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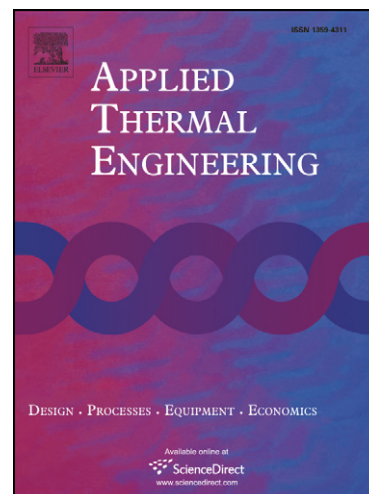
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Artificial Neural Network Modelling of the Thermal Performance of a Compact Heat Exchanger

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Abstract

This paper reports the use of artificial neural network models to simulate the thermal performance of a compact, fin-tube heat exchanger with air and water/ethylene glycol anti-freeze mixtures as the working fluids. The model predictions were compared with experimental data over a range of flow rates and inlet temperatures and with various ethylene glycol concentrations. In addition, the inlet air flow was distorted by obstructing part of the inlet ducting near the front face of the exchanger. The artificial neural networks were able to predict the overall rate of heat transfer in the exchanger with a high degree of accuracy and in this respect were found to be superior over conventional nonlinear regression models in capturing the underlying non-linearity in the data. Moreover the detailed spatial variations in outlet air temperature were also adequately predicted. The results indicate that appropriately trained neural networks can simulate both the overall and “local” characteristics of the compact heat exchanger. In addition the paper demonstrates how an alternative type of neural network, the so-called Self-Organising-Map (SOM), can be employed for heat exchanger condition monitoring by identifying and classifying the deterioration in exchanger performance which, in this case, was associated with different levels of inlet obstruction.

Keywords: Neural Networks, Non-linear Regression, Heat Exchangers, Fault Detection, Modelling

1. Introduction

Heat exchanger systems are essentially nonlinear in behaviour so that they can be difficult to control effectively. Consequently accurate prediction of the steady state and dynamic performance of heat exchangers is vitally important for optimum system design and heat recovery. The performance is often predicted using empirical convective heat transfer correlations based on best fit “least squares” analysis of experimental data (which may only be applicable to the particular exchanger and flow conditions), and corrected logarithmic mean temperature differences. This method, however, does not provide reliable predictions if the thermal and transport properties of the fluids cannot be specified accurately or if there is substantial mal-distribution of the inlet flows. This paper presents an alternative approach based on artificial neural network (ANN) models to represent the behaviour of the exchanger. These networks can be “trained” to represent complex, non-linear physical processes and data with a high degree of accuracy without requiring an explicit knowledge of the relationships between the inputs and outputs of the system. A neural network has a computational structure, which is analogous to a biological neural system in that it consists of a series of interconnected nodes or neurons. These are arranged in input, output and one or more so-called hidden layers linked by non-linear transfer functions. During “training” the network is presented with data for the process which can be obtained experimentally or, if this is not feasible, by using predictions from an appropriate, rigorous mathematical model of the process. The weightings between nodes and the detailed configuration of the ANN are varied until any differences or errors

between the predicted and actual values of the output variables are reduced to a specified level. The networks have only modest computational requirements so that they have been employed as “black box” models in the analysis of a wide range of thermal applications including air-water spray systems [1], heat transfer data analysis [2, 3, 4], heat pumps [5], and solar domestic water heating systems [6]. A comprehensive review of the use of these networks in thermal systems can be found in Sen and Yang [7].

More specifically neural networks have also been applied to heat exchangers. Diaz *et al* [8] studied single phase compact fin-tube systems and concluded that, for a wide range of exchanger geometries, a neural network was able to predict the overall heat transfer rate between the two fluids with much less scatter than the conventional technique based on available correlations. In addition Pacheco-Vega *et al* [9] successfully employed manufacturer’s data to train and test an ANN to model the thermal performance of a range of compact evaporators used for refrigeration. Also Pacheco-Vega *et al* [10] analysed heat transfer in compact fin-tube condensers using data from McQuiston [11] and found that the use a neural network yielded more accurate predictions than those derived by conventional regression analysis of the data. More recently neural networks have again been used for performance prediction in a further refrigeration application, Islamoglu *et al* [12]. This ability to model the behaviour of heat exchangers indicates that neural networks can be used for control purposes particularly since the network model can be updated on-line to take into account fouling or other changes in the characteristics of the system. Consequently a number of authors have investigated neural control of heat exchangers including Ayoubi [13], and Diaz *et al* [14, 15].

The present paper is concerned initially with the neural network prediction of the overall and detailed heat transfer characteristics of a compact fin tube exchanger under distorted flow conditions. The experiments were conducted with air and water/ethylene glycol anti-freeze mixtures as the exchanger fluids over a wide range of flow rates and inlet temperatures. The inlet air flow was distorted by partially obstructing the cross section of the inlet duct. In practice non-uniform air flows can arise from the presence of sharp bends before the exchanger inlet, partially open dampers or other flow control valves in the inlet flow ducting, system leakage or accidental ducting collapse or distortion, see Chiou [16] and Sparrow and Ruiz [17], and generally result in a reduction in thermal performance of the exchanger. The paper also examines the use of an alternative type of neural network, the so-called Self-Organising-Map (SOM), to identify and classify the deterioration in exchanger performance associated with different degrees of inlet obstruction. This ability to classify exchanger characteristics provides a potential method of detecting changes in the performance of the heat exchanger, due for example to fouling or sudden changes in fluid composition, using data only from the normal operating conditions. Consequently, artificial neural networks can offer an attractive method for identifying both sudden and gradual degradation in the performance of complex multiple heat exchanger systems.

