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Application Of Neural Network For The Performance Prediction Of Single Stage Solar Adsorption Refrigeration System

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Abstract

This paper proposes a new approach for the performance analysis of a single stage solar adsorption refrigeration system (SAR) with activated carbon-methanol as working pair. Use of artificial neural network (ANN) has been proposed to determine the performance parameters of the system namely, coefficient of performance, specific cooling power and solar cooling coefficient of performance. The ANN used in the performance prediction was made in MATLAB (version 7.8) environment using neural network tool box. In order to gather the data for training and testing the proposed ANN an experimental system has been set up and tested for its performance at different evaporator loads. In this study the temperature, pressure and solar insolation are used in input layer. The back propagation algorithm with three different variants namely Scaled conjugate gradient (SCG), Pola- Ribiere conjugate gradient (CGP), and Levenberg-Marquardt (LM) and logistic sigmoid transfer function were used, so that the best approach could be found. After training, it was found that LM algorithm with 14 neurons is most suitable for modeling solar adsorption refrigeration system. The ANN predictions of performance parameters agrees well with experimental values with correlation coefficient (R^2) values close to 1 and maximum percentage of error less than 5%. The RMSE and covariance values are also found to be within the acceptable limits.

Key words: *Adsorption Refrigeration, Activated carbon-Methanol, Neural network*

Nomenclature

A_c	aperture area (m^2)
C_p	specific heat (kJ kg^{-1} K^{-1})

COP	coefficient of performance
SCP	specific cooling power
$\dot{m}$	mass flow rate (kg s^{-1})
p	pressure (Pa)
$\dot{Q}$	rate of heat transfer (kW)
q_u	useful heat gain (kW)
S	solar intensity (W m^{-2})
T	temperature (K)

Subscripts

1, 2, 3, 4/ a,b,c ,d	state points in the diagram
a	adsorbent
ads	adsorption/adsorbent bed
c	cooling
cyc	cycle
des	desorption
i/in	inlet
o/out	outlet
f	fluid
r	refrigerant
s	solar

1. Introduction

Environmentally friendly refrigerants with zero ozone depletion potential are to be used in the refrigerators and heat pumps according to Montreal protocol to regulate the production and trade of ozone depleting substances such as CFCs and HCFCs. Use of ozone friendly refrigerants and ability to utilize the renewable energy sources the adsorption systems can be preferred as an alternative to the conventional refrigeration systems [1, 2]. The low COP and SCP values as compared to the conventional refrigeration systems are the barriers for the commercialization of the adsorption refrigeration systems [3, 4]. For the improvement of the system a detailed computational and thermodynamic analysis must be carried out. The thermodynamic analyses of adsorption systems are complex because of the complex differential equations involved. To simplify this complex process this paper proposes a new approach (Artificial Neural Network, ANN) for the performance predictions of solar adsorption refrigeration system. The advantage of using ANN as compared to the conventional classical approaches is speed, simplicity and capability to learn from the examples. Kalogirou [5] summarized the applications of artificial neural network modeling for various energy systems reported by different investigators. Betchler et al. [6] dealt with an ANN model for predicting the performance parameters of a vapour compression chiller and reported that the experimental and ANN predicted values are found to be with in ±5%. They also modeled the steady state performance of a vapour compression heat pump with different refrigerants [7]. Chouai et al. [8] studied the ANN modeling of the thermodynamic properties of several refrigerants. Sozen et al. [9] developed an ANN model for the analysis of ejector- absorption refrigeration systems and compared its predictions with the predictions of analytic functions. Arcaklioglu [10] applied an ANN to model the COP and total irreversibility of a vapour compression refrigeration system. Islamoglu [11] studied ANN modeling of outlet temperature and refrigerant mass flow rate of a suction line heat exchanger used in the refrigerators. Ertunc and Hosoz [12] predicted various performance parameters of a vapour compression refrigeration system with an evaporative condenser using ANNs. Rajindar et al. [13] use fuzzy model for the prediction of refrigerant mixture temperature at evaporator outlet. Mohanraj et al. [14] model a direct expansion solar assisted heat pump using ANN to predict its performance parameters. In this study, the ANN approach is used for investigating the performance of solar adsorption refrigeration system. Utilising the data obtained from the experimental system, an ANN model for the system is developed. With the use of this model, various performance parameters of the system namely the coefficient of performance, specific cooling power and solar cooling coefficient of performance are predicted and compared with the actual values.

2. Description of the system and experimental data

2.1 Experimental setup

The schematic diagram of solar adsorption refrigeration system used to conduct experiments is depicted in Fig.1, and its photograph is shown in Fig.2 . The specifications of components used in the system are given in Table 1.

