Australian Journal of Basic and Applied Sciences, 9(27) August 2015, Pages: 1-8

ISSN:1991-8178

Australian Journal of Basic and Applied Sciences

Journal home page: www.ajbasweb.com

Radial Basis Function (RBF) based Prediction of Compact Solar Refrigeration System Performance

Achuthan M and Murali RV

Caledonian College of Engineering, Sultanate of Oman, Department of Mechanical and Industrial Engineering, Post Box.2322, PC 111, Muscat, Sultanate of Oman

ARTICLE INFO

Article history:
Received 23 June 2015
Accepted 25 August 2015
Available online 2 September 2015

Keywords:
RBF model, Solar Refrigeration, Performance Evaluation, Neural Networks

ABSTRACT

Basic ground works on application of artificial neural networks (ANN) into prediction of performance of solar refrigeration system have been already laid by the authors. The main motivation for the above work is that the research domain on solar energy and its applications continues to remain a potential area of research among the young researchers. This is clearly evident from growing number of research articles and publications in the recent times from this thrust area. Particularly, number of research publications on one such application namely, refrigeration systems, is on the rise because of the potential benefits derived from using solar energy for refrigeration purposes. The common objective of all these research endeavors is to maximize the energy usage from the Sun although solar insolation is not constant every day. At present in this paper, authors have expanded their endeavor of experimenting their study and analysis on use of a different class of neural networks on the performance of compact solar refrigeration system (CSRS). New class of neural network used in this attempt is radial basis function (RBF) which is proposed to evaluate the performance of the CSRS for different climate conditions. Metrological values obtained through an experimental set up are supplied as input values to RBF network class while the actual performance of CSRS pertaining to the recorded data are used as target values to drive the ANN training process. Results from the application of RBF into the present study affirm that a number of ANN techniques would have a greater potential in predicting and evaluating the performance CSRS. Advantages and limitations of such ANN application is analysed at the end and finally, further possible works in this direction are identified.

© 2015 AENSI Publisher All rights reserved.

To Cite This Article: Achuthan M and Murali RV, Radial Basis Function (RBF) based Prediction of Compact Solar Refrigeration System Performance. ***Aust. J. Basic & Appl. Sci.,*** *9(27): 1-8, 2015*

INTRODUCTION

Solar refrigeration is a technique where in conventional cooling systems such as Vapour Compression Refrigeration (VCR) and Vapour Absorption Refrigeration (VAR) systems, utilize the solar energy for their operation. Figure 1 presents an operational flow diagram of solar refrigeration system with absorption cycle. The advantages of resorting to use of solar energy in those cooling systems are reduced impact on the environment, much reduced cooling load during winter seasons and finally cost effectiveness (Achuthan, 2011). Further harvesting becomes cheaper and more effective at this age, thanks to the introduction of advanced techniques using nano to macro technologies on collectors and PV panels. PV panels are used in VCR systems and whereas solar collectors are used in VAR systems. Overall performance of the solar system depends on effective recovery and utilization of solar energy and further concentrators used to boost the additional temperature of the water in the solar collector (Hammad *et al*.1992). Specific efforts such as development of adsorption chiller using solar energy were carried out in recent years and were implemented in an air conditioning system driven by solar energy (Wang *et al*. 2007). The heat source used to drive the adsorption chiller is variable at any moment because the solar radiation intensity or the waste heat from engines varies frequently. Further research (Pongsid 2001) explored other possible methods of optimizing the energy production and prediction of energy values of CSRS experimental set up and ANN model. The performance of the CSRS is dependent on range, rate, and average temperature of the heat source. A design of a cooling system using waste Heat recovery in a refractory

Corresponding Author: Achuthan M. Assistant Professor, Caledonian College of Engineering, Sultanate of Oman, Department of Mechanical and Industrial Engineering, Post Box.2322. PC 111, Muscat. Sultanate of Oman.
E-mail: achuthan@caledonian.edu.om

industry was developed (Aziz 2012) in order to make an organization self-reliant to meet its energy demand and needs as well as resorting to a better method of waste disposal. Another effort in 2000 reviewed the endeavours thus far directed into the field of solar powered air-conditioning systems with the absorption pair of lithium bromide and water (Li 2000). Through a number of attempts reported in this paper to improve the performance of the solar applied air-conditioning subsystems, it is seen that the generator inlet temperature is the most important parameter in the design and fabrication of the system. Subsequently, a mathematical model of a solar-powered, single stage, absorption cooling system, using a flat plate collector and water–lithium bromide solution, was made and a critical study and analysis though this model, it is found that high reference temperature increases the system COP and decreases the surface area of system components but lower reference temperature gives better results for FNP than high reference temperatures (Mittal *et al*. 2006).

