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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 set up 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

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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 avoids microbial growth in ducting by the use of dry cooling coils. Desiccant cooling are used in several applications such as pharmaceutical plants, supermarkets, theatres, hotels, office buildings, hospitals, health clubs and swimming pools. Different configurations of desiccant cooling system have been proposed by many investigators so far to attain higher system performance. The earliest form of desiccant cooling cycle was proposed by coupling dehumidifier with heat source and evaporative cooler [1]. Similar cycle was proposed by Dunkle [2] using dehumidifier of molecular sieve with additional heat exchanger to achieve the better performance than the earlier one. Later on, Munter [3] further enhanced the performance of the desiccant cooling cycle by introducing parallel passages in dehumidifier and provided backup of vapor compression system to tackle the cooling load. Since then, number of efforts has been made for the performance evaluation of rotary desiccant dehumidifiers used in the desiccant cooling systems. Important among those were the analogy theory by Banks [4], the pseudo-steady state model by Barlow [5], combined potential technique by Jurinak [6], finite difference method for cross-cooled dehumidifiers [7] and finite difference method by Maclaine-Cross [8] which are now widely used by other researchers in getting better performance of desiccant cooling cycles [9]. Burns et al. [10] evaluated the performance of hybrid desiccant cooling cycle used for supermarket and shows better performance than conventional VCR system [11-17]. From literature review [18-27], one can observe that some researchers developed mathematical models for evaluating the performance of desiccant cooling system while others conducted expensive experimental studies. The mathematical approach requires a large number of parameters defining the system, which may not be readily available and their predictions may not be sufficiently accurate in many cases [28-34]. As an alternative, use of artificial neural networks (ANNs) requires less effort, time and cost to model the system. This new modelling technique is used in many engineering applications, where classical approaches are too complex to be used. So, ANNs allow modelling of physical phenomena in complex systems without requiring explicit mathematical representations or without requiring exhaustive experiments. ANNs can predict the desired output of a system when enough experimental is data available.

System Description

A test room having dimensions 3m × 3m × 3m, has been selected for the study. The sensible and the latent cooling loads are taken as 1.371 kW and 0.391 kW, respectively. Sensible heat ratio (SHR) has been obtained as 0.78. Flow rates of the process air stream and the regeneration air stream are measured as 322.7 m^3/hr and 196.8 m^3/hr respectively. The comfort conditions are taken as 50% relative humidity and 26°C dry bulb temperature. The schematic diagram and the photographic view of solid desiccant and vapor compression hybrid air-conditioning system have been shown in figure 1. The return room air at state 1 passes through the rotary desiccant dehumidifier. Its moisture is adsorbed significantly by the desiccant material and the heat of adsorption raises its temperature up to state 2. The hot and dry air is first sensibly cooled in an air-to-air heat exchanger (2-3) and then in cooling coil of VCR system up to state 4. In the regeneration airline, ambient air at state 6 enters the air-to-air sensible heat exchanger and cools the supply process air. Consequently, its temperature rises when exiting from sensible heat exchanger at state 7. At this point, it is heated to reach temperature at the state point 8 which is high enough to regenerate the desiccant material. Moist air at the outlet of dehumidifier is exhausted to atmosphere at state 9. The rotary desiccant dehumidifier used is 360 mm diameter and 100 mm width. Rotational speed of the dehumidifier is kept constant as 20 rph. Synthesized metal silicate is the desiccant material used in desiccant wheel [35-37].