2. The Experiments

2.1. Experimental Set-up and Test Procedure

A schematic representation of the overall arrangement of the experimental facility used in the tests is presented in Figure 1. The compact fin-tube heat exchanger was constructed with 8 tube passes and the tubes were fitted with 945 fins/m. The cross sectional dimensions of the exchanger were 274 mm wide by 136 mm high and it had a depth of 55 mm. The test liquids (water or various mixtures of water and ethylene glycol) were supplied to the exchanger from a heated reservoir and were contained in a closed flow circuit. The liquid in the reservoir was heated by two 3 kW electrical heating elements one of which was operated continuously whilst the power input to the other was

controlled to maintain a specified constant inlet temperature to the exchanger (in the range 80 to 90°C). The mass flow rate of the liquid was varied during the tests from 0.032 to 0.185 kg/s and the proportion of ethylene glycol (anti-freeze) in the mixture ranged from 0 to 40%. The flow rates were measured by a rotameter which had been previously calibrated by direct collection and weighing of the test liquids. The inlet and outlet liquid temperatures were measured in the pipework connections to the heat exchanger using previously calibrated thermistor temperature sensors.

The air flow was supplied by a centrifugal fan and controlled by a damper at the fan inlet. A honeycomb flow straightener was mounted in the inlet ducting to the exchanger to provide a relatively uniform air flow in the undistorted flow tests. The air flow rate was measured by a standard orifice plate arrangement positioned in a circular duct well downstream of the test section and the flows were varied from 0.050 to 0.091 kg/s during the tests. The outlet ducting from the exchanger incorporated a gradual transition from the rectangular test section to the circular outlet and sufficient duct lengths were employed before and after the orifice plate in accordance with British Standards for flow measurement. A second honeycomb device was mounted downstream of the heat exchanger to “straighten” the flow before entry to the air flow measurement section. The whole length of the inlet and outlet ducting was insulated to minimise heat losses to the surroundings.

The inlet flows were distorted by inserting a steel plate or baffle through the side of the duct downstream of the initial honeycomb section near the inlet face of the exchanger. The percentage of the cross sectional area of the inlet, which was obstructed in this fashion, varied from 0% (the undistorted case) to 50%. The positions of the thermistor sensors, which were used to measure the air temperatures, are indicated in Figure 1. The inlet temperature was measured 10 mm downstream of the initial flow straightener and the outlet temperature was measured at several positions downstream of the exchanger. The most reliable exit temperature data were obtained from the sensor positioned after the second honeycomb where mixing resulted in an essentially uniform value. An additional sensor was placed after the orifice plate to provide further information for temperature correction of the flow rate. The detailed air exit temperature distribution was determined using a vertical array of eight equally spaced thermistors, which was traversed in ten 27 mm steps across the duct at a distance of 5 mm downstream from the outlet face of the heat exchanger. All the thermistors were individually calibrated in an environmental chamber by comparison with the temperatures measured by a platinum resistance thermometer, which had an accuracy of 0.1°C over the temperature range studied in the tests. Data were collected when the system achieved steady-state conditions and overall 359 test conditions were examined.

2.2. Selected Experimental Results and Discussion

This section is included to illustrate the main effects of obstructing the inlet air flows into the heat exchanger by briefly presenting some of the data gathered in the tests. However, to assess the consistency and reliability of the results the rates of heat transfer to the air were compared with the corresponding values from the liquid, see Figure 2, which presents the comparisons for the “unobstructed” cases. In these calculations the specific heats of the antifreeze mixtures were determined using manufacturer’s data. It is evident that there is generally satisfactory agreement between the heat transfer rates with significantly less than 5% difference in virtually all cases. Similar good agreement was obtained with all the obstructed flows even at an obstruction of 50% when the resultant non-uniformity of flow downstream of the exchanger would have been more likely to lead to potential errors in the measurement of the mean exit air temperature. Consequently it appears that the experimental technique is capable of yielding consistent, reliable data. In the remainder of the paper the mean of the air and liquid side rates are employed as the rate of heat transfer in the exchanger.

Obstructing the inlet air flow by a baffle results in a substantial reduction in the performance of the system, see Figure 3 which presents heat transfer data for various air flow rates at constant fluid inlet temperatures and a water flow rate of 0.085 kg/s. Similar deteriorations in performance were observed at other liquid flow rates and for all water/anti-freeze mixtures. The inlet blockage “channels” the air flow so that velocities, mass flow rate and heat transfer coefficients are all increased in the unobstructed section of the exchanger. However a relatively stagnant separated flow ensues behind the baffle and in this region the mass flows, velocities and heat transfer coefficients are reduced. This effect may be exacerbated at very high levels of obstruction when the momentum of the relatively high velocity air leaving the unblocked side of the exchanger can result in a recirculation or reverse flow of “hot” exiting air back through part of the obstructed region. Overall it is clear that the performance of the heat exchanger deteriorates at an increasing rate as the degree of obstruction increases. The presence of the inlet baffle also markedly affects the outlet air temperature distribution, see Figure 4, which presents data for an unobstructed flow and a 50% blockage. The normal unobstructed flow results in a relatively flat distribution, except at locations close to the side wall, whilst there are sharp discontinuities with the obstructed flow. The exit air temperatures associated with the section “covered” by the baffle (positions 5-10) are significantly higher because of the relatively low mass flow rates in this region, whereas the temperatures over the remainder of the outlet face are reduced as a result of the enhanced mass flow rates through the unobstructed exchanger passages. The addition of ethylene glycol anti-freeze in the liquid mixture also reduces the specific heat capacity which in turn reduces the overall thermal performance of the compact heat exchanger.

3. Modelling of the Performance of the Heat Exchanger

3.1. Artificial Neural Network Models of the Overall Performance

A Multi-Layer Feed-Forward ANN [18] was utilised in this study. This type of network contains a layer of input nodes or neurons which are interconnected to the nodes in one or more hidden layers which are linked in turn to the nodes in the output layer see Figure 5. This type of neural network is “trained” by using input and the corresponding output data derived from the experimental measurements. The input values are fed forward through the network and during transmission are modified by the weighting and transfer function (a tan-sigmoid¹ transfer function was used in the present study) associated with each link. Each neuron therefore receives multiple inputs from other neurons and generates a single output, which is then fed on to the neurons in the next layer. The eventual predicted values, which are fed into the output nodes, are compared with the corresponding measured results and any differences, i.e the “errors”, are propagated back through the network and used to adjust the weightings of the connections. This process is known a single training cycle or iteration. The cycle is repeated sequentially using this back propagation algorithm so that training proceeds iteratively until the mean square error between the predicted outputs and corresponding measured values is reduced to an acceptable level. The trained network can be subsequently “tested” and independently validated by using previously unseen input and output data to assess the ability of the ANN to generalise the process or system it has been trained to represent.

