

A computation ANN model for quantifying the global solar radiation: A case study of Al-Aqabah-Jordan

I M Abolgasem¹*, M A Alghoul*, M H Ruslan, H Y Chan, N G Khrit, K Sopian

Solar Energy Research Institute, Univeristi Kebangsaan Malaysia
Bangi 43600 Selangor DE, Malaysia

*E-mail: : malk_197716@yahoo.com, dr.alghoul@gmail.com

Abstract. In this paper, a computation model is developed to predict the global solar radiation (GSR) in Aqaba city based on the data recorded with association of Artificial Neural Networks (ANN). The data used in this work are global solar radiation (GSR), sunshine duration, maximum & minimum air temperature and relative humidity. These data are available from Jordanian meteorological station over a period of two years. The quality of GSR forecasting is compared by using different Learning Algorithms. The decision of changing the ANN architecture is essentially based on the predicted results to obtain the best ANN model for monthly and seasonal GSR. Different configurations patterns were tested using available observed data. It was found that the model using mainly sunshine duration and air temperature as inputs gives accurate results. The ANN model efficiency and the mean square error values show that the prediction model is accurate. It is found that the effect of the three learning algorithms on the accuracy of the prediction model at the training and testing stages for each time scale is mostly within the same accuracy range.

1. Introduction

Solar energy technologies with appropriate designs can utilize the solar energy effectively to meet human needs in various applications. However, this depends on the availability of information on solar radiation characteristic of the location, where these systems are to be built. In this regard, scientists and engineers developed various approaches and methods to collect information and characterize solar radiation components of a proposed site. There are also approaches that rely on mathematical-based measurements. Nonetheless, the best solar radiation information is obtained through experimental measurements but however this method may be hindered by technical and financial constraints. The assessment of solar energy involves huge challenges and uncertainties, resulting from the complex processes of quantification (prediction), shortage in data measurements, and variability of spatio-temporal parameters. Thus, there is an urgent need to develop smart techniques of assessment that manage to (1) produce reliable and representative information on solar conditions with minimum error and high certainty, and (2) assist in identifying the optimum requirements of estimation that ensure high performances and trusted scheme of assessment.

¹ To whom any correspondence should be addressed.



One of the methods is advanced computation method that diagnosing solar energy and creating better, quicker, and more practical forecasting than any of the traditional methods are the artificial intelligence (AI) techniques. These techniques include [1]: artificial neural network (ANN), fuzzy logic (FL), Adaptive Network based Fuzzy Inference System (ANFIS), and Data Mining (DM). Artificial intelligence methods aim to provide time-and cost-effective framework of automation, recognition, data storage, retrieval and processing, problem solving, communication, system training, and information super-intelligence [2]. Contrary to conventional statistical methods used in scientific investigations, ANNs deal with forecasting and modeling linear and non-linear systems to arbitrary accuracy without the need for implicit assumptions. They are self-training systems where they adaptively construct linkages between a given pattern of input data and particular outputs [3, 4]. Due to the fact that they exhibit robustness, parallel architecture, fault tolerant capabilities, and the ability to work as universal function approximators, ANNs are profoundly used in solving complex science and engineering problems [5], and in comprehending the phenomena of multidimensional informational domains. The aim of this study is to develop an artificial neural network model to estimate monthly and seasonal global solar radiation in Aqaba city, Jordan.

2. Methodology

The methodology of this study includes data collection, data processing, analysis, and interpretation as well. In this work, solar radiation potential in Aqaba city (Jordan) was estimated by two cases of selected neural network model. The modeling results were validated to assess the reliability of the estimation process.

2.1. Database

The surface meteorological parameters for Aqaba were collected from the Jordan meteorological department over a period of two years. The collected information included sunshine duration, maximum and minimum air temperature, relative humidity and global solar-radiation. The global solar radiation component was measured by a pyranometer. The datasets showed that the daily average values of clearness index (H/H_0) were found to vary between approximately (0.0540 - 0.7930), and the sunshine ratio were found to vary between approximately (0.00 - 0.92 hour). During the same period of observation, the daily average values of relative humidity were found to vary between approximately (13-98%).