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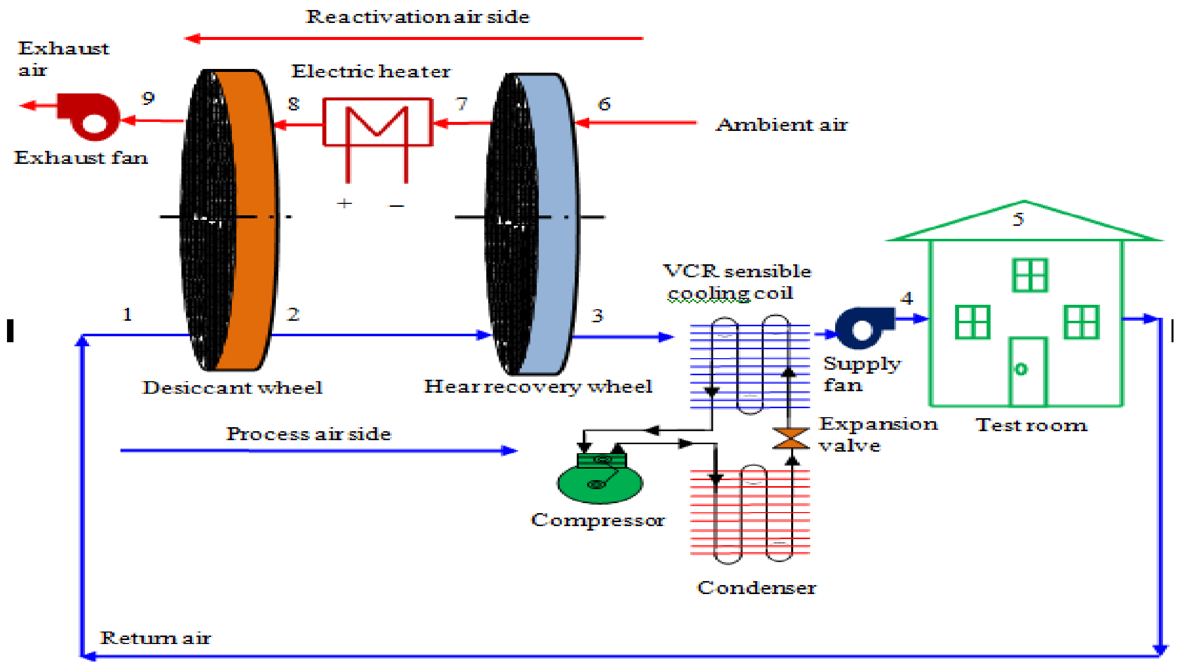

Figure 1: Schematic diagram of solid desiccant - VCR hybrid air-conditioning system.

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

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

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Where R is a given function of the independent variables x1,x2 ....,xn and w1,w2,....,wn 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

$$COP = \frac{Q_{CC}}{E_t} \quad (2)$$

where, Qcc is the cooling capacity and it is defined [43-44] as

$$Q_{cc} = \dot{m}_{pa}\,(h_1 - h_4) \quad (3)$$

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

$$E_t = E_c + E_f + E_o + E_h \quad (4)$$

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.

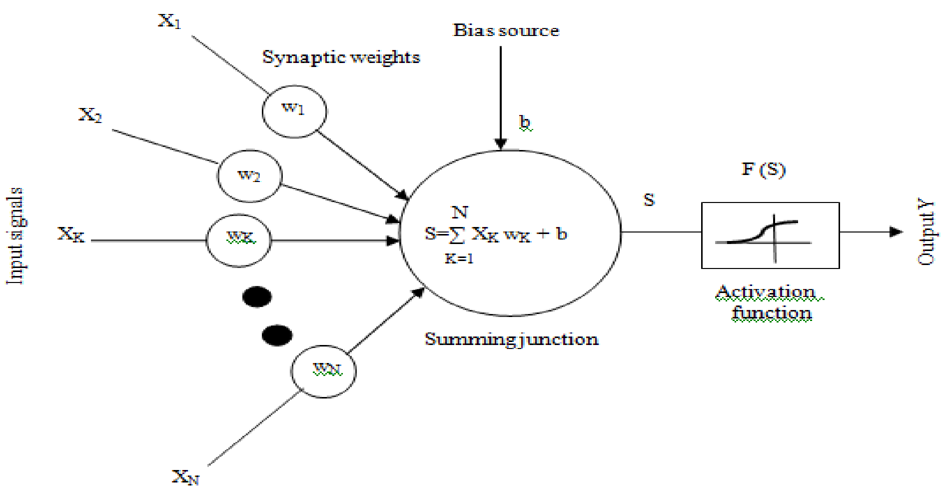

Figure 2: Structure of an Artificial Neural Network.