In the current study, a single hidden layer was found to be appropriate and the number of neurons in this layer was varied to optimise the performance of the neural network. The performance of an ANN is heavily influenced by the number of neurons in the hidden layer. The use of too few neurons

¹ tan-sigmoid transfer function is an exponential function that maps the input to the interval (-1,1)

can result in poor representation of the process because the network failing to “learn” the underlying patterns between the input and output data. Conversely the use of a large number of nodes in this layer can result in “over fitting” whereby the individual training data points are accurately fitted, but substantial errors occur when the network is asked to generalise the patterns associated with new unseen input data. An ANN was developed initially to represent the overall behaviour of the heat exchanger over the whole range of flow rates, inlet temperatures, liquid compositions and blockage ratios studied in the experiments. The inlet temperatures of the liquid (80 to 90°C), the air inlet temperatures (20 to 24°C), liquid mass flow rates (0.032 to 0.185 kg/s), air mass flow rates (0.050 to 0.091kg/s), inlet obstructions (0, 16.5, 33, 41.5, 50%) and ethylene glycol anti-freeze mass concentrations (0, 10, 20, 30, 40%) were used as input vectors to the ANN whilst the single output neuron represented the overall rate of heat transfer between the two test fluids. In this case a total of 6 hidden neurons were found to be most suitable by a “trial and error” process.

For an un-biased assessment of the network performance, the 359 sets of experimental measurements were randomly sampled into 4 equal-sized subsets of data. The first two subsets (training data) were used to train the network whilst the third subset of data (test data) was used to monitor the likelihood of over-fitting the model during training. Unlike the training data, these test data do not influence the adjustment of the network weights and biases but solely provide an indication of the suitability of the network to generalise unseen results. The resultant network was then independently validated using the remaining fourth subset of data (validation data). To provide a more severe test of performance of the ANN model, the results obtained at specific test conditions were subsequently eliminated from the data used for training. In this case all data corresponding to ethylene glycol anti-freeze mass concentrations of 20% and 40% at inlet obstructions of 33% and 50% were used as independent validation data. Similarly, the test data corresponded to zero ethylene glycol anti-freeze at inlet obstructions of 33% and 50%. In this manner, the ANN was trained to extrapolate to conditions which fell outside the region of the training data.

3.2. Nonlinear Regression (NLR) Models of the Overall Performance

This section describes the application of a model based on a nonlinear “least squares” regression technique to predict the overall thermal performance of the heat exchanger. An overall analytical model of the exchanger is complex so that the NLR model assumes that the rate of heat transfer between the two fluids can be represented as the product of a series of independent variables so that

$$Q = a \cdot (T_{wi} - T_{Ai})^b \cdot M_w^c \cdot M_A^d \cdot (100 - AFC)^e \cdot (100 - OBS)^f \quad (1)$$

where,

- Q = rate of heat transfer in the exchanger (kW)
- T_{wi} = hot stream inlet temperature (°C)
- T_{Ai} = cold stream inlet temperature (°C)
- M_w = hot stream mass flow rate (kg/s)
- M_A = cold stream mass flow rate (kg/s)
- AFC = antifreeze mass concentration (%)
- OBS = inlet obstruction (%)

The unknown parameters a , b , c , d , e and f in this nonlinear equation were estimated by minimising the sum of the squared differences between the measured heat transfer rates and the corresponding model predictions. This involved a gradient based iterative procedure using a Gauss-Newton algorithm with Levenberg-Marquardt modifications [19] to achieve convergence between the measured and predicted heat transfer rates. However, a multivariate nonlinear model of this type can

be difficult to fit to the available data, unless the iteration process is started with “good” initial estimates of the values of the unknown parameters. Moreover gradient-based optimisation was made even more difficult in the present study as there were discontinuities in the data gathered in the tests (as is the case in many other experimental studies). To overcome these difficulties, a genetic algorithm (GA) was first of all used to yield preliminary values of the unknown parameters. Genetic algorithms are loosely based on the principles of biological evolution such as “survival of the fittest”. A number of sets of initial individual values of the parameters, a to f in equation (1), (the so-called initial population) were selected in a random fashion. These sets or cases are then assessed in terms of their ability to predict the rate of heat transfer in the exchanger. A proportion of the individual sets which provided the “best fit” was then retained and together with an appropriate number of new sets of parameter values constituted the population for the second generation. The process was repeated until an appropriate agreement between predicted and measured heat transfer rates was achieved. The genetic algorithm therefore essentially searched a wide range of possible solutions in a computationally efficient manner. In this present study it was not necessary for the GA to fully converge since it was only employed to provide preliminary estimates of the unknown parameters in the regression equation which were reasonably close to the optimum values. These GA-estimated parameters can then be further refined by means of the gradient-based technique to yield the optimal solution. A comprehensive review of the use of genetic algorithms in thermal systems can be found in Sen and Yang [7]. The NLR model was trained, tested and independently validated in the same manner as the neural network model. The overall performance of the ANN and NLR models is discussed in section 3.3 below.

3.3 Comparison of ANN and NLR Model’s Predictions

Figure 6 presents the performance of the ANN model when all the data are used in the selection of the training, test and validation data (Simulation-1). There is very good agreement between the predicted and measured overall heat transfer rates. The differences can be more clearly seen from the corresponding error histograms which indicate that the ANN model was able to accurately generalise the experimental data with only a very small number of predictions (2 out of a total of 359 training, test and validation results) exceeding a 5% error margin. Overall, the Mean Absolute Error (MAE) of the ANN’s predictions was 0.6%, 0.9% and 0.9% respectively for the training, test and validation data sets. In comparison, there was considerably greater scatter in the NLR model predictions with 17% (61 out of 359 results) in error by more than 5%, see Figure 7. This regression model is clearly less able to represent the experimental overall performance of the heat exchanger since the MAE for the training, test and validation data sets were 2.9%, 2.8% and 3.2% respectively.

