DOI : https://dx.doi.org/10.26808/rs.st.i7v5.14
International Journal of Advanced Scientific and Technical Research Issue 7 volume 5 Sep-Oct 2017
Available online on http://www.rspublication.com/ijst/index.html ISSN 2249-9954

Predication of packed column absorber performance in absorption cooling system using (FFNN) Neural Networks

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Abstract

Absorption refrigeration system presents a promising alternative for the vapor compression system due to the increase of the environmental problems and electricity cost. In recent years, research has been increased to improve the performance of the ASs An experimental setupwas designed to study the increase in the absorption rate by using a new model of absorber component [Packed column absorber] by changing the type, height, and porosity of the packing. In this study, an artificial NN (ANN) has been used as a new approach for predicting the effect of using packed column absorber on the performance of the absorption cooling system using water–lithium bromide as the working fluid pair. The results showed that ANNs can be used as analternative way to determine the effect of different parameterson the absorption process of LiBr–water solutions. Equations derivedby using the ANN approach gives much faster and simplersolutions in comparison with the complex and limitedexperimental data provided in earlier literature.

Keywords: Absorption system (AS), Artificial neural network ANN, neural network (NN), Absorber.

1. Introduction

In recent years, interest in Vapor ASs has been growing because they use friendly refrigerants and absorbents which don't deplete the ozone layer conforming Montreal and Kyoto Protocols. They use cheap alternative energy sources, such as solar energy or a waste byproduct heat source helping in the control of global warming. [1]

Theoretical and experimental research studies on the Vapor ASs (VAS) have increased because these systems harness inexpensive energy sources like waste heat from gas and steam turbines, solar, geothermal and biomass in comparison to the vapor compression system. [2]

Therefore, in recent years, research has been increased to improve the performance of the absorption refrigeration systems.The absorber is one of the most critical components in the ASs from the viewpoint of its size and performance since it is one of the largest components and has complicated heat and mass transfer mechanisms, which influences the system performance significantly [3].

There are four types of absorber: spray, the falling film absorber, plate column, and the packed column absorber. In the spray absorber, the solution is sprayed by a Nozzle or stirred to improve the mass transfer while the cooling takes place in a separate heat exchanger [4]. Film absorbers are very popular because of their high performance. Plate columns are cylindrical vessels where liquid and gas flow in a counter-current or a crosscurrent configuration [5]. Plate columns can be classified according to the flow configuration of the streams in the internal plates. The packed column consists of a cylindrical shell having a support plate for the packing material and a liquid distributing device designed to provide effective irrigation of the packing [6].

Instead of complex equations and limited experimental data, faster and simpler solutions are obtained with artificial NNs (ANNs). This technique can be used in the modeling of complex physical phenomena such as those we come across in the thermal engineering field [7].In recent years, studies on the applications of ANN in energy systems were carried out by several researchers [8-13]. A more sophisticated control strategy from an overall point of view was developed by Chow et al. [14]. They used a NN and genetic algorithm optimizing the use of fuel and electricity in a direct-fired absorption chiller system. Palau et al. [15] used a NN to control the chilling stages in a gas/ solid sorption chilling machine. The expert system with NNs was used in predicting the end time of each stage so it could decide when to operate a set of control valves. An Artificial NN (ANN) method was used again by Hernández et al. [16]. They presented the inverted model of a NN in an absorption heat transformer with energy recycling to predict the input parameter that needs to be controlled to find the ideal COP value.

Sencan et al. [17] used ANN models to predict the enthalpy of both LiBr-water and LiCl-water working pairs with a coefficient of multiple determinations equal to 0.999. The same author [18] used ANN to develop a model for predicting the performance of ammonia-water refrigeration systems based on data taken from the literature. One of the last studies reported by Rosiek and Battles [19] uses ANN to derive the model for predicting the performance of both the absorption chiller and whole solar-assisted air-conditioning system (Fig.1).

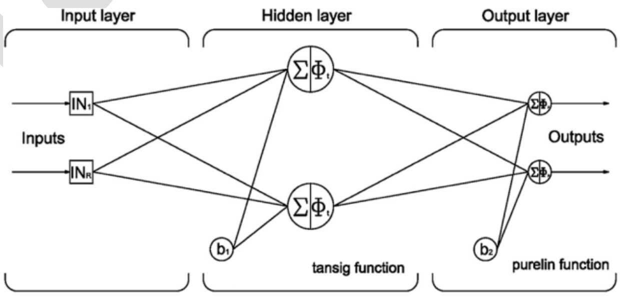

Fig. 1. NN model.