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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

$$Y = F(S) = F\left[\sum_{K=1}^{N} X_K\, w_K + b\right] \qquad (5)$$

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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Sr. No.	Operating parameter	Operating range
1	Process air dehumidifier inlet temperature (°C)	24.1 - 28.5
2	Process air dehumidifier inlet relative humidity (%)	44.1 - 57.1
3	Room supply air temperature (°C)	7.5 - 11.2
4	Room supply air relative humidity (%)	76.2 - 94.6
5	Regeneration air heater inlet temperature (°C)	35.1 - 41.5
6	Regeneration air heater inlet relative humidity (%)	27.8 - 49.4
7	Regeneration air heater outlet temperature (°C)	98.6 - 141.0
8	Regeneration air heater outlet relative humidity (%)	1 - 3
9	Ambient air temperature (°C)	26.1 - 33.2
10	Ambient air relative humidity (%)	59.1 – 86.3
11	Process air flow rate (kg/hr)	325.12 - 474.14
12	Regeneration air flow rate (kg/hr)	165.67 - 204.40

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.

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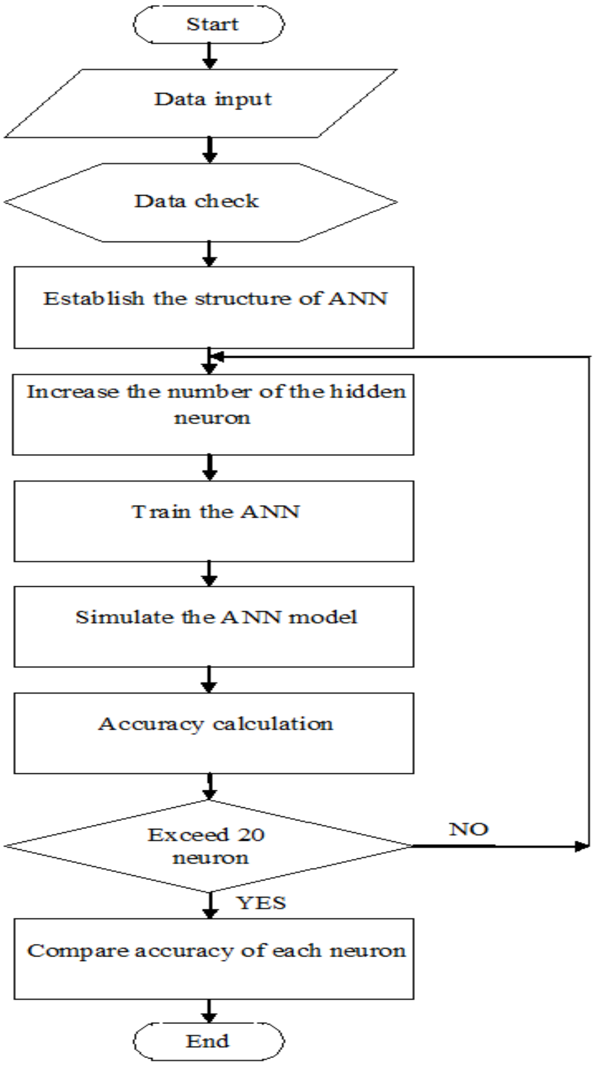

Figure 3: Flow chart of the developed simulation model.

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.

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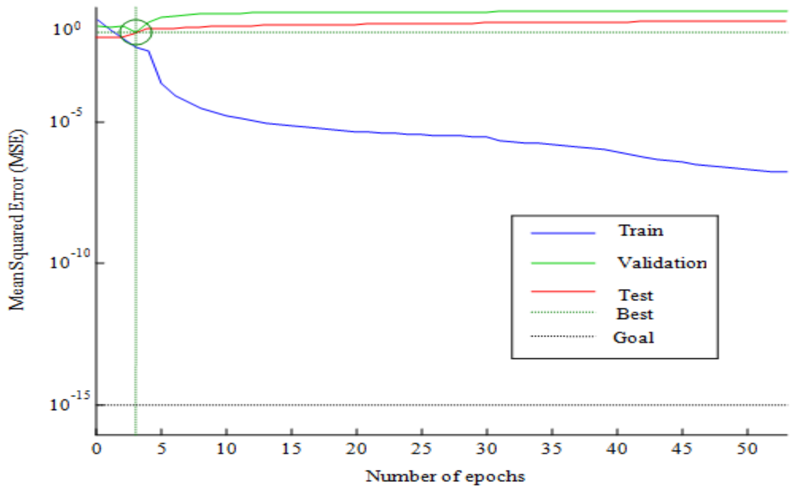

Figure 4: Performance plot.

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.

