COMPARATIVE ANALYSIS of SOLAR RADIATION CHARACTERISTICS by USING INSOLATION MODELS

Abstract

Solar energy keeps increasing its potential to replace conventional sources of energy. However, the need for initial investment requires careful planning and efficient use of financial resources. The most vital part of such in-depth analysis is dependable data. Solar radiation values are of great significance to be able to estimate the potential of solar systems. On the other hand, solar radiation measurements are very limited in global scale. Thus, many models have been proposed in the literature to satisfy the need for the missing data. However, these models are dependent on the specifics of the region to be examined. Climatic conditions play significant role in model development. There are four climatic regions in Turkey and each of them need to be studied on its own. In this study, in order to design PV system for maximum efficiency under certain climatic conditions in Turkey, a comperative analysis of solar energy potential for two cities in the third climatic region is conducted.

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

1. Introduction

Adoption of solar energy is vital to meet the growing energy demand worldwide. The fact that share of carbon-based fuels in energy supply need to be reduced due to the environmental concerns, intensify the research efforts on solar energy as one of the most significant alternative. Its ability to reduce environmental side-effects and relatively simple technology help increase the popularity among other sources of renewable energy. Fig.1 displays the renewable energy distribution of the world [1].

Fig. 1. Renewable energy distribution in the world [1]

Fig. 2 shows solar radiation received on the earth. (A blackbody curve at the temperature of 5800 K is over plotted on the solar irradiance curve). In this figure, Pw is 10 15 Watts (PetaWatt) [2]. Global net radiation map is displayed in Fig. 3 [3].

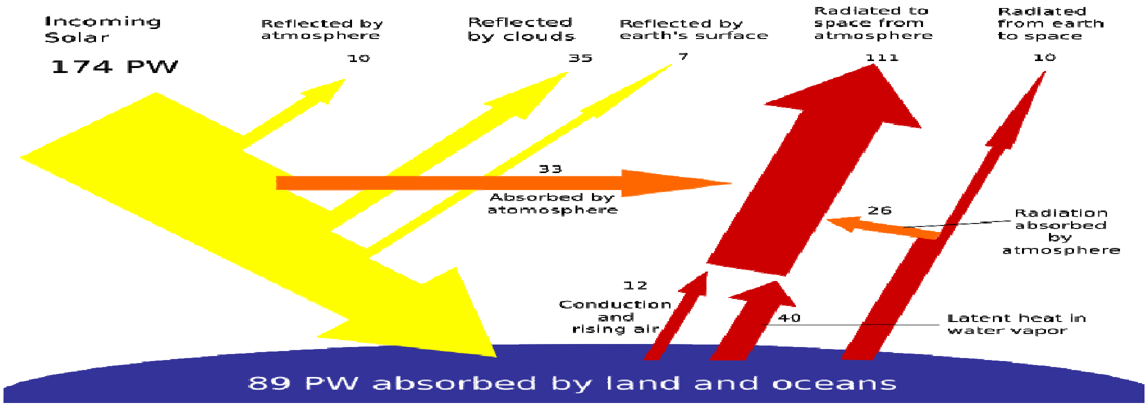


Fig. 2. Solar Radiation received on the earth [2].

Measuring solar radiation which shows the energy radiated from the sun is a significant indicator of true potential of solar energy. Lack of meteorological stations raises the need for estimation models to assess the feasibility of solar energy investments. There is a wide range of deterministic models that have been developed for this purpose. In order to evaluate and compare the appropriateness of selected provinces in second climatic region for solar investments, a selection of these models are utilized in this study as discussed in the following section.

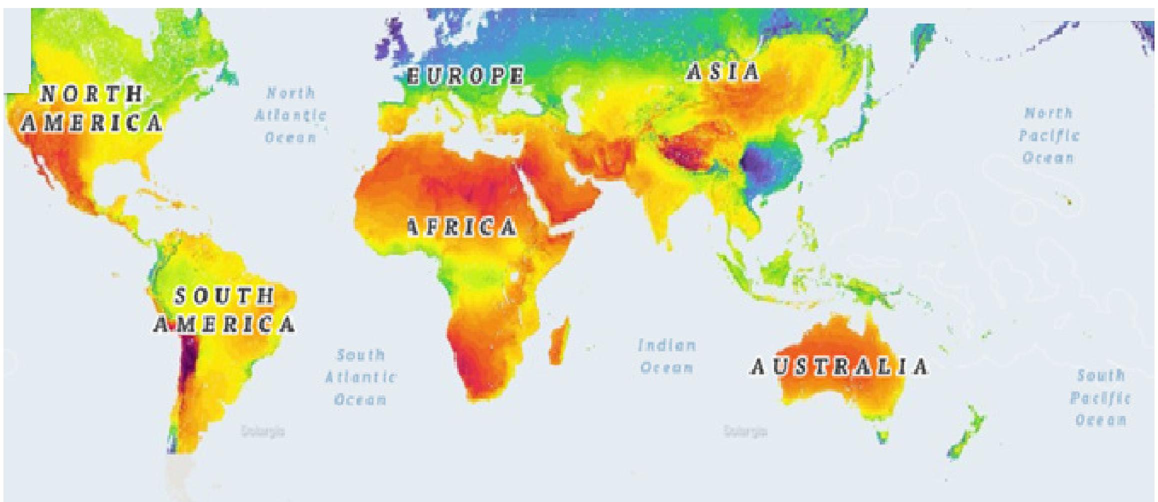


Fig. 3. Global net solar radiation map [3]

