Performance Analysis of Hybrid Cooling Systems Using Artificial Neural Network

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Abstract: In the present study, an 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%) were used for training the ANN model while the remaining (20%) were used for the testing of the ANN model. Experimental data were collected during the 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.

1. INTRODUCTION

Integration of the desiccant dehumidification system with traditional vapor compression refrigeration (VCR) air-conditioning system results in a hybrid cooling system that efficiently meets both the sensible and latent cooling loads by handling them separately. VCR system operates at higher evaporator temperature and requires no post-heating resulting in higher performance of the system. The desiccant cooling systems are very good at providing comfortable cooling by reducing the humidity ratio of air. Moreover, hybrid desiccant cooling systems limit the use of chlorofluorocarbons (CFCs) as the size of the 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 airborne pollutants. The desiccant cooling system can be cost-effective when used with renewable (solar) or waste heat for regeneration. It also avoids microbial growth inducted by the use of dry cooling coils. Desiccant cooling is 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 has been proposed by many investigators so far to attain a higher system performance. The earliest form of desiccant cooling cycle was proposed by coupling dehumidifier with heat source and evaporative cooler [1]. A similar cycle was proposed by Dunkle [2] using a dehumidifier of molecular sieve with an 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 the dehumidifier and provided backup of the vapour compression system to tackle the cooling load. Since then, a number of efforts have 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], the 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 the hybrid desiccant cooling cycle used for supermarkets and shows better performance than the conventional VCR system [11-17].

From the literature review [18-27], one can observe that some researchers developed mathematical models for evaluating the performance of desiccant cooling systems 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, the 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

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are too complex to be used. So, ANNs allow the 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.

2. 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 Fig. **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 the cooling coil of the 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 the 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.

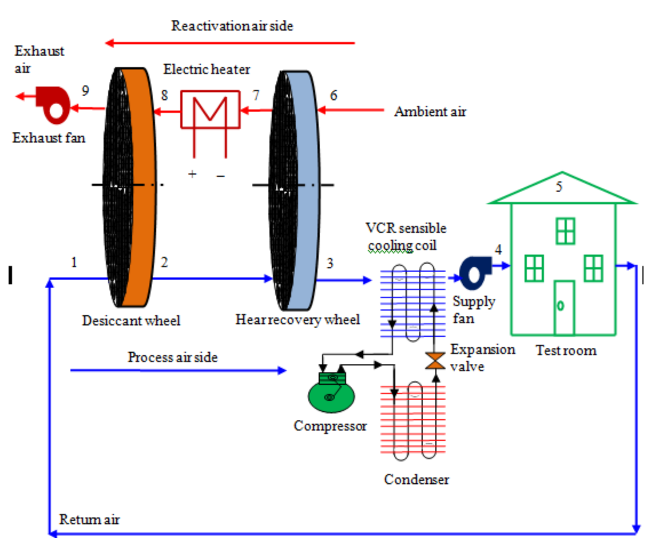

Figure 1: Schematic diagram of solid desiccant – VCR hybrid air-conditioning system.

The rotary desiccant dehumidifier used is 360 mm diameter and 100 mm width. The rotational speed of the dehumidifier is kept constant at 20 rph. Synthesized metal silicate is the desiccant material used in the desiccant wheel [35-37].

3. 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 a 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. An 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 the system running using Masibus data scanner. Experimental data were collected during the 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.

4. 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 terms 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

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

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 are calculated as 10.8% and 9.7%, respectively. The total uncertainty associated with the coefficient of performance is found to be + 14.63%.

5. DATA REDUCTION

The performance of a 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 the 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

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

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 the electrical energy consumption of other equipments that are the desiccant wheel motor and heat wheel motor. E_h is electrical power consumption for the regeneration heater used in the dehumidifier. E_t is measured by using an energy meter.

6. ANN MODEL

A neural network model consists of a 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 layers is determined by the form of the network and the method of input data required. A simplified neural network model (Fig. **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.

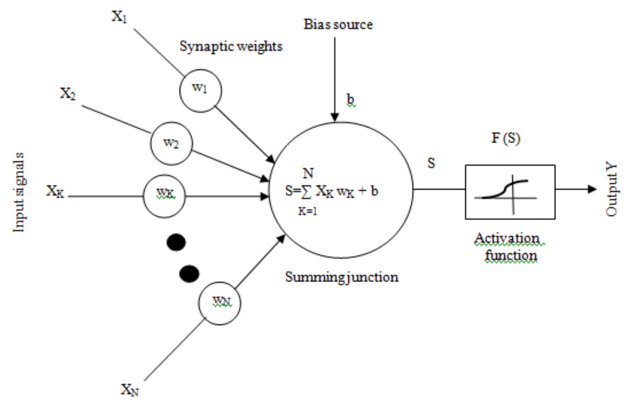

Figure 2: Structure of an Artificial Neural Network.