In the recent times, it is observed that ANN classes are liberally put into use for various tasks relating with cooling systems and subsystems. In 2009, a technical paper presented the suitability of ANN to predict the performance of a direct expansion solar assisted heat pump (DXSAHP). The results obtained from the above work showed that Lavenberg–Marguardt (LM) with 10 neurons in the hidden layer is the most suitable algorithm with maximum correlation coefficients (R2) of 0.999, minimum root mean square (RMS) value and low coefficient of variance (COV). The reported results confirmed that the use of ANN for performance prediction of DXSAHP is acceptable [10]. The current attempt takes reference from the above paper and also additional literatures associated with ANN applications (Achuthan *et al*. 2013) to various other domains in order to structure ANN class and design its architectural parameters.

Developing countries, particularly Southeast and Far East, are still at their infancy in energizing remote areas where electric grids are not connected. Tribes those who are living in the remote places require to safeguard their rare products like herbs and honey etc. against contamination which are in high demand in the main land even internationally.

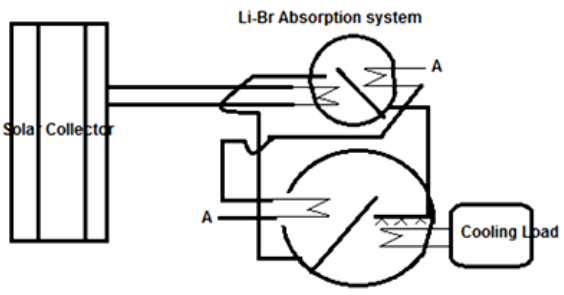

Fig. 1: Solar refrigeration system.

Therefore, it is essential to devise a small refrigeration system to help the needy people not connected with main grids. The earlier proposed system is a small capacity ie. compact refrigeration system utilizes the solar energy. ANNs continue to be employed in a number of engineering applications by researchers for the purpose of classification or prediction, on the basis of known training datasets. They strive to behave in a much similar way as the brain of human beings and it is deemed to perform tasks through gaining knowledge obtained by learning or training process. The human brain consists of a large number (approximately 1011) of highly connected neurons those have many desirable characteristics not present in modern sequential computers.

More precisely, ANNs have the ability to learn from experience, adapt to new situations, and provide reliable classifications and approximations of data. It is evident from literature related to neural networks (Murali, R.V *et al* 2010) that wider use of ANN techniques. ANN classes consist of processing units called artificial neurons (interconnection of simple computing cells) to achieve desired performance in the chosen task. Each neuron or node receives an input data, processes it, and produces an output that acts as an input to other nodes in the network. The connections among the nodes and various learning algorithms to alter the weight factors between the connecting nodes are the strength and flexibility of neural networks. Neural networks are capable of achieving optimal and near-optimal solutions of nonlinear problems through input-output mapping and adaptive characteristics.

A. Problem definition:

Performance evaluation and prediction of the CSRS is the objective of present attempt and this is carried out with a help newly introduced ANN class namely RBF. To achieve the expected task, a CSRS with capacity of 1.75 kW is designed, constructed and operational with Li-Br and H2O as working substances. The source of heat to this system is the solar energy which is recovered by the solar collectors and from this set up, hot water stream is circulated to feed heat to CSRS. This implies that the heat energy is supplied to the CSRS by hot water at the electrical generator. The ratio of the refrigeration effect to the heat supplied is the co-efficient of performance of the system (CoP) which is the measure of the performance of the CSRS. Since the load on the system is fixed, the performance of the system mainly depends on the heat supply which inturn is based on the solar insolation. The performance of the system is studied for over a period of one year in particular location where this system is installed. The CoP of the system is experimentally found to vary from 0.3 to 0.5 during

the abovementioned time period. Subsequently, ANN class RBF is designed, structured and deployed to predict the performance of the system. The training data for this network constitute the experimental readings taken from the set up on day-wise atmospheric temperature, relative humidity, solar insolation and the CoP of the system.

Applicability of Artificial Neural Networks:

A. Artificial neural network:

ANNs, a network classifier based on human biological nervous systems, show enough evidence of classifying the input data of more complex and nonlinear problems through learning and training. Applications of ANNs have been very wider particularly in engineering application areas such as energy optimization, performance prediction solar cells and so on. ANNs have been employed in a number of applications owing to high effectiveness to perform classification, function approximation, predicting outputs for unknown inputs through valid training datasets.