When subjected to the more severe test described earlier in section 3.1 (Simulation-2) the performance of the ANN model was slightly degraded, although, even in this situation still only a relatively small proportion (4 out of 359) of the predictions exceeded the 5% error margin. In this more severe test the mean absolute prediction errors were 0.7%, 2.3% and 1.8% respectively for the training, test and validation data sets. In comparison, the performance of the NLR model was significantly poorer than that of the ANN model with a total of 72% of the predictions exceeding the 5% margin of error. In this case, the mean absolute prediction errors were 8.2%, 5.2% and 5.1% respectively for the training, test and validation data sets. Consequently the neural network model with its inherent ability to represent complex non-linear data provides superior predictions of the overall performance of this compact fin-tube heat exchanger. Various other performance indicators such as the Root Mean Square Error (RMSE) and correlation-coefficient (corr-coef) are also compared for the two models in Table 1 and it is again clear that the neural network model provides better representation of the behaviour of the exchanger.

3.4 Neural Network Representation of the Detailed Behaviour of the Exchanger

Whilst it is clear that an ANN can successfully predict the overall heat transfer rate, the ability to represent the local distorted exit air temperature distribution provides a more severe test of a neural model of the exchanger. Consequently a neural network was developed to predict the ten temperatures measured by the thermistor sensor as it was traversed in steps across the exit of the exchanger at the mid-height of the outlet duct. The input parameters used to train the network were the same as those specified in section 3.1 whilst the ten output nodes corresponded to the individual temperatures measured across the exit face of the exchanger. The optimised network in this case contained 7 neurons in the hidden layer so that it had a 6-7-10 arrangement of neurons. The ability of this trained ANN to predict this detailed behaviour of the plate-fin system was tested at inlet obstructions of 16.5% and 41.5% and ethylene glycol anti-freeze concentrations of 10% and 30% all of which conditions were not included in the training process, see Figure 8, which presents typical results. The overall error in predicting the output exit air temperatures (in °C) was 2.5%. The distribution at the lower blockage of 16.5% was predicted more accurately since this temperature distribution is relatively undistorted and so is likely to be reasonably similar to that for the unobstructed case, which formed part of the training set. Nevertheless there is reasonably good agreement between the measurements and predictions even with the highly distorted flow, which occurs with an obstruction of 41.5%. Consequently an ANN appears to be capable of adequately representing the detailed thermal characteristics of the plate fin exchanger as well as its overall performance.

4. Diagnosis of the “Condition” of the Heat Exchanger.

As described previously, the performance of the heat exchanger can be markedly degraded as a result of flow maldistribution. In addition, over a longer term, fouling (i.e the gradual build-up of deposits on the heat exchanger surfaces) can also result in a similar significant deterioration in performance. This deterioration can be difficult to detect if the inlet conditions (temperatures, flow rates and fluid compositions) are subject to frequent variations. Neural networks with their inherent ability to represent complex non-linear systems have been used in fault diagnosis and condition monitoring applications so would appear to provide a potential means of identifying and categorising the deterioration in heat exchanger performance in the present study. The deteriorations in overall exchanger performance resulting from the insertion of different inlet obstructions are analogous those due to more common causes such as fouling. Consequently the ability of a trained ANN to detect and classify the level of obstruction (i.e. the degree of deterioration in heat exchanger performance) in the present tests was investigated.

A so-called Self-Organising-Map (SOM) neural network [20] was used in this study since this type of network can readily recognise and classify patterns in input data. Unlike the FFMLP network used previously the SOM network only has input and output layers. This latter layer also known as the competitive layer, see Figure 9, is organised as a two-dimensional hexagonal or rectangular grid and each input neuron is connected to each and every output neuron. Each competitive neuron is represented by a n-dimensional weight vector (a so-called codebook vector), where n is equal to the dimension of the input data vector. In a similar manner to that for the FFMLP network, input data (vectors) are presented via the input layer. However, the neurons on the competitive layer behave in a completely different fashion from those in error back-propagation networks. When an input vector is presented to the SOM, the Euclidean distances between each and every competitive neuron and the input vector are computed. The neuron whose weight vector is closest to the input vector (the so-called Best-Matching Neuron (BMN)), is updated so that it is moved closer to the input pattern, a

process known as vector quantisation). The topological neighbours of the BMN are updated similarly so that they are also moved closer to the input pattern, see Figure 10. Successive presentation of the input data results in a group of neurons becoming associated with the pattern of the data. Training of the network is relatively simple and fast so that, the SOM is more robust than a FFMLP network and hence is more suited for online applications.

The SOM in this study consisted of a 15x15 rectangular grid of neurons and half of the experimental data were randomly selected and used for training this network. The four input variables to the SOM were the inlet air temperature, the air mass flow rate, the ethylene glycol concentration and the product of the liquid mass flow rate and the temperature difference between the inlet and outlet liquid temperatures. During the training phase each input vector was also labelled to identify its class i.e. the particular obstruction with which it is associated. The data were presented to the SOM in a batch form and the competitive neurons “organised” themselves in response to the patterns of input vectors so that, upon convergence, specific groups of neurons were associated with each class, see Figure 11. Once the SOM has been trained and all the neurons were labelled with classes (corresponding to inlet obstructions of 0, 16.5, 33, 41.5, and 50%) of the training data with which they were associated, the map was then used to determine the degree of membership of any new ‘unseen’ input vector to each of the categories. This was achieved by first of all determining the five closest neurons and their corresponding neighbours (i.e. the best matching neurons) in the SOM to each new unseen input vector pattern. The Euclidean distances between this input vector and these best matching neurons were then calculated and used as input to a further Radial-Basis-Function (RBF) neural network. This final network then used these distances to calculate the probability of the input vector “belonging” to the particular groups of neurons associated with each of the obstructions. Consequently the RBF network determined the “degree of membership”, as a fuzzy vector, of each new input pattern to each of the obstruction classes. The fuzzy output of the RBF network was subsequently “defuzzified” by allocating the input vector to the class with the highest probability of membership.

