFERENCES


