Prediction of the air temperature and humidity at the outlet of a cooling coil using neural networks

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Abstract

The main objective of this study is to predict air temperature and humidity at the outlet of a wire-on-tube type heat exchanger using neural networks. For this purpose, initially the heat exchanger was coupled to a refrigeration unit and placed in a wind tunnel. Afterwards, its performance was tested under various experimental conditions. We measured nine input parameters, namely, temperature and humidity of the air entering the coil, air velocity, frost weight, the temperature at the coil surface, mass flow rate of the heat transfer fluid and its temperatures at the inlet and outlet of the coil along with ambient temperature. Additionally, we measured temperature and humidity of the air leaving the coil as the output parameters. Then, a feed-forward neural network based on backpropagation algorithm was developed to model the thermal performance of the coil. The artificial neural network (ANN) was trained using the experimental data to predict the air conditions at the outlet of the coil. The predicted values are found to be in good agreement with the actual values from the experiments with mean relative errors less than 1% for outlet air temperature and 2% for outlet humidity. This demonstrates that the neural network presented can help the manufacturer predict the performance of cooling coils in air-conditioning systems under various operating conditions.

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1. Introduction

As the moist air comes into contact with a cold surface such as that of a cooling coil having a temperature below the air dew point temperature, the water vapour starts to condense and deposits on the cold surface [1]. Furthermore, when the surface temperature is below the freezing point, frost formation starts to occur on the cold surface. Thus, the water vapour in the air first changes into a liquid phase, and then to solid phase. In these cases, both heat transfer and mass transfer take place concurrently [2]. Therefore, the heat transfer process becomes very complicated during the transition of the water from the gas phase to solid phase.

On the other hand, the heat transfer rate at the cooling coil decreases as a result of the thermal resistance caused by the frost deposition between the tube and air stream [3]. Because the more the time passes the more the frost quantity
increases, the heat transfer through the frost layer to the cold coil surface decreases with time. Furthermore, growth of the frost layer decreases air flow area, which leads to increase the resistance against the air flow over the heat exchanger surface. Consequently, the capacity of the cooling coil will decrease significantly, thus causing a longer operation time of the cooling system and a higher operation cost due to increasing power consumption.

Various engineering techniques have been employed for designing and modelling heat exchangers that are used for industrial and domestic cooling systems. After the production, the refrigeration systems are tested whether they provides the operating conditions adequately or not. It is well recognized that frost grown on the heat exchangers is one of the major problems for refrigeration and air-conditioning systems [3]. Since frost formation depends on several operating conditions, it is very difficult to identify this process using only mathematical functions. Therefore, frost formation on heat exchangers has been attempted to model based on the data obtained by experimental studies.

Since the experimental research studies are very difficult and time consuming, the artificial neural network ANN techniques have been lately preferred for thermal applications such as heating, ventilating and air-conditioning systems, solar water heating, determination of critical heat flux, refrigeration systems and power generation systems. ANN is applied to estimate actual values within a certain error limits when enough experimental data are provided. Therefore, ANN can model physical phenomena in complex systems without needing explicit mathematical representations.

In literature, one can find considerable amount of research about thermal applications of neural networks. Pacheco-Vega et al. [4] applied the ANN for modelling the thermal characteristics of fin-tube refrigerating heat exchanger systems with limited experimental data. They presented a methodology based on the cross-validation technique to find
the regions where not enough data are available to construct a reliable neural network. Islamoglu [5] presented a neural network model to predict the heat transfer rate of the wire-on-tube type heat exchanger using the limited experimental data presented by Lee et al. [6]. In another work, Islamoglu [7] predicted the suction line outlet temperature and mass flow rate of a non-adiabatic capillary tube suction line heat exchanger. Diaz et al. [8] performed simulation of the time-dependent behaviour of a heat exchanger by using neural network techniques to control the temperature of air coming out of the heat exchanger. Kalogirou [9] presented various applications of neural network in energy problems related to approximation techniques. In all these studies and the others that are not referred here, ANN is a suitable approach to predict some process parameters of thermal systems used in engineering applications.

From the point view of end users of refrigeration and air-conditioning systems, the most important point is to obtain the desired conditions such as outlet temperature and humidity rather than frost formation, heat transfer performance and heat exchanger efficiency. Therefore, the objective of the present study is to predict the outlet air temperature and humidity at the outlet of the cooling coil using an ANN method without the need of understanding the frost growth.

2. Experimental setup and data

The experimental setup used in this study is illustrated in Fig. 1. Basically, the setup consists of two main parts: a low-velocity wind tunnel and a refrigeration unit. The wind tunnel has a heater and humidifier, a transition section, a honeycomb, a rectangular test section and a fan section. The refrigeration unit is coupled to the cooling coil and located outside of the wind tunnel as seen in Fig. 1.

