Available online at http://www.journalcra.com

International Journal of Current Research
Vol. 7, Issue, 01, pp.11492-11496, January, 2015

INTERNATIONAL JOURNAL
OF CURRENT RESEARCH

ISSN: 0975-833X

RESEARCH ARTICLE

GLOBAL SOLAR RADIATION PREDICTION USING RECURRENT NEURAL NETWORKS

[1]Kadhambari, T., [2]Yokesh V and [3,*]Selva Remya, T.S

[1]Assistant Professor, ECE Department, Prathyusha Institute of Technology and Management, Tiruvallur, India
[2]Assistant Professor, ECE Department, Prathyusha Institute of Technology and Management, Tiruvallur, India
[3]Second Year M.E Communication Systems, Prathyusha Institute of Technology and Management, Tiruvallur, India

ARTICLE INFO

Article History:
Received 14th October, 2014
Received in revised form
21st November, 2014
Accepted 14th December, 2014
Published online 23rd January, 2015

Key words:
Photo voltaic,
Radial Basis Function,
Multilayer Perceptron,
Recurrent Neural Network,
Stochastic search,
Optimization,
Root Mean Square Error.

ABSTRACT

Renewable energy sources derive enormous energy from the sun's radiation. Global Solar Radiation prediction is essential in Photo Voltaic power plants for efficient sizing and improving the performance of these systems. Some computational Intelligence methods are used in time series prediction of solar radiation based on the statistical data. A number of neural network models like Radial Basis function (RBF) and Multilayer perception (MLP) were used and these are all forward prediction methods which may result in inaccuracy of prediction. Here, Recurrent Neural Network (RNN), in which a feedback from the output layer is given as input to one of the hidden layers has been used. Input variables used for prediction are Day of the month, daily mean air temperature, Relative humidity, Air Pressure and Solar azimuth angle.RNN is being trained using Particle Swarm Optimization (PSO) and Evolutionary algorithm (EA).EA is stochastic search and optimization heuristics derived from evolutionary theory.PSO is an optimization based technique used for solving non-linear and multidimensional problems. Also, performance of these algorithms is compared by calculating Root Mean Square Error (RMSE).

INTRODUCTION

A strong increase in energy demand and reduction of energy from fossil fuels leads to the development of solar power generation industries. The energy generated from solar panels depends on the amount of solar radiation falling on the grid infrastructure. Solar radiation plays an important role in estimating the potential power levels that can be generated from the photovoltaic cells and also necessary for determining cooling loads of a buildings (Tzu-An Chiang *et al.,* 2011). A number of multi linear regression equations (Aggarwal *et al.,* 2013) have been derived using several meteorological variables by Angstrom-Prescott model. This includes prediction of solar radiation using clearness index (Abdelouhab Zeroual and Iqdour, 2008), daily mean air temperature, sun shine hours (Ogolo, 2010). Another important method for predicting is time series regression models (Hassan *et al.,* 2012). Three forecasting methods are used in this model using meteorological datas like Global Horizontal Irradiance (GHI), Direct Normal Irradiance (DNI), Diffuse Horizontal Irradiance (DHI). Several computational Intelligence based methods have also been used.

Corresponding author: Selva Remya, S.
Second Year M.E Communication Systems, Prathyusha Institute of Technology and Management, Tiruvallur, India.

Artificial Neural Network (ANN) (Christophe Paoli *et al.,* 2010) provides an efficient way of determining non-linear relation between a number of inputs and output. ANN trained by Levenberg-Masquard algorithm (Behera and Nian Zhang, 2012), used for prediction of solar radiation provides an better performance as it uses Multilayer feed forward networks. Different types of neural networks, which include Multilayer Perceptron (Hassan *et al.,* 2012), Radial Basis Function Networks (Crispim *et al.,* 2008), Nonlinear Auto Regressive Exogenous Neural Network (Eman *et al.,* 2013), Wavelet neural network (Chenghui Zhu *et al.,* 2011) has also been proposed for predicting.

