Journal of Renewable Energies 25 (2022) 157 – 167 - **DOI:** https://doi.org/10.54966/jreen.v25i2.1079

Journal of Renewable Energies

Revue des Energies Renouvelables

journal home page : https://revue.cder.dz/index.php/rer

Research Paper

Artificial neural network-based modeling for the prediction of heat and mass transfer coefficient of the adiabatic liquid desiccant system

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ARTICLE INFO

Article history:
Received 21 February 2022
Accepted 28 November 2022

Keywords:
Artificial neural network
Liquid desiccant
Heat and mass transfer coefficient
Dehumidification

ABSTRACT

This work, based on the data obtained from the literature reported by (Varela et al., 2018), aims to use the artificial neural network approach to predict the heat and mass transfer in a dehumidifier system, using lithium chloride as a liquid desiccant. A neural network model was developed in MATLAB environment based on multilayer perceptron that included an input, hidden, and output layer. The network input parameters are air velocity, air temperature, air humidity ratio, liquid desiccant temperature, liquid flow rate, and liquid desiccant concentration. The network output includes two variables which are the heat transfer coefficient (K_h) and mass transfer coefficient (K_m). The performance of the ANN model was evaluated using the statistical parameters between the prediction results and experimental values. The performance regression yields R^2 and MSE values of 0.9344 and 9.0032, respectively, for the test data set of heat transfer coefficient (K_h). Moreover, for the mass transfer coefficient (K_m), the regression parameter R^2 and MSE values for the ANN tests were found to be 0.9657 and 2.0414, respectively. In addition, air velocity, air temperature, solution mass flow rate, and solution concentration are the most influential parameters on the heat and mass transfer between the air and liquid desiccant.

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ISSN: 1112-2242 / EISSN: 2716-8247

1. Introduction

The desiccant liquid dehumidification technique is a tool for controlling the humidity and temperature in a hot and humid climate. The research on dehumidifier systems using liquid desiccant has concentrated on two aspects. One is the experimental part, to test and enhance the sorption dehumidification of air with different solutions as liquid desiccant materials (Fumo & Goswami, 2002), (Patnaik, Lenz, & Löf, 1990) and (Kumar & Asati, 2016).

The other aspect is theoretical research that is introduced to understand the different processes in dehumidifier systems (Salarian, Fatahian, & Fatahian, 2020). Heat and mass transfer were the main processes that should be studied to characterize the liquid desiccation dehumidification system.

Onda et al.,1968, established an empirical correlation of the mass transfer coefficients for gas absorption and desorption that applied to the vaporization of water and gas absorption by organic solvents (Onda, Takeuchi, & Okumoto, 1968).

Zhang et al.,2010, developed an empirical correlation to predict the mass transfer coefficient of a cross-flow liquid desiccant dehumidifier system using lithium chloride as the liquid desiccant(Zhang, Hihara, Matsuoka, & Dang, 2010).

Su et al.,2019, established a novel correlation for a cross-flow dehumidifier with structured packing based on the experimental operating conditions (Su, Li, Sun, & Zhang, 2019).

Yin and Zhang.,2008, obtained a new method based on the number of NTU-Le transfer units to determine the coupled heat and mass transfer coefficients between air and the liquid desiccant (Yin & Zhang, 2008).

Elsayed et al.,1993, developed a finite difference model to calculate the effectiveness of heat and mass transfer in dehumidification and regeneration with numerous parameters such as column heights, air, and solution flow rates, inlet air and solution temperatures, solution concentrations, and calcium chloride as the liquid desiccant (Elsayed, Gari, & Radhwan, 1993).

Varela et al.,2018, established an empirical correlation between the mass transfer coefficients for an adiabatic dehumidifier and regeneration made of a structure-packed bed by using lithium chloride as a solution desiccant (Varela et al., 2018).

However, in classical methods, the numerical models require a large number of parameters to define the system. Geometric, physical, and thermodynamic properties may not be readily available, and their predictions may often not be precise enough (Zendehboudi, Tatar, & Li, 2017). Artificial neural networks are optimization methods used to predict the desired output of a system when sufficient experimental data is provided (Frey et al., 2014). The main advantages of artificial neural networks are their speed, simplicity, and ability to model a multivariate problem to solve complex relationships between variables, (Mellit & Kalogirou, 2008) and (Bouzeffour, Khelidj, Yahi, Belkacemi, & Taane, 2021).