The inlet air was heated by a high-powered air duct heater. In order to control the inlet air temperature, a controller is attached to a thermocouple. The air inlet temperature could be varied between 20 °C and 50 °C. A humidifier was used to change the humidity of the inlet air from 30% to 70%. To provide a laminar flow of the inlet air to the test section, a honeycomb was employed after the transition section.

The rectangular test section was made up of a 5-mm-thick Plexiglas sheet with the dimensions 1250 mm long, 500 mm wide and 250 mm high. The test section consists of the test coil and the associated instruments. The test coil is a 1830-mm-long flexible refrigerant grade copper tube with 6 passes. The tube is in the form of wire-on-tube-type coil and the total heat transfer surface area is equal to 0.104 m². The test section also contains the instrumentation which are necessary to measure the parameters of the temperature and humidity at the inlet and outlet of the wire-on-tube-type coil. Three thermocouples were positioned upstream the test coil to measure the inlet air temperature. Three thermocouples were also located downstream the coil to measure the outlet air temperatures. In addition, four thermocouples were mounted at the inlet and outlet of the test coil to measure the coolant temperatures. To reduce the reading errors of thermocouples, more than one thermocouple were mounted at the same location and the results were averaged to find the mean values. Similarly, humidity sensors were mounted upstream and downstream the test section.

![Fig. 1. Schematic diagram of the experimental apparatus.](image)
to measure the inlet and outlet air relative humidity. A vane-type anemometer placed at the upstream section measures the air velocity.

The velocity of the air was changed using a fan driven by a DC motor. The speed of the DC motor was varied in the range of 0–1500 rpm. This allowed a very wide range of air velocity for the experiments.

The recirculation cooler unit was connected to the test coil by means of intermediate copper tubing. The coolant liquid was a mixture of 90% methanol and 10% ethylene glycol as antifreeze. The temperature of the coolant that comes from the cooler was controlled by a thermostat which could be set to a certain temperature. The coolant temperature set point was varied between −30 and 0 °C.

3. The basis of artificial neural networks

Artificial neural networks are non-linear mapping systems that have emerged as a result of simulation of biological nervous system, such as the brain, on a computer. Nowadays, neural networks can be used to analyse the phenomena with no or very complicated algorithmic solutions. When there is not a clear relationship between the inputs and outputs, it is not easy to formulate the mathematical model for such systems. Then, ANN can model this system using samples. Their ability to learn by experimental data makes ANN very flexible and powerful than any other parametric approaches. Therefore, neural networks have become very popular for solving regression and classification problems in many fields [10].

An ANN consists of many interconnected processing nodes known as neurons that act as microprocessors. Each neuron receives a weighted set of inputs and produces an output. A neuron evaluates weighted sum of the inputs given by

\[ n = \left( \sum_{i=1}^{P} w_i x_i \right) + b \]  

where \( P \) is the number of elements in the input vector \( x_i \), \( w_i \) is the interconnection weights, and \( b \) is the “bias” for the neuron [11]. Note that neuron output depends only on information that is locally available at the neuron, either stored internally or arrived via the weighted coefficients. The neuron output is calculated by the summation of weighted inputs with a bias through an “activation function.” This activation function computes its output as follows

\[ f(n) = f \left( \left( \sum_{i=1}^{P} w_i x_i \right) + b \right) \]  

In general, neural networks are trained by adjusting the weighting coefficients to reach from a particular input to a specific target using a suitable learning method until the network output matches the target. The error between the output of the network and the target, i.e., the desired output, is updated by optimizing the weights and biases. The training process is ceased when the error falls below a determined value or the maximum number of epochs is exceeded. Then this trained network can be used to predict the output parameters as a function of the input parameters which have not been presented before. Because the neural network does not require any detailed information about the system or process, it operates like a black box [12]. This type of learning is known as supervised learning.

A neural network is usually divided into three parts: the input layer, the hidden layer and the output layer. The information in the previous layers obtained by updating the weighting coefficients is supplied to the next layers through the intermediate hidden layers. This structure is known as multilayer perceptron (MLP). More hidden layers can be added to obtain a quite powerful multilayer network. The MLP architecture has been successfully employed as a universal function approximator in many modelling situations [10].

4. The prediction of the outlet air temperature and humidity

It is very important to have a precise knowledge of the parameters governing the process for the sake of a good performance of an experimental study. The parameters which govern the process of frost formation are primarily the temperature and humidity of the inlet air, air velocity and coil surface temperature. These parameters affect the heat and mass transfer processes in the cooling coil.
The experiments in this study were conducted under various operating conditions. The ranges for the input parameters are as follows:

Coolant temperature $-25$–$0$ °C
Air inlet temperature $25$–$45$ °C
Air humidity $20$–$50\%$
Air velocity $1.5$–$11$ m/s.