In recent years, researchers have begun to focus on the evolution for local solar radiation related to model at photovoltaic system design. Many articles also pointed out that artificial neural network methodology is better than empiric models [4-6]. For four stations, Li et al. assessed eight sunshine duration fraction models in China. For calibration, data for eleven years are used. Four years of data are used for validation. The root mean square error (RMSE) is used as statistical indicator. RMSE of linear model changed from 1.26 to 0.72 MJ/m^{2}day. RMSE of the eight models changed from 1.33 to 0.7 MJ/m^{2}day [7]. Tang etal. studied a hybrid model fixed by Koike and Yang for the prediction of daily solar radiation [8]. The model computed the clear sky index and clear-sky global radiation. These models used sunshine duration, thickness of ozone layer, 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^2day, respectively [9]. To predict average hourly sun irradiation, Janjai etal. obtained a satellite-based model. For hours, the relative root mean square error during 15:00 and 9:00 varied from 10.7% to 7.5% [10]. For 17 cities in Iran, Behrang et al. searched eleven models by applying particle swarm optimization technique [11]. For two sites in Iran, Jamshid et al. researched three sunshine duration fraction (SDF) models one modified sunshine duration fraction model. They used the method of support vector regression. RMSE of them ranged between 2.14 and 3.70 MJ/m^2day. The minimum and maximum temperature, relative humidity, and sunshine duration selected as inputs for kernel function [12]. For Spain, Gorka et al. compared three temperature-based empirical models, artificial neural networks (ANN), gene expression programming, and adaptive neuro-fuzzy inference system. 2855 observations obtained from 4 stations were utilized for testing and 4420 observations were utilized for training purposes. The models used five combinations of minimum and maximum air temperature, clear sky radiation, extraterrestrial radiation, and day number as inputs. The optimized GEP's RMSE varied between 3.31 and 3.49 MJ/m^2day. The corresponding optimized adaptive neuro-fuzzy inference system's RMSE changed between 3.33 and 3.14 MJ/m^2day. The optimized artificial neural networks' root mean square error of the applying other 3 combinations as inputs varied between 2.97 and 2.93 MJ/m^2day [13]. For 79 sites in China with data for 10 years, Li et al. [14] applied a combined model (sine and cosine functions). The mean absolute percentage error varied from 15.43% to 4.00% while RMSE changed between 1.03 and 1.83 MJ/m^2day. Amit etal. searched numerous articles that used ANN for the estimation of sun irradiation in three reviews and predict sun irradiation on horizontal surfaces. They pointed out that artificial neural network models were better than empiric models [15]. For 35 sites in China Zang et al. [16] researched the same model by reducing two coefficients [17]. The mean absolute percentage error and RMSE for the 35 sites ranged from 16.22%, to 4.33% and from1.88 to 1.10 MJ/m^2day, respectively. 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, mean temperature, and the day of the year were involved. The eight models' root mean square error changed from 3.25 to 2.70 MJ/m^2day and the mean absolute percentage error varied between 29.18% and 16.37% [18]. For sixty nine sites in China, Zhou et al. analyzed six SDF models and used three SDF models to predict monthly average sun irradiation. The altitude and latitude are added as parameters in modified models. The coefficient values are derived separately. The sunshine duration fraction ranged from 1.634 to 1.636 MJ/m^2day [19]. 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 and 70% of the data were analyzed to derive 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^2day, respectively [20]. For four sites in Tunisia, Chelbi et al. researched five empiric models [21]. For six provinces in Iran, Khorasanizadeh et al. assessed three mean SDF models and three NSDF models for the prediction of 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^2day [22]. Wan 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% [23]. For seven locations in Turkey, Hacer et al. investigated five sunshine duration fraction models to predict monthly average radiation [24]. For 9 sites in China, Zhao et al. researched the linear model. RMSE varied between 1.72 and 5.24 MJ/m^2day [25]. For Dezful, Iran, Behrang etal. investigated multi-layer perceptron network and radial basis function network. Six combinations of the parameters (wind speed, relative humidity, day number, evaporation, sunshine duration, and mean air temperature) were used. To train the models, 1398 days were used. For testing, 214 days were used. The mean absolute percentage error changed from 5.21% to 22.88%. [26]. 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 [27]. For 4 sites in Thailand and 5 sites in Cambodian, Janjai et al. researched a satellite-based model. The root mean square error is obtained as 1.13 MJ/m^2day [28]. For twenty two sites in South Korea, Park etal. searched linear empiric model [29]. El-Sebaii et al. performed three mean SDF models, three SDF models and NSDF for the prediction of average monthly global sun irradiation for Saudi Arabia. 