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

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

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. The 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, which are important in performing studies of the solid desiccant – vapor compression hybrid air-conditioning system.

7. 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 was 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**.

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. Fig. (**3**) shows the performance graph of the 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, the mean squared error for the 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 Fig. (**4**).

Table 1: Operating Parameters Used for Generating the Data

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)	32.12 – 474.14
12	Regeneration air flow rate (kg/hr)	165.67 – 204.40

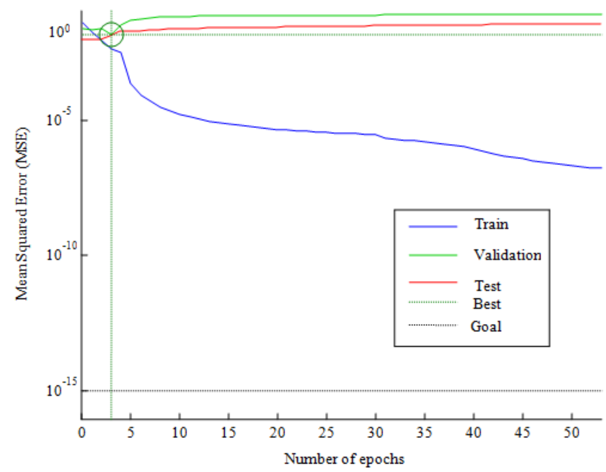

Figure 3: Performance plot.

The training state of the system showing the gradient, mutation and validation check graphs for ANN are shown in Fig. (**4**). 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 the present case), the training will stop. Plot (b) shows the learning rate (mutation) against increasing numbers of iterations. This plot shows that the network error reduces as training progresses.

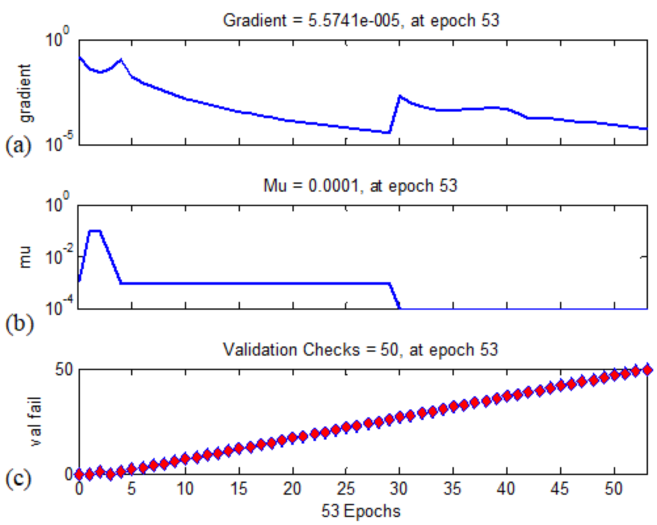

Figure 4: Training state plots for (a) gradient (b) mutation (c) validation checks.

The regression plot between the predicted values from ANN and the experimental results is shown in Fig. (**5**). It depicts the correlation between output and target data. This plot also shows up to what extent the network is learned 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.

The effect of ambient air temperature and humidity ratio on the performance of the dehumidifier has been