The main focus of the present study is based on the experimental data obtained from the literature reported by (Varela et al., 2018) for predicting the heat and mass transfer coefficient of an adiabatic liquid desiccant dehumidifier system. To achieve this, multilayer feed-forward neural networks, tangent sigmoid TANSIG transfer function, and a back-propagation algorithm were used to build the method of the neural network. The mathematical validation criteria between the predicted and experimental results were also examined.

2. Artificial neural network method

An artificial neural network called also a "neural network" is a mathematical or computational model whose design is inspired by a working method of the human nervous system. The artificial neural network (ANN) is more powerful than the parametric approaches and can identify, predict and solve complicated phenomena, and has been used to simulate various topics including mathematics, medicine, economy, meteorology, and engineering sciences (Kalogirou, 2000).

A neural network consists of an input, a hidden, and an output layer. Fig.1 illustrates the architecture of a typical neuron in a neural network. This configuration is known as a multilayer perceptron. It consists of single or multiple hidden layers, which are responsible for the performance of the network output.

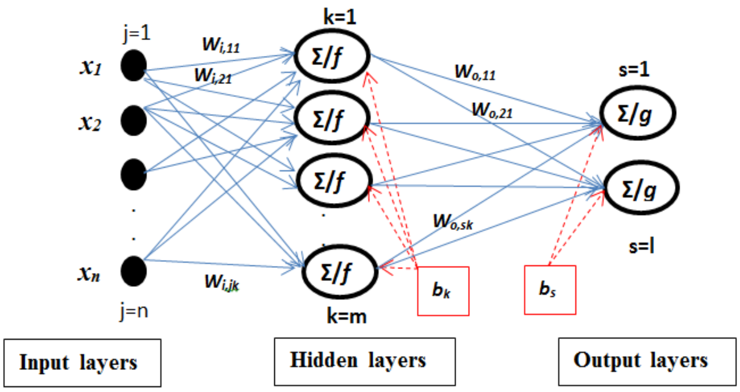

Fig 1. The architecture of a typical neuron in a neural network

The neural network training process is based on modifying connected weights and biases using the learning method. The weighted sum of inputs goes through a non-linear function to produce the neuron output.

The neural network model is described by the following equation:

$$Net_k = \sum_{j=1}^{j=n} W_{i,jk}.x_j + b1_k \tag{1}$$

Where;

x1, x2, ..., xj: the input signals; $W_{i,11}$, $W_{i,21}$, ..., $W_{i,jk}$: the respective synaptic weights of the input neuron k; $W_{o,11}$, $W_{o,21}$, ..., $W_{o,sk}$: the synaptic weights of the output neuron s;

b_{1k} and b_{2s}: is the biases or threshold;

In this study, the network output of the heat transfer coefficient $\mathbf{K_h}$ and mass transfer coefficient $\mathbf{K_m}$ is expressed as follows:

$$Output\_net_{K_h/K_m} = Purelin\left[W_{o,sk} \times \left(Tansig(W_{i,jk} x_j + b1_k)\right)\right] + b2_s \tag{2}$$

$$output\_net_{K_h/K_m} = \sum_{k=1}^{k=m} \left(W_{o,sk} \left[\frac{2}{1+\exp\left(-2\times\left(\sum_{j=1}^{j=n} W_{i,jk} x_j + b1_k\right)\right)} - 1 \right] \right) + b2_s \tag{3}$$

Where ;

Wi, Wo, b_{1k}, and b_{2s} are weights and biases.

The ANN model was developed for the adiabatic liquid desiccant system with six parameters in the input layer and three neurons in the hidden layer. The input variables are air velocity (U_{ai}), air temperature (T_{ai}), air humidity ratio (W_{ai}), the liquid solution flow rate (m_s), the liquid solution temperature (T_s), and the concentration of the liquid desiccant (X_s). The output parameters in the neural networks model are the heat and mass transfer coefficients $\mathbf{K_h}$ and $\mathbf{K_m}$. The architecture of the network for this current study is shown in Fig. 2.

