Performance prediction of solid desiccant rotary system using artificial neural network

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Abstract

This paper presents an artificial neural network model for solid desiccant rotary system to predict its performance in terms of temperature and relative humidity of process air leaving the desiccant wheel after losing latent heat. Present paper also explains the experimental test setup that is used for taking reading. The experimental readings are all taken at steady state by varying the input conditions such as process air inlet velocity, regeneration air inlet velocity and regeneration temperature and process air inlet temperature and relative humidity. Majority of data taken from experiments is used to train the model (85%) and rest (15%) is used for testing of the model. The performance output predicted by the ANN model have high correlation factor(R>0.98336). The results predicted by the ANN model shows that ANN model can be successfully applied to predict the performance of solid desiccant wheel with sufficient accuracy and reliability.

1. Introduction

Addition of solid desiccant wheel as desiccant dehumidification system in the traditional air conditioning system gives efficient cooling system, since this type of system handles latent and sensible heat load separately. Now a day's this kind of hybrid systems are widely used in several applications such as in pharmaceutical plants, supermarkets, theatres, office buildings, health clubs, and swimming pools [1]. Desiccant air conditioning involves the technology of desiccant dehumidification and evaporative cooling. While the first involves the water as refrigerant and can be activated by low grade thermal energy such as solar energy, waste heat, bioenergy, and district heating and the second one is near zero cost energy [2].desiccant air conditioning system is not only energy efficient and environment friendly but it is also cost competitive, particularly for hot humid and hot dry conditions. Also desiccants remove moisture in vapor form without using any liquid condensate, so desiccant dehumidification can work when dew point temperature of air is below freezing, while dehumidification based on cooling is restricted by freezing point i.e. 0^0C. While desiccant systems can work up to temperature as low as -40^0C [3], traditional vapor compression systems can work up to 4^0C [4]. Rotary desiccant air condition systems are compact and less prone to corrosion as compared to other systems and can continuously work for sufficient time this may be one of the reasons that they attract more attention. Extensive studies have been carried out for rotary desiccant air conditioning based on mathematical simulation [5-7], thermodynamic analysis [8-10], experimental investigation [11-

13], and practical application [14-16].Many efforts have been made to predict and enhance the performance of rotary desiccant dehumidifier incorporated in desiccant cooling systems. Some of the important ones are such as analogy theory by Banks [17], pseudo-state model given by Barlow [18], method by Maclaine-Cross of finite difference [19] finite difference method for cross-cooled dehumidifiers [20] and   method by Jurinak of combined potential [21].

From the literature review one can observe that mathematical models have been developed by some of the researchers for performance evaluation of air conditioning system using rotary desiccant systems, and some of them have also developed model for the performance evaluation of desiccant system but they involve large no of mathematical equation and engineering calculation on the other hand model developed by the author's using ANN involve least mathematical and calculation effort and works satisfactorily for the given normal working conditions. To the best of the author's knowledge none of the previous authors have used ANN in predicting the performance of rotary desiccant system although ANN is used by some authors in predicting the performance of solid desiccant- vapor compression hybrid air conditioning system [22]. In the present study, artificial neural network (ANN) model has been developed using MATLAB software using feed forward back propagation method which uses previous experimental data to evaluate the performance of solid desiccant rotary system in terms of output process air temperature and relative humidity. Model uses inlet process air velocity, inlet regeneration air velocity, regeneration temperature, and inlet temperature and relative humidity of process air as well as regeneration air as input parameters. These experimental readings are used for training and prediction of ANN model results and also used for validation of results obtained using ANN model. Designed model of ANN works satisfactorily within the range of given data.