The ability of the SOM network to classify the degree of inlet air obstruction was simulated by training it with 50% of the test measurements (selected randomly) and so leaving the remaining 50% of the data to test the network performance. Results suggested that the SOM network was able to classify correctly the unseen test data with a reasonably high degree of success rate of 79.3% in comparison to a conventional Multiple Linear Regression model which only able to deliver a success rate of 20.1%. Therefore the SOM network was better able to represent the non-linearity in the heat exchanger data patterns. Moreover a level of success of approximately 79% is likely to be satisfactory for a monitoring system since remedial action to correct the deterioration in exchanger performance would not be instigated by an individual prediction of poor performance but would require a significantly large number of predictions falling in severe categories over a period of time. Therefore an artificial neural network may be capable of monitoring the condition of an exchanger even for situations in which there are substantial variations in the composition, temperatures and flow rates of the individual fluid streams.

In a separate exercise, the effect of increasing the amount of training data was also investigated. In these tests the percentage of total data used for training the SOM network was increased from 50% to 70% and then 90%, thus leaving the remaining 30% and 10% of data respectively for testing the performance of the network. The results (see Table 2) showed that the percentage of successful classifications of the test data was considerably improved from 79.3% to 88.6%. Therefore it can be concluded that the performance of the neural network monitoring system is sensitive to the amount of representative training data.

5. Conclusions

This study has demonstrated that, once trained, an artificial neural network was able to predict the overall heat transfer rate between the liquid and air steams in a compact fin-tube heat exchanger with a high degree of accuracy. The neural network predictions were in much closer agreement to the experimental data than corresponding predictions derived by the use of a conventional non-linear regression model. A SOM neural network was also able to classify the degree of inlet air obstruction with a success rate of approximately 80 to 90%. This level of success is likely to be satisfactory for a system to monitor the deterioration in heat exchanger performance since any consequent remedial action would not be instigated by an individual prediction of poor performance but would require a significantly large number of predictions indicating severe underperformance over a period of time. Therefore the application of artificial neural networks appears to have potential for monitoring the condition of an exchanger even for situations in which there are substantial variations in the composition, temperatures and flow rates of the individual fluid streams.

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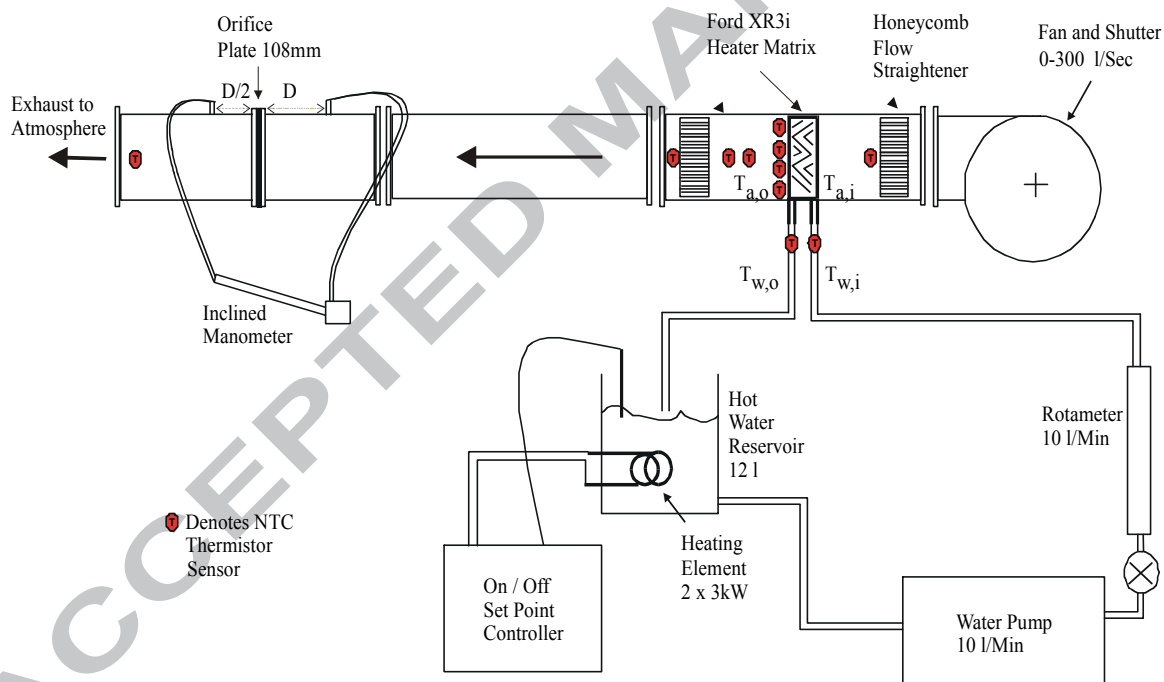