ANN is originally developed to simulate the function of the human brain or neural system, resulting in systems that learn by experience. The use of ANNs has increased dramatically in recent years in the field of applied mechanics, logistics, manufacturing and etc. in order to model complex system behavior.

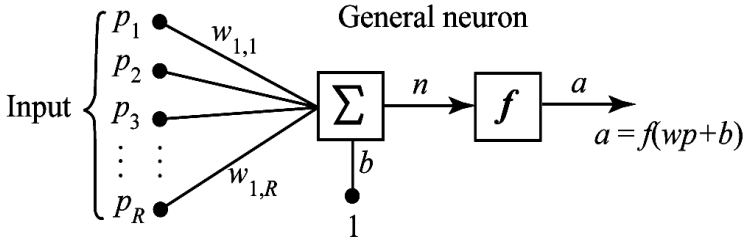

Fig. 1: General ANN Structure.

ANN involves processing elements or neurons and interconnection weights between neurons. These interconnection weights determine the nature and the strength of the connection between neurons. In ANN, information processing occurs at many neurons and signals are passed between neurons over interconnection links. Each interconnection link has its associated weight that multiplies the signal transmitted and each neuron applies an activation function to determine its output signal. A single neuron with R element input vector is shown in Figure 1.

One of the widely used classes of ANNs is RBF network, which is deployed in this attempt to formulate a predictive model and to map a set of inputs derived from an experimental set up onto a set of outputs i.e., coefficient of performance index.

B. Radial Basis Function (RBF) Networks:

RBF, one of the most popular network classes of neural networks, consists of two layers whose output units form a linear combination of the basic functions computed by the hidden units and Gaussian spheroid function is used in this structure. Figure 2 presents the general structure of a RBF network with R inputs with corresponding weight vector w and the bias b.

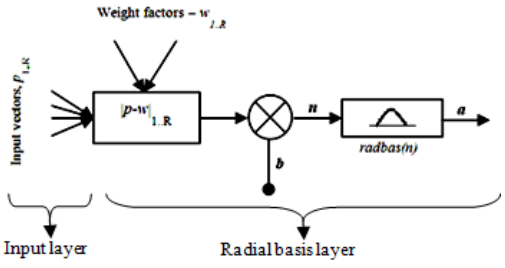

Fig. 2: RBF network structure.

The transfer function for a radial basis neuron is given by the equation (1).

$$a = \text{radbas}(n) = e^{-n^2} \quad (1)$$

From the previous study undertaken by the authors, feed forward classes of neural networks take more training time to reach convergence process because of many training factors such as hidden neurons, training tolerance, initial weight distribution and function gradient. However, a RBF network's learning is based on three parameters namely number of pattern units, width of a radial basis function and the initial weight distribution between the pattern and output layers. This has simplified the operation and the network is able to classify or predict clusters of data quickly and accurately.

It is also observed from the literature that though RBF networks need more neurons than other feed forward networks, the training time is very much reduced although processing time may be more. This is because the linear weights associated with the output layer are treated separately from the hidden layer neurons. The radial basis function has a maximum of 1 when its input is 0. As the distance between w and p decreases, the output increases. Thus, a RBF neuron acts as a detector, producing 1 whenever the input p is identical to its weight vector w.

Prediction of coefficient of performance:

An experimental set up on CSRS was developed earlier and input datasets are continuously taken from this setup in order to calculate coefficient of performance (CoP) using standard formulae. These data are used as training datasets for the RBF structure and an unknown dataset is fed into the network to see the capability of the network in predicting the values of CoP.

An extended new approach based on ANN is developed in this study to determine the performance of CSRS. The experiments are performed under the meteorological conditions of Tiruvannamalai, India. Performance parameters obtained from the experimentation are used as training data. Ambient temperature, solar insolation, declination angle, azimuth angle and tilt angle are used in the input layer and the coefficient of performance is the output. Estimated values are compared with measured goal values in terms of Sum squared error goal value.

Despite the fact that feed forward artificial neural networks prove to be a preferred area of research in the recent past, there are still perceived drawbacks in relation to the development of an ANN model and eventual uncertainty on its reliable performance.

A number of different approaches have investigated all aspects of the ANN modeling procedure, from training data collection and pre/post-processing to elaborate training schemes and algorithms. Increased attention is especially directed to proposing a systematic way to establish an appropriate architecture in contrast to the current common practice that calls for a repetitive trial-and-error process, which is time-consuming and produces uncertain results.

