# SOLAR RADIATION ESTIMATION FOR MODELLING HIGH PERFORMANCE PHOTOVOLTAIC SYSTEM DESIGNS

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***ABSTRACT***

*Estimation of solar radiation levels involves various techniques such as using data obtained from weather stations, commercial softwares, and mathematical models which cover a wide range of forms within. The limited number of weather stations as well as the cost of required equipment result in higher interest in taking advantage of estimation models due to their time and cost efficiency. However, such models heavily depend on the characteristics of the specific region to be analyzed. Geographic and climatic conditions make significant differences in terms of model accuracy. This study involves model selection for two cities in the third climatic region of Turkey and calculating the solar radiation characteristics both on horizontal and inclined surfaces. The obtained results carry the potential of serving as an integral part of constructing country-wide model for solar radiation estimation. Within the scope of this study, the solar radiation potential of the region was evaluated in order to be a reference for both system feasibility and selection of the most efficient solar panels in a photovoltaic power plant to be designed in the selected provinces. One of the most abundant among sustainable energy sources are calculated using the most realistic solar radiation models, meteorological data and MATLAB. The best solar radiation values and the days when these values were obtained were also determined and evaluated for the feasibility and sustainability potential of a designed photovoltaic system.*

***KEYWORDS****: Solar Energy, Photovoltaic Systems, Panel Efficiency, Data Analysis, Renewable Energy.*

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## 1.0 INTRODUCTION

The solar power is one of the most attractive sustainable energy alternatives from safety, efficiency, and financial perspectives. Thus it has a great potential in replacing the fossil-based energy resources which is limited in nature. However, to take advantage of solar potential, the solar radiation levels need to be determined through the geographical locations under investigation for energy investments. For January and June (Figure 1 and Figure 2) shows the global annual loop of monthly mean net radiation and energy flow through the ecosystems, respectively.

Number of meteorological stations with the required equipment measuring the solar radiation is limited in number. Thus various radiation models that aim to estimate the radiation exist's levels in the literature. Accuracy of these models widely based on the specifics of the region and its climatic conditions.

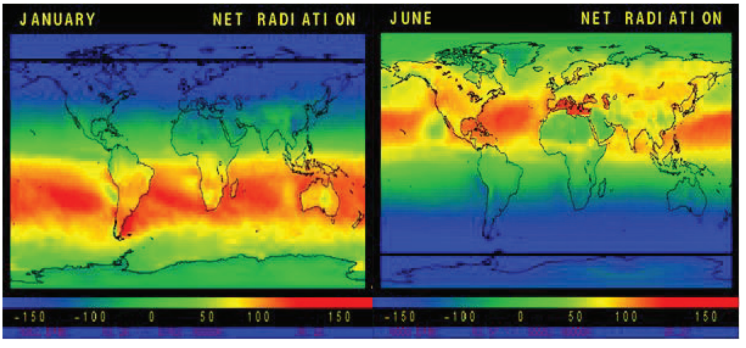



**Figure 1** The monthly mean net radiation's annual loop

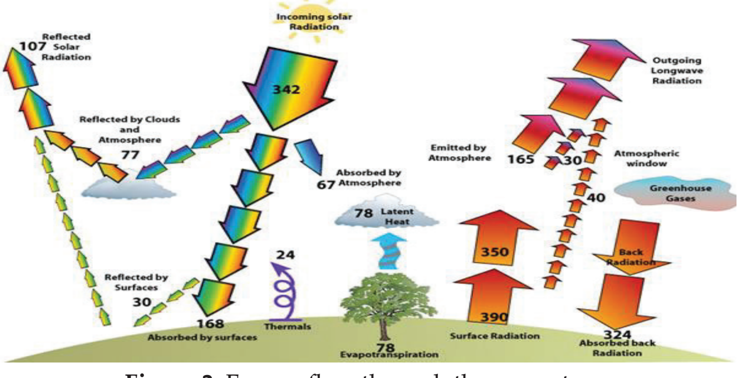



**Figure 2** Energy flow through the ecosystems

In recent years, researchers have begun to focus on the local solar radiation models related to photovoltaic system design. Many articles pointed out that artificial neural network methodology is better than empiric models (Qazi et al., 2015; Piri & Kisi, 2015; Teke et al., 2015). By employing general characteristics, Lam et al. obtained the best performance. This may be because of that each of the zones has a few sites. From diverse sites, data is gathered. This may decrease the amplitude the solar radiation changes (Wan et al., 2008; Lam et al., 2008).

For Dezful, Iran, Behrang et al (2011) investigated networks of radial basis function and multi-layer perceptron. The parameters' six combinations used wind speed, day number, relative humidity, evaporation, duration of sunshine, and mean air temperature. To train models, 1398 days were used. For testing, 214 days were used. The mean absolute percentage error changed from 5.21% to 22.88% (Behrang et al., 2010). To predict average hourly sun irradiation, Janjai etal. obtained a model based on satellite. For hours, the relative root mean square error during 15:00 and 9:00 varied from 10.7% to 7.5% (Janjai et al., 2009). For eleven meteorological sites on Tibetan, Pan et al. investigated the exponential model based on temperature. The temperature difference is used as input. To calibrate the model, data for 35 years were applied. For testing, data for 5 years were analyzed. For the stations, the root mean square error (RMSE) of model changed from 2.54 to 3.24 MJ/m$^2$day (Pan et al., 2013). For two sites in Iran, Fortin et al, 2008. researched two support vector regression models. For inputs, the minimum and maximum temperature, duration of sunshine, and relative humidity were used. Root mean square errors were obtained from 1.63 to 4.47 MJ/m$^2$day (Fortin et al., 2008). For 3 sites in Liaoning city, China, Chen et al. researched 5 sunshine duration fraction models. From each site, Data for 35 years was obtained. Seventy percent of this data were analyzed to obtain the empirical coefficient values. For testing, 30% of the data were used. For each station, the empirical coefficient values are determined. For Chaoyang, RMSE varied between 1.98 and 2.73 MJ/m$^2$day, respectively (Chen et al., 2013).

To daily solar irradiation, Yao et al. surveyed the hourly solar radiation ratio's 11 mathematical expressions. For three years to confirm the models, they utilized the data of 10979 pairs. RMSE varied between 0.481 and 0.321 MJ/m$^2$hour, corresponding to 142.22 and 88.33 W/m$^2$. (Yao et al., 2015). For

4 provinces in Iran, Khorasanizadeh et al. (Khorasanizadeh & Mohammadi, 2013; Khorasanizadeh et al., 2014) analyzed 6 models. The first model is based on exponential, the second on polynomial and other four models on cosine and sine functions. These six models' RMSE varied between 1.26 and 0.72 MJ/m$^2$day, and the mean absolute percentage error changed from 5.72% to 3.38%. Yang et al. searched the hybrid model fixed by Koike and Yang in order to estimate level of daily solar radiation (Yang et al., 2006). The model computed the index of clear sky and clear-sky global radiation. These models used sunshine duration, ozone layer thickness, air temperature, surface elevation, relative humidity, air pressure, and Angstrom turbidity as input parameters. For ninety-seven meteorological stations in China, the obtained irradiation data from 2000 to 1993 used to confirm the hybrid model. The root mean square error determined 0.7 and 1.3 MJ/m$^2$day, respectively (Tang et al., 2010). For 35 sites in China Zang et al. (Zang et al., 2012) researched the same model by reducing two coefficients (Li et al., 2010). The mean absolute percentage error (MAPE) and RMSE for the 35 sites varied between 16.22% and 4.33% and from 1.88 to 1.10 MJ/m$^2$day, respectively. For two sites in Iran, Fortin et al. researched 1 modified sunshine duration fraction model and 3 sunshine duration fraction models. They used the method of support vector regression. RMSE of them ranged between 2.14 and 3.70 MJ/m$^2$day. Minimum and maximum temperature, sunshine duration, and relative humidity were selected as kernel function inputs (Piri et al., 2015).