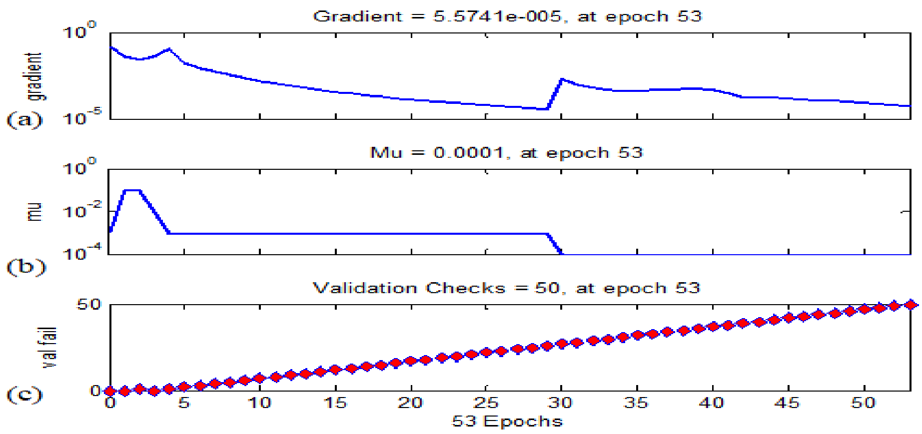

Figure 5: Training state plots for (a) gradient (b) mutation (c) validation checks.

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.

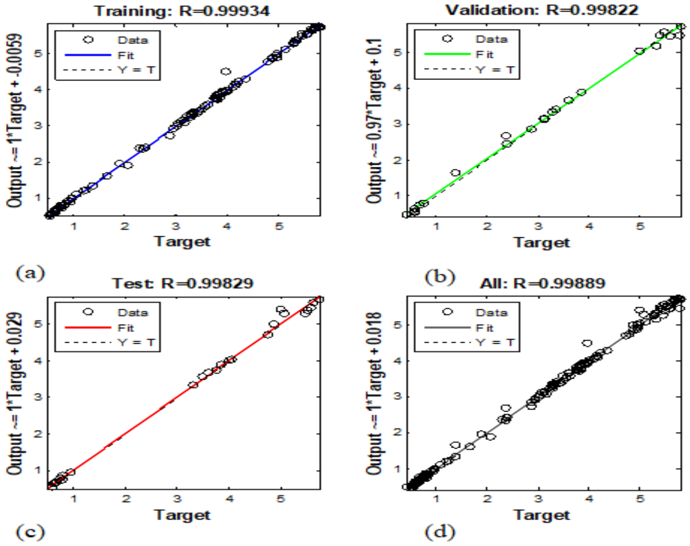

Figure 6: The regression plot between ANN predictions and the experimental results for (a) Training, (b) Validation, (c) Test, and (d) Combined set.

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.

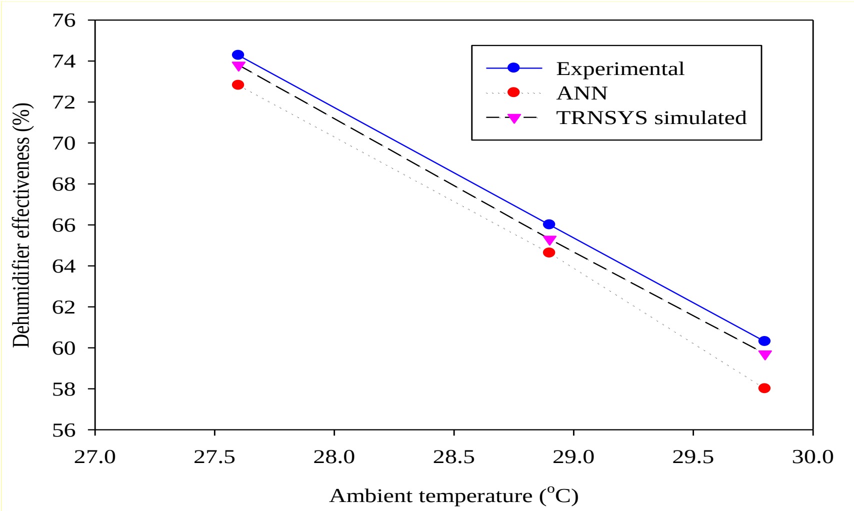

Figure 7: Influence of ambient air temperature on dehumidifier effectiveness.