2. Experimental setup

Experimental setup for solid desiccant wheel system is at mechanical engineering department of Indian Institute of Technology (ISM) Dhanbad. The setup provides the arrangement for determining the performance of solid desiccant wheel for range of regeneration temperature i.e. 60-100^{0}C. Arrangement has also been made to vary the inlet flow velocity of process air as well as regeneration air by varying the inlet area. Heat energy used for heating the regeneration air is obtained from electric heater. In the desiccant wheel silica gel is used as desiccant material since it can be easily regenerated even at low temperature of about 60-100^{0}C. The matrix of wheel is made in honeycomb structure with alternate layers of metal silicate sheets and silica gel. Honeycomb structure is chosen for matrix construction since it provides large surface area with relative low pressure drop and has high structure durability. Figure below shows the schematic of experimental setup.
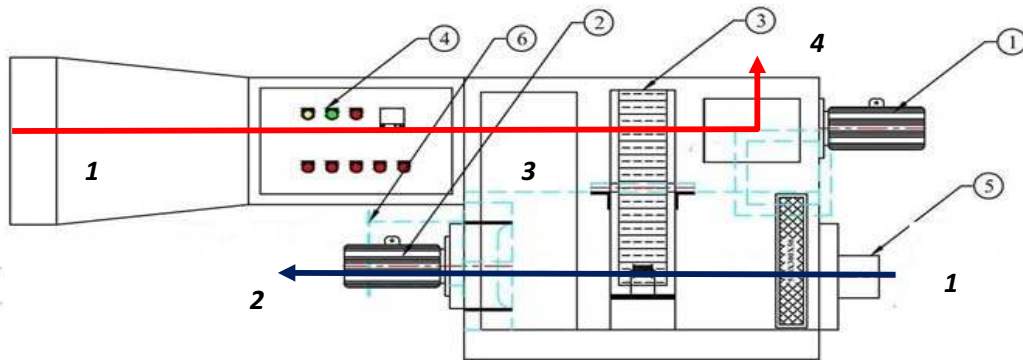
Figure-1 Schematic of experimental setup

Desiccant Wheel can handle 600 m^3/h of process air and 200 m^3/h of regeneration air. Wheel area is divided into two parts from 1/4th part regeneration air passes while from 3/4th part process air passes the diameter and thickness of desiccant wheel is 460mm and 100mm respectively, and the wheel is rotating at 27 RPH(revolutions per hour).
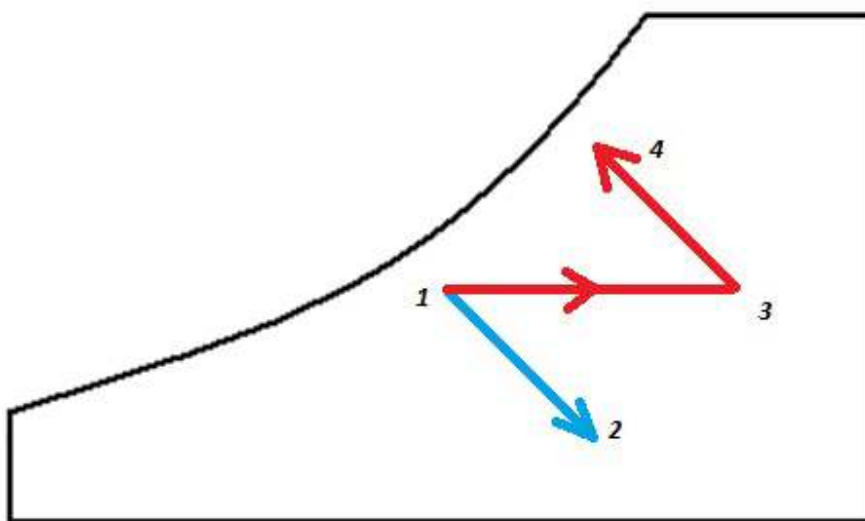

Figure-2 Process diagram on psychrometric chart

3. Measurement

Process marked 1-2 corresponds to path followed by process air while process marked 1-3-4 corresponds to flow path of regeneration air. All the readings for testing are taken at steady state condition. Two air streams, of regeneration air and process air are taken at temperature T_1, and relative humidity RH_1.process air passes through the desiccant wheel and gets dehumidified, and

regeneration air first passes through the electric heater at stage 3 and then passes through the desiccant wheel to absorb the moisture and gets humidified final state of regeneration is air is that of heated and humidified. The dry bulb temperature and relative humidity of regeneration and process air streams at inlet and outlet are measured with the use of 'K' type thermocouple($\pm 0.70^0$C) and RH sensors($\pm 2.5\%$RH) respectively. The air flow rate of process and regeneration air is taken using hot wire anemometer ($\pm 03\%$F.S).