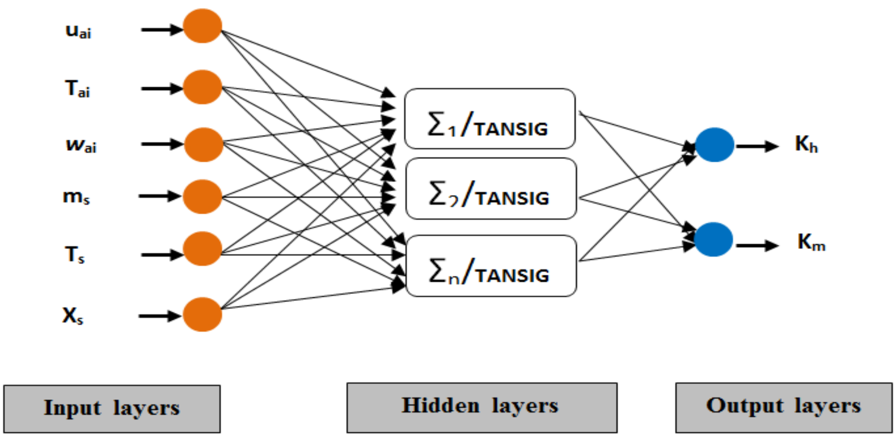

Fig 2. Typical feed-forward ANN structure

The range of the measured values at the inlet and outlet of the adiabatic liquid desiccant system are listed in Table 1.

Table 1. the measured values at the inlet and outlet of the adiabatic liquid desiccant system (Varela et al., 2018)

Working parameters	Minimum and Maximum ranges	Units
Air velocity (Uai)	0.44 – 2.38	m/s
Air temperature (Tai)	33.92 – 34.06	°C
Air humidity ration (Wai)	19.4 – 19.6	g/kg
Solution mass flow rate (msi)	38.8 –187.98	g/s
Solution temperature (Tsi)	16.9 – 17.12	g/kg
Solution concentration (Xsi)	29.18 – 30.19	%
Heat transfer coefficient (**K_h**)	11.34 – 42.4	W/m2.K
Mass transfer coefficient (**K_m**)	10.98 – 29.74	g/m2.s

Moreover, to enhance the learning process of the network model, the inputs and the outputs variables were normalized between -1 and 1 (Wang, Zhao, & Zhang, 2006), using the following equation:

$$val^{nor} = \frac{(val_i - val_{\min})}{(val_{\max} - val_{\min})}(y_{\max} - y_{\min}) + y_{\min} \tag{4}$$

Where;

val_{nor}, represent the normalized value, val_i represents the actual input or output.

y_{min}, y_{max}, are -1 and 1, respectively, val_{min}, and val_{max}, represent the minimum and the maximum experimental values of the inputs or outputs. The inlet and outlet experimental values are also listed in Table 1.

3. Results and discussion

To develop the artificial neural network for the adiabatic liquid desiccant system, the available data set from the experimental work of (Varela et al., 2018). The data set consisted of 38 input-output pairs. While 70 % of the data set was randomly assigned as the training set, the remaining 30% was employed for testing the network. The developed neuronal model uses the MATLAB Neural Network toolbox to search for a better configuration network applying multilayer feed-forward neural networks, the hyperbolical tangential (TANSIG) transfer function in the hidden layer, and the backpropagation learning algorithm.

In this study, several parameters are selected to develop the neural network training such as the number of neurons in the input, hidden and output, the structure of the network, the transfer function between the input and hidden layer, and the learning algorithm. Figure 4 shows the steps involved in the training of the artificial neural network used for predicting the dehumidifier performance.

The prediction performances of the networks were evaluated using Mean-Square Error (MES), Root Mean-Square Error (RMES), statistical coefficient of multiple determinations (R), and the Mean Relative Error (MRE), which were calculated using the following expressions:

$$MSE = \frac{1}{N}.\sum_j \left(Q_{j,\exp} - Q_{j,ANN}\right)^2 \tag{5}$$

$$RMSE = \left(\sqrt{\frac{1}{N}.\sum_j \left(\left|Q_{j,ANN} - Q_{j,\exp}\right|\right)^2}\right) \tag{6}$$

$$R^2 = 1 - \left(\frac{\sum_j \left(Q_{j,ANN} - Q_{j,\exp}\right)^2}{\sum_j \left(Q_{j,\exp}\right)^2}\right) \tag{7}$$

$$MRE(\%) = \frac{1}{N}\sum_j \left|\frac{\left(Q_{j,\exp} - Q_{j,ANN}\right)}{\left(Q_{j,\exp}\right)}\right| \times 100 \tag{8}$$

Where :

$Q_{j,exp}$ is the real value (experimental),

$Q_{j,\ ANN}$ is the predicted value (output network),

N is the data number.