Table 1

The specifications of main components of solar adsorption refrigeration system

Component	Technical specification
Condenser	Type: Shell and Coil Capacity: 200 W Water cooled
Evaporator	Type: Shell and Coil Material: Copper Capacity: 150 W
Expansion device	Capillary tube
Adsorbent bed	Type: Rectangular Material: Stainless steel
Parabolic solar concentrator	solar concentrator of area 3 m^2 made of stainless steel.
Adsorbent	Activated carbon Type: Granular Particle size: 0.25 mm
Adsorbate	Methanol

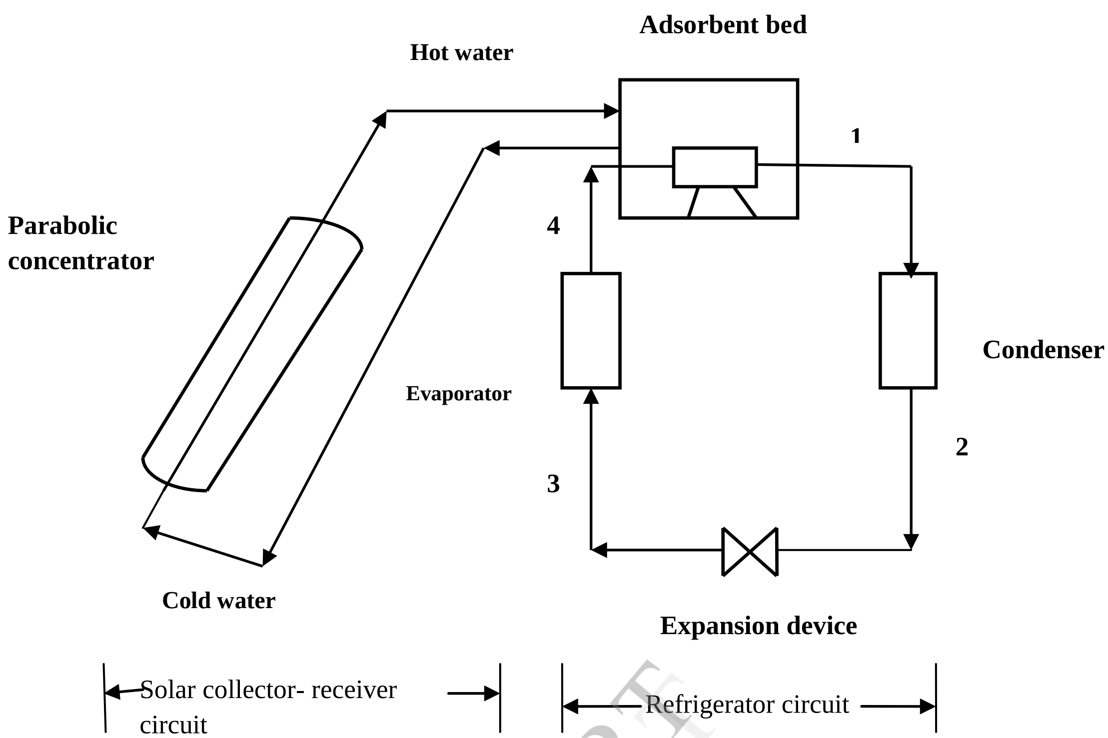

Fig. 1 Schematic of Solar adsorption refrigeration system

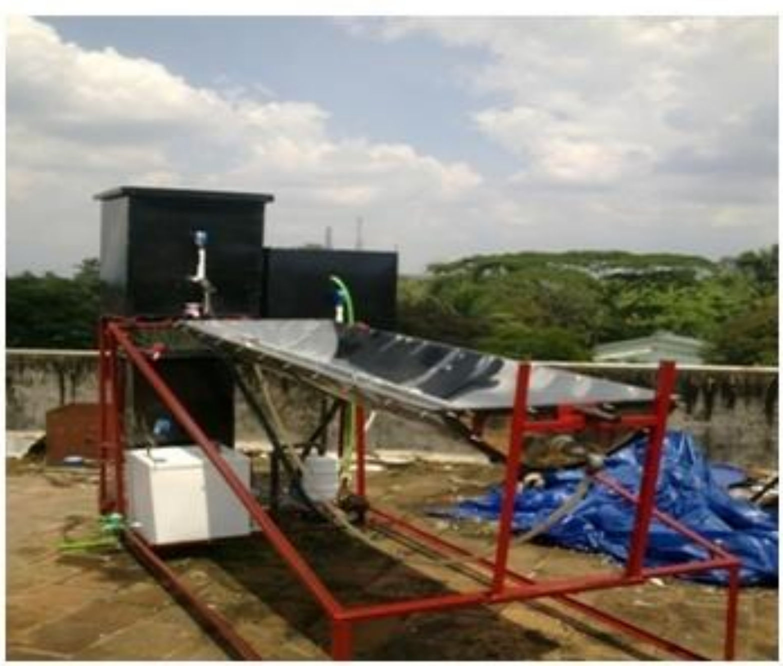

Fig. 2 Photograph of the system

The system consists of a parabolic solar concentrator, water tank, adsorbent bed, condenser, expansion device (capillary tube) and evaporator. The solar concentrator is tilted at an angle of 20^{o} with respect to horizontal and it is oriented towards east-west direction to maximize the solar insolation incident on the receiver. The adsorbent bed is filled with 3.5 kg of activated carbon. The adsorbent bed along with the activated carbon is placed inside the water tank made up of GI sheets by using suitable stands for support.

2.2 Working of system and experimental procedure

The experimental set up is located in the Solar Energy centre at National Institute of Technology Calicut, Kerala, India. The solar adsorption refrigeration system is tested under the meteorological conditions of Calicut (latitude of 11.15^{o} N, longitude of 75.49^{o} E) during April 2011. Figure 3 shows a typical single stage vapour adsorption compression cycle on the Clapeyron diagram.

