A Neural Network Model for Estimating Global Solar Radiation on Horizontal Surface

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Abstract- **This research focuses on the development of artificial neural network (ANN) model for estimation of daily global solar radiation on horizontal surface in Dhaka. In this analysis back-propagation algorithm is applied. Day of the year, daily mean air temperature, relative humidity and sunshine duration were used as input data, while the daily global solar radiation was the only output of the ANN. The database consists of 1827 daily measured data, between 2008 and 2012, in term of daily mean air temperature, relative humidity and sunshine duration and global solar radiation. The data has been collected from Bangladesh Meteorological Department. The 1461 daily measured data between 2008 and 2011 are used to train the neural networks while the data of 366 (leap year) days from 2012 are used to test the neural network. MATLAB neural network toolbox is used to train and test the network. Both estimated and measured values of daily global solar radiation on horizontal surface were compared during testing phase statistically using two methods: Root Mean Square Error (RMSE) and Regression R Value (R), giving a value of 113.6 Wh/m² and 0.9744, respectively. The results of this study have shown a better accuracy than other conventional prediction models that have been used up to now in Bangladesh. This ANN model may be suitable for predicting solar radiation at any location in Bangladesh, provided that samples of the sunshine duration data from the locations are available.**

Keywords— Artificial Neural Network, Global Radiation, Solar Radiation, Prediction, Sunshine Duration.

I. INTRODUCTION

Energy certainly plays a vital role in development and welfare of human being. There exists a direct correlation between the development of a country and its consumption of energy. To meet the future energy needs the world is looking for a non-exhaustible energy source. If used in a cost effective manner, solar energy can be the best choice among the all non-conventional energies. The amount of solar energy the earth receives each year is ten times more than the energy that can be produced from all fossil reserves available on earth [1]. Generation of electricity from solar energy is gaining popularity as a solution to the growing energy demands. The most important parameter in renewable energy applications is solar radiation. It is expected that the present worldwide research and development program on solar energy will help to solve the future energy crisis of the world.

The applications of solar energy require information of the availability of solar energy for its optimum use. Due to the utilization of solar energy potential in many areas, there is an increasing need for more precise modeling and prediction of solar radiance. Solar radiation data are required by solar engineers, architects and agriculturists for many applications such as solar heating, cooking, drying and interior illumination of buildings [2–5]. Since solar radiation is not uniform over all places on the earth, any solar energy conversion installation at a certain place requires knowledge of the amount of solar radiation at that place which again varies from time to time. But unfortunately, for any cases, solar radiation measurements are not easily available due to the cost and maintenance and calibration requirements of the measuring equipment.

Various solar models have been used to predict daily global solar radiation all over the world. Solar prediction models can be categorized in two distinct groups. First group in this classification are empirical models. Empirical models were used by many researchers to estimate global solar radiation [6–8]. These models usually consist of a few measurable meteorological parameters. Empirical methods to estimate global solar radiation requires the development of a set of equation that relate it to other meteorological parameters. Artificial neural network (ANN) models are the second type of solar prediction models. ANN provides a computationally efficient way of determining nonlinear relationship between a number of inputs and one or more outputs. In recent years, ANN models were used by many researchers to estimate global solar radiation [9–12]. Almost all the literatures concluded that ANN model is superior to other empirical regression models.

Bangladesh is endowed with abundant sunshine for at least 8 months of the year. The prospect of utilization of solar energy is thus very bright. But solar radiation data are not available in many locations of Bangladesh due to absence or malfunction of measuring instruments. However, the climatological data such as sunshine hour, temperature, humidity etc. are available at meteorological department for most districts of Bangladesh. These data can be used in ANN models to estimate the global solar radiation at any location. In Bangladesh, ANN has not been used yet to estimate daily global radiation. There are few papers on solar radiation estimation using empirical models only [13-15]. In this paper, ANN will be used to estimate the daily global solar radiation in Dhaka which lies in the tropics between latitudes 23°43′N and longitudes 90°25′E.

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II. ARTIFICIAL NEURAL NETWORK

Artificial neural network models employ artificial intelligence techniques and are data driven; they learn and memorize a data structure and subsequently simulate the structure. They are able to learn key information patterns within a multidimensional information domain [16]. In a way, artificial neural network mimic the learning process of a human brain and therefore do not need characteristic information about the system; instead, they learn the relationship between input parameters and the output variables by studying previously recorded data. This makes artificial neural network ideal for modeling non-linear, dynamic, noisy data and complex systems [17]. Further, artificial neural networks are good for tasks involving incomplete data sets [18]. Fig. 1 shows a typical neural network, which consists of an input layer, a hidden layer and an output layer. An input x_j is transmitted through a connection, which multiplies its strength by a weight w_{ij} to give a product $x_j w_{ij}$. This product is an argument to a transfer function *f*, which yields an output y_i represented as:

$$y_i = f\left(\sum_{j=1}^{n} x_j w_{ij}\right)$$

Where i is an index of neurons in the hidden layer and j is an index of an input to the neural network.

There are three steps in solving an ANN problem which are 1) training, 2) generalization and 3) implementation. Training is a process that network learns to recognize present pattern from input data set. We present the network with training examples, which consist of a pattern of activities for the input units together with the desired pattern of activities for the output units. For this reason each ANN uses a set of training rules that define training method. Generalization or testing evaluates network ability in order to extract a feasible solution when the inputs are unknown to network and are not trained to network. We determine how closely the actual output of the network matches the desired output in new situations. In the learning process the values of interconnection weights are adjusted so that the network produces a better approximation of the desired output. ANNs learn by example. They cannot be programmed to perform a specific task. The examples must be selected carefully otherwise useful time is wasted or even worse the network might be functioning incorrectly. The disadvantage is that because the network finds out how to solve the problem by itself and its operation can be unpredictable. In this paper the effort is made to identify the best fitted network for the desired model according to the characteristics of the problem and ANN features.