For one year, Ayodele et al. performed a function to present the clearness index's distribution. By using 7 years, the coefficient values determined daily sun irradiation data. Except for October, the effectiveness of all months are obtained. The root mean square error varied from 0.221 to 0.213 MJ/m$^2$day (Ayodele & Ogunjuyigbe, 2015). To predict sun irradiation, Sun et al. assessed influence of autoregressive moving average model. They investigated the data of 20 years from 2 sites in China (Sun et al., 2015). For six provinces in Iran, Khorasanizadeh et al. assessed three mean sunshine duration fraction models, five mean sunshine duration fraction models and three non-sunshine duration models to be able estimate average monthly global sun irradiation. In mean sunshine duration fraction models, the relative humidity and temperature are added as parameters. Compared with sunshine duration fraction models, the root mean square error of all models changed from 0.82 to 0.47MJ/m$^2$day (Khorasanizadeh & Mohammadi, 2013). Bakirci investigated sixty empiric models developed to predict global monthly with average daily sun irradiation, in which many of the predictions had same formulas just with diverse regressive constant parameters. However, according to the conclusions of many articles, these constant parameters are generally based on the investigation areas (Bakirci, 2009). For Spain, Linares et al. compared three temperature-based empirical models, ANN (artificial neural networks), adaptive neuro-fuzzy inference system, and gene expression programming. 2855 observations obtained from 4 stations were utilized for testing. 4420 measurements were utilized to train the models. The models used minimum and maximum air temperature, extra-terrestrial radiation, clear sky radiation and day number as inputs. The optimized GEP's root mean square error ranged from 3.31 to 3.49 MJ/m$^2$day. The corresponding optimized adaptive neuro-fuzzy inference system's root mean square error changed between 3.33 and 3.14 MJ/m$^2$day. The optimized artificial neural networks' root mean square error of the applying other 3 combinations varied between 2.97 and 2.93 MJ/m$^2$day (Linares et al., 2013). For Iseyin in Nigeria, Olatomiwa et al. used ANN and the adaptive neuro-fuzzy inference system. Sunshine duration, minimum and maximum temperature were used as inputs. Data of 6 years are utilized to train the model while data for 15 years are utilized for testing purposes. For testing and training stages, RMSE varied between 1.76 and 1.09 MJ/m$^2$day, respectively (Olatomiwa et al., 2015).

For Chongqing, China, Li et al. searched twelve non-sunshine duration models. For first 3 models, the parameters of fog, rainfall, and mean dew point temperature were connected. Minimum and maximum temperature were included for the last nine models. For testing, 2552 days were utilized. To calibrate the models, data for 2921 days were utilized. RMSE of the first set of models changed between 6.24 and 5.18 MJ/m$^2$day. The last nine models' RMSE varied between 3.05 and 2.52 MJ/m$^2$day (Li et al., 2010). Qin et al. used Levenberg-Marquardt algorithm with inputs of area temperature difference between night and daytime, mean area temperature, air pressure rate number of days, vegetation index, and monthly precipitation. For Tibetan Plateau, data of seven years from twenty two sites are used to train the artificial neural networks (Qin et al., 2011). Amit etal. searched variety of articles that had used ANN to predict sun irradiation in three reviews and predict sun irradiation on horizontal surfaces. They pointed out that ANN models were better than empiric ones (Yadav& Chandel, 2014). Antonio etal. designed a linear formula to correlate sun irradiation with the daily temperature variation and product of sunshine duration by using the power balance between adjacent atmosphere layer and soil layer (Dumas et al., 2015). For 41 sites in China, El Mghouchi et al. applied the linear Angstrom–Prescott model to predict daily global sun irradiation. Those sites divided into seven sun climate regions and nine thermal climate regions depending on diverse criteria, respectively. They applied the ANN model with latitude, altitude, longitude, day number, sunshine duration fraction, and daily mean temperature (El Mghouchi et al., 2016).

To obtain most effecting input characteristics for prediction, Yadav et al. performed the Waikato Environment's software. They determined the minimum and maximum temperatures, sunshine duration, average temperature, and altitude as input characteristics, while longitude and latitude were the least effective characteristics. The prediction was for monthly average global sun irradiation. By the artificial neural networks, the maximum mean absolute percentage error is obtained as 6.89% (Yadav et al., 2014; Yadav et al., 2015). Besharat et al. searched seventy eight empiric models. They grouped them into four classes of cloud-based, sun ray-based, meteorological characteristics-based, and other temperature-based models. To develop a case study, they applied a few models from each of the classes for Iran. The best performance is determined through a sun ray-based model with exponential expression (Besharat et al., 2013). For Shiraz in Iran, Shamshirband et al. assessed two sunshine duration fraction models, two mean sunshine duration fraction models and one non-sunshine duration model. RMSE of the 5 models changed from 1.55 to 1.3 MJ/m$^2$day (Shamshirband et al., 2015). For Shanghai in China, Yao et al. evaluated eighty nine monthly average radiation models. Using various coefficients, many models are applied with same mathematical expressions. For five sunshine duration fraction models in Shanghai, they derived new fitting coefficients (Yao et al.,2014). For 4 cities in India, Katiyar etal. searched the cubic, quadratic, and linear models to predict monthly average radiation using annual data. The values ranged from 0.8 to 0.43 MJ/m$^2$day (Katiyar & Pandey, 2010). For Saudi Arabia, Mohandes applied particle swarm optimization to train the ANN. Longitude, latitude, altitude, sunshine duration, and month of the year were used as inputs. However, the prediction was for monthly average global sun irradiation. To train the artificial neural networks, thirty one sites' data are utilized. The average mean absolute percentage error is obtained as 8.85% (Mohandes, 2012).