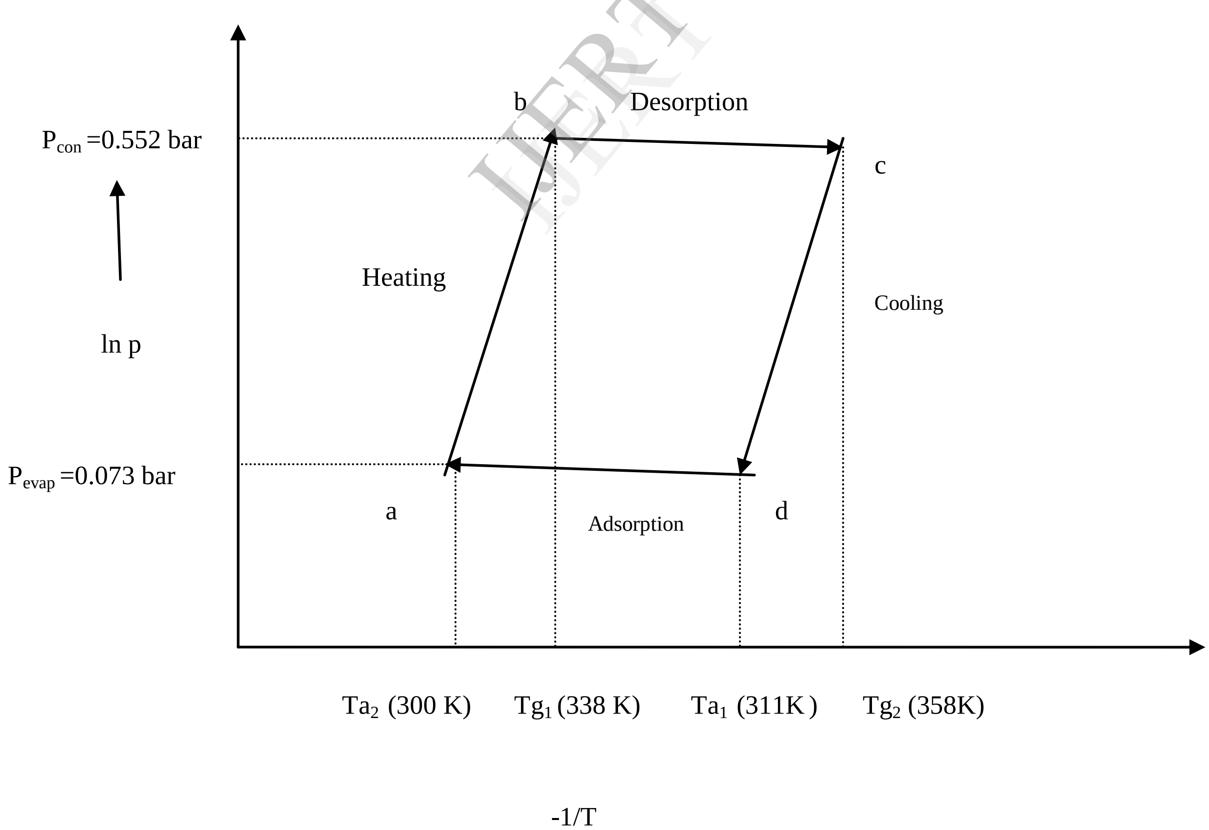

Fig. 3 The Clapeyron diagram of ideal adsorption refrigeration cycle.

The system was initially charged with methanol refrigerant. The heating of water starts in the morning through the solar concentrator by natural circulation. With the increase in water temperature, the temperature in the adsorbent bed increases (Ta_2-Tg_1). This causes the vapour pressure of the adsorbed refrigerant to reach up to the condensing pressure (P_{con}), desorption at constant pressure is initiated. The desorbed vapour is liquefied in the condenser. The high pressure liquid refrigerant is expanded through the expansion device to the evaporator pressure. The low pressure refrigerant then enters the evaporator. The temperature of adsorbent bed continues to increase (Tg_1-Tg_2) due to solar heating. In the evening, the hot water from the tank should be drained off and the tank is refilled with cold water. The temperature of the adsorbent bed reduces rapidly (Tg_2-Ta_1) and pressure in the adsorbent bed drops to the evaporator pressure (P_{con}-P_{evap}). The cooling by cold water and low ambient temperature causes the adsorbent bed temperature to drop from Ta_1 to Ta_2. During experimentation, the temperature and pressure of refrigerant at different points of the system are noted down when the evaporator temperature reaches at steady state.

2.3 Measurements

A digital pyranometer with an accuracy of ± 5 W/m^2 is placed near the solar collector to measure the instantaneous solar insolation. Pressure is measured during heating (desorption) of refrigerant i.e. condensing pressure and during cooling (adsorption), i.e. evaporator pressure. The pressure gauges are fixed at the adsorbent bed in order to measure the pressure inside the adsorbent bed at each stages of adsorption and desorption processes. The temperature at various points in the solar adsorption refrigeration system is measured by calibrated thermocouples. The various temperatures observed are: (1) temperature of the adsorbent bed during various processes, (2) temperature of the refrigerant at inlet and outlet of the condenser, expansion device exit and evaporator outlet (3) temperature of water entering the water tanks and (4) temperature of chilled water in the evaporator box.