4. Artificial neural network model

A neural network is an interconnected assembly of simple processing elements, units or nodes whose functionality is loosely based on animal neuron. The processing ability of the network is stored in the inter unit connection strengths or weights, obtained by a process of adaptation to, or learning from, a set of patterns. Neural network implementation involves loading of data source, setting of attributes required ,decision on training, validation, and testing method, manipulation of data and target generation, selection of network architecture and initialization, network training and testing and evaluation of performance. Neural network is consisted of large number of neurons which acts as processing elements, and are connected by weights to each other which acts as communication links. A basic neural network model usually consisted of an input layer and an output layer and at least one hidden layer can be more also. The introduction of hidden layers makes it possible for the network to exhibit non linear behavior. The optimal number of hidden units could easily be smaller than the number of inputs, there is no rule or relation between numbers of input and number of hidden layer. Sometimes just 2 hidden layer works best with little data, but researches have shown for difficult object many hidden layers give good results. A simplified neural network consists of inputs, synapses which are nothing but connection between input and activating function, bias function and output. Bias function help neural network to learn the patterns by shifting the activating function to the left or to the right, which may be critical for successful learning. Bias functions are separate for each layer as they are not connected to previous layer. The network is trained to give the desired output from given input. The given output from the neural network model is compared with the one obtained from experiments, if there is some difference in the experimental and the result obtained from the model then weights and bias are again adjusted and network is trained and results are then again compared till the error minimizes and comes within a satisfactory limit. The above method is back propagation theorem which comes under one of the most important function approximation in neural network namely Multilayer preceptor other is Radial basis function. The output of node i of ANN network is given by

$$y_i = g_i = g\left[\sum_{j=1}^{k} w_{ji}x_j + \theta_i\right]$$

Where y_i output of ith node, g is activation function, w is weight, x is input variable, and θ is the bias term.

$$y_i = g\left(\sum_{j=1}^{3} w_{ji}^2 g(n_j^1) + \theta_j^2 \right) = g\left(\sum_{j=1}^{3} w_{ji}^2 g\left(\sum_{k=1}^{K} w_{kj}^1 x_k + \theta_j^1 \right) + \theta_j^2 \right)$$
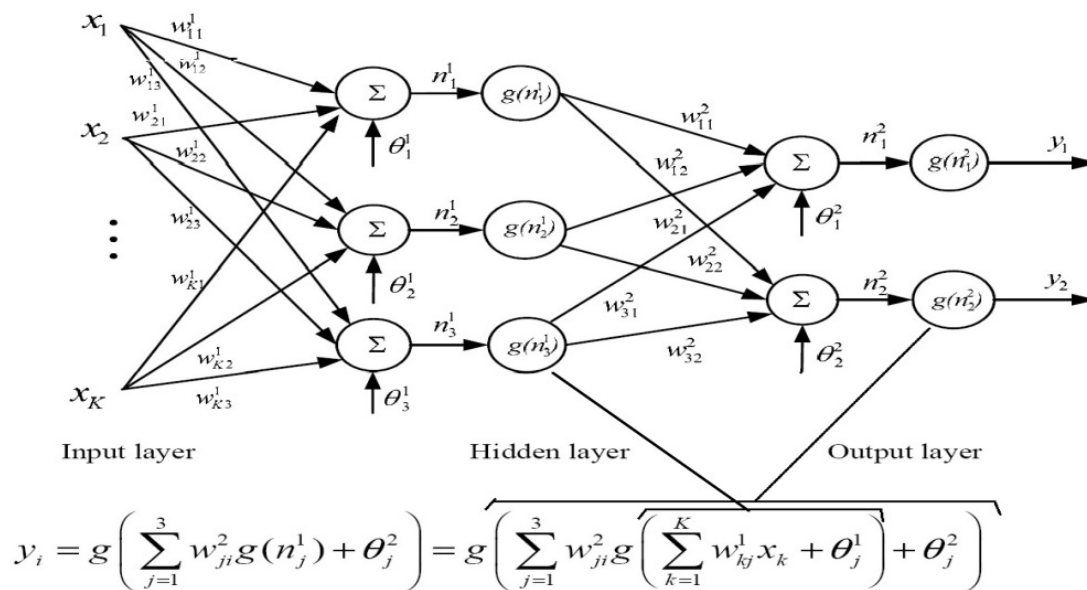
Figure-3 Representation of neural network model

