Use of artificial neural network in performance prediction of Solid desiccant powered Vapor compression air conditioning systems

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Abstract

In the present study, artificial neural network (ANN) model for a solid desiccant-vapor compression hybrid air-conditioning system is developed to predict the cooling capacity, power input and coefficient of performance (COP) of the system. This paper also describes the experimental test setup for collecting the required experimental test data. The experimental measurements are taken at steady state conditions while varying the input parameters like air stream flow rates and regeneration temperature. Most of the experimental test data (80%) are used for training the ANN model while remaining (20%) are used for the testing of ANN model. Experimental data were collected during cooling period of March to September. The outputs predicted from the ANN model have a high coefficient of correlation ($R>0.988$) in predicting the system performance. The results show that the ANN model can be applied successfully and can provide high accuracy and reliability for predicting the performance of the hybrid desiccant cooling systems.

Keywords: Artificial neural network; Coefficient of performance; Dehumidifier effectiveness; Moisture removal rate, TRNSYS

Introduction

Integration of the desiccant dehumidification system with traditional vapor compression refrigeration (VCR) air-conditioning system results in hybrid cooling system which efficiently meets both the sensible and latent cooling loads by handling them separately. VCR system operates at higher evaporator temperature, requires no post heating that resulting in higher performance of the system. The desiccant cooling systems are very good at providing comfort cooling by reducing the humidity ratio of air. Moreover, hybrid desiccant cooling systems limit the use of chlorofluorocarbons (CFCs) as the size of VCR cooling unit gets reduced by handling the latent heat load separately. Desiccant cooling systems also allow larger flow rates of ventilation air to improve indoor air quality by removing air borne pollutants. The desiccant cooling system can be cost effective, when used with renewable (solar) or waste heat for regeneration. It also
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This page contains a detailed discussion on the use of artificial neural networks (ANNs) for performance prediction in solid desiccant powered vapor compression air conditioning systems. The text explains the advantages of ANNs over classical approaches and their application in various engineering applications. It highlights the use of ANNs in modeling complex systems, where classical approaches are insufficient.

The system description includes a test room with dimensions 3m x 3m x 3m, where the cooling loads are taken as 1.371 kW and 0.391 kW, respectively. The sensible heat ratio (SHR) is 0.78. The flow rates of the process air and the regeneration air are 322.7 m³/hr and 196.8 m³/hr, respectively. The system includes a rotary desiccant dehumidifier, a cross-cooled dehumidifier, and a vapor compression system for cooling.

The text also discusses the use of ANNs in modeling the system, providing a more accurate and efficient approach compared to traditional methods. ANNs can predict the desired output of a system when enough experimental data is available.
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Figure 1: Schematic diagram of solid desiccant - VCR hybrid air-conditioning system.

Measurements

Experiments are carried out by simultaneous measurement of temperature, relative humidity, pressure drop and flow rate with the help of multifunctional temperature, humidity and velocity digital transmitters connected via Masibus- 85XX micro-controller-based scanner with control panel, to control and operate the system. All the sensors are connected to a central computer via data acquisition unit. The inaccuracies in measurement of temperature, relative humidity and flow rate are found + 0.3 K @ 296 K, + 2.0 %, + 3.0 % respectively. Energy meter is also used to measure the electrical power consumption of the system. The measurements were carried out once the temperature and humidity of the system attain steady state condition. Measured data can be recorded continuously over system running using Masibus data scanner. Experimental data were collected during cooling period of March to September. Humidistat is fitted inside the test room to control the dehumidifier operation according to the room humidity [38-40]. Temperature controller is also fitted inside the test room to control the compressor operation through relay, so as to maintain the room temperature constant.