3.1 Statistical parameters

The statistical parameters MSE and R obtained by backpropagation algorithms TRAINLM of the ANN model during the training and testing steps concerning the heat and mass transfer coefficient of the adiabatic liquid desiccant system are listed in Table.2.

Table 2. ANN performance results for heat and mass transfer coefficient

	Heat transfer coefficient (**K_h**)		Mass transfer coefficient (**K_m**)	
Network structure	6-3-1		6-3-1	
ANN Performance	Training	Test	Training	Test
MSE	0.0287	9.0032	0,0012	2,0414
RMSE	0.1694	3.0005	0.0346	1.4287
R^2	0.9997	0.9344	0.9999	0.9657
MRE (%)	0.4110	8.8946	0.1026	6.1093

The MSE and R^2 values are excellent numerical criteria for evaluating the performance of a prediction tool. A well-trained ANN model produces small MSE and higher R values. In the current study, the heat transfer coefficient results of the adiabatic liquid desiccant system obtained from a neural network with a 6-3-1 structure provided a reasonable degree of accuracy with MSE= 0.0287 and 9.0032 for the training and the test respectively. The ANN prediction and the experimental values yielded a statistical coefficient of multiple determinations (R) in the range of 0.9997 and the mean relative error (MRE) in the range of 0.1410 % for the training step, and for the ANN test the (R) obtained was 0.9346 and the (MRE) was 8.8946%, as shown in Table2. Also, the prediction values of the mass transfer coefficient yielded the (R-values) of 0.9999 and 0.6957 for the training and test respectively, and the mean relative error (MRE) in the range of 0.1026 and 6.1093% for the training and for the ANN test the (R) obtained was 0.9657 and the (MRE) was 6.1093% with 6-3-4 ANN structure.

Figures 3 and 4 show the evolution of mean squared errors (MSE) against the number of iterations (epochs) of the training and the testing process for the heat and mass transfer coefficient of the adiabatic liquid desiccant system.

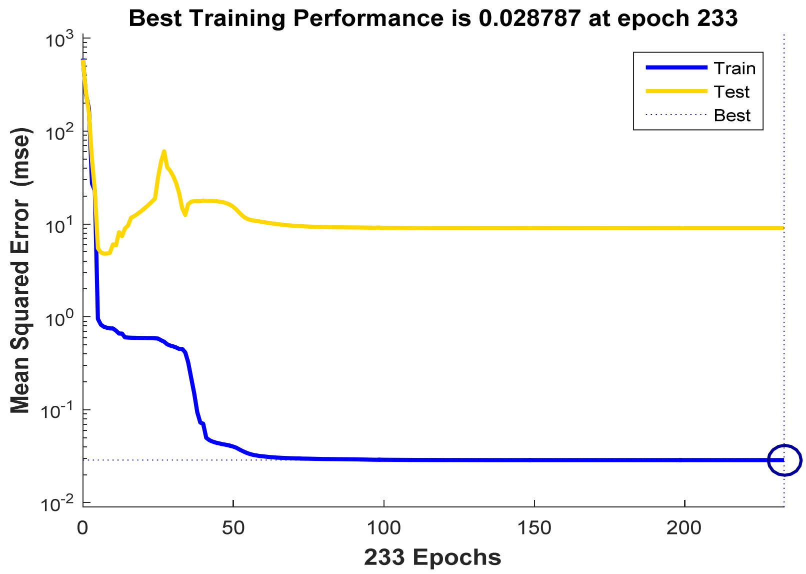

Fig 3. Training and Test results of heat transfer coefficient $\mathbf{K_h}$ based on the 6-3-1 configuration

