A Method to Estimation of Global Solar Radiation with Meteorological Parameters under Cloudless Sky Condition using Artificial Neural Network

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Abstract

In this work, variation of global radiation hourly basis and model developed to estimate the radiation under cloudless sky condition were purposed at Lopburi province (14.83°N, 100.62°E). Data of global radiation and meteorological parameters from 2012 to 2017 were investigated. For the variation of global radiation, the maximum and minimum of radiation are 3.46 MJ/m^2 in April and 2.40 MJ/m^2 in December, and there are some meteorological parameters influencing on the radiation. Therefore, a model for estimation of hourly global solar radiation under cloudless sky condition at this site was proposed based on the artificial neural network (ANN). This ANN has one input layer, two hidden layers and one output layer. The input layer consists of some meteorological parameters that are solar zenith angle, visibility, air temperature, relative humidity, wind speed and air pressure, and the output layer is global solar radiation under clear sky condition. The ANN was trained using the input and output data collected at Lopburi meteorological station during the year: 2012-2014. It was then validated against an independent data at the site for the period of three years (2015-2017). The validation result indicates that the estimated solar radiation under clear sky condition obtained from ANN are in good agreement with that from the measurement, with root mean square difference (RMSD) of 8.52% and mean bias difference (MBD) of 1.22%. Therefore, the model can be applied for estimation of global radiation under cloudless sky condition at other meteorological stations with similar climate. The estimated solar radiation data are useful for management in solar power plant, solar thermal energy system and also for the studies in the atmospheric field.

Keywords: solar radiation, meteorological parameter, artificial neural network

Introduction

Solar radiation reaching the earth's surface consists of direct and diffuse radiation. The summation of two components is called global radiation. Global solar radiation (300-3,000 nm) is a main source of energy for organism and is an important parameter in solar energy applications especially for solar power plant system and solar thermal energy system. The amount of solar radiation at the earth's surface can be varied as it depends on atmospheric parameters, sky conditions and geography. The magnitude of solar radiation under cloudless sky condition is usually higher than that under other sky conditions. The amount of solar radiation for each area can be obtained from ground-based measurements i.e. radiometer. However, the price of such radiometers is very high and the radiometer is required well maintenance. Thus, ground-based measurement is very scarce. Therefore, many scientists have attempted to develop models or methods for estimating solar radiation in several regions (Janjai, Pankaew, & Laksanaboonsong, 2009; Jacovides, Tymvios, Boland, & Tsitouri, 2013; Kalogirou, 2001; Mellit & Kalogirou, 2008; Benghanem, Mellit, & Alamri, 2009). For example, Janjai et al. (2009) have presented a physical model for estimation monthly average hourly global solar radiation in the tropics based on satellite data. The earth-atmospheric albedo and the absorption and scattering coefficients of various atmospheric conditions were included in the model. The model can be calculated the global radiation with the root mean square difference of 10% when compared with those from the measurement. Jacovides et al. (2013) presented simple artificial neural network models for calculating daily solar radiation. Input of the model are extraterrestrial radiant flux, air temperature, relative humidity, sunshine duration, theoretical sunshine duration and precipitable water. The data of one year were used for training and an independent data of one year were used for model validation. It was found that daily global radiation estimated from the model and from the measurement are in good agreement with the root mean square difference of 7.9% and mean bias difference of 0.6%. Yadava, Malik, & Chandel (2014) studied global radiation measured in 26 cities in India with different climates. The artificial neural network (ANN) form Waikato Environment for Knowledge Analysis (WEKA) software was used in this work. Input data of the ANN model consist of latitude, longitude, maximum and minimum temperature, sea level and sunshine duration. The model can be estimated global radiation with root mean square difference of less than 21%. Chiteka & Enweremadu (2016) were also used ANN model for calculation global radiation at Zimbabwe. Input data of ANN model consist of attitude, longitude, sea level, relative humidity, air pressure and temperature. The model can be estimated global radiation with the error of less than 19%. From the above researches, they found that the amount of global solar radiation depends on atmospheric parameters such as cloud, aerosol, water vapour and other gases. Kaushika, Tomar & Kaushik (2014) have presented a method for estimating global, diffuse and direct radiation under clear sky condition, in term of clearness index in India. The ANN model consists of latitude, longitude, altitude, local mean time, month, relative humidity, total rainfall and sunshine per hour as input of the model. The results shown that the ANN model can be estimated global, diffuse and direct radiation with root mean square error less than 7.2%, 16.22% and 18.74%, respectively. In addition, many researchers attempt to study the ANN method for prediction of solar radiation for design photovoltaic applications and thermal system (Mellit & Kalogirou, 2008; Mellit, Kalogirou, Hontoria & Shaari, 2009; AI-Alawi & AI-Hinai, 1998).