Figure1: A schematic representation of the heat exchanger system

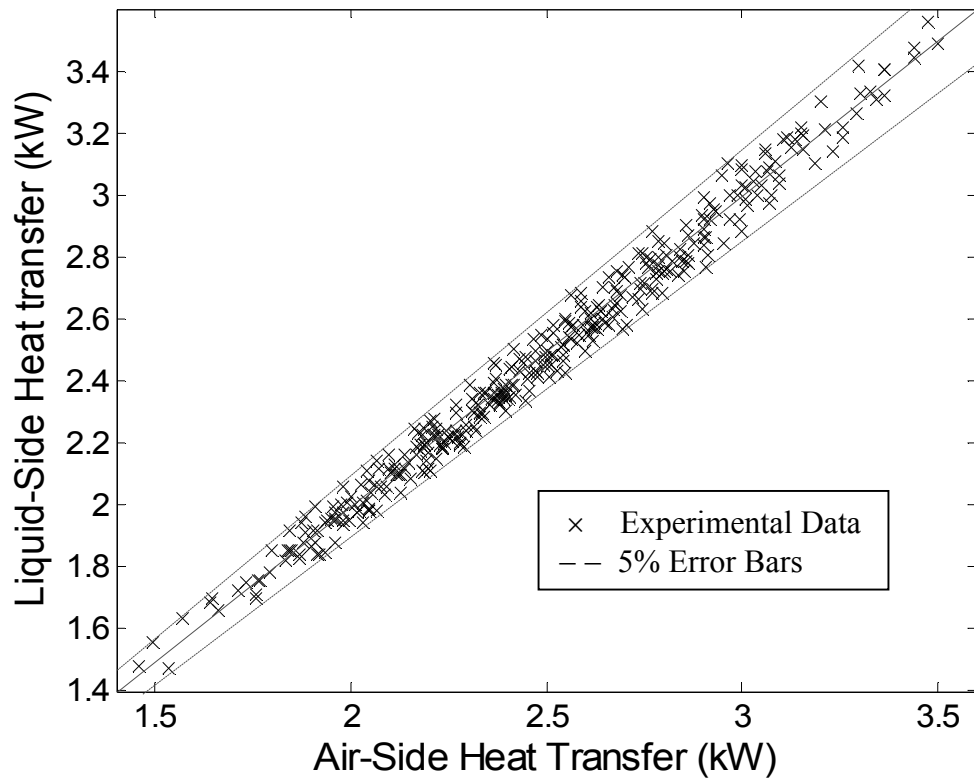


Figure 2: Comparison of the Liquid and Air-Side Heat Transfer Rates

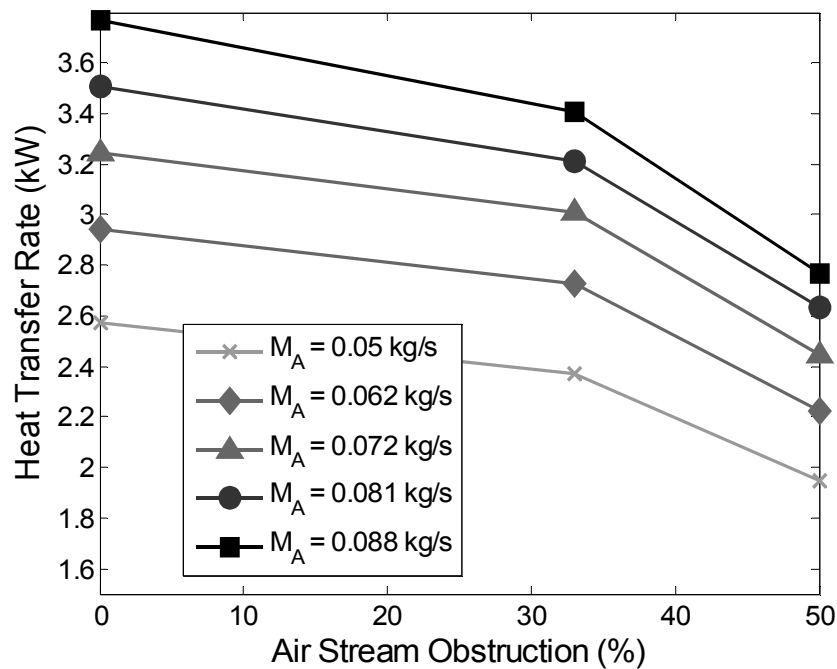


Figure 3: Effect of Inlet Obstructions on the Heat Exchanger Performance at Different Air Flow Rates

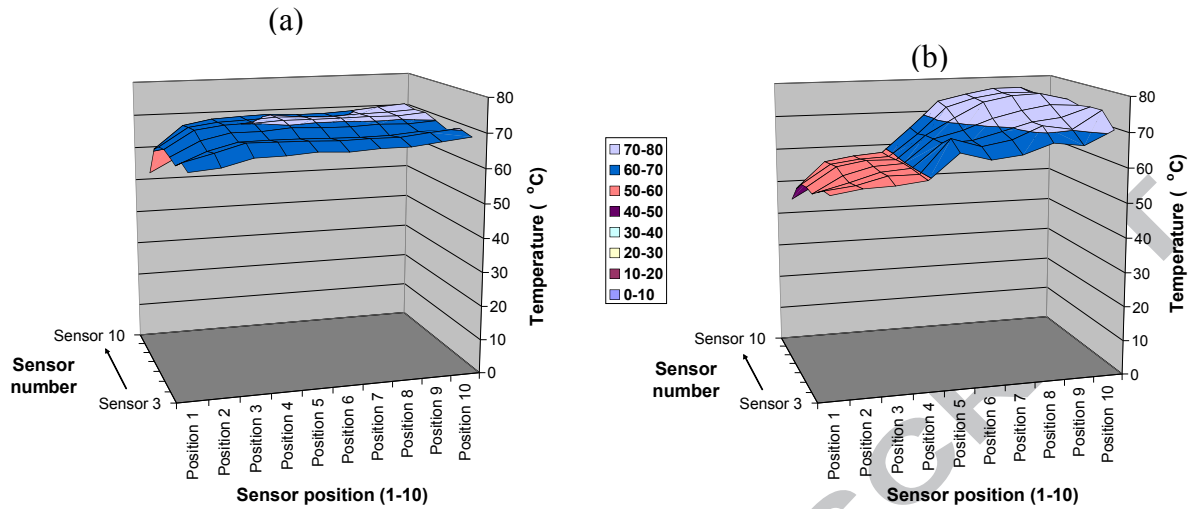


Figure 4: Air Temperature Distributions Over the Outlet Face of the Heat Exchanger
 (a) Normal Unobstructed Flow (b) 50% Obstruction