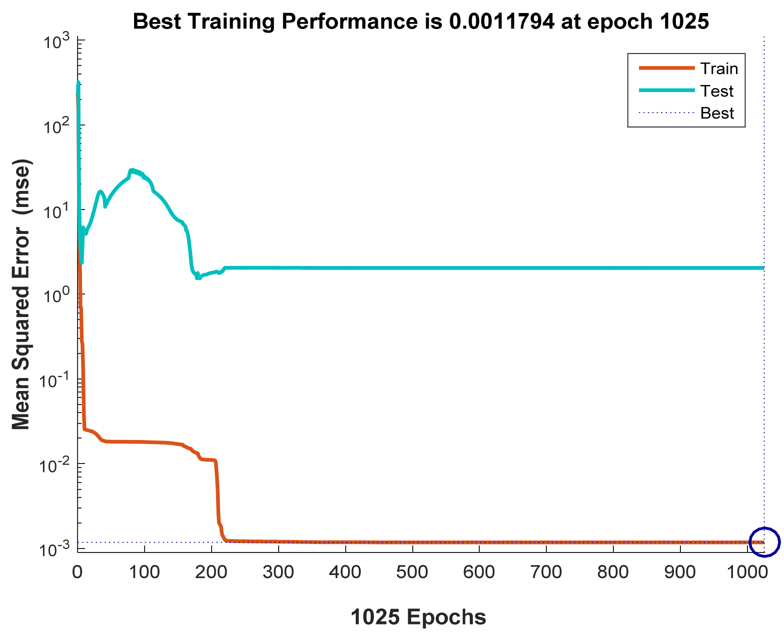

Fig 4. Training and Test results of mass transfer coefficient $\mathbf{K_m}$ based on the 6-3-1

Figures 5 and 6 show the regression coefficients of the heat and mass transfer coefficient, in which the best fit between the simulated data provided by ANN and the experimental values are presented.

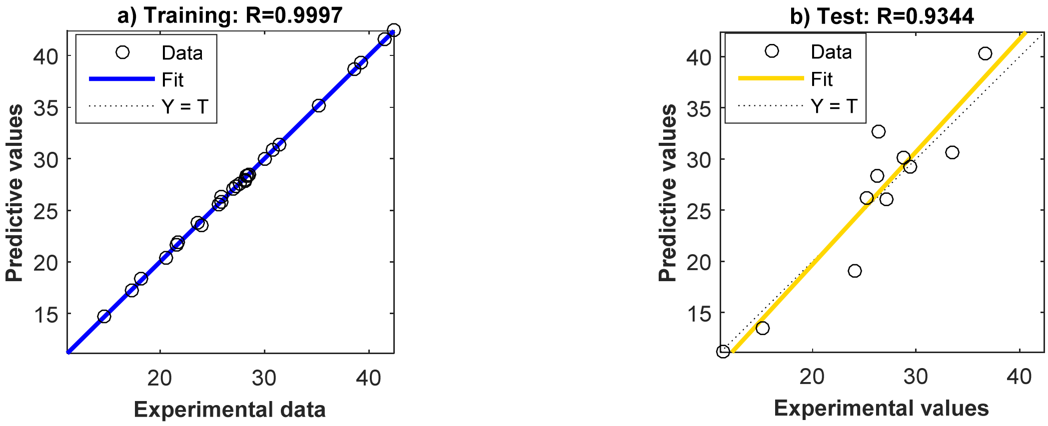

Fig 5. Regression coefficients (R); a: Training data, b: Test data for heat transfer coefficient $\mathbf{K_h}$

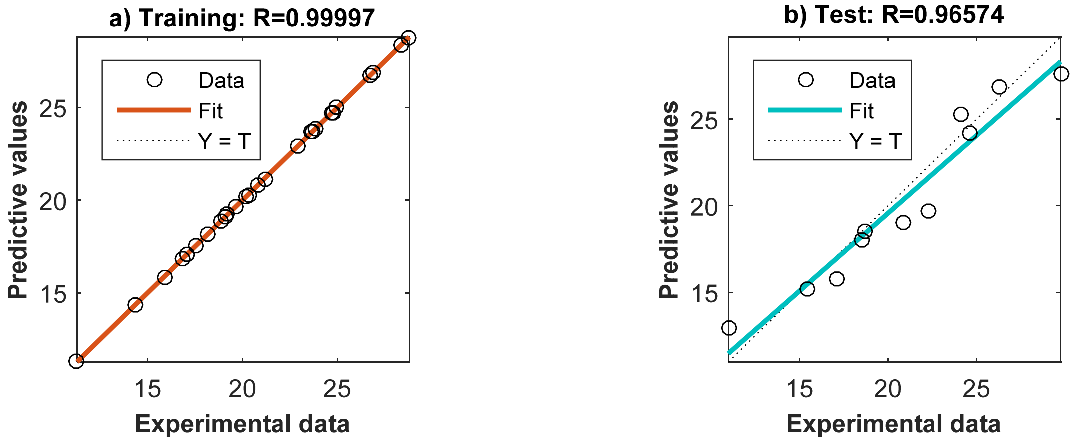

Fig 6. Regression coefficients (R); a: Training data, b: Test data for mass transfer coefficient $\mathbf{K_m}$