Bakirci studied seven different sunshine duration fraction models with data measured from 18 sites in Turkey. He used various models including exponential, logarithmic, quadratic, and linear equations to estimate the long-term average daily global solar radiation on a monthly basis. For the same sites, the performances of the applied models are obtained with slight differences (Bakirci, 2009). For four stations, Li et al. assessed eight sunshine duration fraction models in China. For calibration, data for eleven years are used. Data' four years are utilized for validation. The RMSE is used as statistical indicator. RMSE of linear model changed between 1.26 and 0.72 MJ/m$^2$day. The eight models' RMSE changed between 1.33 and 0.7 MJ/m$^2$day (Li et al., 2011). For Saudi Arabia, El-Sebaii et al. performed three mean sunshine duration fraction models, three sunshine duration fraction models and non-sunshine duration models to estimate the average monthly global sun irradiation. The characteristics grouped in mean sunshine duration fraction models were cloud cover, temperature, and relative humidity. To derive novel empirical coefficient values, the data of nine years are employed. The 9 models' RMSE ranged between 0.02 and 0.15 MJ/m$^2$day (El-Sebaii et al., 2009; El-Sebaii et al., 2010 ). For 4 sites in Thailand and 5 sites in Cambodian, Janjai etal. researched a satellite-based model. The root mean square error is obtained as 1.13 MJ/m$^2$day (Janjai et al., 2011). For Shiraz in Iran, Shamshirband et al., used the artificial neural network and extreme learning machine algorithm. The relative humidity, average air temperature, temperature difference, and sunshine duration fraction are applied as inputs. For testing, data' 3 years are utilized. The RMSE varied between 0.93 and 0.86 MJ/m$^2$day (Shamshirband et al., 2015). For Akure in Nigeria, Adaramola searched six non-sunshine duration models to predict long-term monthly average sun irradiation and Angstrom-Page model. In non-sunshine duration models, precipitation, relative humidity, and ambient temperature were utilized. Root mean square error changed from 8.25 to 4.78 MJ/m$^2$day for linear model (Adaramola, 2012). Jiang et al. performed to priori association rules and Pearson correlation coefficients to choose the relevant input characteristics. The wind speed, total average opaque sky cover, precipitation, minimum and maximum temperature, opaque sky cover, relative humidity, daylight temperature, average temperature, cooling degree days, and heating degree days are chosen as parameters (Jiang, 2015). For four sites in Tunisia, Chelbi et al. researched five empiric models (Chelbi et al., 2015).

For Turkey, Ozgoren et al. used the artificial neural networks model of multi non-linear regression to obtain proper independent characteristics for the input layer. They selected 10 characteristics, including altitude, sunshine duration, cloudiness, soil temperature, month of the year, minimum and maximum atmospheric temperature, mean atmospheric temperature, latitude, and wind speed. Levenberg-Marquardt optimization algorithm is utilized to train ANN (Ozgoren et al., 2012). For four provinces in Turkey, Teke & Yıldırı researched cubic, linear, and quadratic empiric models (Teke & Yıldırım, 2014). For 79 sites in China with data for 10 years, Li et al. (Li et al., 2010) applied a combined model (sine and cosine functions). The mean absolute percentage error varied from 15.43% to 4.00% while the RMSE changed between 1.03 and 1.83 MJ/$m^2$day. For Bandar Abass province in Iran, Mohammadi et al. (2015) used wavelet transform algorithm and support vector machine. Data for 10 years are used to train the models. The difference between minimum and maximum ambient temperatures, sunshine duration fraction, water vapor pressure, relative humidity, extraterrestrial global sun irradiation, and average ambient temperature are used as parameters. The RMSE varied between 1.81 and 1.79 MJ/$m^2$day, respectively (Park et al., 2015). Senkal proposed an artificial neural network model using altitude, longitude, latitude, land surface temperature and two diverse surface emissivity as inputs. The last 3 characteristics were determined using satellite data. To train the artificial neural networks, one year of data from ten sites is used. The root mean square errors in testing and training stage were reported as 0.32 and 0.16 MJ/$m^2$day, respectively (Senkal, 2010).

For sixty nine sites in China, Jin et al. analyzed three sunshine duration fraction models to predict monthly average sun irradiation. The altitude and latitude are added as parameters in the modified models. The coefficient values are derived separately. The sunshine duration fraction ranged from 1.634 to 1.636 MJ/$m^2$day (Jin et al., 2005). For 17 cities in Iran, Behrang et al. searched eleven models by applying particle swarm optimization technique (Behrang et al., 2011). Nik et al. analyzed 6 mathematical expressions of the hourly solar radiation's ratio to daily radiation. For monthly average hourly irradiation, the prediction was made. From three sites of Malaysia, data for three years were utilized to test the models. They obtained that the relative root mean square error varied from 26.49% to 8.22% (Nik et al., 2012). For seven locations in Turkey, Hacer et al. investigated five sunshine duration fraction models to predict monthly average radiation (Duzen & Aydin, 2012). For seven sites in Spain, Almorox et al. researched eight non-sunshine duration models which were primary based on the minimum and maximum temperature. In some models, the characteristics of latitude, altitude, the day of the year, and mean temperature were involved. The eight models' root mean square error changed between 3.25 and 2.70 MJ/$m^2$day and the mean absolute percentage error varied between 29.18% and 16.37% (Almorox et al., 2011). For Isfahan in Iran, Mohammadi et al., presented four sunshine duration fraction models with data for nine years. Data for four years are used to test the data. RMSE changed between 1.18 and 1.1 MJ/$m^2$day (Mohammadi et al., 2015). For Gaize in Tibetan, Liu et al. investigated 3 non-sunshine duration models, 2 sunshine duration fraction models and 3 modified sunshine duration fraction models. For calibration, 1085 days were analyzed. Data for 701 days were used for validation. The root mean square error varied from 1.68 to 3.13 MJ/$m^2$day. For various seasons, they argued that deriving coefficient values respectively was unnecessary (Liu et al., 2012).

For twelve provinces in Turkey, Senkal et al. studied artificial neural networks model. The mean beam radiation, mean diffuse radiation, altitude, longitude, and latitude were utilized as inputs. The satellite-based method to predict the monthly average irradiation is proposed. Root mean square error changed from 2.75 and 2.32 MJ/$m^2$day (Şenkal & Kuleli, 2009). For twenty two sites in South Korea, Lu et al. searched linear empiric model (Lu et al., 2011). Zhao et al. researched the linear model for 9 sites in China. RMSE varied between 1.72 and 5.24 MJ/$m^2$day (Zhao et al., 2013). Korachagaon & Bapat investigated sixteen non-sunshine duration models to predict monthly average clearness values. As inputs, the moisture, wind speed, altitude, longitude, relative humidity, and five other temperature related characteristics are used. Data for 875 sites are evaluated to analyze the models (Korachagaon & Bapat, 2012). For Yazd in Iran, Besharat et al. analyzed the cloud-based model and Hargreaves model. The data of sixteen years are utilized to obtain empiric constants. RMSE changed between 1.12 and 0.71 MJ/$m^2$day (Besharat et al., 2013). For twenty five sites in Spain, Manzano et al. assessed the linear Angstrom–Prescott model. For calibration, More than data' 10 years were utilized. Except for 4 sites, the root mean square error changed between 0.8 and 0.36 MJ/m$^2$day (Manzano et al., 2015).

This paper presents a comparative analysis of two provinces chosen in the same climatic region to be able to eliminate the effect of climatic factors on the accuracy of the models used. A survey of deterministic estimation models is also provided in the next section before the analysis of selected provinces.