Also, Fuzzy based techniques (Abdelouhab Zeroual and Iqdour, 2008) based on Takagi-Sugeno models provides a better forecast accuracy. A comparative study of prediction using Fully Recurrent Neural Network (FRNN) and RBF (Mehrdad Naderian *et al.,* 2014) proved that a better accuracy can be achieved with RNN. Several algorithms (Abdelaziz Abdallouri and Hicham El Badoui, 2013) like Gradient Descent back propagation, Gradient Descent with Adaptive back propagation, Gradient Descent with momentum back propagation and LM back propagation algorithms are used for training neural networks and their performance are compared. All the above algorithms have been proposed cannot be used for training RNN. Most of the above computational methods are all forward prediction techniques and can result in inaccuracy of prediction. In this paper, Elman style based Recurrent Neural Network which is trained by PSO and Evolutionary algorithm has been used.

Data Collection

In this study, a one hour average data on air temperature, Relative Humidity (RH), air pressure, solar azimuth angle, Global solar Radiation (GSR) for Thiruvallur region located at 13^{o} latitude and 70.4^{o} longitude are collected from National Renewable Energy Laboratory (NREL). The data for 6 months during January 2004 to June.2004 at a distance of 10m above the horizontal surface of the Earth has been used for training and validating RNN. The GSR values measured during January month is shown in Fig. 1. These datas must be normalized before fed into the network.

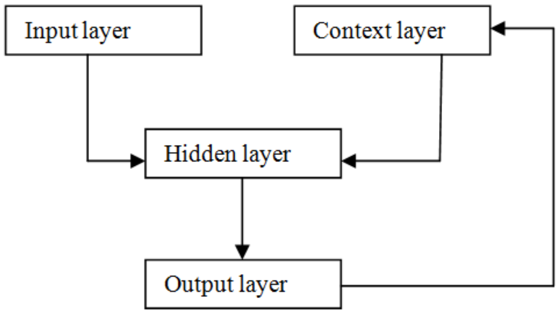

Fig. 2. Structure of RNN

Algorithms

Particle Swarm Optimization

PSO is a population based optimization technique optimization technique which is capable of optimizing non-linear and multi dimensional problems.