3.2 Working parameters effects on heat and mass transfer coefficient

To evaluate the sensitivity of the input variables to the performance of the dehumidifier, an equation proposed by Garson (1991) cited by Hernández et al., (2012) and Hamzaoui et al.,(2011) was used. The developed equation is based on the partitioning of connection weights between the input network and hidden layers, and between the hidden layers and the output network. Thus equation (9), for the relative importance (Ij, %) was expressed as follows:

$$I_j(\%) = \frac{\sum_{m=1}^{N_h}\left(\left(\frac{\left|W_{jm}^{i,h}\right|}{\sum_{n=1}^{N_i}\left|W_{nm}^{i,h}\right|}\right)\times\left|W_{ml}^{h,o}\right|\right)}{\sum_{n=1}^{N_i}\left[\sum_{m=1}^{N_h}\left(\frac{\left|W_{nm}^{i,h}\right|}{\sum_{n=1}^{N_i}\left|W_{nm}^{i,h}\right|}\right)\times\left|W_{ml}^{h,o}\right|\right]} \tag{9}$$

Where;

Ij: is the relative importance of the j input variable on the output variable, W: is the connection weight, Ni and Nh: are the numbers of input and hidden neurons, respectively.

The superscripts 'i','h', and 'o' refer to input, hidden and output, respectively. 'n', 'm', and 'l' refer to the number of neurons in input, hidden, and output.

The relative importance of various variables as calculated in Eq. (9) is shown in Table 3.

According to the weight values of the artificial neural network model, the working parameters have a strong effect on the mass transfer coefficient. As can be seen from table 3, the air velocity at the inlet of the adiabatic liquid desiccant represents the highest influential parameters of 28.29 % on the heat transfer coefficient (**K_h**). Also, the air temperature and the solution concentration at the inlet have a significant effect on the heat transfer coefficient of 22.70%, and 20.83%, respectively.

Table 3. Sensitivity of the inputs variables on heat and mass transfer coefficient

Input variable	Relative importance **(%)**	
	heat transfer coefficient (**K_h**)	mass transfer coefficient (**K_m**)
Air velocity (Uai)	28.29	34.64
Air temperature (Tai)	22.70	2.26
Air humidity ration (Wai)	13,14	18.71
Solution mass flow rate (msi)	9,28	21.53
Solution temperature (Tsi)	5,76	1.63
Solution concentration (Xsi)	20,83	21.23
Total	100	100

Similarly, the relative importance of the input variables on the mass transfer coefficient is shown in table 3. As can be seen, the air velocity of 34.64% represents the most influential parameter on the mass transfer coefficient, followed by the solution mass flow rate of 21.53%, solution concentration of 21.23%, and air humidity ratio of 18.71%.

4. Conclusion

In the present work, artificial neural network methodology has been successfully applied to an adiabatic liquid desiccant system to determine the heat and mass transfer coefficient.

The developed neuronal model uses the MATLAB® environment based on the experimental results obtained from (Varela et al., 2018). The ANN architecture which consists of six input layers, three hidden layers, and two outputs presents a good agreement of the experimental data compared to those predicted by using the Levenberg-Marquardt network training function.

The high accuracy of the neural network training function prediction and the experimental data of heat transfer coefficient (K_h) was revealed by the low mean square error (MSE) which is 0.0287 and the high correlation coefficient (R2 = 0.9975) for all datasets.

Similarly, perfect accuracy between the TRAINLM neural network training function predictions and experimental data of mass transfer coefficient (K_m) was achieved with mean square error (MSE) of 0,0012% and correlation coefficient (R) that was 0,9997 for training.

The sensitivity analysis showed that all six input variables have a significant effect on the adiabatic liquid desiccant system and that the air velocity, the air temperature, the air humidity ratio, the liquid desiccant temperature, and the solution concentration proved to be the most influential parameters on the heat and mass transfer coefficient.

These results show the good reliability of the artificial neural networks (ANN) and can be used to make prediction parameters of the different processes of heat and mass transfer in an adiabatic liquid desiccant system.

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