The measured variables were temperatures and humidity of the air entering and leaving the wind tunnel, coolant inlet and outlet temperatures, the temperature of the air entering the test section, the ambient temperature, the deposited frost mass, the velocity of the air inside the wind tunnel and the coolant mass flow rate.

In order to predict the outlet air temperature and humidity, a four-layer feed forward neural network with standard backpropagation algorithm was applied. The architecture of the neural network with the input and output parameters obtained by the experimental study is schematically illustrated in Fig. 2. The input data are presented to the neural network using backpropagation algorithm, the most popular algorithm in engineering applications.

By trial and error with different ANN configurations, the network was decided to consist of one input layer with 9 neurons, two hidden layers with 9 and 20 neurons, respectively, and one output layer with 2 neurons corresponding to the number of the output variables which are outlet air humidity, $\phi_{\text{air out}}$, and temperature, $T_{\text{air out}}$. The activation functions in the hidden layers were chosen as tangent sigmoid in this study. Since the output layer has linear neurons, activation function was a purely linear function for this layer. Because tangent sigmoid activation function in the hidden layer was chosen, all the input and output values were normalized by pre-processing so that they fall in the interval $[-1,1]$.

As show in Fig. 2, the inputs of the network are the inlet air temperature; $T_{\text{air in}}$, the inlet humidity ratio of air; $\phi_{\text{air in}}$, the inlet and outlet refrigerant coolant temperature, $T_{\text{cool-1}}$ and $T_{\text{cool-2}}$, the temperature of the inlet air for test section in the setup; $T_{\text{iats}}$, the ambient temperature; $T_{\text{amb}}$, the deposited frost mass; $m_{\text{frost}}$, the velocity of the air inside the wind tunnel; $V_{\text{air}}$, and the coolant mass flow rate; $m_{\text{coolant}}$.

![Fig. 2. The structure of the neural network.](image)
In order to develop the neural network presented, the available experimental data set is divided into training and validation groups. The data set was obtained from 761 test runs of the experimental setup. The ANN was trained using randomly selected 70% of the data set while the remaining 30% was utilized for testing of the network. The input vector consisting of nine parameters and its corresponding target vector with two variables from training set are used to train the network until it yields an approximate function between the input and output parameters. The weighting coefficients in the training procedure were adjusted using Levenberg–Marquardt algorithm. Then the trained network becomes ready to accept input vectors from the test data set to predict the target vector.

Table 1 shows some of the parameters obtained by the experiment and also predicted values of output variables by the network. Because of a lot of data points in the whole data set, only some of them were chosen as samples in the table. The experimental and predicted values of temperatures and humidity are presented in the last four columns of the table.

### Table 1
The experimental and predicted data obtained under various operating conditions

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5. Performance measurement

The performance of the neural network prediction was evaluated by a regression analysis between the predicted parameters, and the experimental values. Figs. 3 and 4 show the plots of predicted versus target values for the output variables, outlet air temperature and humidity, respectively. As shown in the figures, while the correlation coefficient ($r$) calculated for outlet air temperature is 0.999, the correlation coefficient ($r$) for outlet air humidity is found as 0.982. On the other hand, both two output parameters have the same absolute fraction of variance ($R^2$) with the value of 0.999. The figures demonstrate excellent agreement for outlet air temperature and quite satisfactory agreement for outlet air humidity between the predicted and target values.

Both the correlation coefficient ($r$) and absolute fraction of variance ($R^2$) show the consistency of the predicted parameters with the actual values. As the correlation coefficient approaches to 1, the accuracy of the prediction would be higher.
improves. In the presented case, the number for outlet air temperature is very close to 1, which indicates excellent agreement between the experimental (actual) and the neural network predicted results.

Figs. 3 and 4 also show another prediction performance measurement that is ±5% and ±10% error band based on error analysis, respectively. While all of the prediction errors for outlet air temperature are inside the ±5% error band, a few prediction errors are bigger than ±10% in some cases for humidity prediction. Further, the mean relative error (MRE) was calculated as 0.53% for outlet air temperature and 1.97% for outlet air humidity according to following expression:

\[
MRE(\%) = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{100(a_i - p_i)}{a_i} \right|, \tag{3}
\]

Finally, the root mean square error (RMSE) was also used to show the performance of the prediction. RMSE is a statistical measure of the magnitude of a varying quantity expressed by

\[
RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (a_i - p_i)^2} \tag{4}
\]

The ANN predictions have very low RMS error for both outlet air temperature and humidity which are 0.22 °C and 1.21%, respectively.

