# Prediction of Monthly Average Daily Global Solar Radiation in Al Ain City –UAE Using Artificial Neural Networks

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*Abstract:* Measured air temperature, relative humidity, wind and sunshine duration measurements between 1995 and 2007 for Al Ain city in United Arab Emirates (UAE) were used for the estimation of monthly average daily global radiation on horizontal using Artificial Neural Network technique. Weather data between 1995 and 2006 were used for training the neural network, while the data of year 2007 was used for validation. The predications of Global Solar Radiation (GSR) were made using four combinations of data sets namely: 1) Sunshine, Temperature, Humidity and wind 2) Sunshine, Temperature and Humidity 3) Sunshine, Temperature and wind 4) Sunshine, wind and Humidity and 5) Temperature, Wind and Humidity. The ANN models with different input parameters have $R^2$ = 0.87883 or higher, RMSE values vary between 0.276 to 0.39118 and small MBE ranging from -0.00013749 to 0.0000882.

*Key-Words: Monthly Average Daily Global Solar Radiation, Meteorology, Artificial Neural Network, modeling, Root Mean Square Error, Mean Bias Error*

## 1 Introduction

With the increased concern and interest on energy conservation and environmental protection, the world today is moving into a new era; transition from almost total dependence of the fossil fuel to a greater use of alternative renewable sources of energy. The solar radiation reaching the Earth's surface depends upon climatic conditions of a location, which is essential to the prediction, and design of a solar energy system. Global solar radiation has been the focus of many studies due to its importance in providing energy for Earth's climate system [1]. The potential of solar radiation in UAE is significant, with an average annual solar hours of 3568 h (i.e. 9.7 h/day), which corresponds to an average annual solar radiation of approximately 2285 kWh/m2 (i.e. 6.3 kWh/m2 per day) [2].

Mohandes et al. [3] have used weather data from 41 stations in Saudi Arabia. Data from 31 stations was used in training the network and the remaining data was used for testing. Input variables to the network included: latitude, longitude, altitude and sunshine duration. J. Lam et al. [4] have used Artificial Neural networks ANNs to develop predication models for daily global solar radiation using measured sunshine duration for 40 cities covering 9 major thermal climatic zones and sub-zones in China. S. Alam et al. [5] have used ANNs to estimate monthly mean hourly and daily diffuse solar radiation. Solar radiation data from 10 Indian stations which have different climatic conditions was used. Alawi and Hinai [6] have used ANNs to predict solar radiation in areas not covered by direct measurement instrumentation. The input data that was used for building the network were the location, month, mean pressure, mean temperature, mean vapor pressure, mean relative humidity, mean wind speed and mean duration of sunshine. I. Tasadduq et al. [7] have used neural networks for the prediction of hourly mean values of ambient temperature 24 h in advance. Full year hourly values of ambient temperature are used to train a neural network model for a coastal location — Jeddah, Saudi Arabia. T. Krishnaiah et al. [8] have used artificial neural network (ANN) approach for estimating hourly global solar radiation (HGSR) in India. The ANN models are presented and implemented on real meteorological data. The solar radiation data from 7 stations are used for training the ANN and data from two stations are used for testing the predicted values. H. Elminir et al. [9] have used ANN models to determine solar radiation data in different spectrum bands from data of meteorology for Helwan (Egypt) monitoring station. S. Rehman and Mohandes [10] have used Artificial Neural networks ANNs to develop estimation of global solar radiation for Abha city in Saudi Arabia; by using different combination of day of year, time day of year, air temperature and relative humidity. The current work utilizes the air temperature, sun duration, relative humidity, and wind data as input for ANNs to predict the monthly average daily GSR on horizontal surfaces for Al Ain city in UAE. Moreover, it investigates the ability of ANNs to predict the global solar radiation even if one or more parameters are missing.

## 2 Artificial Neural Network

A neural network is a massively parallel distributed processor made up of simple processing units that have a natural propensity for storing experiential knowledge and making it available for us. Artificial neural network (ANN) is a type of Artificial Intelligence technique that mimics the behavior of the human brain. ANNs have ability to model linear and non-linear systems without the need to make assumptions implicitly as in most traditional statistical approaches, applied in various aspects of science and engineering. [11-13].

The network usually consists of an input layer, some hidden layers and an output layer. In its simple form, each single neuron is connected to other neurons of a previous layer through adaptable synaptic weights. Knowledge is stored as a set of connection weights. Multilayer feed-forward neural-network architecture is shown in Fig.1.