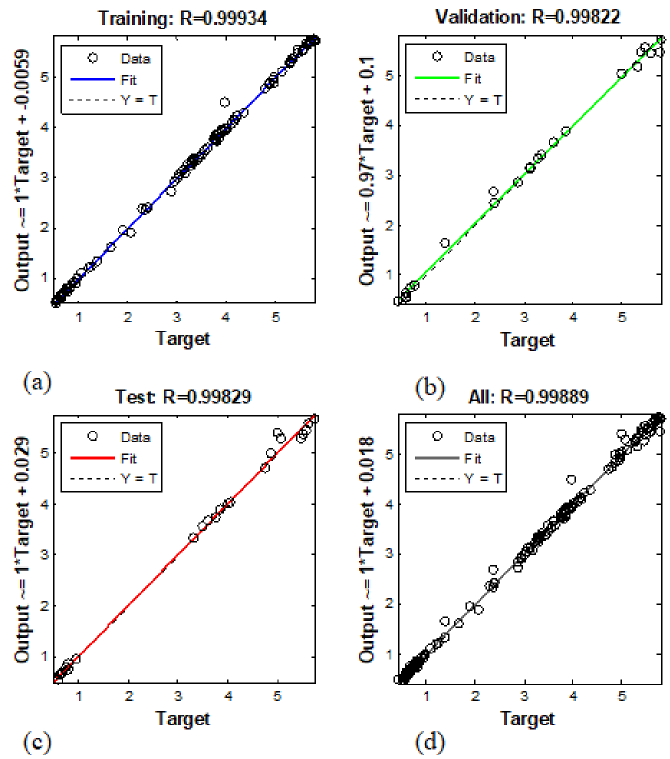

Figure 5: The regression plot between ANN predictions and the experimental results for (a) Training, (b) Validation, (c) Test, and (d) Combined set.

observed. Figs. (**6** and **7**) 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 the 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 the desiccant material surface in the 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 the dehumidifier is exothermic hence it is favoured 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 the inaccuracies involved in the ANN model because of selection of hidden layer, learning rate, momentum, etc.

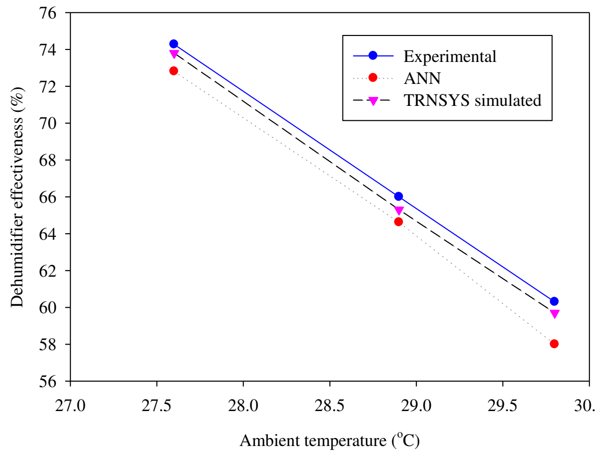

Figure 6: Influence of ambient air temperature on dehumidifier effectiveness.

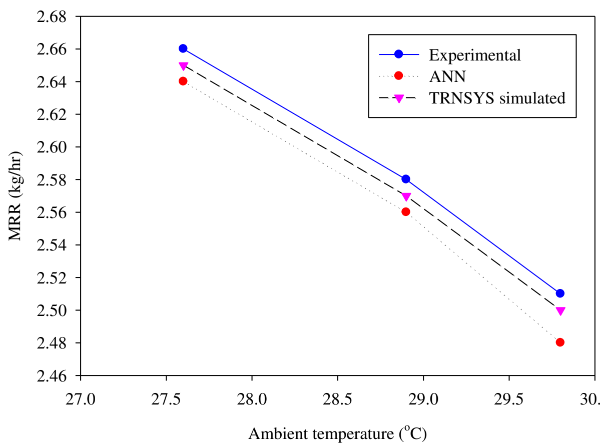

Figure 7: Influence of ambient air temperature on moisture removal rate.

Comparisons between the results predicted by the artificial neural network model and the experimental findings for validation purposes 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 the artificial neural network model greatly relies on network structure, amount of training and testing data, and selection of learning as well as performance function.

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, the following conclusions were drawn:

- The maximum percentage difference between the ANN predictions and the experimental values for the coefficient of performance (COP) were found to be 13.40%, respectively.
- The results indicate that the accuracy of the ANN model is satisfactory and coincides with the experimental data.
- The ANN model can be efficiently used to predict the performance of a 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.

Table 2: Comparison of ANN Testing Results with the Experimental Data for the Coefficient of Performance

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

The accuracy of the 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 the accuracy of the 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.

NOMENCLATURES

a	=	actual output (experimental output)
b	=	bias
E	=	energy consumption (kW)
h	=	enthalpy (kJ/kg)
$\dot{m}$	=	mass flow rate (kg/hr)
MRR	=	moisture removal rate (kg/hr)
p	=	predicted output (network output)
R	=	correlation coefficient
RH	=	relative humidity (%)
RPH	=	revolutions per hour
T	=	temperature (°C)
TRNSYS	=	transient system simulation
w	=	synaptic weights
X	=	input signal
Y	=	output

Subscripts

c	=	compressor
f	=	fan
i	=	inlet
o	=	others
pa	=	process air
ra	=	regeneration air
reg	=	regeneration
t	=	total
1,2, etc.	=	reference state points

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