2.2 ANN-based implementation of solar radiation models

The ANN model selected for forecasting GSR was a simple multilayered feed forward perception. The network architecture consisted of an input and output layers, and two hidden layers between them. Each hidden layer contained a number of neurons. The input layer consisted of the following three data: sunshine ratio, temperature and humidity; while the output layer consisted of the data of clearness index. The neurons in the layers were interconnected with weights characteristic of the information passing through them; the learning algorithm of error back propagation determined the weights. The configuration pattern (model) of training that was presented to the network is in the following form:

Case 1:

$$\left[\frac{H}{H_0} \right]_{monthly} = f \left(\left[\frac{S}{S_0} \right], \left[\frac{T_{Min}}{T_{Max}} \right], [h] \right)_{monthly} \quad (1)$$

Case 2:

$$\left[\frac{H}{H_0} \right]_{Seasonal} = f \left(\left[\frac{S}{S_0} \right], \left[\frac{T_{Min}}{T_{Max}} \right], [h] \right)_{Seasonal} \quad (2)$$

Where Case 1 is monthly GSR and Case 2 is seasonal GSR. (H/H_o) represents the clearness index with H, H_o are the solar radiation and the maximum solar radiation respectively. (S/S_o) is the sunshine ratio, such that S, S_o are the sunshine duration and the maximum sunshine duration; (T_{Min} / T_{Max}) is the temperature ratio, with T_{Min}, T_{Max} are the minimum and maximum the temperature respectively, and (h) represent the humidity. (f) is the function model depend on the architecture of the neural network. This procedure will allow predicting the monthly and seasonal GSR of the site.

In the training process, neurons were trained and adjusted using the error back propagation rule (algorithm) to adjust the adaptation of the synaptic weights. The outputs are dependent on variables produced for the corresponding input. This algorithm is a supervised iterative training method commonly applied for multilayer feed forward nets, with nonlinear sigmoidal threshold units. The nonlinear sigmoidal transfer function is:

$$f(x) = \frac{1}{(1 + e^{-x})} \quad (3)$$

The iterative process continued until a tolerance level was reached. This procedure was conducted on the training and testing datasets. The following training parameters were set during the training process: Epochs of training was set to 10e-4, Training goal was set to 10e-3, Maximum time of training the network is depend on the learning algorithm, Momentum constant =0.92, number of neurons = (30 15 1). In order to suit the consistency of the model, input and output data were firstly normalized in the (0, 1) range, using the following formula:

$$x' = \frac{x - x_{Min}}{(x_{max} - x_{Min})} \quad (4)$$

Then input and output data will be returned to the original values after the simulation. Where (x) represent the inputs/outputs of the network, and (x') is normalized inputs or outputs of the network. The value of normalized input or output is 1 when the input or output is x_{max} and the value of normalized input or output is 0 when the input or output is x_{Min} . The activation function applied in the designed ANN was the sigmoid function. In this study, the ‘‘Tansig’’ transfer function was used in the hidden layer and a linear activation function, and the ‘‘Purelin’’ transfer function in the output layer. The ‘‘Tansig’’ transfer function is defined as:

$$\tan sig(x) = \frac{2}{1 + e^{(-2x)}} - 1 \quad (5)$$

2.3 ANN Model Error Analyses

Initially, the collected meteorological data was used for training, validating, and testing the designed feed-forward back propagation neural networks. The estimated value of clearness index was tested for its accuracy. The predicted value resulted was compared with the true (measured) data in order to verify the performance of the prediction model (for training and testing stages). The comparison between measured and estimated value was evaluated by statistical error of mean square error (MSE) to check the stability of the model using by the following formula:

$$MSE = \frac{1}{N} \sum_{i=1}^N (X_{Estimated} - X_{Measured})^2 \quad (6)$$

Where (N) is the number of input-output pairs, X is the measured or estimated value of the output. In addition, the efficiency (EFF) of the prediction model for training and testing stage is defined as:

$$Model_{Efficiency} (EFF) = 1 - \left(\frac{MSE}{Var} \right) \quad (7)$$

Where variance (Var) equals the square of standard deviation.