Consequently, the main aim of this paper is to develop a methodologyto predict the effect of different parameters for the optimal performance of packed column absorber in the A Susing the NN(ANN) based on the experimental data in various steady-state case studies.

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2. Experimental Setup

A Packed column absorber is proposed as a new trend for the absorber used in the AS by using different types of packing. As shown in Fig. 1, the experimental apparatus is arranged to study the effect of the absorber model on the system performance. The apparatus consists of four units, Evaporator, Absorber, Vacuum pump, and the solution pump as shown in Fig. 2 and the parts of the absorption unit are stated in Table (1).

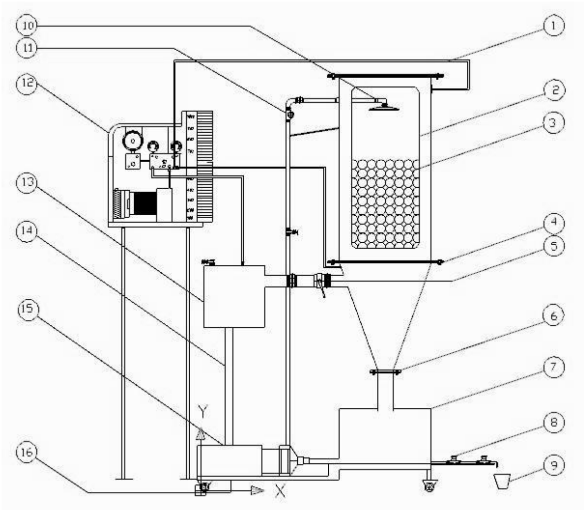

Fig. 2. Schematic diagram of Absorption unit using the packed column absorber

TABLE I:PARTS OF ABSORPTION UNIT

Item	*Name*	*Item*	*Name*
1	Flexible Hoses	9	Sample Extraction
2	Absorber	10	Li-Br Distributor
3	Packing	11	Digital Flow Meter
4	Iron mesh	12	Vacuum Pump
5	Isolation Valve	13	Evaporator
6	Accumulator	14	Stand of Evaporator
7	Tank	15	Solution Circulating Pump
8	Valves	16	**Base Frame**

The steps of the experimental work begin from the vacuum pump. The vacuum pump is turned on and starts to evacuate the absorber and the evaporator to the desired pressure respectively. The solution pump starts to circulate the lithium bromide solution with monitoring the water temperature in the evaporator. The isolated valve in the connecting pipeline then is opened and the vapor starts to go towards the absorber through the wire mesh. The distributor starts to spray the lithium bromide solution towards the upcoming vapor.The vapor is mixed with the lithium bromide solution through the packing type.

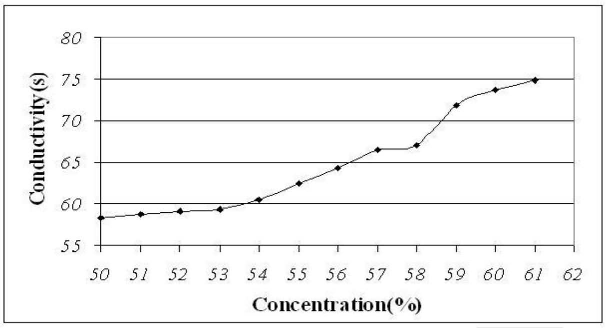

Fig. 3. The conductivity versus the concentration at constant Temperature (20 ^{o}C)

The lithium bromide solution is accumulated in the tank and a sample of the lithium bromide solution is taken through the two valves. The conductivity meter is then used to measure the conductivity of the solution through its probe. By using the correlation curve between the conductivity and the concentration as shown in figure (3), the concentration will be determined.

Throughout the experimental investigations, it wasnecessary to study the different parameters affecting theabsorption rate of the absorber. From literature, theimportant parameters needed to evaluate the absorberperformance are height, type, theoretical contact area andthe Porosity of the packing. The experimental cases arerepresented in four:

- Spray Absorber.
- Glass balls packing
- PVC packing
- Plastic and Glass packing.