Uncertainty Analysis

Accurate measurement of physical quantities is very difficult. Uncertainties in measuring any physical quantity are always present due to instrumental, physical and human inadequacies. Uncertainty analysis is the procedure employed to assess the uncertainty from measured variables with known values of uncertainties. An important parameter for the present experimental scheme is the system performance in term of its COP. It has a measurement error because of the least count or the accuracies defined for each measuring device. For the calculation of uncertainty, the root of the sum square is used in this study and can be expressed as

$$w_{w} = \left[ \left( \frac{\partial R}{\partial x_1} w_1 \right)^2 + \left( \frac{\partial R}{\partial x_2} w_2 \right)^2 + \ldots \ldots + \left( \frac{\partial R}{\partial x_n} w_n \right)^2 \right]^{\frac{1}{2}}$$

(1)
Where R is a given function of the independent variables \( x_1, x_2, \ldots, x_n \) and \( w_1, w_2, \ldots, w_n \) are the uncertainties in the corresponding variables. The uncertainties for the deducted quantities such as dehumidifier effectiveness and humidity ratio is calculated as 10.8% and 9.7%, respectively. The total uncertainty associated with the coefficient of performance is found to be +14.63%.

**Data Reduction**

The performance of solid desiccant – vapor compression hybrid air-conditioning system is evaluated by calculating the cooling capacity, power input and coefficient of performance (COP).

The COP of system based on electrical energy input is defined as the ratio of the cooling capacity to the total electrical energy input \( (E_t) \) to the system. It is given \([41-42]\) by

\[
\text{COP} = \frac{Q_{cc}}{E_t}
\]

where, \( Q_{cc} \) is the cooling capacity and it is defined \([43-44]\) as

\[
Q_{cc} = \dot{m}_{pa} (h_1 - h_4)
\]

where, \( \dot{m}_{pa} \) is the mass flow rate of process air at the dehumidifier inlet. While in eq. (1) \( E_t \) total represents total electrical power used to drive the system. Hence, \( E_t \) is calculated \([45-51]\) as

\[
E_t = E_c + E_f + E_o + E_h
\]

where, \( E_c \) and \( E_f \) represent the electrical power used to drive the VCR compressor and fans. Fans are employed to force circulate the regeneration air as well as process air streams and also for the conventional VCR unit. \( E_o \) shows electrical energy consumption of other equipment’s that are desiccant wheel motor and heat wheel motor. \( E_h \) is electrical power consumption for regeneration heater used in the dehumidifier. \( E_t \) is measured by using energy meter.

**Ann Model**

A neural network model consists of large number of processing elements called neurons. They are interconnected by communication links called weights. A simplified ANN model has an input layer, an output layer, and at least one hidden layer. The selection of layer is determined by the form of the network and the method of input data required. A simplified neural network model (figure. 2) consists of three basic elements; synapses or connecting link, summing node with a squashing function and an externally applied bias to increase or decrease the net input of the activation function.

![Figure 2: Structure of an Artificial Neural Network.](image-url)
The network performance is determined by the weights and biases value in every single neuron. The network needs to be trained to give the desired output using input data sets. The outputs from the ANN model are compared with the actual (experimental) output. There may be a difference between the network’s output and the target output. The weights are adjusted such that the error function minimizes the differences between actual experimental outputs and model outputs. This process is continued until the error function comes under the desired tolerance limit. This repetitive process of training and correction of the weights, is known as back propagation algorithm. While training the ANN model, the weights and bias which minimize the error between the measured output and the ANN network output are obtained as [52-54] follows

\[ Y = F(S) = F \left[ \sum_{k=1}^{N} X_k w_k + b \right] \] (5)

The working of an artificial neural network model is described as follows. The experimental results are the input parameters to the model. Neural network understands the underlying correlations in the entered input data and stores them as inter-neuron connection strengths or corrected weights. Number of neurons, number of iterations and the desired accuracy are gathered and the training sets and the target sets are developed. The network needs to be trained using training data set consisting of a group of input data and corresponding output data. Training involves the revision of synaptic weights. The network reads and processes each set of input data and produces an output, which is compared with the actual experimental output. Based on the difference between the network output and the target output, the model parameters are adjusted so that the network would exhibit the desired or targeted results. The network performance was largely determined by the weights and bias values in every single neuron. In the present ANN model, cooling capacity, power input and coefficient of performance (COP) are fixed as the output parameters, important in performance studies of the solid desiccant – vapor compression hybrid air-conditioning system.