Artificial neural network structure is made by feeding weight to each input and sending it to a summation function and there after adding a bias term and the result is fed to the activating function as input which results in a desired output(in simple ANN model) or acts as input to other layer present(in multiple hidden layer model as shown in figure.3). The values of weight are calculated using feed forward back propagation method. Error evaluation is done during training the model by calculating the RMS (root mean square) error and procedure is done until the RMS error value comes under tolerance level. The prediction of performance of neural network is done by calculating MSE (mean square error) between the predicted value and experimental value using expression no.

$$MSE = \frac{\sum_{i=1}^{N}\left(x_{calculated(model)} - x_{measured(experiment)}\right)^2}{N}$$

Lesser value of MSE means better the result is. RMS error is given by expression no.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(x_{calculated(model)} - x_{measured(experiment)}\right)^2}$$

Value of absolute regression factor(R) is given by equation no.

$$R^2 = \frac{\sum_{i=1}^{N}\left(x_{calculated(model)} - x_{measured(experiment)}\right)^2}{\sum_{i=1}^{N}\left(x_{calculated(model)}\right)^2}$$

Value of R^2 lies between 0 and 1 where 0 indicates poor fit while 1 indicates perfect fit.

Working of neural network: experimental data is fed as input, neural network understands the relation between input data and store them as corrected weights, and the network is trained using a set of given input and corresponding output data, training includes revision of weights and desired result is obtained which lies within tolerance limit. In the present model of ANN calculation and comparison of process air outlet temperature and relative humidity is done with the experimental results.

5. ANN results and discussion

Feed forward back propagation technique is used with TRIANLM, LEARNGDM, MSE, and TANSIG for training, learning, performance, and activating (transfer) function. The size of network structure is 12-12-10-1 which gives the best performance in terms of MSE (MSE $<1e^{-04}$) for both temperature and relative humidity. Five parameters namely process air input velocity, regeneration air input velocity, regeneration temperature, and inlet air temperature and relative humidity (same for process air and regeneration air (varies only with season)) are at the input layer and two parameters which are output temperature and relative humidity of process air are added at the output layer. Range of input parameters given for training the model is given the Table.1

Table-1 Operating parameters for the model

Sr. No.	Operating parameters	Range
1	Process air inlet velocity	5.4 - 12.1 m/s
2	Regeneration air inlet velocity	13.6 – 18.39 m/s
3	Regeneration temperature	60 – 100 ^{o}c
4	Ambient temperature	24.1 – 29.5 ^{o}c
5	Ambient relative humidity	21 – 91