### 1.1 Climate, Electric Production, and Solar Energy Potential in Kars and Hakkari

The solar radiation levels' accuracy are of big significance for diverse industries such as renewable energy, agriculture, construction etc. (Nandwani, 2007; Arabkoohsar, 2016; Wu et al., 2009 ). Lack of equipment along with their high maintenance cost, the stations' number measuring solar radiation is limited, thus meteorological variables are used widely to calculate solar radiation (Rensheng et al., 2006; Yorukoglu & Celik, 2006; Almorox & Hontoria, 2004). The land and sunshine period are of big importance for facilities to be established depend on solar energy. Hence, comprehensive research need to be undertaken about solar energy potential, climate, and current facilities. A view of solar map of Turkey and total solar radiation are presented in Figure 3. Solar Map for Kars and Hakkari is displayed in Figure 4.

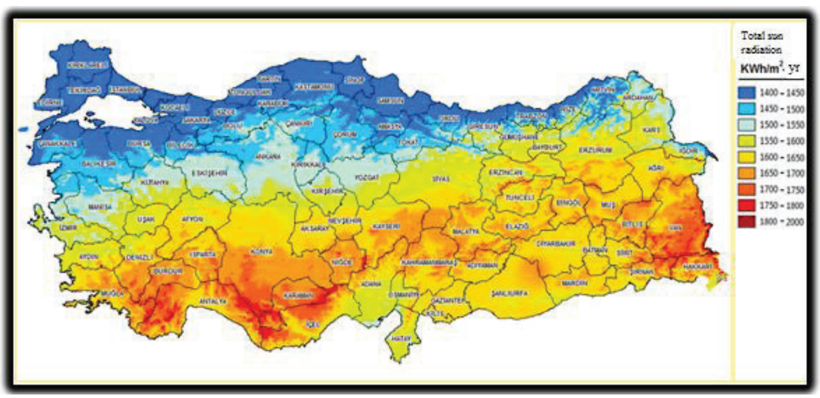



**Figure 3** Solar Map of Turkey

Turkey has 7 geographic regions with various climate conditions because of altitude effect and diverse geographic conditions. In terms of solar energy potential, both cities are placed in the third climatic region.

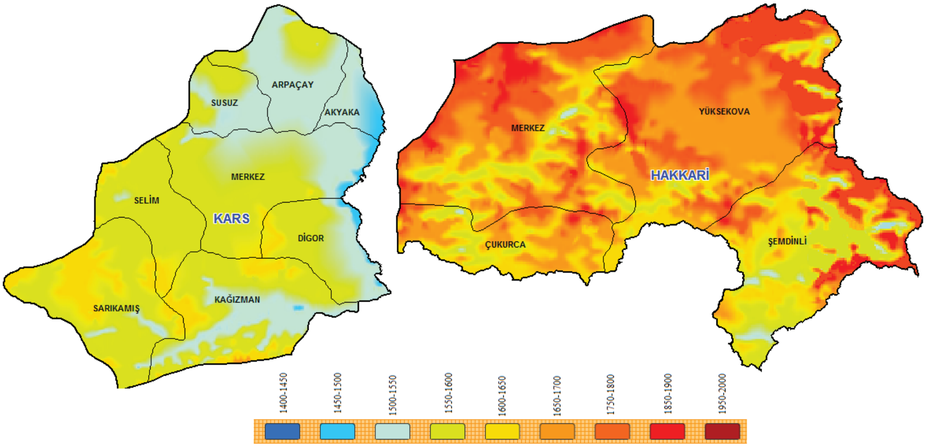



**Figure 4** Solar Map of Turkey

Average solar radiation, radiation function phase shift, radiation function frequency, and latitude values for both cities are presented in Table 1.

**Table 1** Radiation Values

| City | Iort (MJ/m$^2$ .day) | FGI (MJ/m$^2$.day) | FKI | Latitude |
|---|---|---|---|---|
| Kars | 13.2 | 6.47 | 8.52 | 40.36 |
| Hakkari | 15.8 | 7.52 | 6.95 | 37.50 |

In the next section, a comperative analysis is conducted on Matlab platform for both cities to reveal their solar radiation characteristics and potential.

## 2.0 SOLAR RADIATION INTENSITY CALCULATION

Wong and Chow have used different solar radiation models to calculate daily and hourly total, direct and diffuse radiation and presented the comparative results (Wong & Chow, 2001). Almorox and Hontoria have developed 12 different mathematical models for each month in determining the solar radiation for Toledo, Spain (Almorox & Hontoria, 2004). Li et al. have tested the data obtained from four different stations in Tibet. The measured results are statistically compared with the two models developed specifically for Tibet (Li et al., 2011). The comparative results indicate that the simple linear model meet the measured values at satisfactory levels.

The selection of models to be used in calculating the solar radiation levels also depend on the surface being horizontal or inclined. Thus, the most appropriate models for each case is chosen in sections below and the necessary calculations are made on Matlab platform.

## 2.1 Horizontal Surface

### *2.1.1 Daily Total Solar Radiation*

On a given day, total solar radiation on a horizontal surface can be calculated through the below formula (Derse, 2014):

$$I = I_{ort} - FGI \cos\left[\frac{2\pi}{365}\left(n + FKI\right)\right] \tag{1}$$

where
n: days,
FKI: radiation function phase shift,
FGI: radiation function frequency
Iort: daily total radiation's annual average of.

### *2.1.2 Daily Diffuse Solar Radiation*

On a horizontal surface, the daily total diffuse solar radiation can be obtained using formula 2 (De Miguel et al., 2001).

$$Iy = I\left(1 - B\right)^2\left(1 + 3B^2\right) \tag{2}$$

where,
B: Transparency index,
Io: Out-of-atmosphere radiation.

### *2.1.3 Momentary Total Solar Radiation*

On a horizontal surface, momentary total solar radiation can be obtained through the formula 3 (Notton et al., 2006; Erbs et al., 1982 ).

$$I_o = \frac{24}{\pi} I_s \left( Cos(e) Cos(d) Sin(ws) + wsSin(e) \sin(d) \right) f \tag{3}$$

where;
Is (W/m2): solar constant, e: latitude angle; ws: sunrise hour angle, d; declination angle, f: solar constant correction factor can be determined utilizing the related formulas and tables.

Out-of-atmosphere radiation can be obtained utilizing formula 4 (De Miguel et al., 2001).

$$I_{ts} = A_{ts} Cos[\frac{\pi}{t_{gi}}(t - 12)] \tag{4}$$

where;
Ats: solar radiation and
tgi, : imaginary day length.