In Thailand, the artificial neural network technique is not widespread for estimation of the global radiation especially at areas which have meteorological parameter measurements. Therefore, the objective of this work is calculating hourly global radiation under cloudless sky condition from meteorological parameters using an artificial neural network technique.

Methods and Materials

Materials

Global solar radiation

In this work, a pyranometer (Kipp & Zonen, model CM11) was installed at a roof top of a building of Lopburi meteorological station (14.83°N, 100.62°E) as shown in Figure 1a. This pyranometer measures global solar radiation in the range of 310 - 2800 nm every second. The detector is thermopile sensor which consists of many thermocouples. The voltage signal was recorded the averaged value every ten minute by a data logger (Yokogawa, DC100) as shown in Figure 1b.

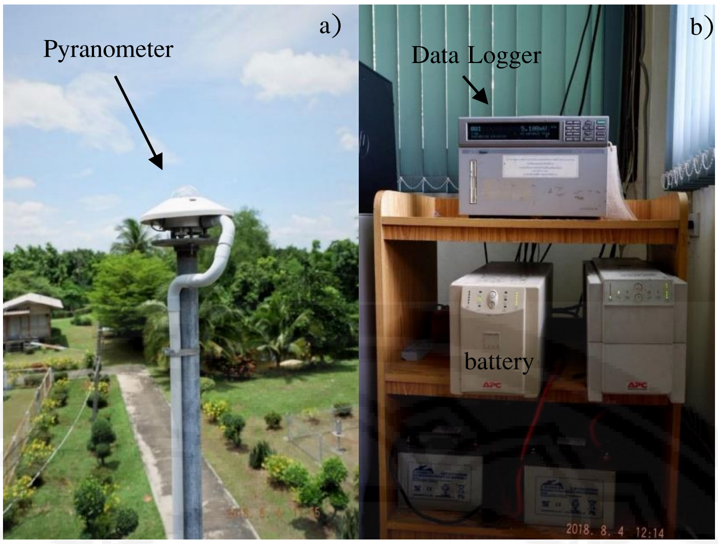

Figure 1 a) Pyranometer and b) a data logger (Yokogawa, DC100) at Lopburi meteorological station

The ten-minute voltage data was converted to global irradiance by using a sensitivity of the instrument as shown Equation 1:

$$I = \frac{V}{S} \tag{1}$$

where I is global radiation intensity (W/m^2), V is voltage signal of the detector (V), and S is sensitivity of the the instrument (V/Wm^{-2}).

The data were then averaged to hourly global radiation. After that the data were selected only cloudless sky condition determined by cloud cover data (cloud cover is zero). The examples of hourly global radiation are shown in Figure 2-3. These hourly data were then used for model formulation and validation.