During Training process the connection weights are modified in certain way by using a suitable learning method. The network uses a learning mode, in which an input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce the desired output. Therefore, the weights, after training contain meaningful information.

Fig.2 shows how information is processed through a single node (neuron). The node receives weighted activations of other nodes through its incoming connections. First, the weighted inputs are added up through the summation phase. The result is then passed through an activation function, the outcome being the activation of the node. For each of the outgoing connections, this activation value is multiplied by the specific weight and transferred to the next node [14].

## 3 Methodology

The database (meteorological data provided by the National Center of Meteorology and Seismology in Abu Dhabi for the periods between 1995 and 2007) used was divided into two sets: A training data set having air temperature, relative humidity, wind and sunshine duration records for each day for the years from 1995 to 2006 (12 years), and a test data set for all days of 2007. The training data set has been used for the training of the artificial neural network, while the test data set has been used for validation of the network. Matlab tool was used for building, training and testing models.

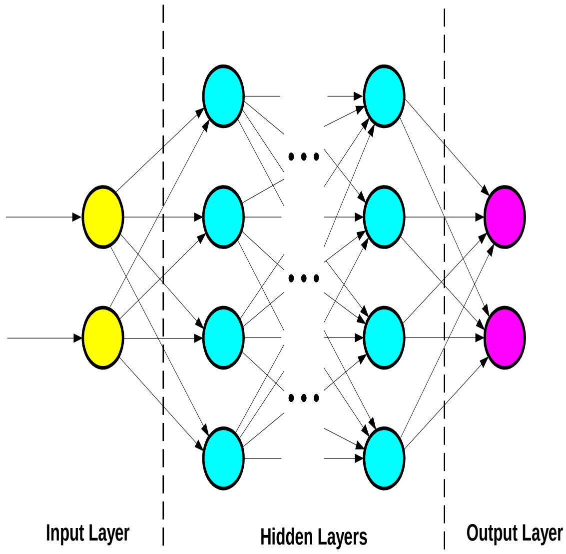


Fig.1

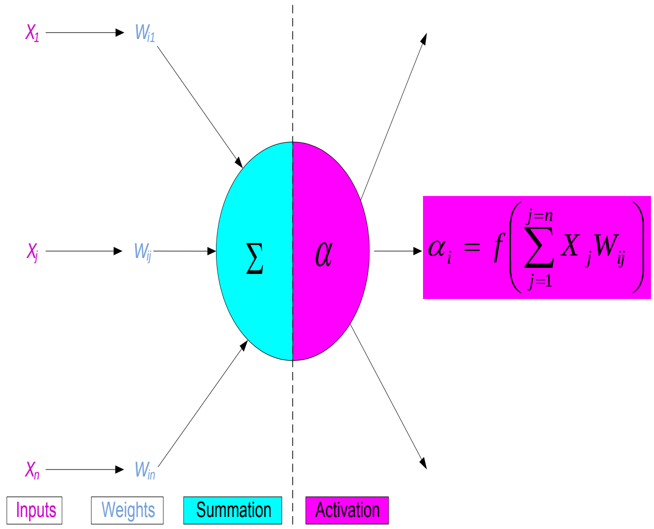


Fig.2

In order to determine the optimal network architecture, various network architectures were designed; different training algorithms were used; the number of neuron and hidden layer and transfer functions including the tangent sigmoid, log sigmoid and linear functions in the hidden layer/output layer were investigated.

Fourteen back-propagation training algorithms were tested in order to obtain the most appropriate for the training process The algorithms included: Levenberg-Marquardt, Bayesian regularization, BFGS quasi-Newton, Powell -Beale conjugate gradient, Gradient descent, Gradient descent with momentum, Gradient descent with adaptive lr, Gradient descent w/momentum & adaptive lr, One step secant, Fletcher-Powell conjugate gradient, Random order incremental training w/learning, Resilient, Polak-Ribiere conjugate gradient and Batch training with weight & bias learning rules.

The procedure used in the development of the ANN models starts with normalizing inputs (i.e. target values) in the range of -1 to 1, then defining the matrix size of the dataset. After that sub-datasets will be created for training and test, and then feed-forward neural network will be created and trained. The output values will be generated and denormalized, and finally the performance of the neural network will be checked by comparing the output values with target values.

In order to investigate the ANN model capability; different input parameters have been investigated.