3. Performance parameters

The main performance parameters used for the present study are cycle coefficient of performance, specific cooling power and solar cooling coefficient of performance [15, 16].

3.1 Cycle COP

Cycle COP is defined as the ratio of cooling effect to the total energy required for desired cooling effect.

$$\mathrm{COP} = \frac{\text{cooling effect}}{\text{total energy input}}$$

$$\mathbf{COP} = \frac{\mathbf{Q_e}}{\mathbf{Q_T}} \qquad (1)$$

The total energy input to the system is given by,

$$\mathrm{Q_T} = \mathrm{Q_{isosteric\ \ heating}} + \mathrm{Q_{desorption}} \qquad (2)$$

3.2 specific cooling power (SCP)

Specific cooling power indicates the size of the system as it measures the cooling output per unit mass of adsorbent per unit time. Higher SCP values indicate the compactness of the system.

$$SCP = \frac{\text{Cooling effect}}{\text{Cycle time per unit of adsorbent mass}}$$

$$\mathrm{SCP} = \frac{\mathrm{Q_e}}{\mathrm{m_a} \times \tau_{\mathrm{cycle}}} \qquad (3)$$

3.3 Solar COP

Since the system is solar powered the solar coefficient of performance is also to be defined. This is defined as the ratio of cooling effect to the net solar energy input.

$$\text{Solar COP} = \frac{Q_e}{Q_s} \qquad (4)$$

3.4 Average efficiency of solar concentrator

The efficiency is given by

$$\boldsymbol{\eta = \frac{q_u}{S\,A_c}} \qquad \mathbf{(5)}$$

Where useful heat gain is given by,

$$\boldsymbol{q_u = \dot{m}C_p\left(T_{fo} - T_{fi}\right)}$$

4. Neural Network Design

Artificial intelligent (AI) systems are widely used as a technology offering an alternative way to tackle complex and ill defined problems. They can learn from examples in the sense that they are able to handle noisy and incomplete data, are able to deal with the non linear problems, and once trained, can perform prediction and generalization at high speed [17]. Artificial neural network system resembles human brain in two aspects, the knowledge is acquired by the network through learning process, and the neuron connection strengths known as synaptic weights are used to store the knowledge. Artificial neural network is an interconnected assembly of simple processing elements, units or nodes, whose functionality is loosely based on the animal neuron. The fundamental processing element of a neural network is a neuron. Basically a biological neuron receives input information from other sources, combines them in other ways, performs generally a non linear operation and outputs the final results. The network usually consists of an input layer, some hidden layer and an output layer [17]

An important stage of a neural network is the training step, in which an input is introduced in the network together with the desired output and the weights are adjusted so that the network attempts to produce the desired output. There are different learning algorithms. A popular algorithm is a standard back propagation algorithm which has different variants. It is very difficult to know which algorithm is faster for the given problem. The artificial neural network with back propagation algorithm learns by changing the weights and these changes are stored as knowledge. Some statistical methods, in fact root mean square (RMSE), correlation coefficient (R^2), and covariance (COV) are used for comparison [6].

$$RMSE = \left(\frac{1}{n}\sum_{j=1}^{n}\left[t_j - o_j\right]^2\right)^{\frac{1}{2}} \tag{6}$$

$$R^2 = 1 - \left(\frac{\sum_j\left[t_j - o_j\right]^2}{\sum_j\left(o_j\right)^2}\right) \tag{7}$$

$$COV = \frac{RMS}{\sum_j o_j} * 100 \tag{8}$$

Where t is the target value, o is the output value, n is the pattern.

5. Modelling of Solar Adsorption Refrigeration System by Artificial Neural Network

The performance parameters such as cycle COP, SCP and solar COP are predicted by using artificial neural network. The architecture of an ANN used for the performance prediction of SAR indicating input and output is shown in Fig. 4.