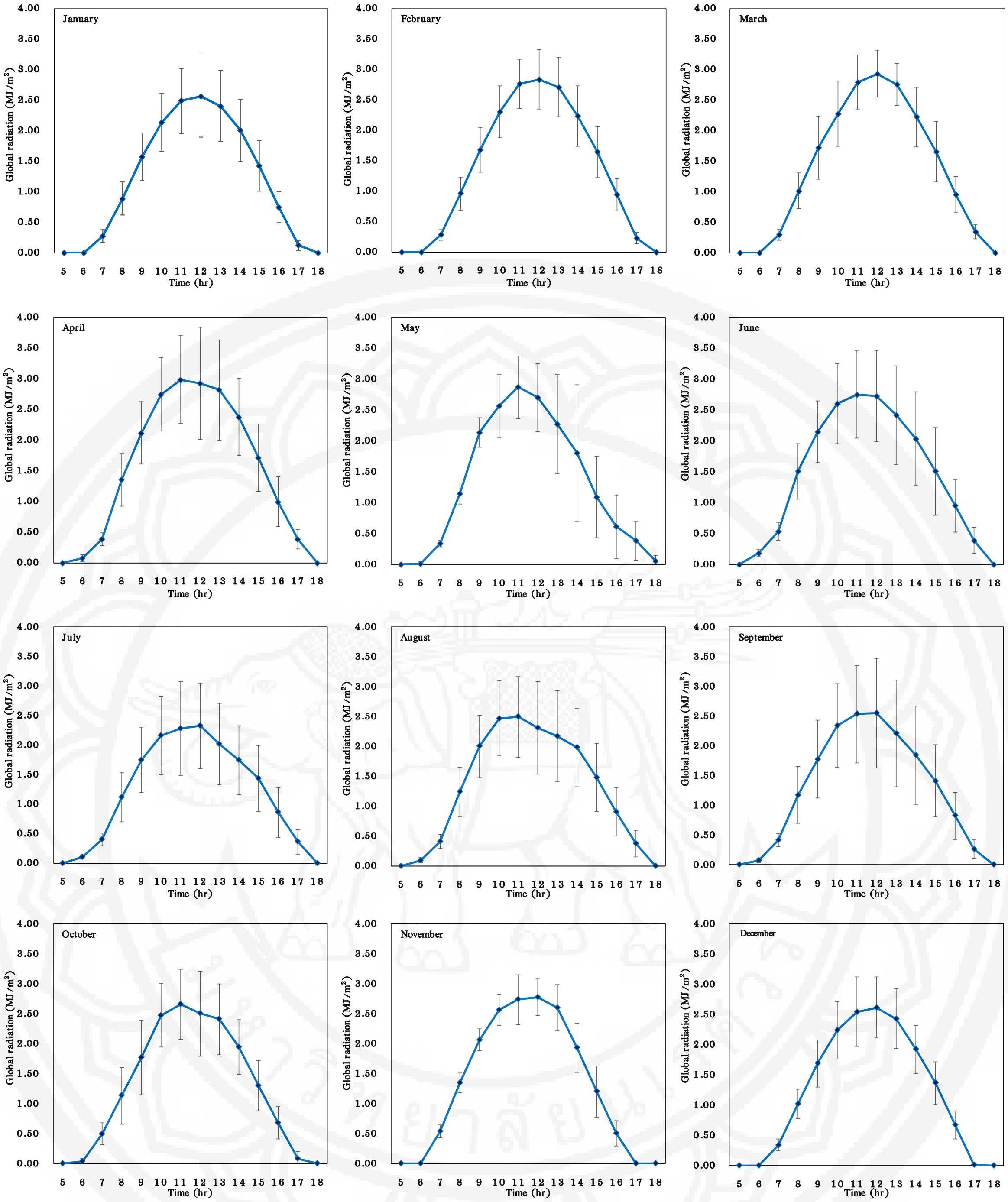

Figure 2 Example of variation of monthly average hourly global radiation at Lopburi meteorological station in 2017