### *2.1.4 Momentary Direct and Diffuse Solar Radiation*

On a horizontal surface, amount of momentary direct and diffuse solar radiation can be obtained utilizing formulas 5 and 6 (Notton et al., 2006; Erbs et al., 1982 ) where Ays is function frequency.

$$I_{ys} = A_{ys} Cos[\frac{\pi}{t_g}(t - 12)] \tag{5}$$

$$I_{ds} = I_{ts} = I_{ys} \tag{6}$$

## 2.2 Calculating Solar Radiation Intensity on Inclined Surface

### *2.2.1 Momentary Direct Solar Radiation*

On inclined surfaces (30°-60°-90° angles), the momentary direct solar radiation can be determined utilizing the formula below (Erbs et al., 1982).

$$I_{be} = I_b R_b \tag{7}$$

$$R_b = \frac{Cos\theta}{Cos\theta_z} \tag{8}$$

$$cos\theta_z = \sin(d)\sin(e) + \cos(d)\cos(e)\cos(w) \tag{9}$$

$$cos\theta = \sin(d)\sin(e - \beta) + \cos(d)\cos(e - \beta)\cos(w) \tag{10}$$

### 2.2.2 *Momentary Diffuse Solar Radiation*

On an inclined surface, the momentary diffuse radiation's value can be obtained utilizing formula below (Erbs et al., 1982).

$$I_{ye} = R_y I_{ys} \quad (11)$$

$$R_y = \frac{1 + \cos(a)}{2} \quad (12)$$

For vertical surface ($a=90^0$), $R_y$ value is 0.5. $R_y$ parameter provides the slope of the surface.This way, the diffuse radiation's momentary values on inclined surfaces with 30°, 60°, 90° angles for 24-hour time period can be calculated.

### 2.2.3 *Reflecting Momentary Solar Radiation*

On inclined surface, the reflecting radiation (Erbs et al., 1982) can be determined utilizing formula below:

$$I_{ya} = I_{ts} p \frac{1 + \cos(a)}{2} \quad (13)$$

The environment reflection ratio is shown with ϱ parameter and utilized with average value of ϱ=0.2 in calculations.

### 2.2.4 *Total Momentary Solar Radiation*

On inclined surface, the momentary total radiation (Erbs et al., 1982) can be calculated utilizing formula below:

$$I_t = I_{de} + I_{ye} + I_{ya} \quad (14)$$

## 3.0 METHODOLOGY

Figure 5 provides the values of; (a) change in annual momentary total solar radiation values for 24-hour time period, (b) change in annual momentary diffuse solar radiation values per hour, (c) change in annual momentary direct solar radiation values for 24-hour time period on a horizontal surface.

Figure 6 provides the daily changes of; (a) total solar radiation values per day, (b) declination angle, (c) hourly angle for sunrise, (d) solar constant for correction factor, (e) solar radiation values out of atmosphere, (f) graph of function frequency (Ays), (g) diffuse solar radiation (Ats), (h) transparency index (B) for a horizontal surface.