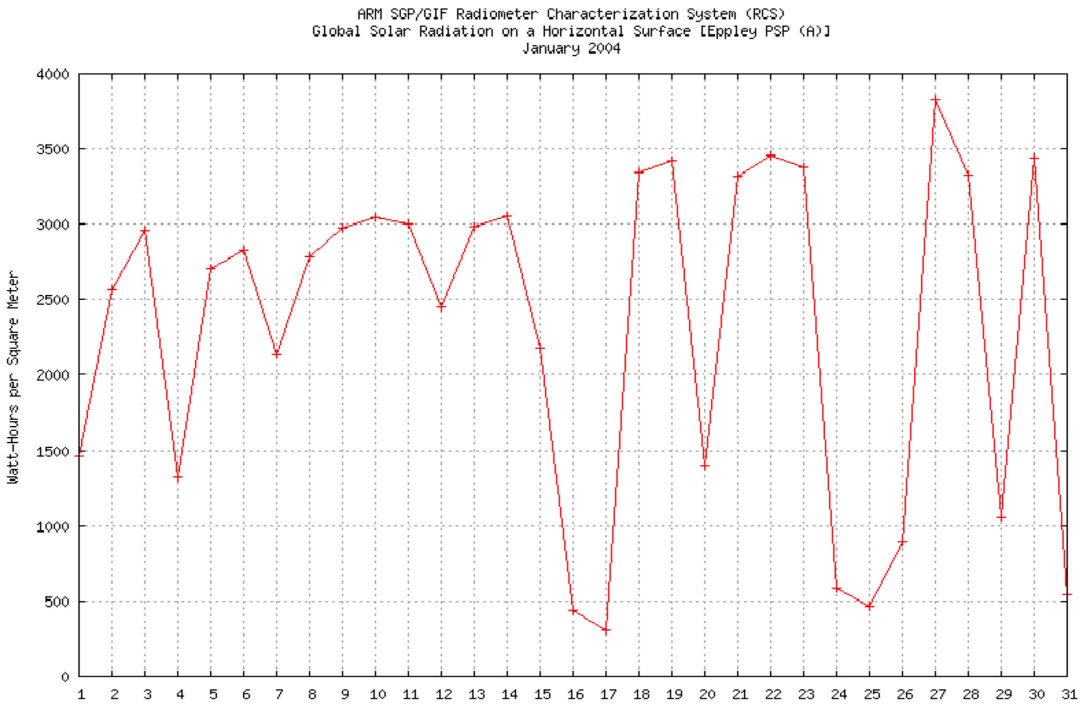

Fig.1. Global Solar Radiation measured at Thiruvallur Region during the month of January 2004

Recurrent Neural Network

A Multi layer feed forward neural network with at least one feedback connection to its input is known as RNN. In this study, an Elman based RNN with four layers have been proposed. The input layer has 30 neurons, hidden layer has 15 neurons, context layer has 7 neurons and the output layer has only one neuron. Here, a feed back is given form the context layer to hidden layer. The transfer function known as trans sig is used in hidden layer and context layer. The structure of RNN is shown in Fig.2. The weights are adjusted during the training process to achieve the desired output. The Net = $\sum x_i w_i$

where, x_i and w_i are the input and weighted function.

The basic concept of the algorithms is to create a swarm of particles which moves in the space around them. Each particle have a current position (X_{id}) and moves through the search space with a velocity (V_{id}).For each time, the fitness function f is evaluated by giving X_i as input. Each particle keeps track of its best fitness function and also the global best position among the population. According to the individual best position and the global best position, each particle will update its new velocity which can be calculated as follows:

$$V_{id}(it+1) = V_{id}(it)+C_1*Rnd(0,1)*(pb_{id}(it)- X_{id}(it))+Rnd(0,1)*(gb_{id}(it)-X_{id}(it))$$

where, i-particle's index, d-Particle's dimension, it-Iteration number, X_{id}-Position of particle i in dimension d, V_{id}-Velocity of particle i in dimension d, C_1 - acceleration constant for the cognitive component, Rnd - Stochastic component of the algorithm (a random value between 0 and 1).

Based on the updated velocities, each particle will update its new position which is calculated as:

$$X_{id}(it+1) = X_{id}(it) + V_{id}(it+1)$$

Based on the updated position and velocity, all the particles cluster together and moves in a random direction. The procedure for PSO algorithm is shown in Fig.3

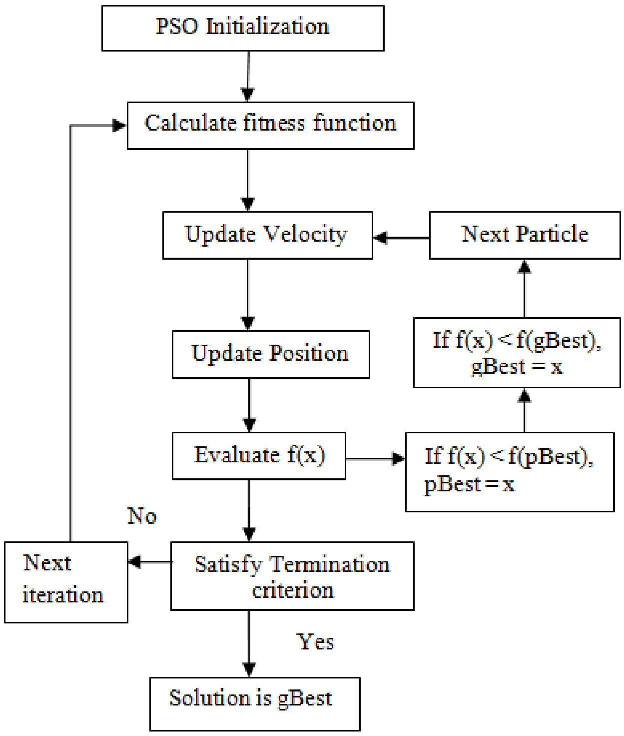

Fig.3. Flow chart of PSO algorithm

Evolutionary Algorithm

Evolutionary algorithms (EA) are stochastic search and optimization heuristics derived from Evolution theory. One major property of EA is that the search space is not explored by starting with only one possible solution but with a population of possible solutions and that the individuals of the population can exchange solution attributes between them.