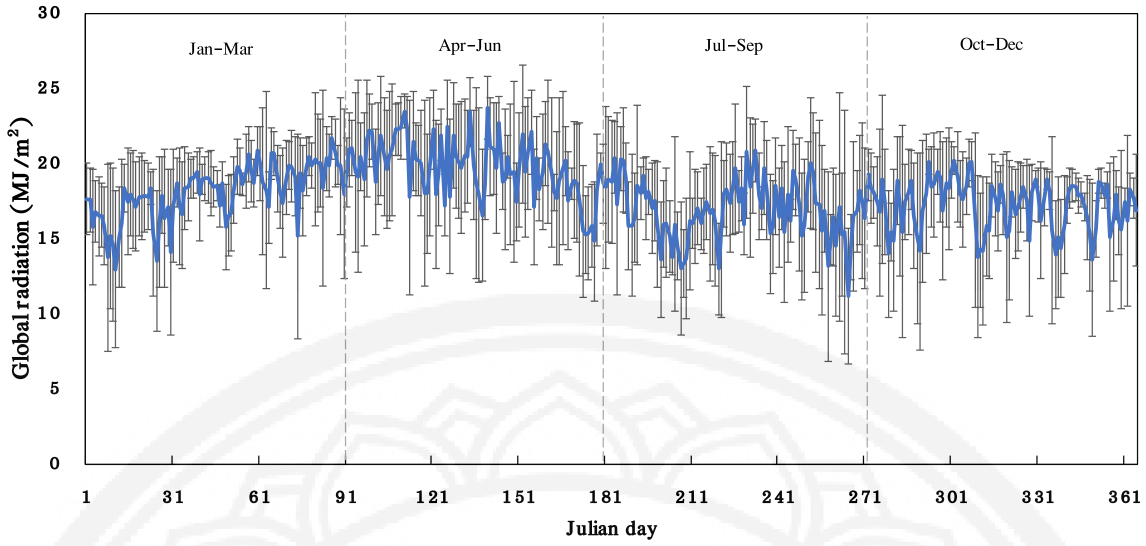

Figure 3 Daily global radiation at Lopburi meteorological station from 2012 to 2017

From the collected solar radiation data, an example of diurnal variation of the radiation is shown in Figure 2. From Figure 2, the hourly global radiation increases from the morning to reach the maximum value at noontime and then decreases to the minimum value in the evening. The maximum and minimum hourly value are 3.46 MJ/m^2 in April and 2.4 MJ/m^2 in December. This is due to variation of the position of the sun resulting in the optical path length. For seasonal variation, the radiation has a maximum in summer (March-April) and the radiation is lower in winter (October -February) and rainy seasons (May-September) (Figure 3). This is mainly due to an effect of optical path length for each month and the local monsoons of Thailand. Thailand have two local monsoons are southwest monsoon (May- October), brings rain and cloud to southern of Thailand, and northeast monsoon (November - January), brings dry air and cloud to northern of Thailand.

In this work, we used the data from 2012 to 2017 (6 years). These data were separated into two groups, the first group (2012-2014) were used for model formulation and the second group (2015-2017) were used for model validation.

Meteorological parameters

Apart from the solar radiation, meteorological parameters including temperature (°C) from thermometer in Thermometer Screen, relative humidity (%) from Psychrometer, visibility (km) from observation by meteorologist, wind speed (knot) from anemometer and air pressure (hPa) from barometer at of the station were collected at the same period with global radiation data (2012-2017). These data are three hourly basis and thus they were interpolated to hourly data using linear interpolation (Li & Heap, 2008). The meteorological fields at Lopburi meteorological station as shown in Figure 4.

Figure 4 the meteorological fields at Lopburi meteorological station

Solar zenith angle

Solar zenith angle is a main parameter effecting on global radiation intensity. Variation of solar radiation depends on the solar path length. High path lengths during sunrise and sunset affect large extinction of solar radiation, while there is small extinction at low path length leading high solar radiation intensity. Solar zenith angle can be calculated following Iqbal (1983) as shown in Equation 2

$$\cos\theta_z = \sin\delta\sin\phi + \cos\delta\cos\phi\cos\omega \quad (2)$$

where θ_z is solar zenith angle in degree, ω is hour angle in degree, ϕ is latitude in degree and δ is declination in degree.

Artificial neural network (ANN) model

Artificial neural network (ANN) techniques was used in this work. The software of ANN, called Waikato Environment for Knowledge Analysis (Weka), was developed by the University of Waikato, New Zealand (Frank, Hall, & Witten, 2016). The Weka software will be continuing development and it is useful in data mining, machine leaning and research. In this work, Weka software in version 3.8 was used. The ANN model is a mathematic program which works like human brain with can be used for physics and engineering simulation system. Many researches use ANN techniques for estimation of solar radiation (Jacovides, Tymvios, Boland & Tsitouri, 2013; Silva, Escobedo, Rossi, Santos, & Silva, 2017; Pratummasoot, Choosri & Buntoung, 2020). The ANN model consists of input layer, hidden layer and output layer (Figure 5a). Hidden layer consist of many neuron, depend on the model formulation.