The experimental work aims to calculate the absorption rate by measuring the concentration of the lithium bromide solution. The concentration changes by absorption vapor through time. The absorption rate which represents the efficiency of the absorber can be calculated through the following equation. The fast decrease in concentration means the most increase in the absorption rate.

$$Absorption Rate = \frac{Mass\ Increase\ In\ Water}{Time\ \ Interval}$$

The reaction of the lithium bromide powder and water is exothermic; this produces a significant rise in the temperature of the solution. The temperature of the solution was controlled by a thermostatically regulated water sink to the desired value. The temperature of the solution was then measured using the conductivity meter with the built-in temperature probe.

The experimental cases are represented in four designations:

- Without using any packing. There are two experiments.

1. Exp (1): 10 liters of lithium bromide solution.

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2. Exp (2): 10 liters of lithium bromide solution mixed with 100 ml octanol.
- Ball packing made of glass of diameter 3 cm. There are four experiments at different heights 6, 12 18 and 24 cm.
- PVC packing. There are three experiments at different heights 15, 20 and 25 cm.
- Plastic rings packing made of 1.5 cm diameter and 1.5 cm height were used with glass balls packing with total column height 12 cm.

3. Artificial NNs

The process of creating ANNs for materials research can, therefore, be summarized in terms of the following stages:

- Data collection: analysis and pre-processing of the data.
- Training of the NN: this includes the choice of its architecture, training functions, training algorithms and parametersof the network.
- Test of the trained network; to evaluate the network performance.
- Use of the trained ANNs for simulation and prediction.

ANN generally consists of several layers: the layer where the input patterns are applied is called the input layer, the layer where the output is obtained is the output layer, and the layers between the input and output layers are the hidden layers. Neurons in each layer are fully or partially interconnected to preceding and subsequent layer neurons with each interconnection having an associated connection strength (or weight).
The back-propagation training algorithm is commonly used to iteratively minimize the following cost function concerning the interconnection weights and neurons thresholds:

$$E = \frac{1}{2}\sum_{1}^{p}\sum_{i=1}^{N}(d_i - O_i)^2$$

Where p is the number of training input/output patterns and N is the number of output nodes. di and Oi are the targets and actual responses for output node i respectively.

The training process is terminated either when the normalized-mean-square-error(NMSE) between the observed data and the ANN outcomes for all elements in the training set has reached a pre-specified threshold or after the completion of a pre-specified number of learning epochs.
Each time a NN is trained can result in a different solution due to different initial weight and bias values and different divisions of data into training, validation, and test sets. As a result, different NNs trained on the same problem can give different outputs for the same input. To ensure that a NN of good accuracy has been found, retrain several times.
Feedforward NNs (FNN). This is the most known and commonly used of networks, although the main success of NNs has been in the application of the multilayer FNN with back-propagation training, they suffer from some drawbacks such as local convergence and the need for large training cases to make adequate modeling generalization [20].

4. Application Design

The absorption process between water and lithium bromide is primarily a function of the change in absorber temperature, the height of packing (porosity) and the flow rate of the solution. These three parameters make up the input vector for the NN while the single output

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of the network is the change of conductivity of solution which can be used to determine the change in the concentration of the solution which used to calculate the absorption rate. The tested NN was trained at different heights of packing, H=6, 12 and 24 cm for glass packing and H=15 and 25 cm forPVC packing, and expected NN values were obtained at H=18 cm forglass packing and H=20 cm for PVC packing.

Appropriate selection of ANN inputs & network structure is very critical in achieving adequate results. The suggested NN architectures, for both packing types, are feed-forward NN with input layer has 10 tan sigmoid neurons and one output layer with one pure-linear neuron. These layers are trained with one hidden layer containing 5, 10, 12, 20 pure-linear neurons. Fig. (4) shows the NMSE for the different number ofhidden layer neurons. A hidden layer of 12 neurons resulted in the best performance [21, 22].

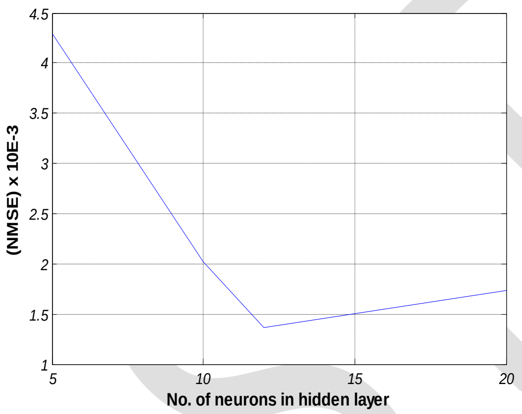

Fig. 4 Effect of numbers of neurons in the hidden layer on the FFNN performance

Figures (5) to (8) show the comparison between the experimental and the suggested FFNNconductivity of solution for H=6, 12,18 and 24 cmfor glass packing type, while Figures (9) to (11) show the comparison between the experimental and the suggested FFNNconductivity of solution for H=15, 20 and 25cm for PVC packing type.In these figures, it is well shown that the FFNN accurately predict the given data, the nonlinear modeling obtained by the FFNN can be utilized to the change of conductivity of solution for glass packing and PVC packing types.