ANN training:

In the process of predicting the performance of CSRS using ANN, an ANN algorithm is developed for the RBF network. Training is given to the network and is tested for minimum error by varying the network design parameters and the predicted values are obtained. The predicted values are compared with the original values evaluated from the experiment for the accuracy of the prediction by evaluating the root mean square value.

During the training, each of the connecting weights of the individual neuron is compared with input signals. The distance between the connecting weights determines the output of hidden neurons as well as the product of input vector and bias. Bias is an additional scalar quantity being added between neuron and fictitious neuron. The output is propagated in a feed-forward direction to output layer neuron, which will give the output, if the connection weights are close to the input signal. This output is compared with target vector.

Table 1: RBF Input Settings.

Sum squared error goal value	Spread Constant	ANN function used	Maximum number of neurons	Number of neurons to add between displays
0.00001	1000	newrb	180	25

Table 2: Sample Training Data

Reading No	Insolation value	Temperature ^{o}C	RH %	COP value
1	4.43	24.15	81.13	0.26
2	4.45	23.66	74.87	0.29
3	4.46	24.86	65.19	0.28
4	4.46	31.44	54.73	0.36
5	4.47	29.01	63.55	0.31
6	4.5	26.78	76.47	0.30
7	4.52	25.13	87.91	0.29
8	4.52	27.94	83.42	0.33
9	4.55	23.2	73.65	0.28
10	4.6	33.97	48.33	0.35

11	4.62	26.9	89.48	0.29
12	4.62	27.7	87.3	0.29
13	4.66	26.48	85.17	0.31
14	4.66	32.16	54.94	0.34
15	4.67	24.24	74.74	0.24
16	4.69	25.64	70.76	0.29
17	4.69	26.92	82.9	0.29
18	4.7	24.22	73.91	0.26
19	4.71	24	83.57	0.26
20	4.71	26.37	70.35	0.31
21	4.71	33.76	49.78	0.35
22	4.72	28.1	84.41	0.35
23	4.77	33.5	45.22	0.36
24	4.78	26.39	81.16	0.28
25	4.8	23.39	72.95	0.25
26	4.8	28.05	79.15	0.30
27	4.8	30.3	62.89	0.30
28	4.81	27	88.65	0.26
29	4.81	32.84	51.64	0.36
30	4.82	26.78	86.59	0.29
31	4.82	27.44	83.43	0.33

If the error reaches the error goal, the training is completed; otherwise, the next neuron will be added. The connecting weights are modified each time by changing maximum neurons and spread constant. The value of maximum neuron and spread constant keeps on changing till the network is trained properly. The input data for the ANN are year, month, day of the recording, daily average insolation, daily average atmospheric temperature, average daily relative humidity and estimated coefficient of performance of the CSRS using related equations with appropriate experimental recordings. Randomly selected meteorological data with corresponding COP taken from the experiment over a period of two years are used to train the network. Problem data selected to train the network covers wide range of the period to obtain the best results.

Table 3: Validating Data Sets.

Reading No	Insolation value	Temperature ^{o}C	RH %	COP
1	5.47	27.38	85.86	0.26
2	5.47	27.73	78.65	0.28
3	5.47	29.6	69.61	0.27
4	5.5	26.15	64.66	0.24
5	5.51	29.73	64.3	0.29
6	5.51	30.43	63.86	0.31
7	5.52	23.73	76	0.23
8	4.78	26.39	81.16	0.28
9	4.8	23.39	72.95	0.25
10	1.28	24.08	87.64	0.96
11	1.36	24.63	85.4	0.88
12	1.42	26.08	78.6	0.88
13	3.12	29.45	54.91	0.46
14	3.13	22.85	85.86	0.41
15	3.13	28.61	79.73	0.47
16	3.14	24.52	88.66	0.38
17	5.07	32.83	49.09	0.35
18	5.08	29.8	58.25	0.31
19	5.08	31.12	53.83	0.32
20	5.08	31.41	48.89	0.32
21	5.53	28.28	76.74	0.28
22	5.53	30.16	74.36	0.30
23	5.54	27.98	79.57	0.27

It is to be emphasized that when input datasets were drawn from the experimental setup, certain calculated values of CoP were erratic due to unsteady values obtained through the experimental set up.