Results and Discussion

The ANN model was trained using back propagation technique with TRAINLM, LEARNGDM, MSE and TANSIG as training, learning, performance and transfer functions respectively. Twelve parameters namely flow rates of process and regeneration air streams, temperature and relative humidity of ambient, process air dehumidifier inlet, supply room air, regeneration air before and after the heater were employed at the input layer while three parameters; cooling capacity, power input and coefficient of performance (COP) were employed at the output layer. The cooling capacity, power input and coefficient of performance (COP) are the important parameters in studying the performance of solid desiccant-vapor compression air-conditioning system. The range of the operating parameters used for generating the data during experimentation is shown in table 1.
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Figure 3: Illustrates the flowchart that describes the steps for to develop and simulate the artificial neural network model. The input parameters of the model is the experimental results. The neural network understands the underlying correlations in the entered input data and the same are stored as inter-neuron connection strengths or corrected weights. The number of neurons and the number of iterations as well as the desired error are gathered and then the training set and the target set are developed. The network needs to be trained to give the desired output using input data sets. The training data set is a group of input set and corresponding desired output set. During the training phase, the training data were put at the input layer. Training involves the revision of the synthetic weights. The training set should be self-sufficient to train the network. The network reads and processes each set of input data and produces an output. The outputs from the model have been compared with the actual experimental output. Before completion of the training, there would obviously be a difference between the network’s output and the target output. The model parameters could be adjusted further so that the network would exhibit the desired or targeted results. The network performance was largely determined by the weights and bias values in every single neuron. The ANN model can identify the outlet parameters in terms of MRR and effectiveness which are important in performance study for the rotary desiccant dehumidifier.

<table>
<thead>
<tr>
<th>Sr. No.</th>
<th>Operating parameter</th>
<th>Operating range</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Process air dehumidifier inlet temperature (°C)</td>
<td>24.1 - 28.5</td>
</tr>
<tr>
<td>2</td>
<td>Process air dehumidifier inlet relative humidity (%)</td>
<td>44.1 - 57.1</td>
</tr>
<tr>
<td>3</td>
<td>Room supply air temperature (°C)</td>
<td>7.5 - 11.2</td>
</tr>
<tr>
<td>4</td>
<td>Room supply air relative humidity (%)</td>
<td>76.2 - 94.6</td>
</tr>
<tr>
<td>5</td>
<td>Regeneration air heater inlet temperature (°C)</td>
<td>35.1 - 41.5</td>
</tr>
<tr>
<td>6</td>
<td>Regeneration air heater inlet relative humidity (%)</td>
<td>27.8 - 49.4</td>
</tr>
<tr>
<td>7</td>
<td>Regeneration air heater outlet temperature (°C)</td>
<td>98.6 - 141.0</td>
</tr>
<tr>
<td>8</td>
<td>Regeneration air heater outlet relative humidity (%)</td>
<td>1 - 3</td>
</tr>
<tr>
<td>9</td>
<td>Ambient air temperature (°C)</td>
<td>26.1 - 33.2</td>
</tr>
<tr>
<td>10</td>
<td>Ambient air relative humidity (%)</td>
<td>59.1 – 86.3</td>
</tr>
<tr>
<td>11</td>
<td>Process air flow rate (kg/hr)</td>
<td>325.12 - 474.14</td>
</tr>
<tr>
<td>12</td>
<td>Regeneration air flow rate (kg/hr)</td>
<td>165.67 - 204.40</td>
</tr>
</tbody>
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Figure 3: Flow chart of the developed simulation model.