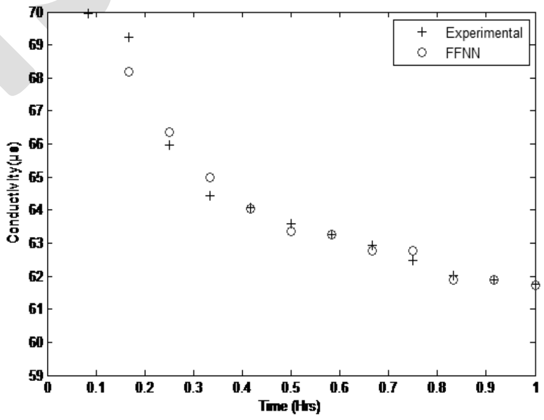

Fig. 5 FFNN Simulation for Glass Balls Packing -10 liters of lithium bromide, Height of packing =6 cm.

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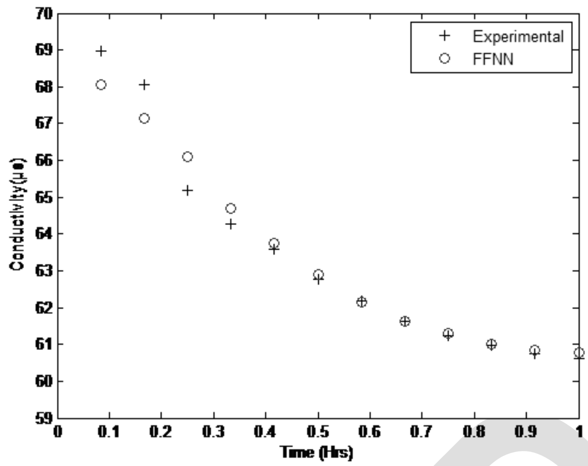

Fig. 6 FFNN Simulation for Glass Balls Packing -10 liters of lithium bromide, Height of packing =12 cm.

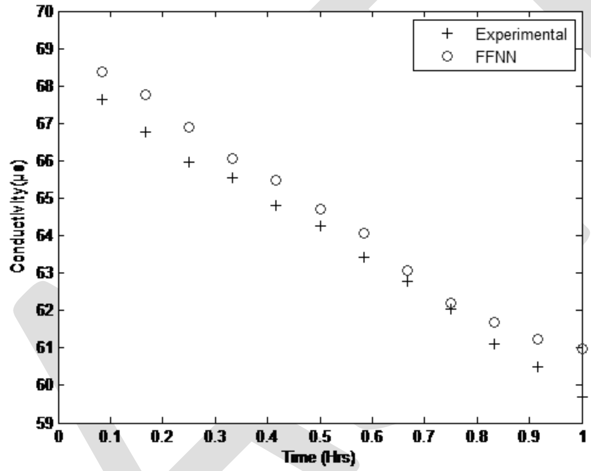

Fig. 7 FFNN Simulation for Glass Balls Packing -10 liters of lithium bromide, Height of packing =18 cm.

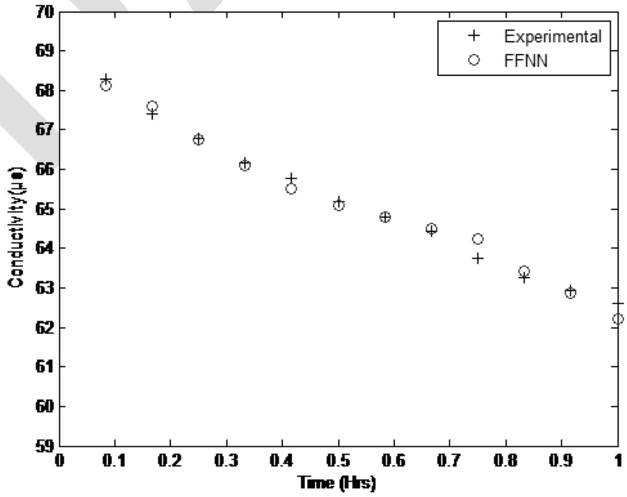

Fig. 8 FFNN Simulation for Glass Balls Packing -10 liters of lithium bromide, Height of packing =18 cm.

