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Assessment of diffuse solar energy under general sky condition using artificial neural network

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ABSTRACT

In this paper, artificial neural network (ANN) models are developed for estimating monthly mean hourly and daily diffuse solar radiation. Solar radiation data from 10 Indian stations, having different climatic conditions, all over India have been used for training and testing the ANN model. The coefficient of determination (R^2) for all the stations are higher than 0.85, indicating strong correlation between diffuse solar radiation and selected input parameters. The feedforward back-propagation algorithm is used in this analysis. Results of ANN models have been compared with the measured data on the basis of percentage root-mean-square error (RMSE) and mean bias error (MBE). It is found that maximum value of RMSE in ANN model is 8.8% (Vishakhapatnam, September) in the prediction of hourly diffuse solar radiation. However, for other stations same error is less than 5.1%. The computation of monthly mean daily diffuse solar radiation is also carried out and the results so obtained have been compared with those of other empirical models. The ANN model shows the maximum RMSE of 4.5% for daily diffuse radiation, while for other empirical models the same error is 37.4%. This shows that ANN model is more accurate and versatile as compared to other models to predict hourly and daily diffuse solar radiation.

1. Introduction

Terrestrial solar radiation components (global and diffuse) are important parameters in designing systems that employ solar energy, such as high temperature heat engines, high intensity solar photo voltaic cell, building designing, horticulture, etc. Most of the parts of India receive abundant quantity of solar energy due to their geographical positions. Therefore, these can play a vital role in the field of the development of solar systems. Solar energy applications are most cost-effective in the remote areas where measurement of solar radiation with reliable and calibrated pyranometers is either absent or only available for a very limited number of locations. In India, at present there are 45 stations, which record global and diffuse radiation. However, other meteorological parameters such as temperatures, relative humidity, wind speed, vapor pressure, and the number of sunshine hours are available for a very large number of locations due to their requirements in many other fields. Many authors such as Erbs et al. [1], Gopinathan [2], Liu and Jordan [3], Modi and Sukhatme [4], Page [5] have developed the correlations to predict the monthly mean daily diffuse solar radiation. However, most of these studies were based on regression analyses which are limited in their accuracy and the number of parameters they can handle effectively [6]. Since the design of any cost-effective solar energy system depends on reliable data, therefore, it is always desirable to develop accurate techniques to predict solar radiation. Hokoi et al. [7] used a stationary auto regressive moving average model (ARMA) to predict global solar radiation. In recent years, considerable attention has been given to developing forecasting and prediction models based on artificial intelligence techniques such as artificial neural networks (ANNs) and expert systems (ESs). The popularity and acceptance of these techniques stem from their ability to handle effectively a large number of input parameters. The artificial neural network (ANN) technique has been used to determine the hourly as well as daily solar irradiance depending on astronomical and meteorological climatic conditions.

Sfetsos and Coonick [8] studied several artificial-intelligence-based techniques such as linear, feedforward, recurrent Elman and radial basis neural networks alongside the adaptive neuro-fuzzy inference scheme. The problem is examined initially for the univariate case, and is extended to include additional meteorological parameters in the process of estimating the optimum model. The results indicate that the developed artificial intelligence models predict the solar radiation time series more effectively compared to the conventional procedures based on the clearness index. They also concluded that the forecasting ability of ANN models can be

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enhanced by introducing some additional meteorological parameters. Dorvlo et al. [9] have estimated global solar radiation by estimating the clearness index. Radial basis functions (RBF), and multilayer perceptron (MLP), models have been investigated using long-term data from eight stations in Oman. They investigated that both the RBF and MLP models performed well on the basis of statistical parameter root-mean-square error between the observed and estimated solar radiations. However, the RBF models are preferred since they require less computing power. Reddy and Ranjan [10] have already attempted to predict global irradiance using ANN techniques based on multilayer perceptrons. Jacyra et al. [11] have estimated hourly diffuse solar radiation in Sao Paulo city, Brazil using ANN model. They concluded that long wave radiation in one of the important parameter to predict diffuse solar radiation. Adnan et al. [12] have determined first the potential of solar energy in Turkey using artificial neural networks. Secondly, in this study, the best approaches have been investigated for each station by using different learning algorithms and a logistic sigmoid transfer function in the neural network with the developed software. Hamdy et al. [13] have adopted Levenberg optimization function to predict the insolation data in different spectral bands for Helwan (Egypt) monitoring station. Tymvios et al. [14] have estimated global solar radiation on a horizontal surface by using traditional and long-utilized Ångström's linear approach and artificial neural networks (ANN) based on sunshine duration measurements along with other climatological parameters. Alam et al. [15] have simulated beam solar radiation at normal incidence for Indian stations using measured surface parameters. They utilized the feedforward back-propagation neural network technique and compared the predicted values with reference beam solar radiation obtained from the measured data. Gabriel and Gueymard [16] have investigated to determine the luminous efficacy of direct, diffuse and global solar radiation under cloudless sky condition using artificial neural network. The solar radiation model (SMARTS) is also utilized to generate both illuminance and solar radiation values covering a large range of atmospheric conditions. The ANN and SMART solar radiation models are compared. The study shows that ANN model can thus be used worldwide, avoiding the need of using detailed atmospheric information or empirical models of the literature if radiometric measurements and precipitable water data (or temperature and relative humidity data) are available. Lam et al. [17] have predicted global solar radiation over China. Artificial neural networks were used to develop prediction models for daily global solar radiation using measured sunshine duration for 40 cities covering nine major thermal climatic zones and sub-zones in China.