The artificial neural network (ANN) model has been trained to estimate the model outputs like dehumidifier effectiveness, MRR and system performance in terms of COP. Figure 4 shows the performance graph of training process. The performance graph describes the plot of mean square error (MSE) against the number of epochs (a run through all training input-output sets) or iterations. As the number of iterations increases, mean squared error for training plot reduces. The neural network training process was terminated when the maximum number of epochs was reached or when the minimum MSE of the validating sets was attained. The experimental results were used to train the feed forward neural network. The best performance obtained by training in terms of the MSE with 12-12-3-3 network structure is 0.015708 at epoch 53 as shown in figure 5.
The training state of the system showing the gradient, mutation and validation check graphs for ANN are shown in figure 5. The magnitude of the gradient and the number of validation checks are used to terminate the training. The gradient becomes very small as the training reaches the minimum of the performance. If the magnitude of the gradient is less than 0.000001, the training will stop. This limit can be adjusted by setting the parameter. The number of validation checks represents the number of successive iterations that the validation performance fails to decrease. If this number reaches 53 (in present case), the training will stop. The plot (b) shows the learning rate (mutation) against increasing numbers of iterations. This plot shows that the network error reduces as training progresses.

The regression plot between the predicted values from ANN and the experimental results are shown in figure 6. It depicts the correlation between output and target data. This plot also shows up to what extent the network is learnt from the complex relationships of data. It is found that experimentally measured values show an excellent match with different outputs of the ANN model. Amongst the different trials, the correlation coefficient $R$ of training results approaches to 1.0 and the corresponding results have the least MSE when the numbers of nodes in hidden layer are 12. The results show that $R$ for training,
validation, test and for the combined set are 0.99934, 0.99822, 0.99829 and 0.99889 respectively. Thus, the predicted values are found in excellent agreement with the experimental values. The selected ANN model demonstrates a good statistical performance with the standard correlation coefficient in the range of 0.998-0.999, and the mean square error (MSE) for the training and predictions are found to be very low compared to the experimental results.

**Figure 6:** The regression plot between ANN predictions and the experimental results for (a) Training, (b) Validation, (c) Test, and (d) Combined set.

The effect of ambient air temperature and humidity ratio on the performance of dehumidifier has been observed. Figure 7 and 8 illustrate the influence of ambient air temperature on dehumidifier effectiveness and moisture removal rate (MRR) respectively. Both effectiveness as well as moisture removal rate tends to decrease as ambient temperature increases. This is because as the ambient air temperature increases, the inlet temperature of process air also increases which in turn decreases the partial vapor pressure of process air at inlet. Due to this, the vapor pressure difference between the air and the desiccant along the channel gets reduced. Since the moisture attraction by the desiccant material from process air is based on the difference in vapor pressure between desiccant material surface in channel and moist air flowing through it, the moisture removal rate and ultimately the effectiveness of the dehumidifier get reduced. Since the adsorption process inside dehumidifier is exothermic hence it is favored by low temperatures of process moist air. Results also show good agreement between outputs predicted by the ANN model and that by experiments for the dehumidifier effectiveness and moisture removal rate of dehumidifier. We got better agreement by using TRNSYS simulated dehumidifier process air outlet humidity ratio of ANN model instead of using directly predicted ANN results for dehumidifier effectiveness and MRR due to due inaccuracies involved in the ANN model because of selection of hidden layer, learning rate, momentum etc.
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Figure 7: Influence of ambient air temperature on dehumidifier effectiveness.

Figure 8: Influence of ambient air temperature on moisture removal rate.

Comparisons between the results predicted by artificial neural network model and the experimental findings for validation purpose are shown in Table 2 for the coefficient of performance (COP), respectively. It can be seen that the maximum difference between the results predicted by the ANN model and that by the experimental measurements for the COP are 13.40% respectively, which can be considered as reasonably accurate. Further, it is worth mentioning that the accuracy of artificial neural network model greatly relies on network structure, amount of training and testing data, and selection of learning as well as performance function.
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Table 2: Comparison of ANN testing results with the experimental data for the coefficient of performance.