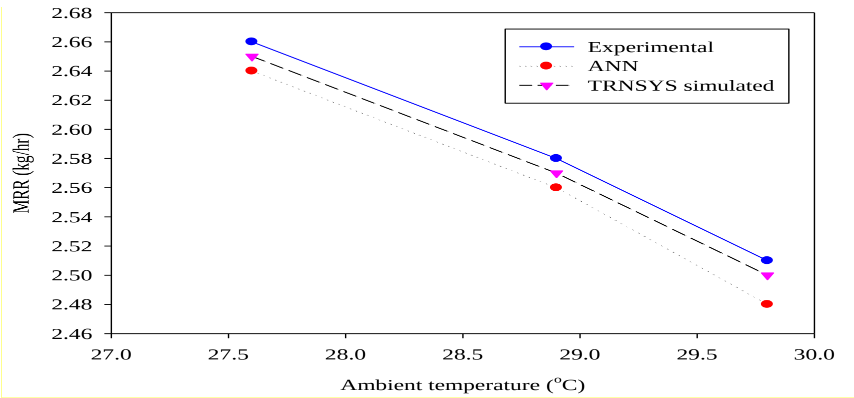

Figure 8: Influence of ambient air temperature on moisture removal rate.

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.

ANN	Experimental	(%) Difference
1.65	1.43	13.40
1.61	1.65	-1.85
1.22	1.24	-1.10
1.21	1.20	0.29
1.34	1.38	-2.52
1.89	2.06	-8.68
0.98	0.96	1.97
1.11	1.07	4.08
0.73	0.77	-5.37
0.91	0.94	-2.86

Table 2: Comparison of ANN testing results with the experimental data for the coefficient of performance.

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

a	actual output (experimental output)
b	bias
E	energy consumption (kW)
h	enthalpy (kJ/kg)
$\dot{m}$	mass flow rate (kg/hr)
p	predicted output (network output)
R	correlation coefficient
RH	Relative humidity (%)
T	temperature (°C)
w	synaptic weights
X	input signal
Y	output

Subscripts

i	inlet
pa	process air
ra	regeneration air
reg	regeneration
1,2, etc.	reference state points

References

1. Pennington NA. 1955. Humidity changer for air conditioning. USA Patent No. 2: 700.
2. Dunkle RV. 1965. A method of solar air conditioning. Mech Chem Eng Trans Inst Eng. 73: 73-78.
3. Munters CG. 1968. Inorganic, fibrous, gas-conditioning packing for heat and moisture transfer. U. S. Patent 3: 377.
4. Banks PJ. 1972. Coupled equilibrium heat and single adsorbate transfer in fluid flow through porous media - I, characteristic potentials and specific capacity ratios. Chem Eng Sci. 27: 1143-1155.
5. Barlow R. 1982. Analysis of the adsorption process and desiccant cooling systems: a pseudo-steady-state model for coupled heat and mass transfer. Technical Report No. SERI/TR-631-1330, Solar Energy Research Institute, Golden.
6. Jurinak JJ. 1982. Open cycle solid desiccant cooling-component models and system simulation. PhD Thesis, University of Wisconsin, Madison.
7. Worek WM, Lavan Z. 1982. Performance of a cross-cooled desiccant dehumidifier prototype. J Solar Energy Eng. 104: 187-196.
8. Maclaine-Cross IL. 1988. Proposal for a desiccant air conditioning system. ASHRAE Trans. 94: 1997-1909.
9. Davanagere BS, Sherif SA, Goswami DY. 1999. A feasibility study of solar desiccant air conditioning system- Part I: Psychrometrics and analysis of the conditioned zone. Int J of Energy Res. 23: 7-21.
10. Burns PR, Mitchell RB, Bechman WA. 1985. Hybrid desiccant cooling systems in supermarket applications. ASHRAE Trans. 91: 457-468.
11. Jani DB, Mishra M, Sahoo PK. 2016. Solid desiccant air conditioning–A state of the art review. Renewable and Sustainable Energy Reviews. 60: 1451-1469.
12. Buker MS, Riffat SB. 2015. Recent developments in solar assisted liquid desiccant evaporative cooling technology-A review. Energy and Buildings. 96: 95-108.
13. La D, Dai YJ, Li Y, et al. 2010. Technical development of rotary desiccant dehumidification and air conditioning: A review. Renewable and Sustainable Energy Reviews. 14: 130-147.
14. Norazam AS, Kamar HM, Kamsah N, et al. 2019. Simulation of adsorption process in a rotary solid desiccant wheel. InAIP Conference Proceedings. 25: 2062.
15. Rafique MM, Gandhidasan P, Bahaidarah HM. 2016. Liquid desiccant materials and dehumidifiers-A review. Renewable and Sustainable Energy Reviews. 56: 179-195.
16. Sultan M, El-Sharkawy II, Miyazaki T, et al. 2015. An overview of solid desiccant dehumidification and air conditioning systems.