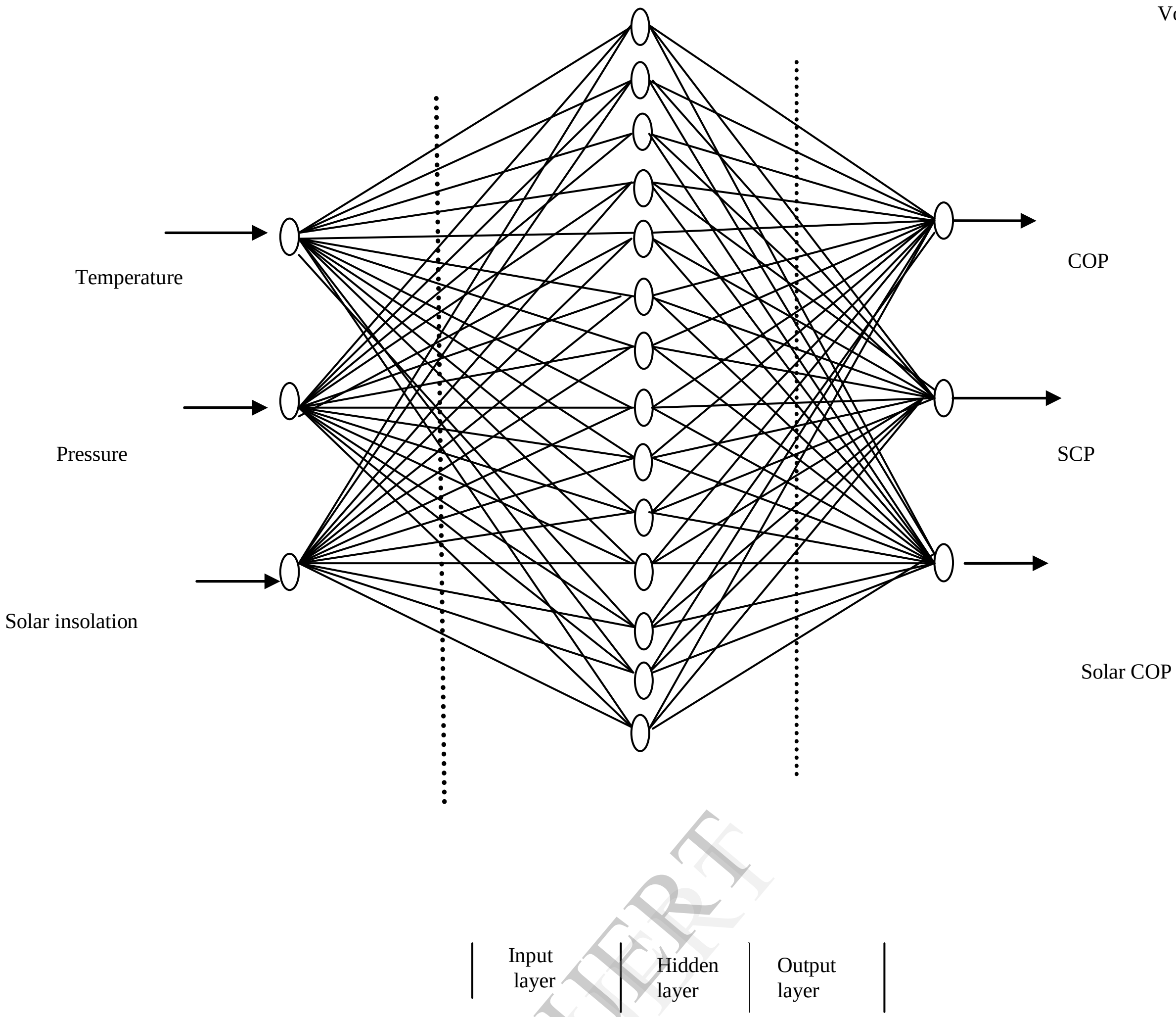

Fig. 4 Artificial neural network

In this study the pressure, temperature and solar intensity are used as input parameters where as the cycle coefficient of performance, specific cooling power and solar cooling coefficient of performance are predicted in the output layer. As seen from the equations (1) (3) and (4), the cycle COP, specific cooling power and solar cooling coefficient of performance calculations utilizing cooling effect produced. The cooling effect produced is depends upon the enthalpy of refrigerant, which in turn varies as a function of pressure and temperature of the refrigerant. The total energy required for isosteric heating and desorption is supplied by solar heated water which surrounds the adsorbent bed. Hence the performance of SAR system is mainly affected by the ambient parameters (ambient temperature and solar intensity) and system operating parameters (such as condensing and evaporator temperatures and pressures). So the temperature, pressure and solar insolation are selected as input for the prediction of various performance parameters of the system.

The back propagation algorithm is used in feed forward single hidden layer network. The back propagation algorithm has different variants. The back propagation algorithms gradient descent and gradient descent with momentum are too slow for practical problems [18] because they require small learning rates for stable learning. The faster algorithms such as Scaled Conjugate Gradient (SCG), Pola –Ribiere Conjugate Gradient (CGP) and Levenberg- Marquardt (LM) are used in the study. The performance of ANN is affected by two important characteristics of the network (number of hidden layers and number of neurons in the hidden layers**).** In the training an increased number of neurons from 10 to 18 is used in hidden layer to define the output accurately. The output of network is compared with the desired output at each presentation and errors are computed. These errors are back propagated to the neural network for adjusting the weight such that the errors decrease with each iteration and ANN model approximates the desired output. After enough trials with the different configurations (changing the number of neurons in hidden layer, changing the transfer functions (log-sig and tan-sig), changing the variants (LM,SCG and CGP)), it is decided that the network consists of one hidden layer with 14 number of neurons and Levenberg-Marquardt (LM) variant is optimum for this system. The neurons in the hidden layer have no transfer functions. The inputs and outputs are normalized in the range 0-1. Logistic sigmoid (log-sig) transfer function is being used in ANN.

The transfer function used is given by

$$f(Z) = \frac{1}{1+e^{-Z}} \tag{8}$$

Where Z is the weighted sum of inputs.

The artificial neural network used in SAR modeling was made in the MATLAB (version 7.8) environment using a neural network tool box. The available data obtained from the experimental observations are divided into training and testing sets. The range of input data used for the ANN modeling is shown in Table 2. The data set consists of 115 input values. From these 105 data sets are used for training and the remaining is used for testing the network. The performance parameters of the network with log-sig transfer function and different variants are shown in Table 3. The weight values of L-M algorithm with 14 neurons are shown in Table 4.