Table1 Developed models using different sets of input parameters

| Model | Input Parameters |
|---|---|
| 1 | Sunshine - Temperature- Wind - Humidity |
| 2 | Sunshine - Temperature - Wind |
| 3 | Sunshine - Temperature – Humidity |
| 4 | Sunshine - Wind – Humidity |
| 5 | Temperature - Wind - Humidity |

## 4 Results and discussion

In order to evaluate the performance of ANN models quantitatively and ascertain whether there is any underlying trend in performance of ANN models, statistical analysis involving mean bias error (MBE) and root mean square error (RMSE) was conducted. MBE is an indication of the average deviation of the predicted values from the corresponding measured data and can provide information on long term performance of the models; the lower MBE the better. A positive MBE value indicates the amount of overestimation in predicated global solar radiation and vice versa. RMSE provides information on the short term performance and is a measure of the variation of predicated values around the measured data. The lower the RMSE, the more accurate is the estimation.

These statistics were determined as follows:

$$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}\left(I_{p,i} - I_i\right) \quad (1)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n}\left(I_{p,i} - I_i\right)^2}{n}} \quad (2)$$

Where $I_{p,i}$ = predicted monthly average daily global solar radiation on horizontal surface, kWh/m$^2$; $I_i$ = measured monthly average daily global radiation on horizontal surface, kWh/m$^2$; and n = number of observations.

Table 2 shows the developed models and their architectures, where the first number indicates number of neurons in the input layer; the last number represents neurons in the output layers, and number(s) in between represent neurons in the hidden layer(s). Coefficients of determination $R^2$ for all models are 0.87883 or higher, indicating reasonably strong correlation between estimation and measured values. RMSE ranges from 0.276 to 0.39118. The low MBE values for the models which vary from -0.00013749 to 0.0000882 imply that they have a good long term performance.

Table 2: Architecture, $R^2$, RMSE and MBE for the developed ANN models

| Model | Archi-tecture | $R^2$ | RMSE | MBE |
|---|---|---|---|---|
| 1 | 4- 16- 16-1 | 0.9212 | 0.276 | 0.00008820 |
| 2 | 3- 6 -4 -1 | 0.91773 | 0.28749 | 0.00054222 |
| 3 | 3- 20- 8-1 | 0.87883 | 0.39118 | -0.00013749 |
| 4 | 3-10-4-1 | 0.89316 | 0.37407 | 0.00061824 |
| 5 | 3-40-1 | 0.91174 | 0.31796 | -0.00034335 |

It can be seen that model (1); has the highest $R^2$ equals 0.9212. The corresponding MBE is 0.0000882 and the RMSE is 0.276 are the lowest. In contrast model (3) has the lowest $R^2$ which is 0.87883 and the highest MBE and RMSE, -0.00013749 and 0.39118 respectively.

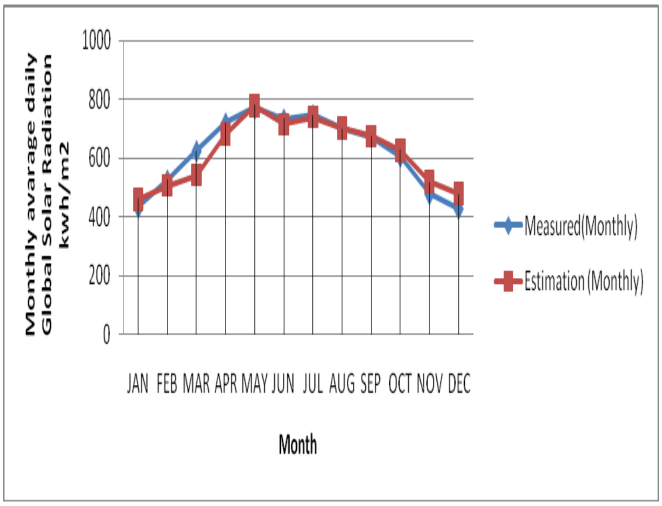


Fig 3: model (1)

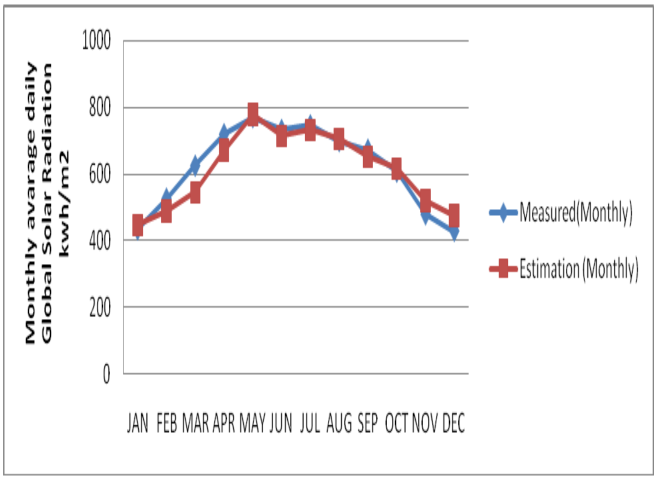


Fig 4: model (2)