Temperature: Figure-4 shows the training performance of case of temperature. The graph is a plot between MSE and number of epoch (a run through all training input – output data set) (iterations) as can be seen from the figure best performance is achieved at 6th iteration corresponding to which mean squared error is $5.1418e^{-005}$. It is also clear from the graph that as the number of iteration increases mean squared error decreases.
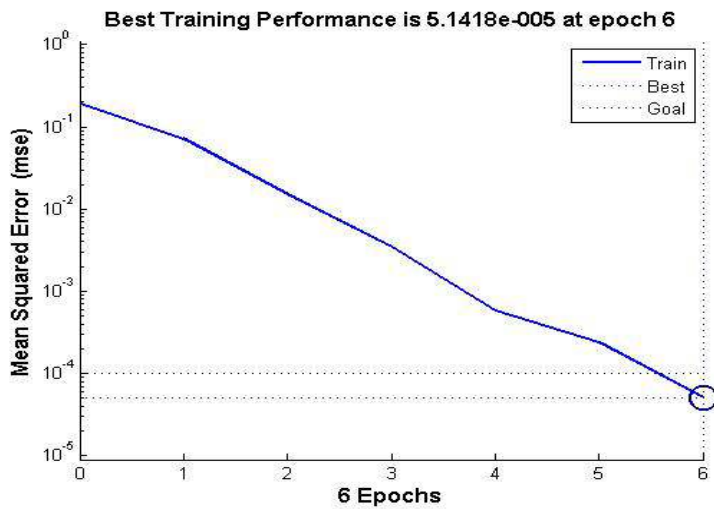
Figure-4 Variation of mean squared error with Epochs

Figure-5 below shows regression plot for training state with target set on x- axis and output of model on y- axis figure shows majority of values coincide with target data resulting in fairly high value coefficient of regression(R=0.98336), which shows closeness of calculated results and experimental results.
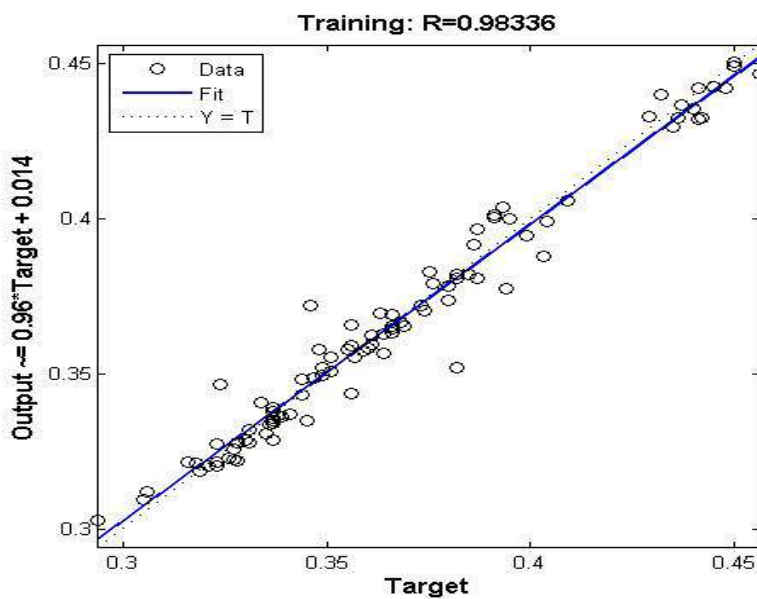

Figure-5 Regression plot for training state between experimental (target) and output

From table 2 one can observe the closeness of results obtained during testing stage from ANN model to the results obtained experimentally maximum percentage difference that occurs between the experimental value and calculated value is nearly 8%(7.89%)   and minimum

percentage difference that occurs is 0.14% which are well under the acceptable range of error and can be considered as correct.

Table 2. Comparison of result of testing of ANN with the results obtained from the experiment

Experimental value(^{0}C)	Calculated value(^{0}C)	Percentage difference (%)
45	44.9354	0.143556
32.4	34.6674	-6.99815
34.6	37.2269	-7.5922
38.7	39.6537	-2.46434
42.9	43.2851	-0.89767
43.2	44.0278	-1.9162
38.2	35.1832	7.897382
39.4	37.7413	4.209898
40.9	40.6059	0.719071
44.1	44.2339	-0.30363
45.6	44.6948	1.985088