EA is initialized by creating a population of n individuals at random and by evaluating a fitness function. Weights and biases are defined for each layer. Parents are selected based on the selection procedure. Parents undergoes crossover to create the new off springs by varying all weights and biases. Then, mutation is done by making small changes at random to an individual. Then; the termination criterion is checked after each generation. The weights and biases are calculated as follows:

$$\sigma(j) = \sigma(j-1)\exp(\tau Nj(0,1)) \quad j = 1,2,\ldots\ldots,Nw$$
$$w(j) = w(j-1) + \sigma(j)Nj(0,1) \quad j = 1,2,\ldots\ldots,Nw$$

where, Nw is the number of weights and biases in the RNN and Nj(0,1) is a standard Guassian random variable. $\tau = 1\big/\sqrt{2\sqrt{Nw}}$

.

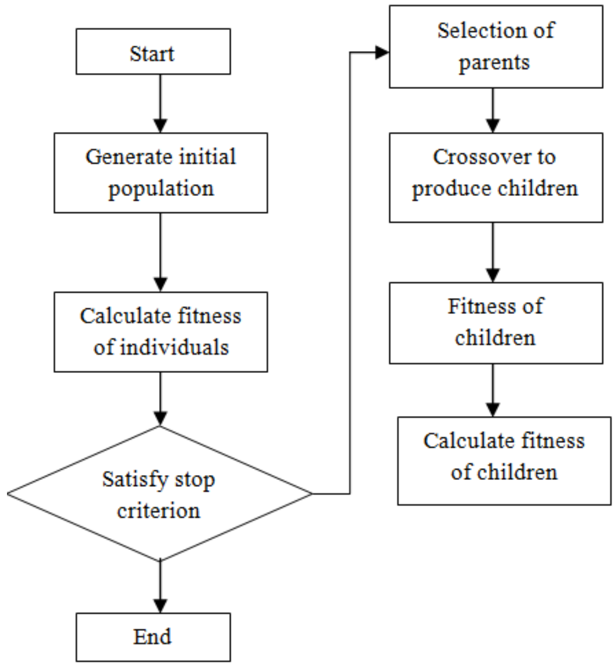

Fig.4. Flow chart of EA algorithm

The procedure for Evolutionary algorithm is shown in Fig.5

Experiment Results

RNN is trained using the PSO and evolutionary algorithms. In both the cases weights are updated based on the cumulative error function. The data collected during the month of June is taken as the training data set. For training the RNN, original time series and series of sequence differences have been used. This series of sequence differences can be calculated as follows:

$$Y'(n) = Y(n) + Y(n-1)$$

where, Y(n) and Y(n-1) are obtained from the given time series data. The original data was normalized. This can be calculated using

$$Xn = \frac{Xr - Xmax}{Xmax - Xmin}$$

In PSO algorithm, the inertia weight w controls the balance of global and local search ability. If the value of w is enhanced, then global search is enhanced while the small values of w enhance the local search. The swarm size is chosen as 30 and the inertia weight is taken as 2.The acceleration contants c1 and c2 are set to 2. A population of 30 particles evolved for 100 iterations. The training error for PSO algorithm is shown in Fig.5