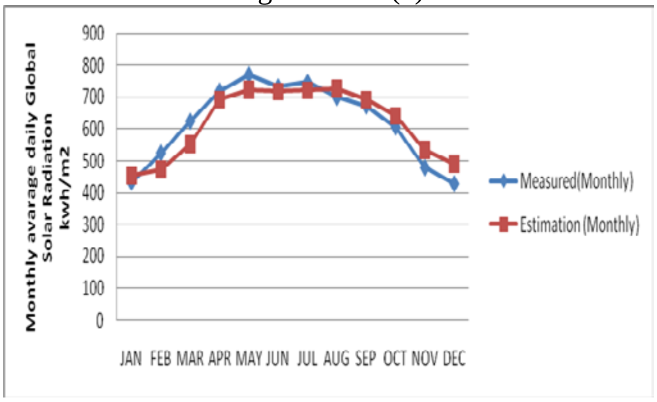


Fig 5: model (3)

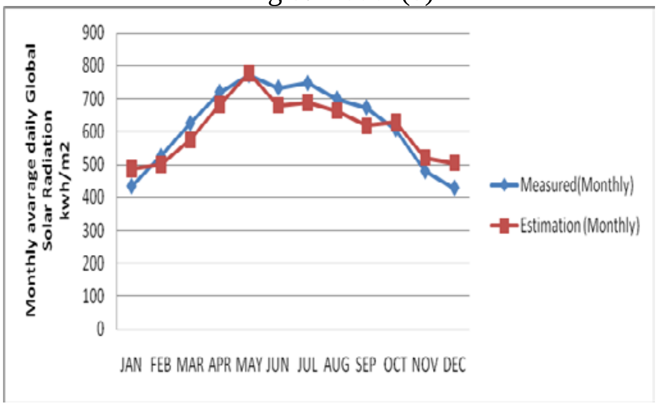


Fig 6: model (4)

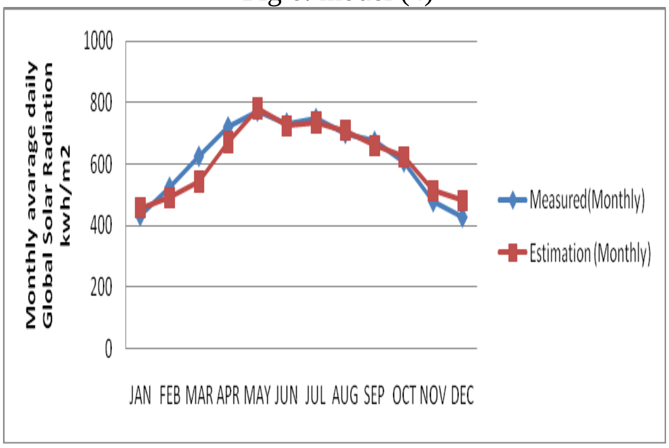


Fig 7: model (5)

Figures 3-7 show comparison between measured and predicted monthly average daily global solar radiation for all five models. It is clear that there is a good agreement between the measured and predicted data. In all models there are underestimation during February and April and overestimation during November and December.

## 5 Conclusion

In this work, ANN is used to develop five different models with different input parameters; for estimating the monthly average daily global solar radiation on a horizontal surface for Al Ain city in UAE. Weather data between 1995 and 2006 were used for training the neural network, while the data of year 2007 was used for validation. The predications of Global Solar Radiation (GSR) were made using five combinations of data sets. All the models have $R^2$ = 0.87883 or higher, RMSE values vary between 0.276 to 0.39118 and small MBE ranging from -0.00013749 to 0.0000882.

***Nomenclature***

*ANN* *Artificial neural network*
*$R^2$* *Coefficient of determination*
*MBE* *Mean bias error*
*RMSE* *Root mean square error*
$I_i$ *Measured monthly average daily global solar radiation on horizontal surface (kWh/$m^2$)*
$I_{p,i}$ *predicted monthly average daily global solar radiation on horizontal surface (kWh/$m^2$)*

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