Figure-6 below represents the regression plot between the values calculated by ANN during testing and experimentally and these results also show good match with the experimental value and therefore having high regression coefficient (R^2=0.855). Such good fit represents how well the model has learned during the training of data.
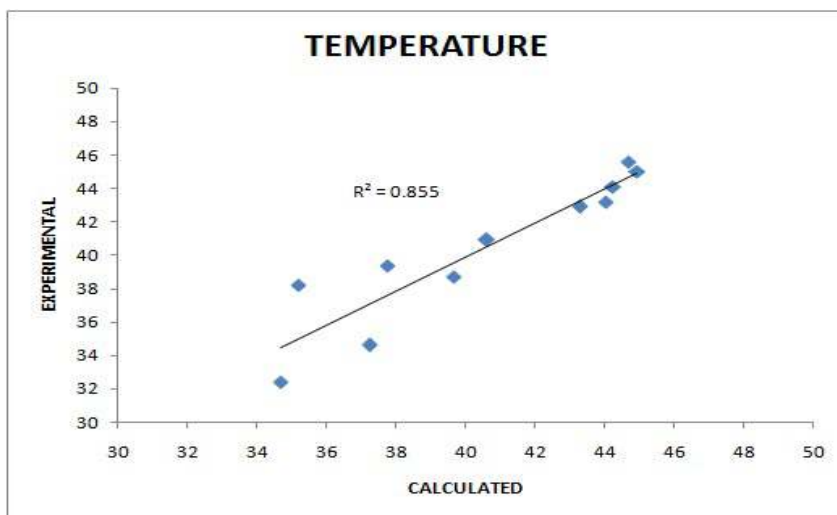

Figure-6 Regression plot for testing stage between experimental and calculated (ANN)

Relative humidity: Figure-7 below shows plot between mean squared error and number of iteration(epoch),it is evident from graph that as number of iteration are increasing mean squared error is also decreasing and it attains its minimum value 9th iteration which is $2.3739e^{-005}$.
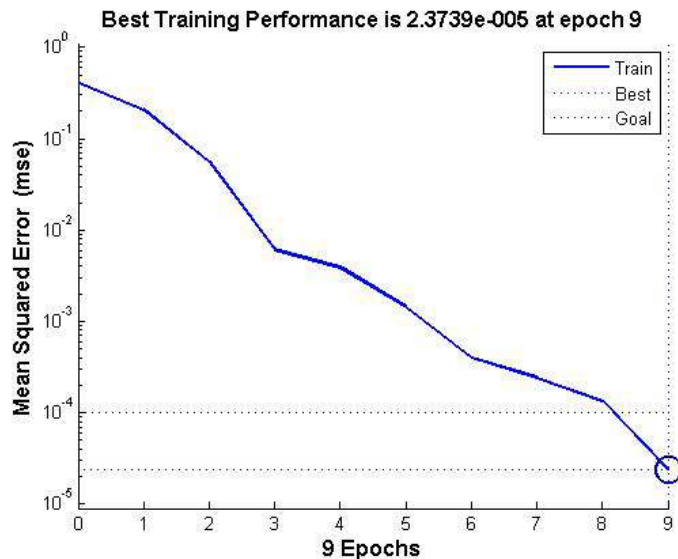

Figure-7 Variation of mean squared error with Epochs

Figure-8 below shows training results for relative humidity with target data, model output plotted on x and y axis respectively. Since majority of data lies along straight fit line, it also shows closeness of actual experimental data with the output data calculated during training period of data and achieves a high correlation factor value R=0.99408
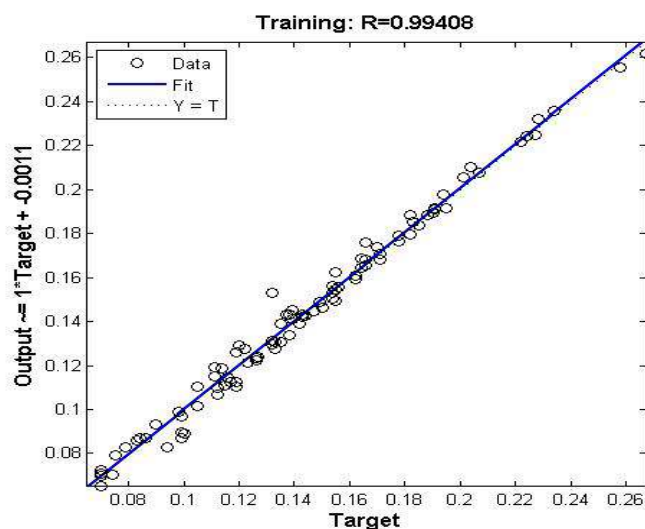