DOI: https://doi.org/10.36811/ijme.2021.110005 IJME: March-2021: Page No: 05-19

Renewable and Sustainable Energy Reviews. 46: 16-29.

17. Kalogirou SA. 2000. Applications of artificial neural-networks for energy systems. Applied energy. 67: 17-35.
18. Jani DB, Mishra M, Sahoo PK. 2017. Application of artificial neural network for predicting performance of solid desiccant cooling systems-A review. Renewable and Sustainable Energy Reviews. 80: 352-366.
19. Kalogirou SA. 2001. Artificial neural networks in renewable energy systems applications: a review. Renewable and sustainable energy reviews. 5: 373-401.
20. Diaz G, Sen M, Yang KT, et al. 1999. Simulation of heat exchanger performance by artificial neural networks. Hvac&R Research. 5: 195-208.
21. Heimel M, Lang W, Almbauer R. 2014. Performance predictions using Artificial Neural Network for isobutane flow in non-adiabatic capillary tubes. International journal of refrigeration. 38: 281-289.
22. Kumlutaş D, Karadeniz ZH, Avcı H, et al. 2012. Investigation of design parameters of a domestic refrigerator by artificial neural networks and numerical simulations. International journal of refrigeration. 35: 1678-1689.
23. Jani DB, Mishra M, Sahoo PK. 2015. Performance studies of hybrid solid desiccant–vapor compression air-conditioning system for hot and humid climates. Energy and Buildings. 102: 284-292.
24. Akbari S, Simonson CJ, Besant RW. 2012. Application of neural networks to predict the transient performance of a run-around membrane energy exchanger for yearly non-stop operation. International journal of heat and mass transfer. 55: 5403-5416.
25. Jani DB, Mishra M, Sahoo PK. 2016. Performance analysis of hybrid solid desiccant–vapor compression air conditioning system in hot and humid weather of India. Building Services Engineering Research and Technology. 37: 523-538.
26. Simonson CJ, Besant RW, Schoenau GJ, et al. Application of neural networks to predict the performance of a run-around membrane energy exchanger (RAMEE) (Doctoral dissertation, University of Saskatchewan).
27. Jani DB, Mishra M, Sahoo PK. 2016. Experimental investigation on solid desiccant–vapor compression hybrid air-conditioning system in hot and humid weather. Applied Thermal Engineering. 104: 556-564.
28. Tan CK, Ward J, Wilcox SJ, et al. 2009. Artificial neural network modelling of the thermal performance of a compact heat exchanger. Applied Thermal Engineering. 29: 3609-3617.
29. Jani DB, Mishra M, Sahoo PK. 2016. Performance prediction of rotary solid desiccant dehumidifier in hybrid air-conditioning system using artificial neural network. Applied Thermal Engineering. 98: 1091-1103.
30. Ermis K. 2008. ANN modeling of compact heat exchangers. International Journal of Energy Research. 2008 May. 32: 581-594.
31. Jani DB, Mishra M, Sahoo PK. 2018. A critical review on application of solar energy as renewable regeneration heat source in solid desiccant–vapor compression hybrid cooling system. Journal of Building Engineering. 18: 107-124.
32. Peng H, Ling X. 2008. Optimal design approach for the plate-fin heat exchangers using neural networks cooperated with genetic algorithms. Applied Thermal Engineering. 28: 642-650.
33. Jani DB, Mishra M, Sahoo PK. 2018. Performance analysis of a solid desiccant assisted hybrid space cooling system using TRNSYS. Journal of Building Engineering. 19: 26-35.