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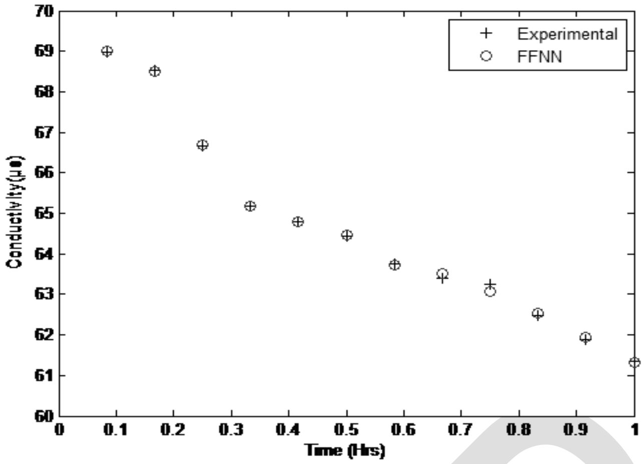

Fig. 9 FFNN Simulation for PVC Packing -10 liters of lithium bromide, Height of packing =15 cm

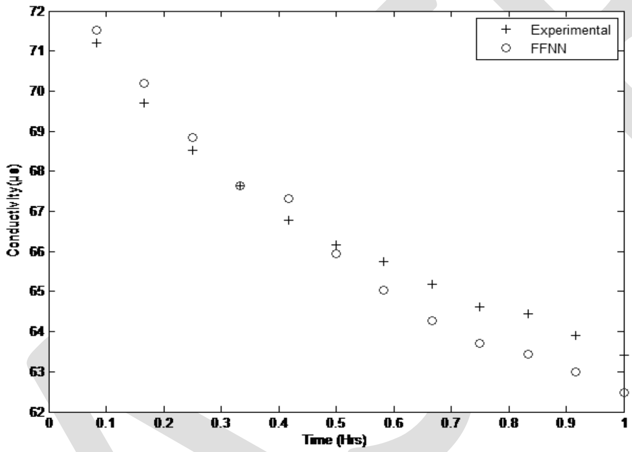

Fig. 10 FFNN Simulation for PVC Packing -10 liters of lithium bromide, Height of packing =20 cm

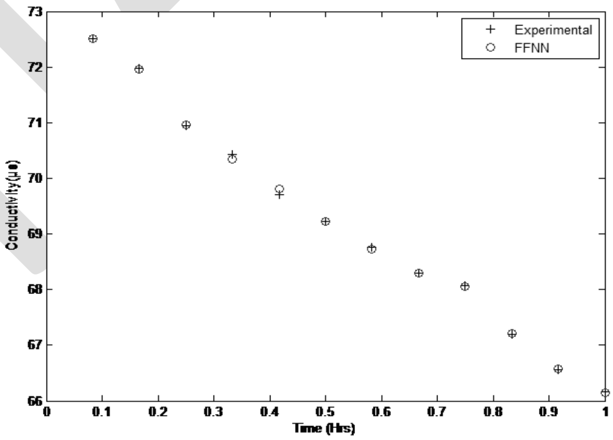

Fig. 11 FFNN Simulation for PVC Packing -10 liters of lithium bromide, Height of packing =25 cm

5. CONCLUSION

The main goal of this study was to definean approach for an artificial NN model which found to be practically applicable to a packed column absorption cooling system.It should be noted that conductivity data were completely unknown to the network. The coefficient of multiple determination (R^2-value) obtained is 0.9999 which is very satisfactory.

- The results showed that the FFNN successes in predicting the untrained values of conductivity at H=18 Cm for glass packing and H=20 cm for PVC packing.
- The results also showed that there is a good agreement between the experimental and FFNN model for all cases: trained cases and untrained cases
- The Maximum mean square error between the experimental and FFNN model was 1.5E-3which is very satisfactory.
- The FFNN model gave results for glass packing type better than the results in the case of PVC packing type.
- The FFNN is successfully applied to determine the conductivity of the Li-Br solution. The R^2-values for all cases are about 0.999, which can be considered as very satisfactory.
- The biggest advantage of FFNN is simplicity and speed of calculations.

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