Table 2

Range of experimental data used for ANN modelling

Parameter	Range	
	Min	Max
Temperature (^oC)	8	92
Pressure (bar)	0.051	2.57
Solar insolation ($W\ m^{-2}$)	300	890

Statistical values of the different networks evaluated

Table 3

Algorithm	R^2	RMSE	COV
LM-13	0.9915	0.027	0.308
LM-14	0.9987	0.0115	0.158
LM-15	0.9945	0.0148	0.159
SCG-13	0.9974	0.049	0.876
SCG-14	0.9944	0.087	0.190
SCG-15	0.9837	0.089	0.204
CGP 13	0.9964	0.0245	0.198
CGP 14	0.9951	0.0213	0.163
CGP 15	0.9932	0.023	0.183

Weight values obtained from L-M algorithm with 14 neurons

Table 4

$$z=w_{1j}*T+w_{2j}*P+w_{3j}*S+w_{4j}$$

Neuron i	w_{1i}	w_{2i}	w_{3i}	w_{4i}
1	-0.91927	-0.35994	0.017768	1.2679
2	-1.1909	1.0395	0.55248	-0.33154
3	-0.89674	-0.17341	0.17769	-0.96772
4	0.081151	-0.78508	-0.44771	0.10847
5	-0.83277	-0.57291	0.67359	-0.65353
6	0.80216	1.4145	0.80689	-0.52273
7	0.21775	-1.1427	1.5902	0.95075
8	0.91623	-0.69765	0.32376	-1.3003
9	-0.3267	-0.52459	-1.2276	-0.88857
10	-0.37511	-1.1491	0.54505	-0.16602
11	0.64497	0.58782	0.55225	-1.2174
12	-1.7065	-0.51768	0.082636	0.28908
13	-0.42355	0.97389	1.015	1.1233
14	0.11845	-0.50894	-1.5245	0.28904

6. Results and Discussion

6.1 Experimental results

Average values of performance parameters of the system obtained by conducting different experiments are shown in Table 5.

Table 5

Average values of performance parameters

Parameters	Value
Refrigerating effect (W)	60.71
Cycle COP	0.1796
Solar COP	0.0735
SCP (W kg^{-1})	45.83
Average efficiency of solar collector	35 %

The variations of refrigerant temperature and solar insolation are shown in Figs. 5 and 6.