Artificial neural networks find their applications in the field of control systems, statistical analysis, modeling, pattern recognition, forecasting and optimization of data. The various applications of neural networks have been demonstrated in the field of solar energy such as for modeling and design of a solar steam generating plant, for the estimation of a parabolic-trough collector's intercept factor and local concentration ratio, for modeling and performance prediction of solar water heating systems, for heating, ventilating and air-conditioning systems, solar radiation modeling, etc. In all such models, multiple hidden layer architecture has been used [18–20].

In the present analysis feedforward back-propagation ANN technique is applied to predict the availability of diffuse solar radiation for Indian stations under different climatic conditions. The artificial intelligence technique is used to express variability of weather phenomenon in terms of clearness indexes, K_d, for diffuse solar radiation. These are determined as a multivariable interpolation parameter based on latitude, longitude, altitude, time of day, months, relative humidity, rainfall, air temperature, long wave length and wind speed.

2. Selection of artificial neural network for solar radiation estimation

According to Haykin [21] neural network is a massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects: the network through a learning process acquires the knowledge, and inter-neuron connection strengths, known as synaptic weights, are used to store the knowledge.

ANN has ability to handle large and complex systems with many interrelated parameters. It ignores excess data that are less significant and concentrates only on the more important inputs [18].

There are two important issues concerning the implementation of artificial neural networks, that is, specifying the network size (the number of layers in the network and the number of nodes in each layer) and finding the optimal values for the connection weights. In the process of specifying the network size, an insufficient number of hidden nodes cause difficulties in learning data whereas an excessive number of hidden nodes might lead to unnecessary training time with marginal improvement in training outcome as well as make the estimation for a suitable set of interconnection weights more difficult [22]. There is no specific rule to determine the appropriate number of hidden nodes; yet the common method used is trial and error based on a total error criterion. This method starts with a small number of nodes, gradually increasing the network size until the desired accuracy is achieved. Fletcher and Goss [23] proposed a suggestion about the number of node in the hidden layer ranging from $(2n + 1)$ to $(2pn + m)$ where n is the number of input node, and m is the number of output node. The number of input and output nodes is problem-dependent, and the number of input nodes depends on data availability. In addition, the selection of input should be based on prior knowledge of the problem, prevailing synoptic weather condition over the study area. A firm understanding of the climatic system under consideration is necessary for the effective selection of input data [24]. Regarding the second issue, several training processes are available to find the values of connection weights. These algorithms differ in how the weights are obtained.

The selection of training algorithm is related to the network type, computer memory and the input data.

There are two commonly used artificial neural networks: feedforward back-propagation network and radial basis function (RBF) for the prediction of solar radiation.

2.1. Feedforward back-propagation network

The most popular and powerful learning algorithms in neural networks are the back-propagation and its variants. This algorithm is based on the error-correction learning rule. Basically, the error back-propagation process consists of two passes through the different layers of the network: a forward pass and a backward pass. In the forward pass, an activity pattern (input vector) is applied to the sensory nodes of the network, and its effect propagates through the network, layer by layer. Finally, a set of outputs is produced as the actual response of network. During the forward pass, the synaptic weights of the network are all fixed. During the backward pass, on the other hand, the synaptic weights of the network are all adjusted in accordance with the error-correction rule. Specifically, the actual response of network is subtracted from a desired (target) response to produce an error signal. This error signal is then propagated backward through the network [21].

2.2. Radial basis function network

Radial basis functions have been applied in the area of neural networks where they may be used as a replacement for the sigmoi-