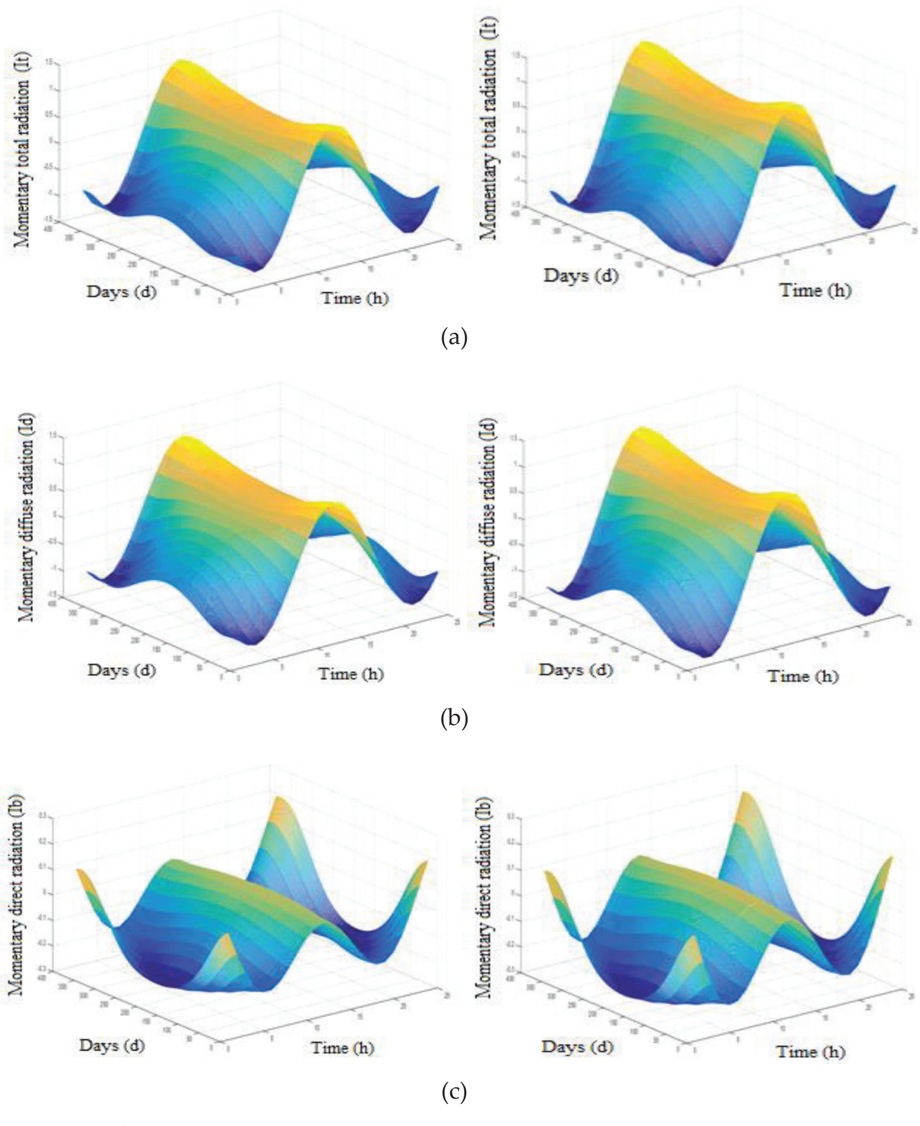



**Figure 5** On horizontal surface, the annual solar radiation values' change for 24-hour period

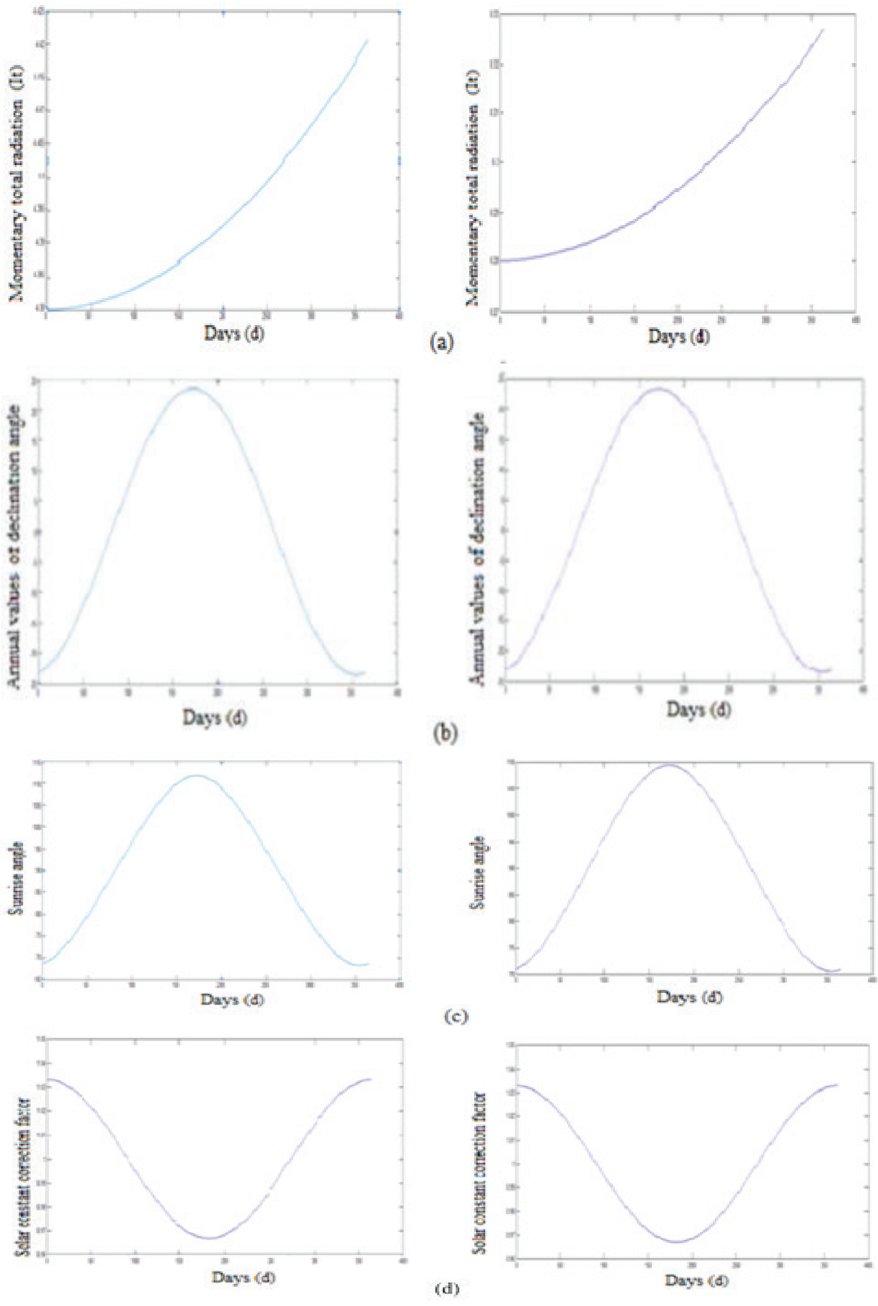



**Figure 6** Solar radiation on horizontal surface

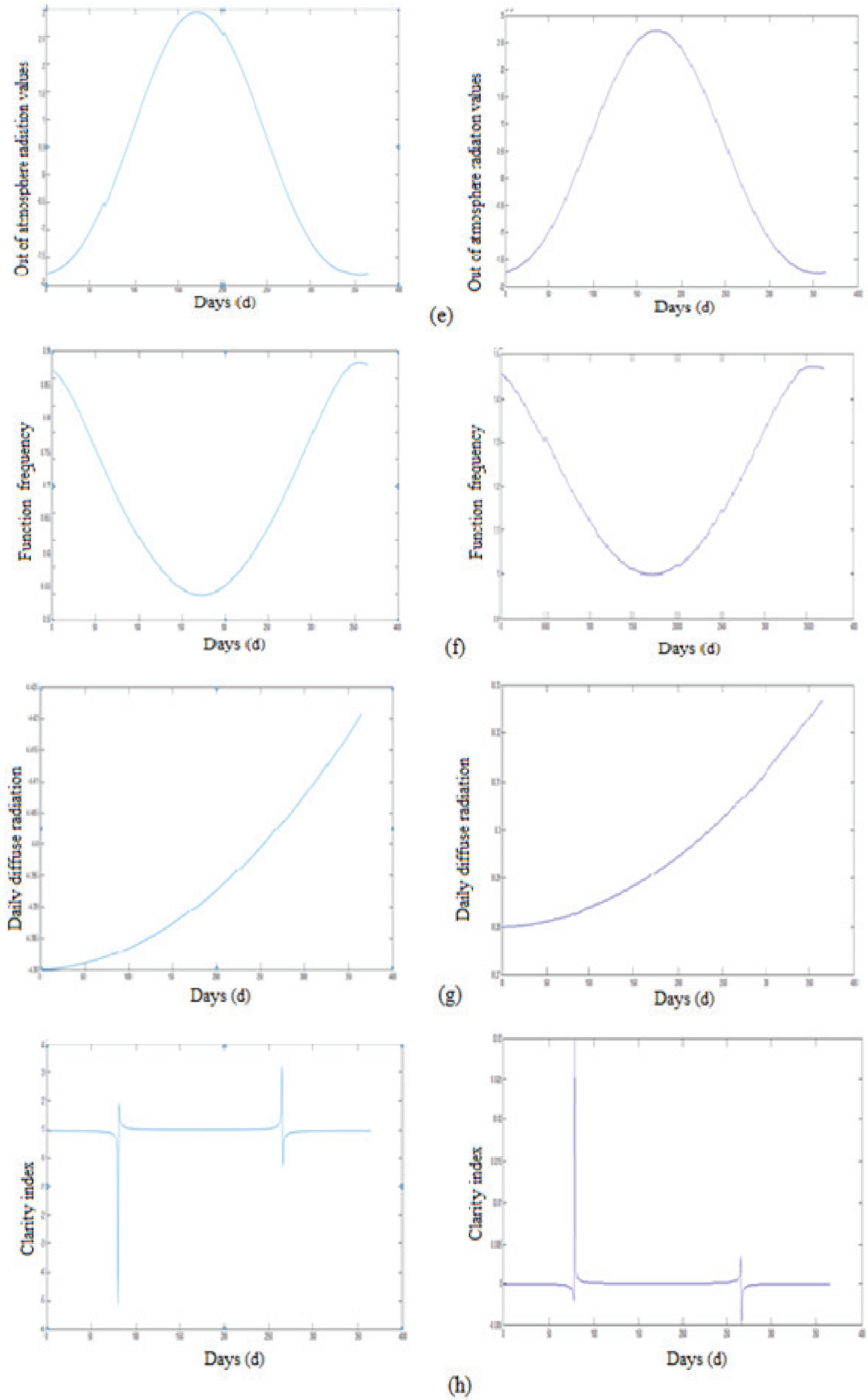
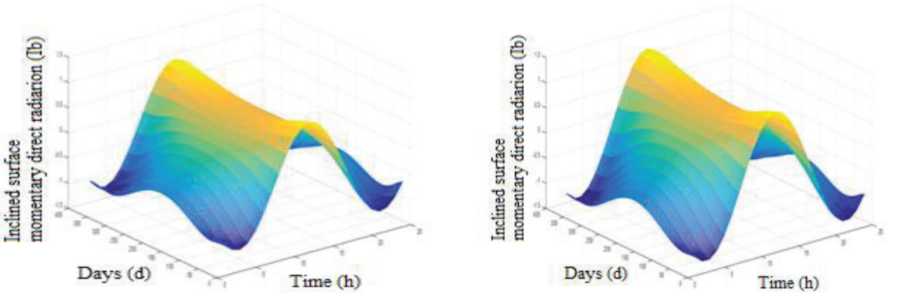
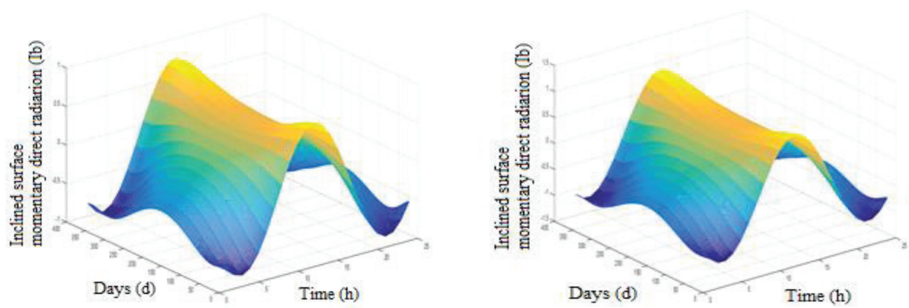