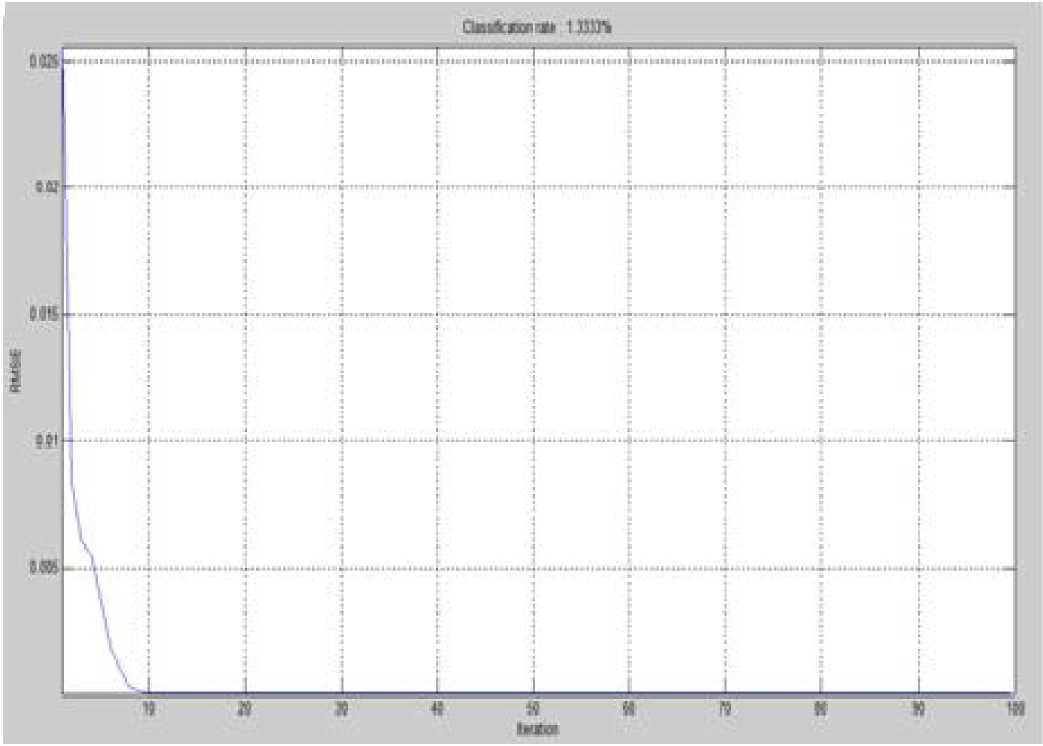

Fig 5. Training error for PSO algorithm

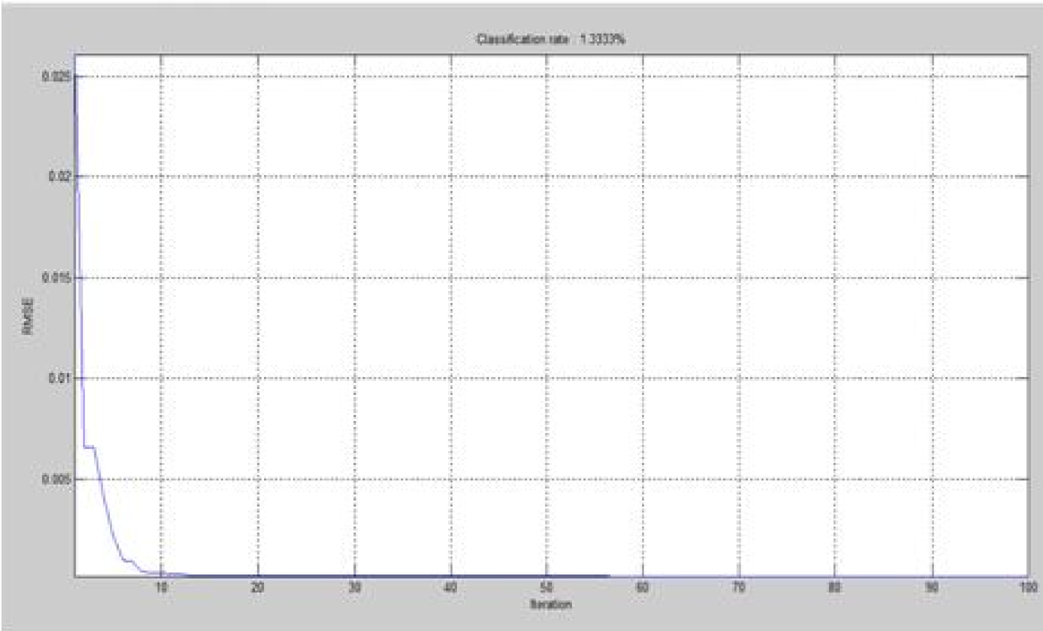

Fig.6. Training error of Evolutionary Algorithm

The above figure reflects the performance of best particle at each generation. In Evolutionary algorithm, the population size chosen as 120.The fitness function depends on the number of individuals in each layer. The training error of EA is shown in Fig.6

The above figure shows the training error of EA which reflects the performance of best mass of individuals in each generation.

Conclusion

In this paper, Recurrent Neural Network are applied to estimate the Global solar radiation at Thiruvallur Region located at 13.4^{o}E Latitude and 79.9^{o}W Longitude. The datas are collected at 10m above the horizontal surface. The Recurrent Neural Networks are trained by Evolutionary Algorithm and Particle Swarm Optimization Algorithm. The performance of these two algorithms are compared by calculating the RMSE.RMSE of Evolutionary algorithm is calculated as 0.0667 which is less than PSO algorithm whose RMSE is calculated as 1.222. This experiment result demonstrated that the performance of Evolutionary algorithm is better than the Particle Swarm Optimization Algorithm. The future work is focused on predicting the Global Solar Radiation by a hybrid learning algorithm based on PSO and EA. Also, it focuses on effective sizing of Photo Voltaic systems using the accurate prediction of Global solar radiation.

REFERENCES

Abdelaziz Abdallouri and Hicham El Badoui 2013. 'Using MLP Networks for predicting global solar radiation, *The International Journal of Engineering and Science,* (IJES), ISSN9(e):2319-1813 ISSN(p):2319-1805.