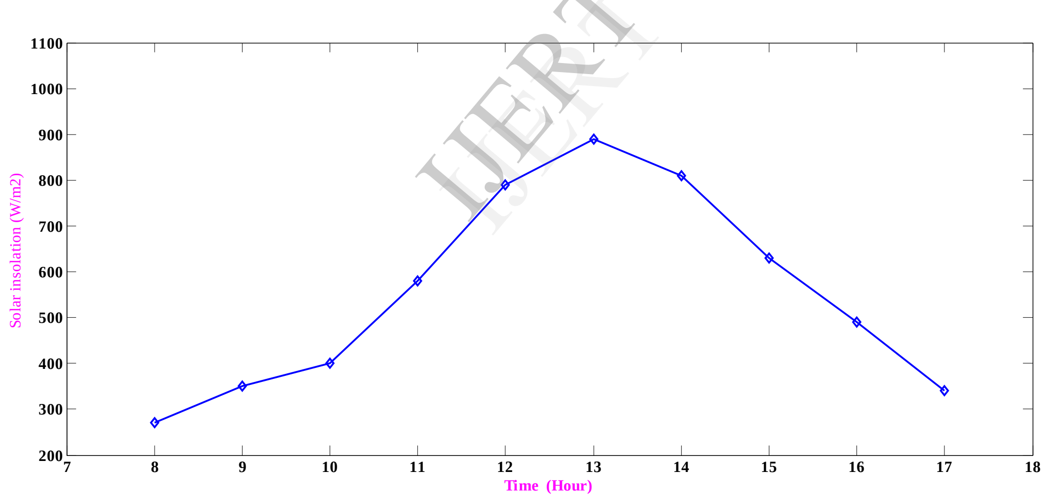

Fig. 5 Solar insolation data

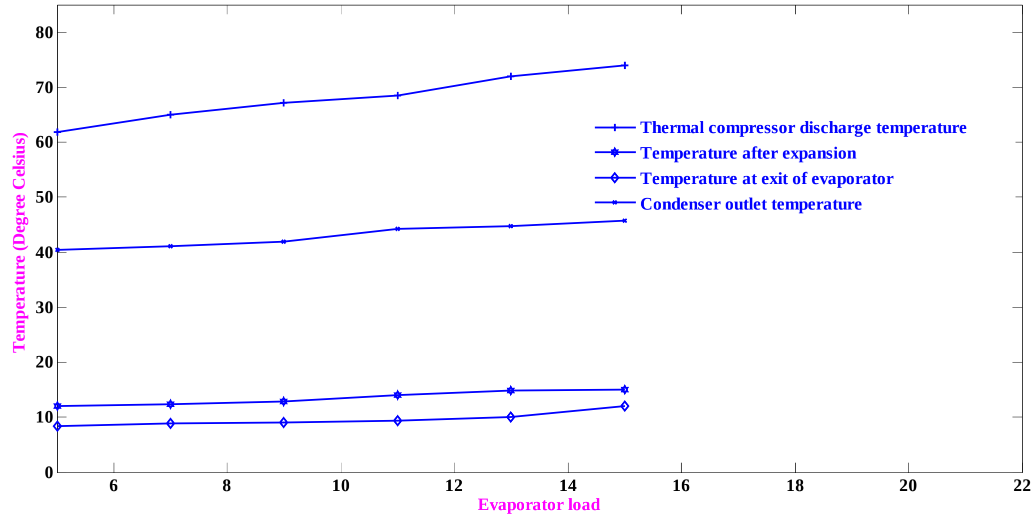

Fig. 6 Variation of refrigerant temperature

From the Fig. 6 it is observed that the average temperature of the refrigerant measured at the thermal compressor suction and exit are 12.4°C and 64.8°C, respectively. The average temperature at the inlet and outlet of expansion device are 42.8°C and 14.2°C, respectively.

6.2 Performance of the network

The experimental and ANN predicted results with statistical values such as RMS, COV, and R^2 for the three different parameters are shown in Table 6.

Comparison between the experimental and ANN predicted results

Table 6

Experimental			**ANN Predicted**			**% error**		
Cycle COP	SCP	Solar COP	Cycle COP	SCP	Solar COP	Cycle COP	SCP	Solar COP
0.104	17	0.057	0.1025	16.4	0.055	-1.44	-3.52	-3.508

0.15	25	0.062	0.148	24.2	0.0608	-2	-2.45	-1.93
0.169	42	0.07	0.172	41.5	0.071	1.78	-1.1902	1.42
0.19	52.5	0.08	0.1935	53.1	0.0809	1.84	1.142	1.125
0.225	64	0.082	0.229	64.4	0.0829	1.77	0.62	1.09
0.24	71.8	0.09	0.244	72	0.0908	1.6	0.278	0.89

R^2	**0.99961**	**0.9998**	**0.9986**
RMSE	**0.0325**	**33.17**	**0.2803**
COV	**0.18**	**0.73**	**3.81**

The maximum percentage of error is 2%, 3.52% and 3.058% for the cycle COP, SCP and solar COP, respectively. The results also show that R^2 values are very close to 1 for all the data and RMSE values are very small. It is clear that the neural model gives a very accurate representation of the statistical data over the full range of operating conditions and indicates good accuracy of the neural network to represent the performance predictions of the solar hybrid adsorption refrigeration system. As seen from the results the performance parameters are obviously calculated within the acceptable uncertainties.

The experimental and ANN predicted values of cycle COP, specific cooling power and solar cooling coefficient of performance are shown in Figures 7-9.

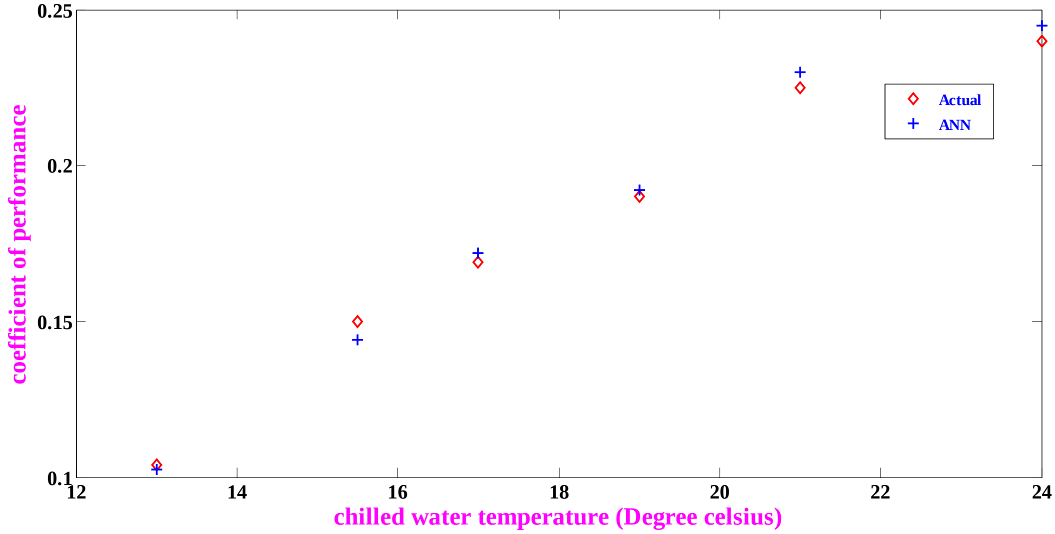

Fig. 7 Comparison of actual and ANN predicted COP values

Figure 7 shows the ANN predicted results and experimentally calculated values with different evaporator loads. In this case an ANN predicted value yields a correlation coefficient of 0.99961. The RMSE and COV values are found to be 0.0325 and 0.18, respectively. The coefficient of performance is an important parameter considered for the rating of SAR system.

A plot of experimental and ANN predicted values for the specific cooling power against chilled water temperature is shown in Fig. 8. These predictions yield a correlation coefficient of 0.9998, RMSE and COV values of 33.17 and 0.73, respectively. The comparison shows that the ANN predicted values are closer to experimental results. Specific cooling power is also an important parameter that determines the size of the system.