**Figure 6** Solar radiation on horizontal surface (*Continue*)

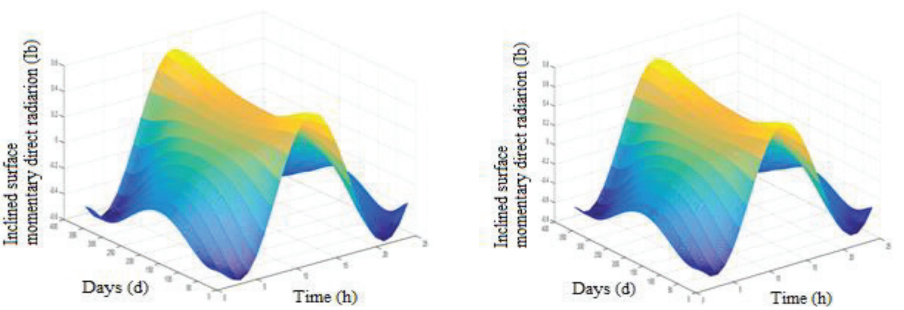
The momentary direct radiation's values with 3 diverse angles (300, 600 and 900) for 24-hour time period are shown in Figure 7. For all 3 angles, the maximum values are determined on the 355th day at 12:00, while the minimum values are determined on the same day at 03:00.




(a) momentary direct radiation values on 30° inclined surface

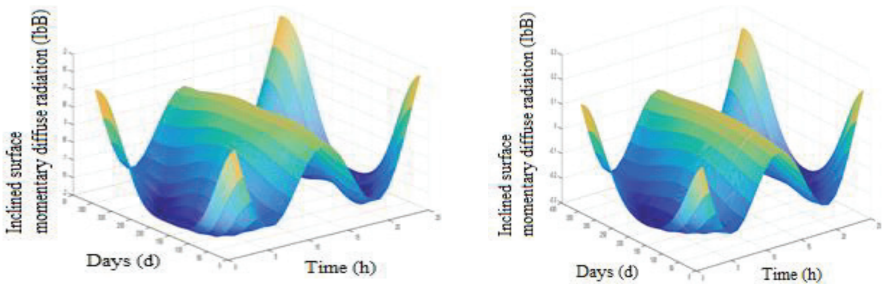



(b) momentary direct radiation values on 60° inclined surface

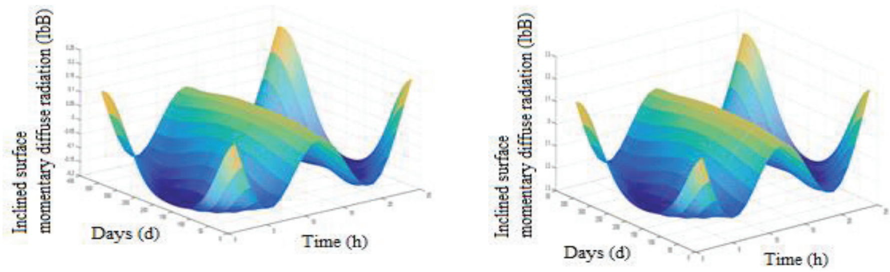



(c) momentary direct radiation values on 90° inclined surface

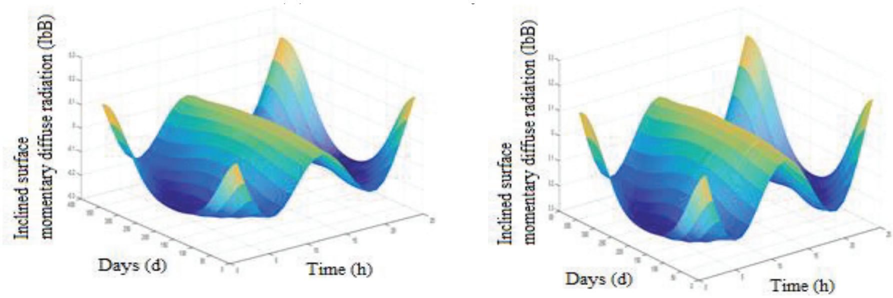
**Figure 7** Annual momentary direct radiation values on inclined surface for 24-hour period




(a) 30° momentary diffuse radiation

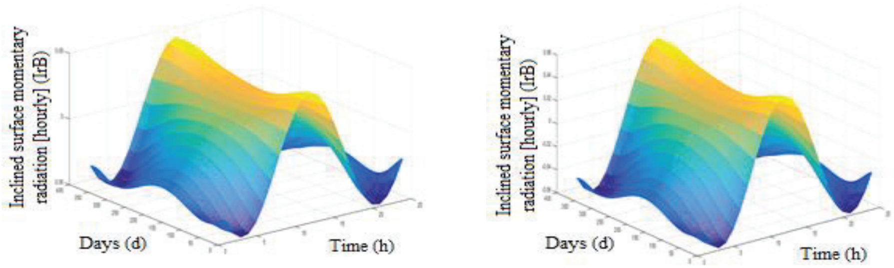



(b) 60° momentary diffuse radiation

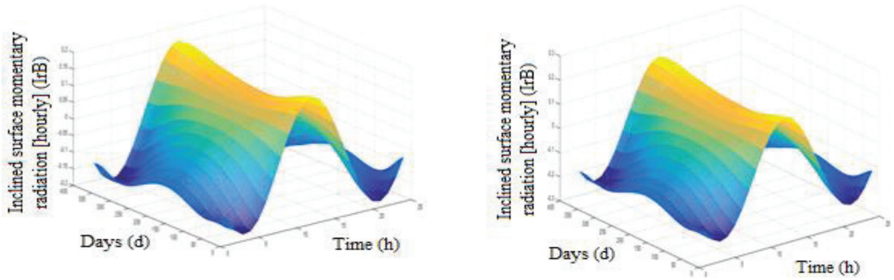



(c) 90° momentary diffuse radiation

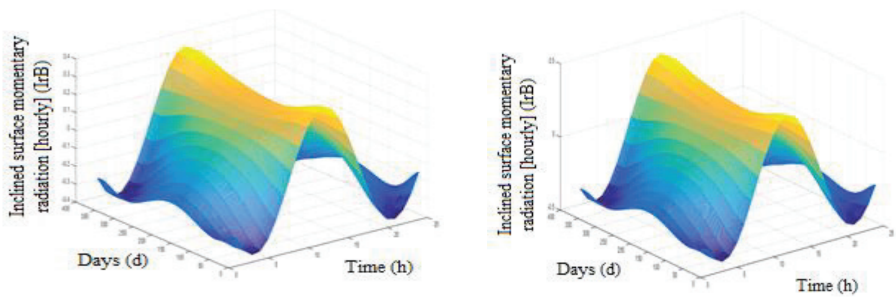
**Figure 8** Annual momentary diffuse radiation values for inclined surfaces




(a) 30° total momentary radiation values




(b) 60° total momentary radiation values




(c) 90° total momentary radiation values

**Figure 9** Annual total momentary radiation values for inclined surface

For three angles (300, 600 and 900), the annual momentary diffuse radiation values are obtained in Figure 8. For 24-hour periods, the total momentary solar radiation's annual values are shown in Figure 9.