Abdelouhab Zeroual and R. Iqdour 2008. 'Prediction of radiation using Fuzzy systems', *International Journal of Sustaionable Enrgy*, DOI: 10.1080/148786450701265371; pages 1026-1037.

Aggarwal, R.K., Rajesh Kumar and J.D. Sharma 2013. 'New rEgression Model to Estimate Global Solar Radiation using Artificial Neural Network', *Advances in Energy,* (AEE) Volume 1 Issue 3.

Atsushi Yona, Tomonobu Senju, Toshihisa Fina bashi and Chul-Hwan Kim, 2013. 'Decision Technique of Solar Radiation Prediction applying Recurrent neural Networks for Short term Prediction Ahead Power Output of Photo voltaic Systems', Smart Grid and Renewable Energy, volume 4 pages 32-48. Ogolo, E. 2010. 'Evaluating the performance of some predictive models for estimating global solar radiation across varying climatic conditions in Nigeria', *India Journal of Radio and Space Physics*, volume 39 no 3; pages 121-131.

Behera P.K and Nian Zhang 2012. 'Soalr radiation prediction based on recurrent neural networks trained by Levenberg-Masquardt back propagation algorithm', *Innovative Smart grid Technologies* (ISGT), IEEE PES.

Capizzi G., C. Napoli and Bonanno F.2012. 'Innovative Second Generation Wavelets Construction with Recurrent Neural Neetworks for Solar Radiation Forecasting', *published don IEEE Transactions on Neural Networks and Learning systems*, vol 23 No:11, pages 1805-1815

Christophe Paoli, Cyril Voyant, Marc Muselli amd Marie – Laure Niver 2010. 'Forecastimg of pre-processed daily solar radiation time series using neural networks', Solar Energy 84, pages 2146-2160.

Crispim, E.M, Ferreeira P.M, Ruano A.E. 2008. 'solar radiation prediction RBF Neural Networks and Cloudiness Indices', *International Joint Conference*, DOI 10.1109/IJCNN.2009 pages 2611-2618.