<table>
<thead>
<tr>
<th>ANN</th>
<th>Experimental</th>
<th>(%差异)</th>
</tr>
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<tbody>
<tr>
<td>1.65</td>
<td>1.43</td>
<td>13.40</td>
</tr>
<tr>
<td>1.61</td>
<td>1.65</td>
<td>-1.85</td>
</tr>
<tr>
<td>1.22</td>
<td>1.24</td>
<td>-1.10</td>
</tr>
<tr>
<td>1.21</td>
<td>1.20</td>
<td>0.29</td>
</tr>
<tr>
<td>1.34</td>
<td>1.35</td>
<td>-2.52</td>
</tr>
<tr>
<td>1.89</td>
<td>2.05</td>
<td>-8.65</td>
</tr>
<tr>
<td>0.99</td>
<td>0.99</td>
<td>1.97</td>
</tr>
<tr>
<td>1.11</td>
<td>1.07</td>
<td>4.08</td>
</tr>
<tr>
<td>0.73</td>
<td>0.77</td>
<td>-5.37</td>
</tr>
<tr>
<td>0.91</td>
<td>0.94</td>
<td>-2.86</td>
</tr>
</tbody>
</table>

Conclusion

An artificial neural network (ANN) model 12-12-3-3 (neurons in input-hidden-output layers) has been developed to predict the performance of a solid desiccant – vapor compression hybrid air-conditioning system. Cooling capacity, power input and coefficient of performance (COP) are considered as output performance parameters. Experimental runs have also been performed and the results are compared with the ANN predictions. The ANN model demonstrates a good statistical performance through correlation coefficient (R) and mean square error (MSE) assessing the performance. Based on experimental and ANN results, following conclusions were drawn:

• The maximum percentage difference between the ANN predictions and the experimental values for coefficient of performance (COP) were found to be 13.40% respectively.
• The results indicate that the accuracy of the ANN model is satisfactory and coincide with the experimental data.
• The ANN model can be efficiently used to predict the performance of hybrid desiccant cooling system in terms of coefficient of performance (COP).
• The accuracy of prediction greatly depends on the type of model containing a particular combination of layers and nodes as well as on the database for training. The accuracy can further be improved by expanding the experimental database for network training.

The accuracy of artificial neural network (ANN) model greatly relies on the network structure, amount of training and testing data, the training and testing characteristics and on the selection of learning as well as performance function. Moreover, the variations in the dimensionality of the data set and the network architecture, specifically the number of hidden units and layers have a significant effect on accuracy of ANN model. The accuracy of the model for better prediction can further be improved by expanding the experimental database for training i.e. the size of the training data set, discriminating variables and by using the proper nature of the training and testing sets as well as network parameters. It can also be done by using swarm intelligent techniques to update the weights, noise reduction in the target data, stable data by use of cross validation techniques etc. The artificial neural network architecture is found to have slightly higher accuracies by using the larger and more complex networks.
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Nomenclatures

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
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<tbody>
<tr>
<td>a</td>
<td>actual output (experimental output)</td>
</tr>
<tr>
<td>b</td>
<td>bias</td>
</tr>
<tr>
<td>E</td>
<td>energy consumption (kW)</td>
</tr>
<tr>
<td>h</td>
<td>enthalpy (kJ/kg)</td>
</tr>
<tr>
<td>m</td>
<td>mass flow rate (kg/hr)</td>
</tr>
<tr>
<td>p</td>
<td>predicted output (network output)</td>
</tr>
<tr>
<td>R</td>
<td>correlation coefficient</td>
</tr>
<tr>
<td>RH</td>
<td>Relative humidity (%)</td>
</tr>
<tr>
<td>T</td>
<td>temperature (°C)</td>
</tr>
<tr>
<td>w</td>
<td>synaptic weights</td>
</tr>
<tr>
<td>X</td>
<td>input signal</td>
</tr>
<tr>
<td>Y</td>
<td>output</td>
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Subscripts

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<th>Description</th>
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<tbody>
<tr>
<td>i</td>
<td>inlet</td>
</tr>
<tr>
<td>pa</td>
<td>process air</td>
</tr>
<tr>
<td>ra</td>
<td>regeneration air</td>
</tr>
<tr>
<td>reg</td>
<td>regeneration</td>
</tr>
<tr>
<td>1, 2, etc.</td>
<td>reference state points</td>
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</table>

References

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