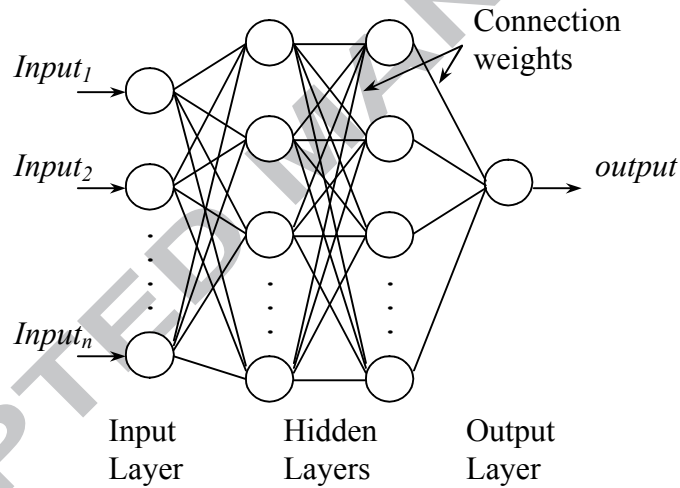


Figure 5: Schematic Representation of a Multi-Layer Perceptron ANN

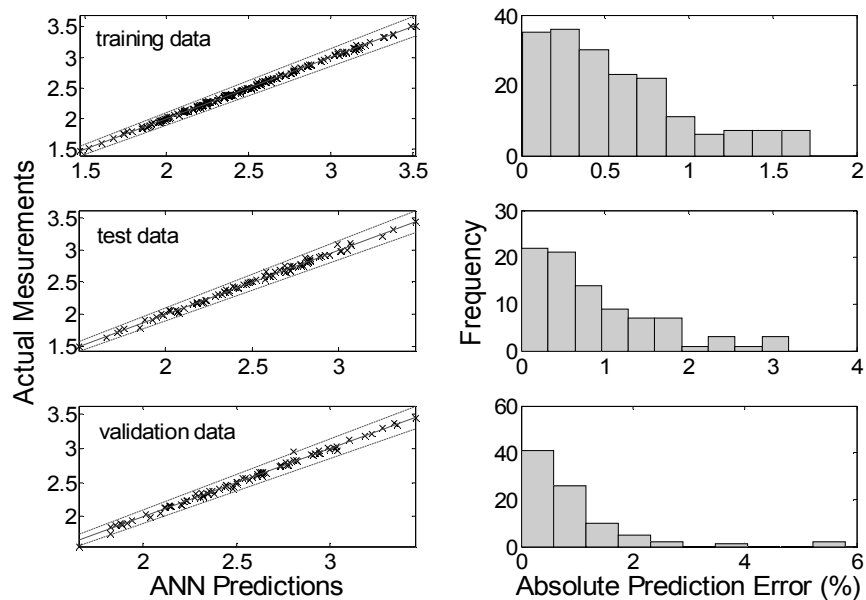


Figure 6: Representation of the Overall Heat Exchanger Performance by the ANN.
 (left) Heat Transfer Rate, kW (right) Error Histogram

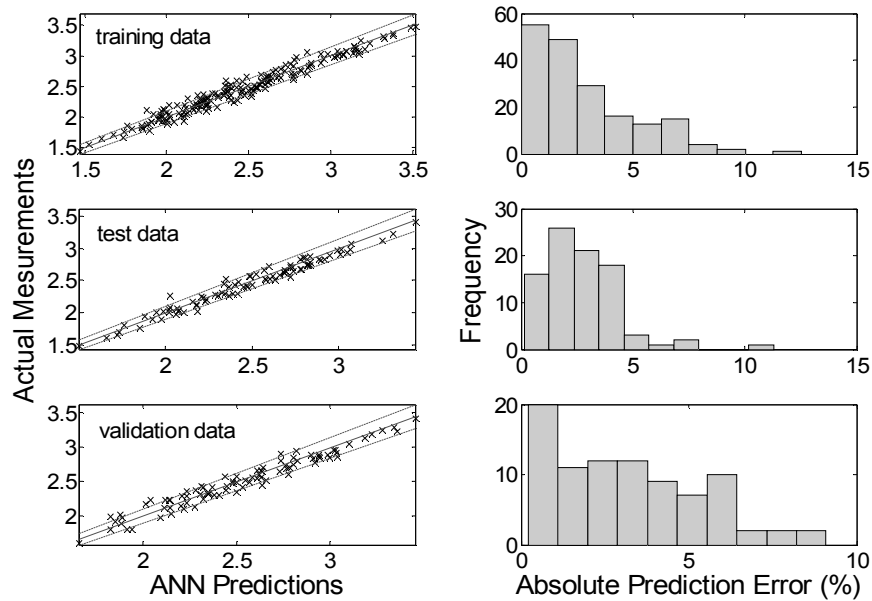
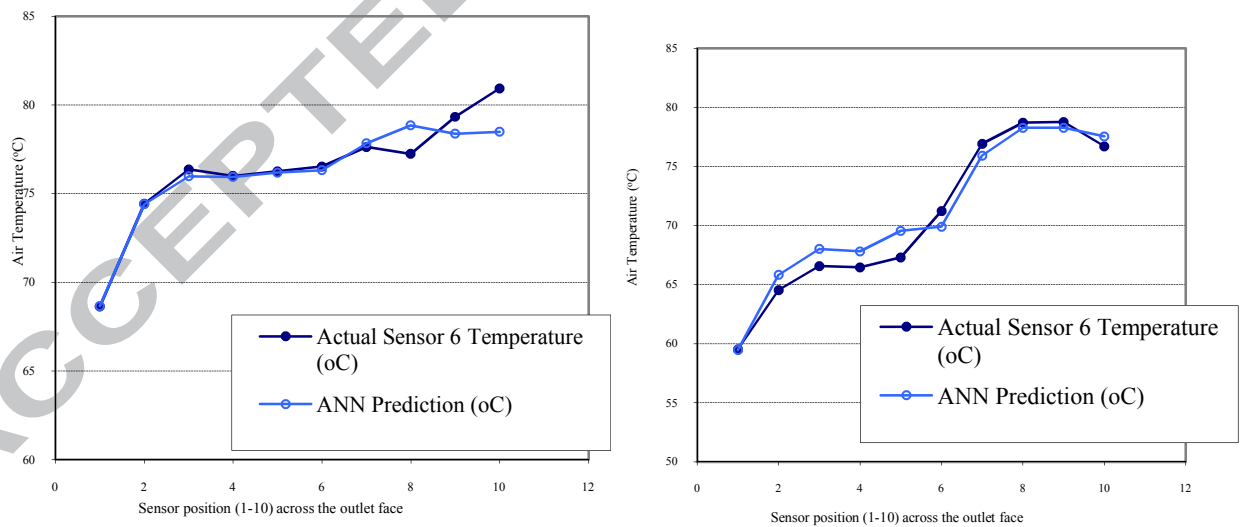