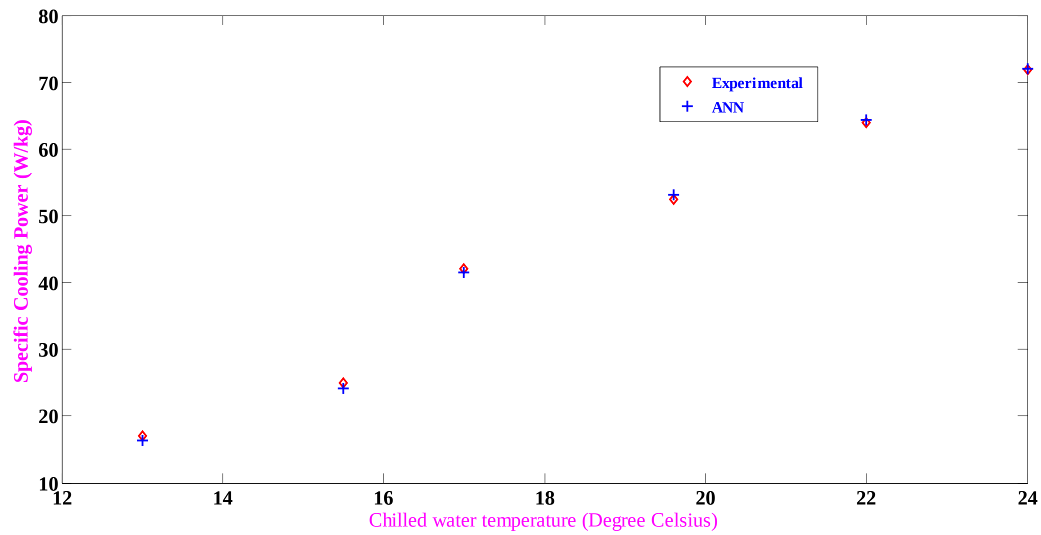

Fig. 8 Comparison of experimental and ANN predicted values of specific cooling power

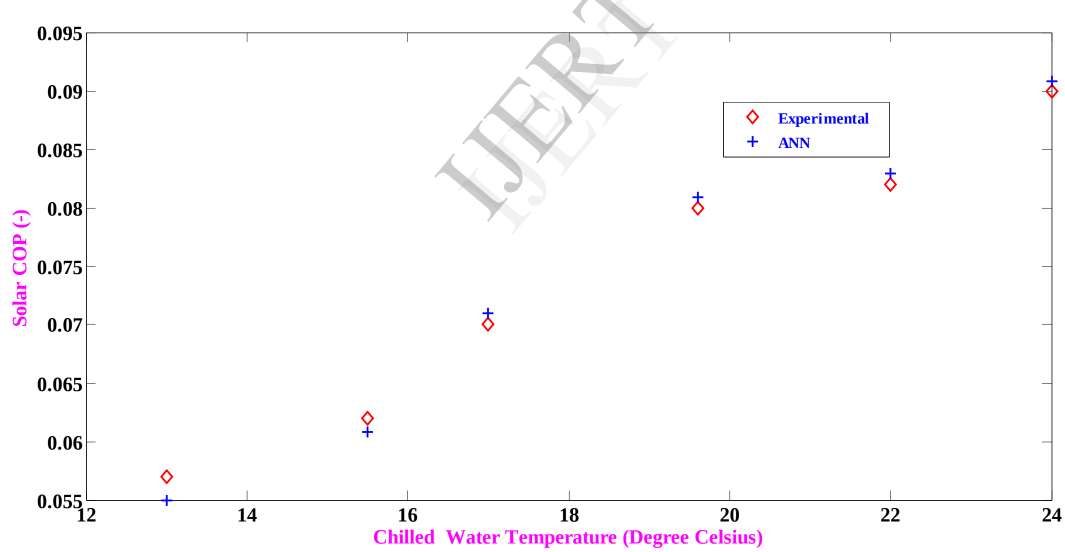

Fig. 9 Comparison of ANN predicted and experimental values of solar cooling COP

Figure 9 shows the experimentally measured and ANN predicted values of solar coefficient of performance for different evaporator loads. The ANN predictions for the solar COP yield a correlation coefficient of 0.9986 with RMSE and covariance values of 0.2803 and 3.81, respectively. The results confirmed that ANN predicts exactly the solar cooling COP for different chilled water temperature. The solar cooling coefficient of performance is an important parameter considered for determining the performance of a solar collector used in a SAR system. The solar COP is also a significant parameter that influences the performance of whole system.

7. Conclusions

The artificial neural network approach has been applied to model the solar hybrid adsorption refrigeration system to predict the performance parameters at different evaporator loads. In order to gather the data for training and testing the proposed ANN, an experimental system has been set up and tested for its performance at different evaporator loads. Using the three different parameters namely temperature, pressure and solar insolation an ANN model based on the back propagation algorithm was proposed. The artificial neural network was used for predicting the performance of the system in terms of coefficient of performance, specific cooling power and solar cooling coefficient of performance. The performance of ANN predictions was measured using the three criteria root mean square error, correlation coefficient and coefficient of variance. The network model demonstrated good results with correlation coefficients in the range of 0.9986-0.9998 and percentage of error 0.278% - 3.52%. This approach helps the researchers to predict the performance of SAR system at different evaporator loads with limited number of experiments instead of performing a comprehensive testing or developing a complicated mathematical model.

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