## 4.0 RESULTS AND DISCUSSION

An integral of planning the photovoltaic systems is comparing the predicted values with the actual ones. The performance of the system depends on various parameters. Using realistic values of radiation has great importance for designing the optimum system. This paper purposes to determine a reference for selecting the most effective solar panel by relying on the real solar radiation values determined for the most effective photovoltaic system design. To design a photovoltaic system, the solar radiation levels are appraised to be at acceptable efficiency levels.

Approximately 173 billion MW of energy comes to the Earth with solar radiation in a year. This energy corresponds to approximately 160 times the fossil fuel reserves in the world. It also corresponds to 15.000 times the energy produced by fossil fuels, nuclear resources and water power in the world annually. Turkey is one of the world's richest countries in terms of sunshine duration owing to its geographic location and proximity to the equator.Utilizing the measured sunshine duration and irradiation data available at the General Directorate of Meteorology Affairs, a study conducted by EIE reveals the Turkey's average annual sunshine time of 2640 hours (daily total of 7.2 hours), the average of the total solar radiation 1311 kWh / $m^2$- year (total 3.6 kWh / $m^2$ per day). With its potential and ease of use, solar energy has an opportunity to expand more easily than other renewable energy sources. However, despite being in the sun belt, Turkey is not able to use this potential in an effective and widespread manner. Thus, although it was supposed to benefit from the developing technologies to get more efficiency from the sun, this potential could not be sufficiently used, and the region's economic performance remained below the desired level.

In the design of solar energy systems, with the help of reliable solar radiation data and the most accurate models, the performance analysis of the region where the system will be applied is very important in terms of obtaining high efficiency photovoltaic systems. The data obtained should be analyzed with the most realistic models and it should be determined whether they have sufficient potential for the establishment of photovoltaic systems planned to be established in the region. In other words, in the photovoltaic systems planned to be installed, it is possible to determine the equipment that is planned to be used in the most efficient, accurate and reliable way to enable the system to operate, by performing the correct analysis.

East and Southeast Anatolia are the regions with the most solar energy potential in the country. In this study, two different provinces (Kars and Hakkari) which are thought to have the most potential within these regions were selected and the existing solar energy potential in these provinces was investigated.

Solar radiation potential based on horizontal and inclined surface radiation values for Kars and Hakkari provinces is calculated using the meteorological parameters, the most widely used solar radiation evaluation models reported in the literature, and Matlab program. For the feasibility of a photovoltaic power plant that can be designed in these provinces, when the results obtained are evaluated, it is seen that the solar radiation potential of both regions is at the efficiency applicable to the system.

Based on the above analysis, true potential of both cities can be evaluated through the solar characteristics calculations provided in Table 2.

**Table 2** Solar Radiation Attributes

| Attributes | | Kars | Hakkari | Attributes | | Kars | Hakkari |
|---|---|---|---|---|---|---|---|
| **Total radiation** | Imax W/m2 | 6.7724 | 8.3288 | **Mom. dir. Rad.** | Idbmax(30°) | 1.3299 | 1.1981 |
| | Imin W/m2 | 8.7300 | 8.2800 | | Idbmin(30°) | -1.5216 | -1.3816 |
| **Declination angle** | dmax | 22.4498 | 24.1212 | | Idbmax(60°) | 0.8690 | 0.8562 |
| | dmin | -22.4498 | -22.9598 | | Idbmin(60°) | -1.0624 | -0.8125 |
| **Sunrise hour angle** | wmax | 112.0186 | 109.8486 | | Idbmax(90°) | 0.5627 | 0.6121 |
| | wmin | 68.9814 | 71.4514 | | Idbmin(90°) | -0.6082 | -0.7182 |
| **Out-of-Atmosphere Radiation** | Io(max) W/m2 | 298010 | 268025 | **Mom. Dif. rad.** | IbBmax(30°) | 0.1857 | 0.2057 |
| | Io(min) W/m2 | -176900 | -176971 | | IbBmin(30°) | -0.2545 | -0.1845 |
| **Transp. Index** | Bmax | 0.0043 | 0.03 | | IbBmax(60°) | 0.1761 | 0.2161 |
| | Bmin | -0.0124 | -0.005 | | IbBmin(60°) | -0.2549 | -0.1949 |
| **Total diffuse radiation** | Iy(max) W/m2 | 6.7722 | 8.3279 | | IbBmax(90°) | 0.1958 | 0.2001 |
| | Iy(min) W/m2 | 8.7300 | 8.2800 | | IbBmin(90°) | -0.3545 | -0.1945 |
| **Function freq.** | Ats(max) | 1.2375 | 1.4675 | | | | |
| | Ats(min) | 0.7794 | 1.0125 | **Mom. reflecting rad.** | IrBmax(30°) | 0.0476 | 0.0586 |
| **Mom. Tot. Rad.** | It(max) | 1.2075 | 1.4175 | | IrBmin(30°) | -0.0505 | -0.0595 |
| | It(min) | -1.5144 | -1.5000 | | IrBmax(60°) | 0.1861 | 0.1892 |
| **Mom. Dif. Rad.** | $(Ays)_{max}$ | 1.17 | 1.3889 | | IrBmin(60°) | -0.2257 | -0.2757 |
| | $(Ays)_{min}$ | 0.72 | 0.8928 | | IrBmax(90°) | 0.3622 | 0.5722 |
| | Id(max) | 1.3253 | 1.2953 | | IrBmin(90°) | -0.4513 | -0.4527 |
| | Id(min) | -1.5165 | -1.4765 | | | | |
| **Mom. direct rad.** | Ib(max) | 0.2063 | 0.2163 | | | | |
| | Ib(min) | -0.2951 | -0.1951 | | | | |

Solar radiation levels on inclined and horizontal surfaces are calculated using Matlab software. Based on the calculations, the values of the indicators show that potential for photovoltaic systems in both cities correspond to expected levels. Calculations for total annual radiation indicate higher values for Hakkari. One of the points worth pointing out is that the solar radiation levels in Hakkari are higher than the one in Kars for horizontal surfaces while there are comparable results for inclined surfaces.

## 5.0 CONCLUSION

From the findings, the solar energy potential with reliable models was succesfully determined. Besides, a literature which was correlated with the analysis made for both provinces from the feasibility studies related to solar energy systems shall serve as a reference for companies, designers and engineers planning application and investment in the region.

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