Figure 7: Representation of the Overall Heat Exchanger Performance by the NLR Model.
 (left) Heat Transfer Rate, kW (right) Error Histogram



(a) 16.5% Obstruction

(b) 41.5% Obstruction

Figure 8: ANN Representation of the Variation in Air Temperature Across the Exit Face of the Exchanger

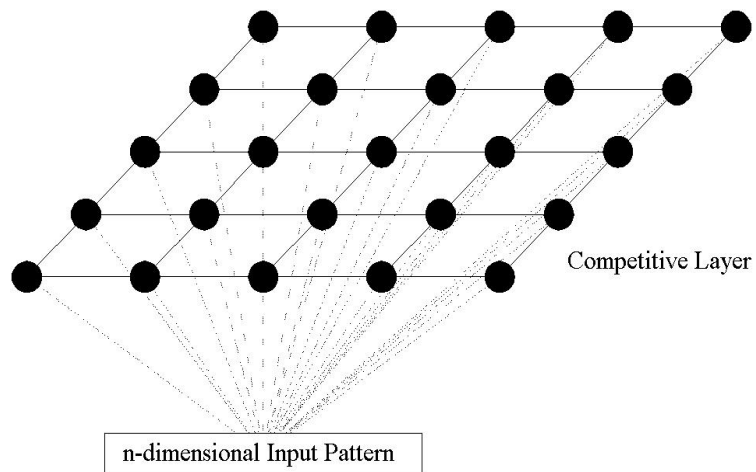


Figure 9. Typical SOM with Rectangular Grid of 5×5 Competitive Neurons

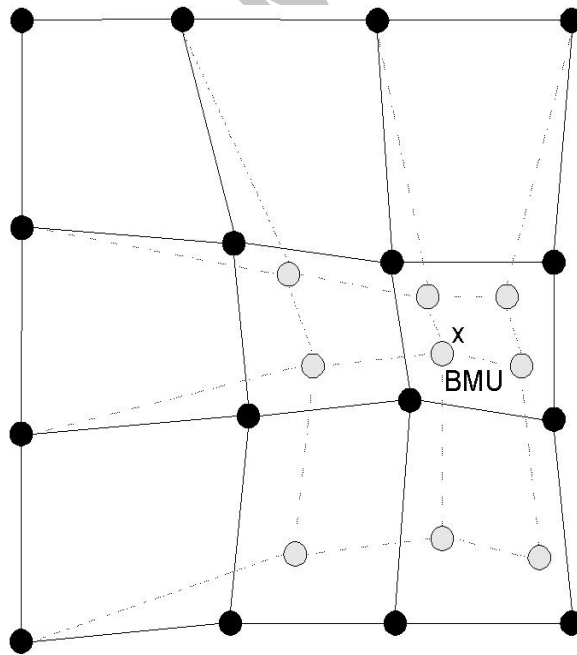


Figure 10: Updating the BMU and Its Neighbours towards an Input Pattern x . The Solid and Dashed Lines Correspond to the Neurons' Position Before and After Updating respectively.

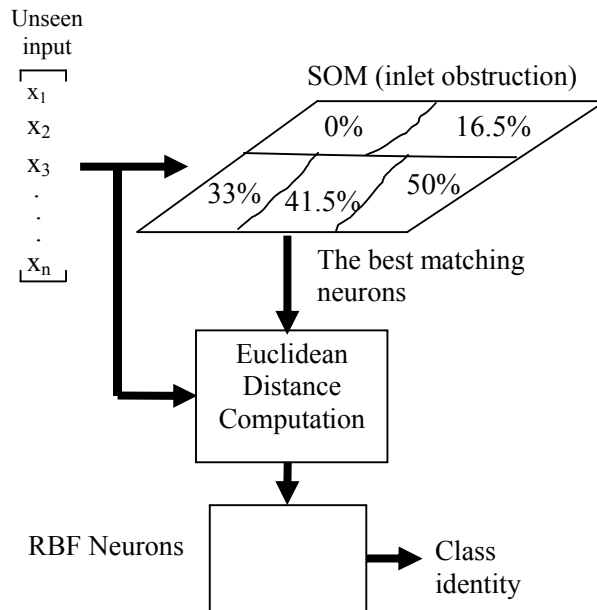


Figure 11: Architecture of the ANN for Classification of the Inlet Obstructions

Table 1: Comparison of ANN and NLR Model Predictions

Performance indicators	Simulation 1					
	Training data		Test data		Validation data	
	ANN	NLR	ANN	NLR	ANN	NLR
MAE (%)	0.6	2.9	0.9	2.8	0.9	3.2
RMSE	0.017	0.086	0.030	0.077	0.032	0.092
Corr-coef	0.999	0.980	0.998	0.984	0.997	0.975
Performance indicators	Simulation 2					
	Training data		Test data		Validation data	
	ANN	NLR	ANN	NLR	ANN	NLR
MAE (%)	0.7	8.2	2.3	5.2	1.8	5.1
RMSE	0.022	0.227	0.062	0.163	0.053	0.143
Corr-coef	0.999	0.980	0.991	0.935	0.995	0.946

Table 2: The Effect of the Size of the Training Data on the Performance of the SOM network.

% of data used for training	Number of mis-classifications	% success rate
50	36 out of 174	79.3
70	17 out of 104	83.6
90	4 out of 35	88.6