34. Peng H, Ling X. 2009. Neural networks analysis of thermal characteristics on plate-fin heat exchangers with limited experimental data. Applied Thermal Engineering. 29: 2251-2256.
35. Jani DB, Mishra M, Sahoo PK. 2017. A critical review on solid desiccant-based hybrid cooling systems. International Journal of Air-conditioning and Refrigeration. 25: 1730002.
36. Pacheco-Vega A, Dı´ az G, Sen M, et al. 2001. Heat rate predictions in humid air-water heat exchangers using correlations and neural networks. J. Heat Transfer. 123: 348-354.
37. Jani DB, Mishra M, Sahoo PK. 2018. Investigations on effect of operational conditions on performance of solid desiccant based hybrid cooling system in hot and humid climate. Thermal Science and Engineering Progress. 7: 76-86.
38. Pacheco-Vega A, Sen M, Yang KT, et al. 2001. Neural network analysis of fin-tube refrigerating heat exchanger with limited experimental data. International Journal of Heat and Mass Transfer. 44: 763-770.
39. Jani DB, Mishra M, Sahoo PK. 2016. Exergy analysis of solid desiccant-vapour compression hybrid air conditioning system. International Journal of Exergy. 20: 517-535.
40. Ding GL, Zhang CL, Zhan T. 2004. An approximate integral model with an artificial neural network for heat exchangers. Heat Transfer-Asian Research: Co-sponsored by the Society of Chemical Engineers of Japan and the Heat Transfer Division of ASME. 33: 153-160.
41. Dadi MJ, Jani DB. 2019. Solar Energy as a Regeneration Heat Source in Hybrid Solid Desiccant–Vapor Compression Cooling System–A Review. Journal of Emerging Technologies and Innovative Research. 6: 421-425.
42. Wu ZG, Zhang JZ, Tao YB, et al. 2008. Application of artificial neural network method for performance prediction of a gas cooler in a CO2 heat pump. International journal of heat and mass transfer. 51: 5459-5464.
43. Vyas V, Jani DB. 2016. An overview on application of solar thermal power generation. International Journal of Engineering Research and Allied Sciences. 1: 1-5.
44. Xie GN, Wang QW, Zeng M, et al. 2007. Heat transfer analysis for shell-and-tube heat exchangers with experimental data by artificial neural networks approach. Applied Thermal Engineering. 27: 1096-1104.
45. Jani DB, Bhabhor K, Dadi M, et al. 2019. A review on use of TRNSYS as simulation tool in performance prediction of desiccant cooling cycle. Journal of Thermal Analysis and Calorimetry. 8: 1-21.
46. Mandavgane SA, Pandharipande SL. 2006. Application of optimum ANN architecture for heat exchanger modeling.Indian J. Chem. Technol. 13: 634-639.
47. Jani DB. 2019. Advances in liquid desiccant integrated dehumidification and cooling systems. American Journal of Environment and Sustainable Development. 4: 6-11.
48. Facao J, Varga S, Oliveira AC. 2004. Evaluation of the use of artificial neural networks for the simulation of hybrid solar collectors. International journal of green energy. 1: 337-352.
49. Bhabhor KK, Jani DB. 2019. Progressive development in solid desiccant cooling: A review. International Journal of Ambient Energy. 24:1-24.
50. Yigit KS, Ertunc HM. 2006. Prediction of the air temperature and humidity at the outlet of a cooling coil using neural networks. International communications in heat and mass transfer. 33: 898-907.
51. Tyagi SK, Pandey AK, Pant PC, et al. 2012. Formation, potential and abatement of plume from wet cooling towers: A review. Renewable and Sustainable Energy Reviews. 16: 3409-3429.

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52. Gao M, Shi YT, Wang NN, et al. 2013. Artificial neural network model research on effects of cross-wind to performance parameters of wet cooling tower based on level Froude number. Applied thermal engineering. 51: 1226-1234.
53. Bisoniya TS, Kumar A, Baredar P. 2013. Experimental and analytical studies of earth–air heat exchanger (EAHE) systems in India: a review. Renewable and Sustainable Energy Reviews. 19: 238-246.
54. Sultan M, Miyazaki T, Koyama S, et al. 2018. Performance evaluation of hydrophilic organic polymer sorbents for desiccant air-conditioning applications. Adsorption Science & Technology. 36: 311-326.