The model that gives the lowest errors (MSE) and best EFF values (approach to 1) is considered stable and the most suitable model.

3. Results and Discussions

This section discusses the modeling results of the GSR for Aqaba city when three different types of learning algorithms are applied in the ANN model for monthly and seasonal GSR. The performance of the prediction is evaluated by checking the (MSE) and Model efficiency (EFF) indicators.

3.1 Modeling results: monthly GSR of Aqaba City

Figure 1 illustrates the results of the monthly GSR modeling when three different types of learning algorithms are applied in the ANN model. The prediction data showed generally excellent accuracy when plotted against the measured data. Table 1 summarizes the ANN model efficiency at training and testing stages using different learning algorithms. From the graph and cross-validation report, it can be seen that the average efficiency of the model at testing stage is (0.9103). The learning algorithm of LM had the lowest MSE of 0.0052 and highest efficiency of 0.9363 compared to the other algorithms. GDX has the highest MSE of 0.01 and the lowest efficiency of 0.8775, with SCG being somewhere in between. The model showed high efficiency in predicting monthly GSR under the training and testing stage. Figure 1 shows the testing stage comparison of monthly GSR at different learning algorithms: Train LM, Train SCG and Train GDX respectively.

Table 1: Efficiency of monthly ANN GSR model at training and testing stages using different algorithms

[30 15 1]	Training		Testing	
	MSE	EFF	MSE	EFF
Train LM	9.4e-04	0.9878	0.0052	0.9363
Train SCG	7.1e-04	0.9908	0.0068	0.9171
Train GDX	9.6e-04	0.9874	0.0100	0.8775
Average				0.9103

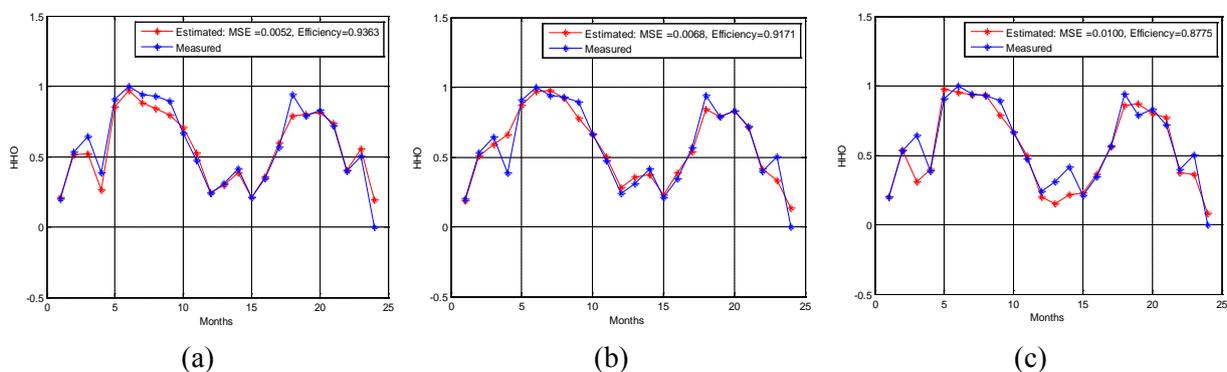


Figure 1. Testing stage comparison of monthly GSR under Train LM, Train SCG and Train GDX learning algorithms respectively

3.2 Modeling results: Seasonal GSR for Aqaba City

This section discussed the outcomes of modeling the seasonal GSR. Table 2 summarizes the seasonal ANN model efficiency at training and testing stages using different learning algorithms.

It is shown that the average testing efficiency of autumn, spring, summer and winter GSR models are 0.876, 0.9275, 0.6450, and 0.9122 respectively. The lowest average testing efficiency is found for summer and the highest for spring. Figures 2-5 show the testing stage comparison of seasonal GSR at different learning algorithms over different time scales.