Therefore, before feeding in the training datasets, a visual inspection was carried out to ensure that the network does not encounter any irrelevant and invalid datasets. This would otherwise lead to confusion and network would not be able to predict the CoP precisely. For example, the CoP value cannot be a value greater value unity, but because of the unsteady conditions initially with the experimental set up, data measured were invalid and resulted in CoP values more than unity. Such datasets have been removed and the remaining datasets have been used as training data. The distribution of the datasets for training, validation and testing was 60%, 20% and 20% respectively.

RESULTS AND DISCUSSION

The trained RBF network is tested for the performance prediction and is subject to different iteration process and thereby different predicted values are obtained. The total number of epochs for training the network is 180 and the sum squared error value obtained is 5.37x10-4.

Several trials were conducted and each time when the network was operated, good results were obtained in terms of better classification success rate and the minimal time taken. One such result is tabulated below in Table 4 and it is for sure that with optimized architectural parameters setting for the RBF network, we would be able to achieve the best possible output as the network would demonstrate its best performance with optimal setting. Authors consider this as a future work along with a comprehensive comparative study of a number of neural network classes into this problem.

Performance Curves:

The predictive model algorithm was developed in MATLAB® 2012(a) version and the results are presented in this section. Table 1 lists various input parameter settings for the RBF model. The errors resulted in each epoch are discovered through sum squared error function and the set value for the error is .0001 and the spread constant set for this network is 1000. Normally, for RBF class of network, the maximum number of neurons to be set is on the basis of size of the input vectors, which are 180 in this case. Number of neurons to add between displays is fixed 25 which is a default value. Initially, the data sets collected through the experimental set up were scrutinized meticulously thoroughly for any erratic patterns or ranges and accordingly the deviations were eliminated. Table 2 lists the sample data used for training the network. Based on the data collected from the experimental set up, CoP was calculated using analytical equations. CoP values are identified as target vectors for these datasets. Table 3 presents datasets for validating the model and the prediction success rate is exceeding 80% and in some case, it attained 100% matching. The results of 180-epoch run model are presented in Table 4.

Table 4: ANN –RBF output

Reading No	COP Values	
	Experimental Value	Predicted Value
1	0.26	0.29
2	0.28	0.29
3	0.27	0.30
4	0.24	0.27
5	0.29	0.30
6	0.31	0.31
7	0.23	0.24
8	0.28	0.28
9	0.25	0.25
10	0.96	0.89
11	0.88	0.87
12	0.88	0.86
13	0.46	0.48
14	0.41	0.42
15	0.47	0.47
16	0.38	0.41
17	0.35	0.33
18	0.31	0.30
19	0.32	0.32
20	0.32	0.32
21	0.28	0.30
22	0.30	0.32
23	0.28	0.30

Table 5: RBF Output Data.

Sum squared error obtained	Number of epochs	Classification Success %
$5.37x10^{-4}$	180	85 % and above In some cases, 95%

Table 4 presents the estimated and the predicted coefficient of performance of the CSRS using RBF network. Figure 3 illustrates graphically the corresponding experimental and ANN predicted values.

The plot shows that the predicted values and the evaluated values are almost in agreement except at few points and the differences are very minimal.

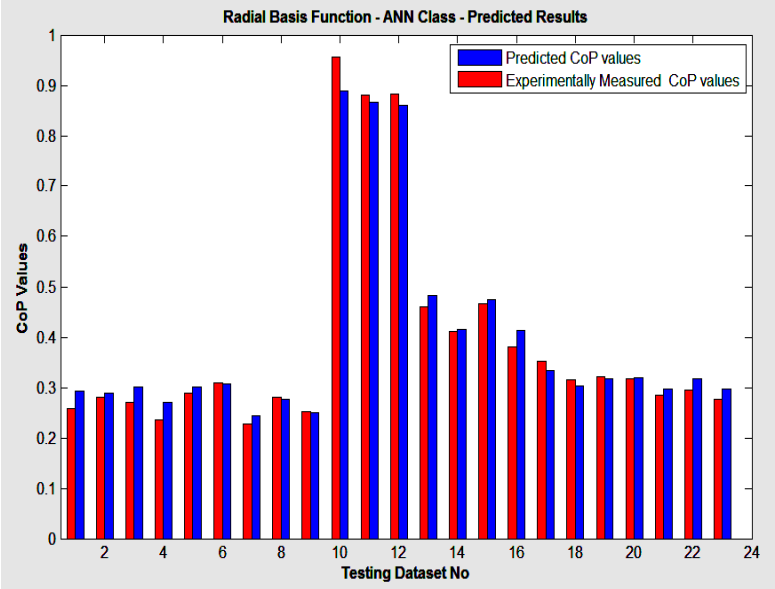

Fig. 3: Predicted Vs Experimental Results – Comparison.