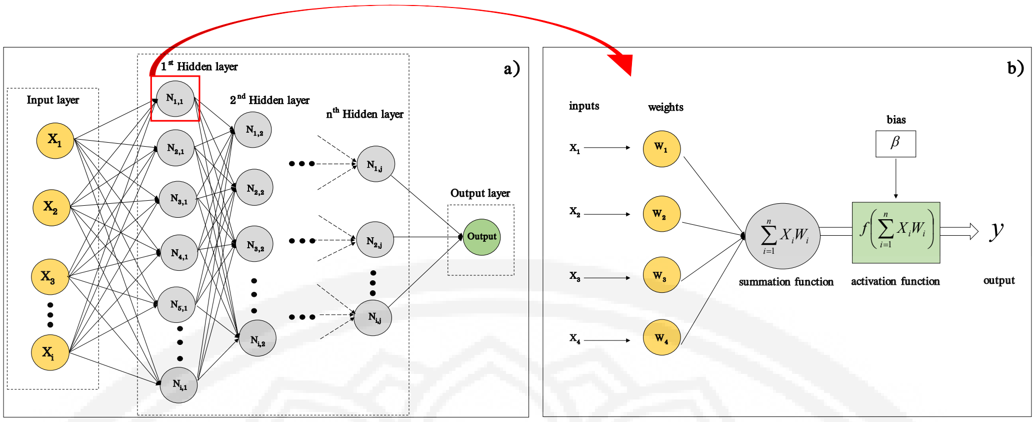

Figure 5 a) Diagram of artificial neural network model and b) diagram for each neuron

Each neuron has two functions that are summation and activation functions. The summation function receives input data and then calculates a result (Figure 5b). The result was then transferred to the activation function by Equation 3 (Hagan, Demuth & Beale, 1996).

$$y = f\left(\sum_{i=1}^{n} w_i x_i + \beta\right) \tag{3}$$

where y is a result of summation function, x is input data, w is weighted value, β is bias value and n is number of the data.

The activation function in the ANN model consists of three functions that are linear function, threshold function and sigmoid function (Patterson, 1996). Sigmoid function is suitable for complicated system especially solar radiation research. Thus, the sigmoid function was used in the work, and multilayer perceptron with back-propagation algorithm (Hagan, Demuth & Beale, 1996) was used for ANN training. The data during 2012-2014 were used to train ANN model and then this ANN which has been trained was used to estimate global solar radiation during 2015-2017 for validation purpose.

Method

In this work, global radiation under cloudless sky condition, solar zenith angle, ambient temperature, relative humidity, visibility, wind speed and air pressure during 2012 to 2017 were analysed. From the result found the solar zenith angle is a main effect on variation of global radiation as shown in Figure 6.