Table 2: Efficiency of training and testing stages at different learning algorithms of the seasonal ANN GSR model

[30 15 1]	Autumn				Spring				Summer				Winter			
	Training		Testing		Training		Testing		Training		Testing		Training		Testing	
	MSE	EFF	MSE	EFF												
Train LM	8.7e-04	0.9548	0.0017	0.8846	6.6e-04	0.9762	0.0019	0.9411	9.7e-04	0.9697	0.0107	0.6213	9.6e-4	0.9755	0.0038	0.9089
TrainSCG	9.8e-04	0.9492	0.0017	0.8832	9.9e-04	0.9645	0.0025	0.9226	9.9e-04	0.9690	0.0078	0.7092	9.9e-4	0.9746	0.0033	0.9192
TrainGDX	0.0012	0.9404	0.0020	0.8610	9.7e-04	0.9654	0.0027	0.9188	0.0087	0.7315	0.0106	0.6047	0.0016	0.9588	0.0038	0.9087
Average				0.8762				0.9275				0.6450				0.9122

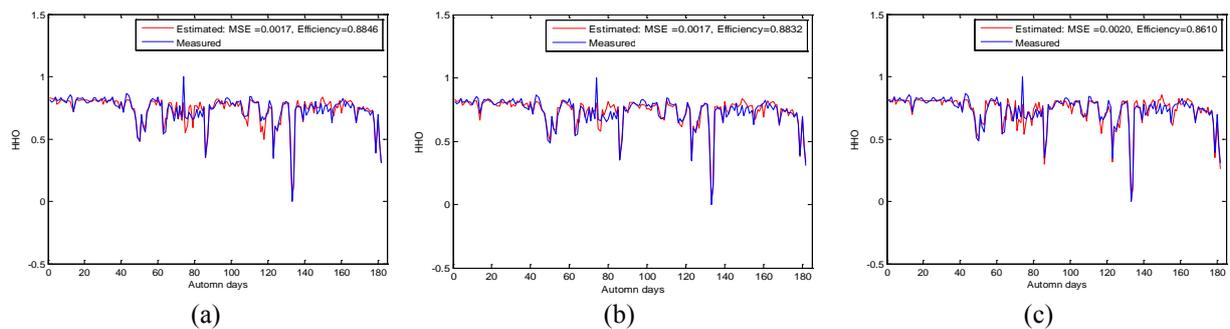


Figure 2. Testing stage comparison of Autumn GSR model under Train LM, Train SCG and Train GDX learning algorithms respectively

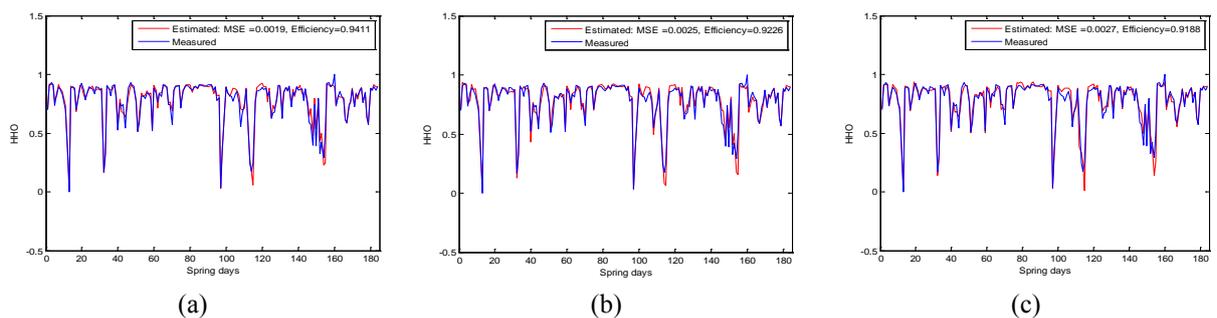


Figure 3. Testing stage comparison of Spring GSR model under Train LM, Train SCG and Train GDX learning algorithms respectively