Figure-8 Regression plot for training stage between experimental (target) and output

Table-3 below shows testing stage results of ANN and experimental results and percentage difference between them for relative humidity. Analyzing the table gives a clear idea how much close the calculated values are to the experimental values and have minimum percentage difference of -0.214% and maximum percentage difference of 15% which are well within acceptable range

Table.3 Comparison of experimental values and calculated values during testing stage

Experimental value (%)	Calculated value (%)	Percentage difference (%)
7	7.2418	3.454286
20.4	21.0451	3.162255
17.1	17.0634	-0.21404
11.9	12.584	5.747899
8.4	8.6779	3.308333
7	7.2299	3.284286
13.2	15.2931	15.85682
12.2	12.7627	4.612295
10.5	11.0207	4.959048
7.9	8.2685	4.664557
7	7.1063	1.518571

Figure-9 below shows the regression plot between experimental and calculated values.

 It can be deduced from the figure that the testing performance of ANN model is quite good since calculated values are in good agreement with the experimental values and are having good fit with regression coefficient R^2=0.985. Due to this reason one can successfully use the ANN model for predicting the values of relative humidity.
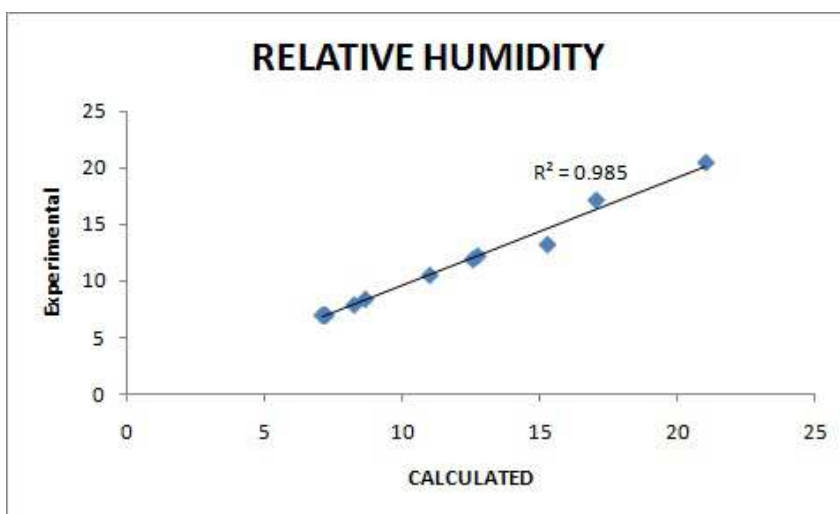
Figure-9 Regression plot for testing stage for relative humidity between experimental and calculated (ANN).

6. Conclusions

The ANN model of 12-12-10-1 network structure (number of neurons in input-hidden-output layer) has been devised to predict the performance of solid desiccant wheel. Relative humidity and temperature of outgoing process air has been considered as output parameter and are compared with the experimental results. Experimental results are used to train and test the model. ANN model represents good results in statistical terms through correlation coefficient(R) and mean squared error, following conclusions are drawn:

- The maximum percentage difference between the experimental and the ANN model result for temperature and relative humidity are 8% and 15% respectively.
- Results show that ANN model values are quite close to the experimental results and are satisfactory.
- ANN model can be successfully used to predict the performance of solid desiccant wheel in terms of temperature and relative humidity of outgoing process air.
- Accuracy of model also depends on type of model having number of hidden layer and amount of data used to train the network, and also learning method of model.

Due to high accuracy and low computational time above model can be effectively used to predict the performance of solid desiccant wheel rather than conducting expensive experiments which consume time as well as money or using other complex mathematical method requiring much more engineering effort.

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