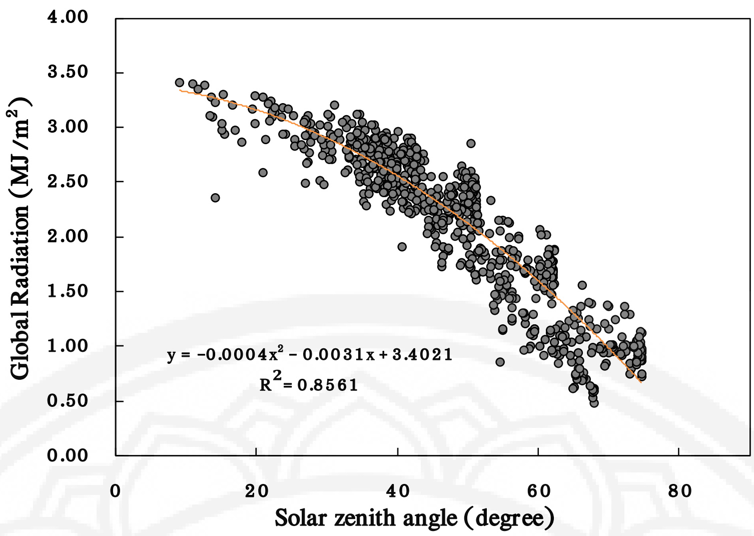

Figure 6 relation between global radiation and solar zenith angle

In the morning and evening, high solar zenith angle as a result low intensity of radiation because it has long photon path lengths and attenuation of atmospheric parameter. Whereas, low solar zenith angle (at noontime) as a result high intensity due to short distance attenuation of atmospheric parameter. For ambient temperature and relative humidity, two parameters can be converted to precipitable water which can absorb the radiation. For visibility, it represents aerosol optical depth value (Janjai, Kumharn, & Laksanaboonsong, 2003 & Iqbal, 1983), aerosol have strongly scatter global radiation as a result the radiation can increasing or decreasing. For wind speed and air pressure is indirectly effect on global radiation. Therefore, The ANN model was designed with four layers as shown in Figure 7.

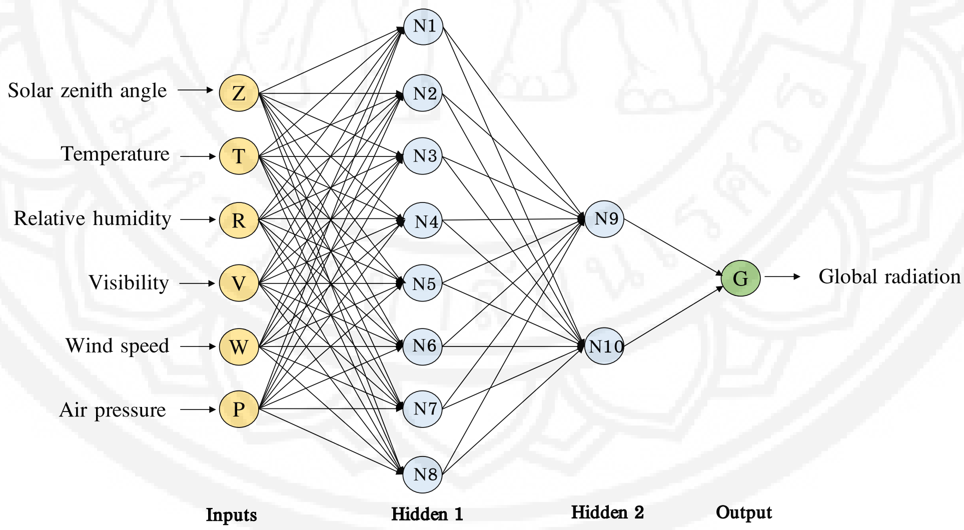

Figure 7 ANN model used to derive hourly global radiation under cloudless condition

From Figure 7, the ANN model consists of one input layer, two hidden layers and one output layer. The input layer are the parameters that affect hourly global radiation. In this work, solar zenith angle (Z), air temperature (T), relative humidity (R), visibility (V), air pressure (P) and wind speed (W) were used as the input data (Elminir, Areed, & Elsayed, 2005; Kaushika, Tomar & Kaushik, 2014; Chiteka & Enweremadu, 2016). First hidden layer consists of eight neurons (N1-N8) and the second hidden layer has two neurons (N9-N10). The number of neuron for each hidden is suitable and it's obtain the best result by Hongkong (2018) method. Firstly, each neuron (N1-N8) will receive the parameters from input layer, then the first result was obtained by Equation (3) with summation and sigmoid functions. The first result was transferred to the second hidden layer (N9-N10), after that global radiation under cloudless sky condition was obtained as shown in Figure 7. The ANN was trained by multilayer perceptron with back-propagation algorithm.

In this work, root mean square difference (RMSD) and mean bias difference (MBD) were used for evaluation of model's performance as described in Equation (4) and (5).

$$RMSD(\%)=\frac{\sqrt{\frac{\sum_{i=1}^{n}(I_{g,model}-I_{g,meas})^2}{N}}}{\frac{\sum_{i=1}^{n}I_{g,meas}}{N}}\times 100 \qquad (4)$$

$$MBD(\%)=\frac{\frac{\sum_{i=1}^{n}(I_{g,model}-I_{g,meas})}{N}}{\frac{\sum_{i=1}^{n}I_{g,meas}}{N}}\times 100 \qquad (5)$$

Where $I_{g,model}$ is global solar radiation under cloudless sky condition from ANN model, $I_{g,meas}$ is global radiation under cloudless sky condition from ground-based measurement, N is total number of the data.