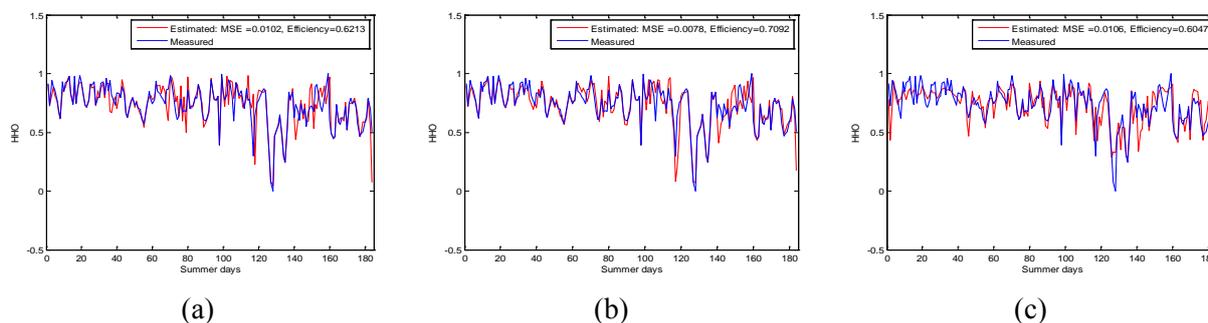


Figure 4. Testing stage comparison of Summer GSR model under Train LM, Train SCG and Train GDX learning algorithms respectively

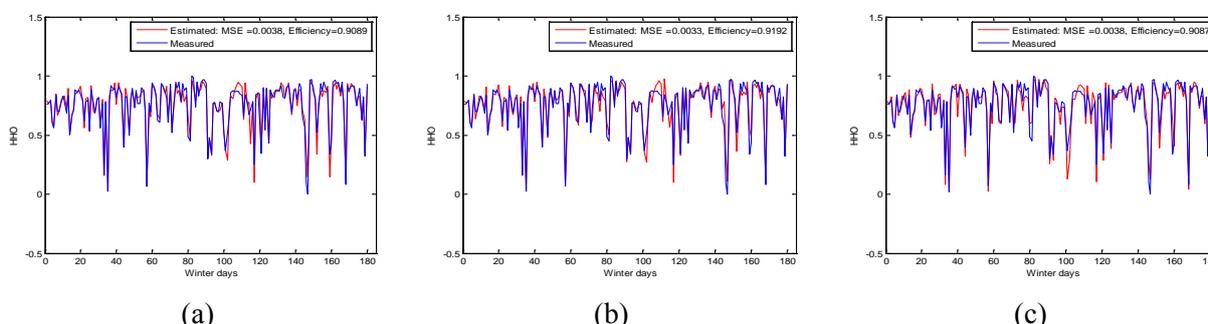


Figure 5. Testing stage comparison of Winter GSR under Train LM, Train SCG and Train GDX learning algorithms respectively

4. Conclusion

The proposed ANN model performed well in evaluating the monthly and seasonal variations in global solar radiation for Aqaba-Jordan, based on the solar parameters measured during a period of 2 years. The ANN model under different learning algorithms showed high efficiency in predicting GSR over different time scales. It demonstrated a significant role in reducing the error between measured and estimated data to minimum levels. The three learning algorithms show close accuracies of the prediction model at the training and testing stages for each time scale.

5. References

- [1] Bourbakis N.G 1992 *Artificial Intelligence Methods and Applications* (Singapore: World Scientific Publishing Co)
- [2] Akerkar, R 2005 *Introduction to Artificial Intelligence* (New Delhi: Prentice-Hall)
- [3] Mellit A, Drif M, Malek A 2010 EPNN-based prediction of meteorological data for renewable energy systems *Revue des Energies Renouvelables* **13** 25-47
- [4] Yang J, Rivard H, Zmeureanu R 2005 Building Energy Prediction with Adaptive Artificial Neural Networks *Ninth International IBPSA Conference Montréal*
- [5] Cybenko, G 1989 Approximation by superposition of a sigmoidal function. *Mathematics of Control Signal and Systems* **2** 303-14.