Fig. 3. Experimental (actual) vs. predicted values for outlet air temperature with correlation factor and Mean Relative Error (MRE). The straight line is the perfect prediction.

Fig. 4. Experimental (actual) vs. predicted values for outlet air humidity with correlation factor and Mean Relative Error (MRE). The straight line is the perfect prediction.
In order to visualize the prediction performance of the ANN developed in the present study, the effects of input parameters on the outputs were investigated. For this purpose, while one of the input parameters was allowed to change from its minimum to maximum values existing in the data set with equivalent intervals, the others were kept constant, and then they were introduced as the inputs to the trained neural network. For example, Fig. 5 indicates the changes in the predicted values of $T_{\text{air\_out}}$ with respect to the $T_{\text{air\_in}}$, which ranges between 20 and 50 °C, when other eight input parameters ($T_{\text{cool-1}}, T_{\text{cool-2}}, T_{\text{in}}, T_{\text{amb}}, m_{\text{frost}}, m_{\text{coolant}}, V_{\text{air}}$) were kept constant at the values shown in the figure. As expected, $T_{\text{air\_out}}$ increase with increasing $T_{\text{air\_in}}$. Similar to ANN results, $T_{\text{air\_in}}$ is always greater than $T_{\text{air\_out}}$ in the experimental results. For instance, one can read 35 °C and 31.6 °C for $T_{\text{air\_in}}$ and $T_{\text{air\_out}}$, respectively, in the figure. In other words, when the initial conditions are given, the ANN model can predict the output parameter without implementing any experiment.

Fig. 6 shows the changes in the predicted values of relative humidity of the output air, $\phi_{\text{air\_out}}$, with respect to that of input air, $\phi_{\text{air\_in}}$, when the rest of input parameters were kept constant at the values shown in the figure. The moist air that enters the experimental setup with a certain relative humidity are condensed when passing on the cold surface, and therefore, the air leaves the experimental setup with a lower relative humidity compared to the input air conditions. For example, $\phi_{\text{air\_out}}$ was predicted as 40% when $\phi_{\text{air\_in}}$ is 44%.

Fig. 7 demonstrates the changes the predicted values of both $T_{\text{air\_out}}$ and $\phi_{\text{air\_out}}$ with respect to air velocity when the other parameters were kept constant. It can be observed that $T_{\text{air\_out}}$ decreases slightly as the air velocity increases up to 6.5 m/s and starts to increase again after making a minimum point. Similarly, $\phi_{\text{air\_out}}$ increases initially, makes a peak when air velocity is 4 m/s, then slightly decrease; after it reaches its minimum value, it starts to increase with a high slope. These graphs show that increasing of air velocity can provide a good performance up to some point and after a
minimum value, the behavior of the output relative humidity can change. The authors observed the same changes in the experimental results.

Finally, Fig. 8 reports the changes in the predicted values of \( T_{\text{air out}} \) and \( \phi_{\text{air out}} \) with respect to mass flow rate of coolant \( (m_{\text{coolant}}) \) when the other input parameters are kept constant at the values shown in the figure. Both of the output parameters decreases first and starts to increase after the mass flow rate reaches the value of 13 l/min. Based on this result, one can conclude that it is not necessary to increase more the value of mass flow rate of coolant when the temperature and relative humidity of the output air have reached to their minimum value. Thus, the minimum value of the mass flow rate of coolant can be determined for the best values of \( T_{\text{air out}} \) and \( \phi_{\text{air out}} \).

6. Conclusions

An artificial neural network based on backpropagation algorithm has been developed to predict air temperature and humidity at the outlet of a cooling coil employed in air-conditioning systems. The presented prediction model demonstrated a very good statistical performance with correlation coefficients of 0.999 and 0.982 between the actual/experimental data and the network predicted values for the outlet air temperature and humidity, respectively. 

![Fig. 7. The ANN predictions for the outlet air temperature and humidity vs. the air velocity.](image7)

![Fig. 8. The ANN predictions for the outlet air temperature and humidity vs. the coolant mass flow rate.](image8)
addition, the mean relative errors were also calculated as 0.53% and 1.97% for the corresponding correlation coefficients. Then, the versatility of the ANN modelling was also demonstrated by presenting the effects of some input parameters on the outputs using the developed network.

This study reveals that the neural network-based prediction model can be used by the manufacturers with a high degree of accuracy and reliability for determining the outlet air temperature and humidity as a function of input process parameters, namely, humidity, temperature and velocity of the inlet air as well as inlet temperature and mass flow rate of the coolant. Furthermore, the neural network presented does not require understanding of the frost growth, which is actually a very complex phenomenon to be expressed by mathematical formulations. Consequently, manufacturers rely on the ANN technique for determining the performance of the cooling coil in air-conditioning systems under various operating conditions.

References