Results and Discussions

The performance of the ANN model was analysed. The hourly global radiation estimated from the ANN model during 2015-2017 was compared with independent data from the measurement. The comparison result is shown in Figure 8.

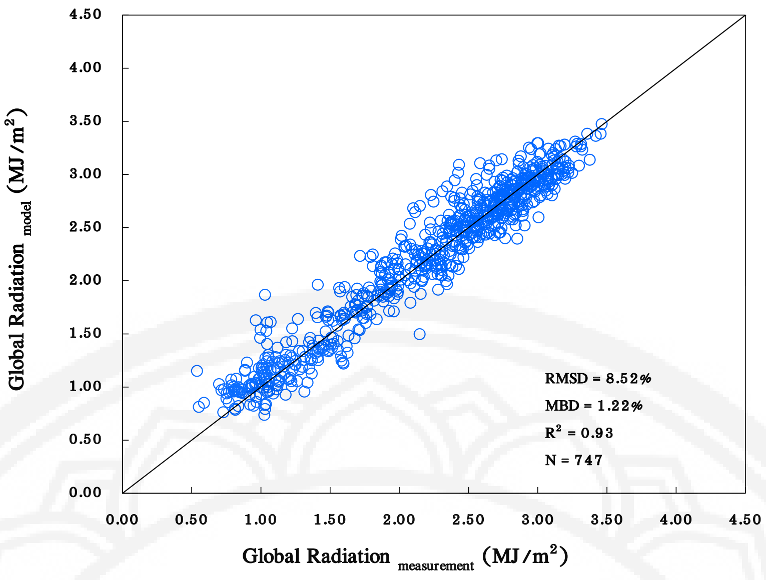

Figure 8 Hourly global radiation using the ANN model versus the measurement values at Lopburi. (RMSD is root mean square difference, MBD is mean bias difference, R^2 is coefficient of determination and N is number of data)

From Figure 8, the result shows that hourly global radiation under cloudless sky condition from the ANN model and that from the measurement at Lopburi are in reasonable agreement, with R^2 = 0.93, a root mean square difference (RMSD) and a mean bias difference (MBD) of 8.52% and 1.22%, respectively. The ANN model gives a slightly overestimation and some points of the data scatter from line 1:1, which may be resulting from other parameters that are not included in the model such as gases and ozone which are not available at the station. The results in this work is comparable to the results in Kaushika, Tomar & Kaushik (2014) which also estimate global radiation under cloudless sky condition. In addition, the model in this this work requires the input parameters less than other models (Azadeh, Maghsoudi & Sohrabkhani, 2005; Mubiru & Banda, 2008; Kaushika, Tomar & Kaushik, 2014). Therefore, meteorological parameters can be used for model formulation and the model can be applied for meteorological stations in other regions to obtain global radiation data.

Conclusions

In this work, hourly global radiation under cloudless sky condition at Lopburi meteorological station was estimated from meteorological parameters by using the ANN model. The model consists of one input layer, two hidden layers and one output layer. Air temperature, relative humidity, visibility and wind speed, air pressure and solar zenith angle were selected as input data. The accuracy of the model when compares with the measurement were assessed by root mean square difference (RMSD) and mean bias difference (MBD). The result shows that the hourly global radiation from the ANN model reasonably agrees with hourly global radiation from the ground-based measurement, with RMSD and MBD of 8.52% and 1.22%, respectively. This study confirms that artificial neuron network technique is a good approach for estimation of global solar radiation using meteorological parameters. In addition, the model can be applied for prediction of hourly global radiation at other similar climate areas.

Suggestions

For further development of research, the method for estimation of global radiation should consider cloud parameter as one of the input of ANN model, in order to estimate global radiation for all sky conditions.

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