Conclusion:

The ANN-RBF model is designed, developed and tested with MATLAB© tool in Intel core i6 CPU, 3 MHz speed system. The success rate of prediction, error values, and the time taken for the simulation portray the acceptability of the model. The proposed ANN RBF model, with relevant testing information as input vectors, is able to predict the performance of CSRS under different climatic conditions and locational data.

Over the years, ANNs have successfully proved to be a worth-applying tool in classifying or predicting in many engineering applications. Literature reveal that although certain type of ANN networks may not yield fruitful results in terms of classification or prediction for the problems in question, it is very much learnt that most of the applications ended up in success. Similarly, previous studies by the author have laid a foundation for implementing ANN technique for performance prediction of CSRS. Present study reaffirmed that ANN techniques particularly, RBF class of network, are found to yield better predicted results with fairly good amount of accuracy and success rates.

Further, this model can be enriched by integrating it with a genetic algorithm (GA) in order to optimize its architectural parameters for obtaining the best predictive abilities of RBF model. Another potential future work could be to do a comprehensive comparative analysis of a number of ANN classes in order to determine the best performance for the given solar refrigeration performance problem.

ACKNOWLEDGMENT

Authors would like to place on record their deep gratitude and appreciation to Executives of Caledonian College of Engineering, Oman for continual support for research and scholarly activities. Authors gratefully acknowledge the support and encouragement provided by the department of Mechanical and Industrial Engineering during the preparation of this paper.

REFERENCES

Achuthan, M., R.V. Murali, 2013. Performance Prediction of Compact Solar Refrigeration System using Neural Networks. *International Journal of Emerging Technology and Advanced Engineering*, 3(4): 43–49.

Achuthan, M., A. Venkataraman, R. Rathnasamy, 2011. Experimental Analysis on the Performance Characteristics of Compact Solar Refrigeration System. *Distributed Generation and Alternate Energy Journal*, 26(3): 68-80.

Achuthan, M., R. Rathnasamy, 2011. Performance Evaluation of locality based Compact Solar Refrigeration System. *International Journal of Energy Technology and Policy*, 7(5/6): 407-416.

Ahmed, H.P., 2008. Performance assessment of an integrated free cooling and solar powered single-effect lithium bromide-water absorption chiller. *International Solar Energy Society (ISES)*, pp: 1021–1030.

Aziz, M., M. Achuthan, 2012. Design of a Cooling System Using Waste Heat Recovery in a Refractory Industry. *3rd NCT Symposium* : Nizwa College of Technology, Oman, 28th - 29th.

Govindarajan, L.A., 2006 . Prediction of vapor liquid equilibrium data by using radial basis neural networks. *Biochem. Engg*., 20(3): 319-323.

Hammad, MA. and M.S. Audi, 1992. Performance of a solar Li Br-Water Absorption Refrigeration System, *Renewable Energy*, 2,(3): 275 282.

Haykin, 1999. Neural Networks: *A Comprehensive Foundation*, 2nd ed. Prentice-Hall, Englewood Cliffs, NJ, USA.

Li, Z.F., K. Sumathy, 2000. Technology development in the solar absorption air-conditioning systems. *Renewable and Sustainable Energy Reviews*, 4(3): 267-293.

Mittal, V.K., K.S. Kasana, NS. Thakur, 2006. Modelling and simulation of a solar absorption cooling system for India. *Journal of Energy in Southern Africa*, 17(3): 65-70.

Mohanraj, MJ.A., 2009. Performance prediction of a direct expansion solar assisted heat pump using artificial neural networks. *Applied Energy*, 86: 1442–1449.

Murali, R.V., 2010. Comparison of Feed Forward and Radial Basis Function Neural Networks for Worker Assignment into Virtual Cells, *21st International Conference on Computer-Aided Production Engineering (CAPE 2010),* University of Edinburgh, Scotland, UK, 13-14 April 2010.

Pongsid, S., 2001. A review of absorption refrigeration technologies. *Renewable and Sustainable Energy Reviews*, 5: 343–372.

Wang, DC., YJ. Wang, JP. Zhang, XL. Tian, J.Y. Wu, 2007. Experimental study of adsorption chiller driven by variable heat source, *Energy Conversion and Management*, 49: 1063–1073.