Eman, A., Abdelhafez Lubna, B. Mohammad, A. Ham, dan and Walid Shaheen 2013. Hourly Solar Radiation Prediction based on Nonlinear Auto Regressive Exogenous Neural Networks, *Jordan Journal of Mechanical and Industrial Engineering,* Volume 7 No.1; pages 11-18.

Ghanbarzadeh, Noghrehabadi A.R, Assreh, E., Behrang M.A. 2009. 'Solar radiation forecasting base don meterological data using artificial neural networks', published by IEEE in International Conference on Industrial Informatics.

Hassan A.N. Hejase and Ali H. Assi 2012. 'Time series Regression model for prediction of Mean Daily Global Solar Radiation in Al. Ain, UAE, ISRN Renewable Energy, Pages: 11-18.

Jianwu Zeng and Wei Qiao 2011. 'Short-Term Solar Power Prediction using RBF Neural Networks', IEEE Power and Energy society General Meeting, IEEE PES.

Jing-Ru Zhanh, Jun Zhang,Tat-Ming Lok, Michael R. Lyu,2007. 'A hybrid particle Swarm Optimization-Back Propagation Algorithm for feed forward neural network training' *Applied Mathematics and Computation*, pages 1026-1037.

Mehrdad Naderian, Hamid Barati, Mohammed Golashashi, Reza Farshidi 2014. Application of Fully Recurrent Neural, Network and Radial Bais Function Neural *Network Bulletin Environment Pharmology and Life Sciences*, vol 3(2); pages:132-139.

Paul D., S.N. Mandal, Mukherji D.,S.R. Bhadra Chaudhuri, 2008, 'Artificial Neural Networl Modeling for Efficient Photo Voltaic system Design, International Conference on Advanced Computer Theory and Engineering. Koffka Khan, Ashok Sahai 2012. 'A comparison of BA, GA,PSO, BP and LM for training Feed forward Neural Networks in e-Learning context', I.J. Intelligent Systems and Applications; volume 7 pages 23-29.

Rami El-Haji, Mahmoud Skaafi Mohamad Ali Massoud HAider, 2014. 'Predicting Global Solar Radiation using Recurrent Neural Networks and Climatological Parameters', World Academy of Science, Engineering and Technology, *International Jouranl of Mathematical, Computational, Physical and Quantam Engineering*.Vol:8 No:2.

Shuanghua Cao, 2010. Total Daily Solar Irradidnace Prediction using Recurrent Neural Networks with Determinants', Power and Energy Energy Conference (APPEEC).

Shuanghua Cao, 2010. Total Daily Solar Irradidnace Prediction using Recurrent Neural Networks with Determinants', Power and Energy Energy Conference (APPEEC).

Tomonobu Senju, Atsushi Yona, Chul-Hwan Kim, Toshihisa Fina bashi 2013. 'Decision Technique of Solar Radiation Prediction applying Recurrent neural Networks forShort term Prediction Ahead Power Output of Photo voltaic Systems', *Smart Grid and Renewable Energy,* volume 4 pages 32-48.

Tzu-An Chiang, Zhen-Guo Che and Zhen-Hua Che 2011. 'Feed Forward Neural Network Training: A comparison between Geneteic Algorithm and Back Propagation Learning Algorithm', *International Journal of Innovative Computing,* Information And Control International, volume 7 No.1.

Wu Ji,Chan, C., Loh. J, Choo, F. 2009. 'Solar Radiation Prediction using Statistical Approaches', Information, Communications and Siganl Processing, IEEE PES pages 1-5. Chenghui Zhu, Jianping Wang Xiaobing Xu and Yunlin Xie 2011. 'Daily solar radiation prediction based on Genetic algorithm optimization of wavelet neural networks', published IEEE; DOI:10.1109/ICECEENG. 2011.6057583.

Yousef A.G., Abdalla and G.M Fergh, 2003, "Contribution to the study of solar radiation in Abu Dhabi", Energy Conservation and Manangement, Volume 28 No pages 63-67.

****