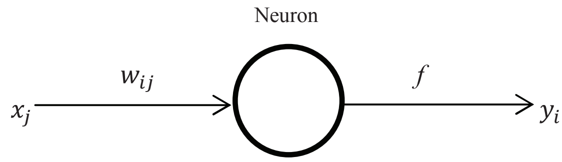

Figure 1. Typical neuron in a neural network system.

III. METHODOLOGY

Day of the year, daily mean air temperature (°C), relative humidity (%), daily global solar radiation (Wh/m²) and sunshine duration (hour) daily data between year 2008 and 2012 are collected from Bangladesh Meteorological Department. The database is consists of 1827 data sets.

The data set was split into two sets. The training data set: the group of data by which the network adjusts, in order to reach the best fitting of the nonlinear function representing the phenomenon and it consisted of 1461 data sets. The testing data set: a set of new data used to evaluate the developed artificial neural network model generalization and it consisted of 366 (leap year) data sets. The training data set was between the year 2008 and 2011. The testing data set was from the year 2012.

The ANN model was developed using neural network tool of MATLAB version R2011b. For the training process of the ANN, a Bayesian regulation back propagation algorithm was used. This algorithm is a supervised iterative training method that updates the weights and bias values according to Levenberge Marquardt optimization [19]. It minimizes a linear combination of squared errors and weights, and then uses Bayesian regularization to determine the correct combination that results in a network that generalizes satisfactorily. The number of hidden neurons in an ANN is a function of the problem's complexity, the number of input and output parameters, and the number of training cases available. A trial and error process was used to determine the number of hidden neurons. After trying a number of different configurations, and repeating each training process ten times to avoid random errors, it was found that 22 neurons in the hidden layer yielded the best results with a reasonable computational effort. Two transfer functions were investigated, including the tangent sigmoid and log sigmoid functions. Linear transfer function was used for both input layer and output layer. Tangent sigmoid function was used for the hidden layer.

MATLAB representation of the final neural network model is presented in Fig. 2. The characteristics of the developed artificial neural network model used in the present study are presented in Table I.

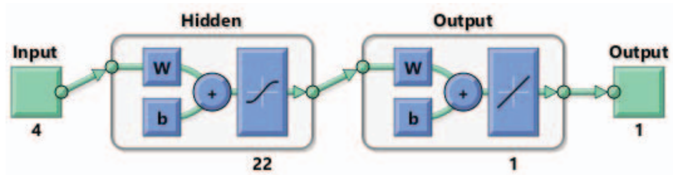

Figure 2. Final neural network architecture.

TABLE I. CHARACTERISTICS OF THE ANN MODEL

Item	Value
Number of Layers	3
Input Layer Nodes	4
Transfer Function	Linear
Hidden Layer Nodes	22
Transfer Function	Sigmoid
Output Layer Nodes	1
Transfer Function	Linear

IV. RESULTS AND DISCUSSION

Although the tested period seems short but it has appeared that the developed artificial neural network model with one hidden layers based on the standard back propagation algorithm, using tangent sigmoid transfer function in hidden layer and linear transfer function in output and input layers, resulted as a very efficient model to estimate daily global solar radiation on horizontal surface at Dhaka city (Bangladesh). The comparison between estimated and measured values during testing is depicted in Fig. 3 for daily global solar radiation on horizontal surface.

The performance of the neural network model is measured using RMSE (Root Mean Squared Error) and Regression R Value. Regression R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship and 0 means a random relationship. Mean Squared Error is the average squared difference between outputs and targets. Lower values are better. Zero means no error.

The value of R was 0.9777 and 0.9744 in training and testing phases, respectively. The proposed artificial neural network model, which accepts 4 input variables, predicts with a RMSE of 113.6 Wh/m². These lower values of errors demonstrate that, the proposed artificial neural network model can estimate daily global solar radiation on horizontal surface for the testing data set with reasonable accuracy.

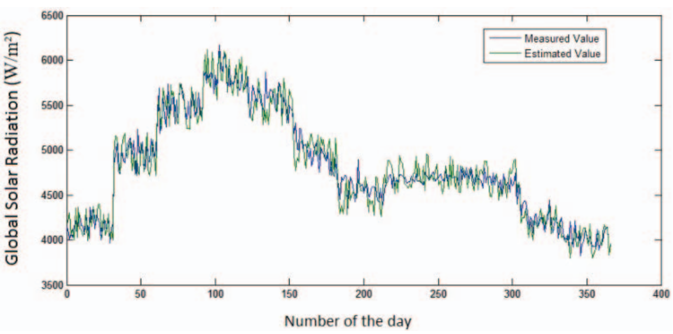

Figure 3. Comparison between estimated and measured values.

When compared with an empirical model [13], it is found that the results calculated by ANN model are better than that calculated by empirical models. Table II summarizes the correlations and error analyses which result from the comparison between estimated values (ANN model and empirical) and measured values.

TABLE II. RESULT OF PERFORMANCE ANALYSES

Model	R	RMSE (Wh/m²)
Empirical Model	0.9304	326.8
ANN Model	0.9744	113.6

V. CONCLUSION

The use of ANN technique in modeling daily solar radiation on horizontal surface at Dhaka has been reported. The results of validation and comparative study indicate that the ANN based estimation technique for solar radiation is more suitable to predict the solar radiation than the empirical regression models proposed by other researchers. This study confirms the ability of the ANN to predict solar radiation values more precisely. Therefore, this ANN model may be suitable for predicting solar radiation at any location in Bangladesh, provided that the necessary data from the locations are available.

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