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. RMSE of the 9 models ranged between 0.02 and 0.15 MJ/m^2day [30, 31]. To predict hourly solar irradiation, Shamim et al. used a fixed technique. To obtain the relative humidity and air pressure, they used a meso-scale meteorological model for diverse atmospheric layers. By using available measured data, they computed the cloud cover index with relative humidity and air pressure. By an empirical correlation, they determined clear sky radiation and transmission factor to compute the actual hourly solar irradiation. The clear sky radiation was predicted by applying irradiation transfer model. For training, Data for one year was used. The root mean square error was obtained as 110.83 W/m^2 [32]. For four provinces in Turkey, Ahmet et al. researched cubic, linear, and quadratic empiric models [33]. For two sites in Iran, Jamshid etal. researched two support vector regression models. As inputs, the minimum and maximum temperature, sunshine duration, and relative humidity were used. Root mean square errors were obtained from 1.63 to 4.47 MJ/m^2day [34]. Bakirci investigated sixty empiric models developed for the prediction of 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 [35]. For 41 sites in China, Kevin etal. 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 using latitude, altitude, longitude, day number, sunshine duration fraction, and daily mean temperature [36]. Kasra et al. presented four SDF models with data of nine years for Isfahan in Iran. Data of four years were used to test the data. RMSE of them changed between 1.18 and 1.1 MJ/m^2day [37]. For Shiraz in Iran, Shahaboddin et al. assessed two SDF models, two mean SDF models and one non-sunshine duration model. RMSE of the 5 models changed from 1.55 to 1.3 MJ/m^2day [38]. In the artificial neural networks model, Alvaro et al. applied the satellite data. The performance obtained is reported to be very good [39]. Fariba et al. searched seventy eight empiric models. They grouped them into four classes of models based on sun ray, cloud, meteorological characteristics, and temperature. 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 [40]. For Turkey, Ozgoren et al. used the artificial neural networks model of multi non-linear regression to obtain the best independent characteristics for input layer. They selected 10 characteristics (soil temperature, month of the year, altitude, sunshine duration, cloudiness, minimum and maximum atmospheric, mean atmospheric temperature, latitude, and wind speed). Levenberg-Marquardt optimization algorithm was utilized to train the ANN [41]. For eleven meteorological sites on Tibetan, Pan etal. 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 applied. RMSE of the model changed from 2.54 to 3.24 MJ/m^2day for all stations[42]. For twenty five sites in Spain, Manzano etal. assessed the linear Angstrom–Prescott model. More than 10 years of data was used for calibration purposes. Except for 4 sites, RMSE changed between 0.8 and 0.36 MJ/m^{2}day [43]. Kadir studied seven different sunshine duration fraction models with data measured from 18 sites in Turkey. Various models including exponential, logarithmic, quadratic, and linear equations were used for the prediction of long-term average daily global solar radiation on monthly basis. For the same sites, the performances of the applied models are obtained with slight differences [44]. For Yazd in Iran, Fariba 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 [45]. For Gaize in Tibetan, Liu et al. investigated 3 non-sunshine duration models, 2 SDF models and 3 modified SDF models. For calibration, 1085 days of data were analyzed while 701 days of data were used to validation purposes. 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 [46]. For 4 cities in India, Katiyar etal. searched the quadratic, cubic, and linear models for the prediction of monthly average radiation using annual data. The values ranged from 0.8 to 0.43 MJ/m^{2}day [47]. To predict sun irradiation, Sun etal. assessed influence of autoregressive moving average model. They investigated the data of 20 years from 2 sites in China [48]. In a 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. RMSE varied between 0.221 and 0.213 MJ/m^{2}day [49]. For Iseyin in Nigeria, Lanre et al. used the adaptive neuro-fuzzy inference system and ANN. Maximum and minimum temperature and sunshine duration were used as inputs. Data of 6 years were obtained for model training while data of 15 years were obtained to test the model. In testing and training phases, RMSE varied between 1.76 and 1.09 MJ/m^{2}day, respectively [50]. Iranna et al. 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 [51]. To obtain the most effecting input characteristics for prediction, Yadav et al. performed the Waikato Environment's software. They determined the minimum and maximum temperature, average temperature, sunshine duration, and altitude as input characteristics, while longitude and latitude were reported to be the least effective characteristics. The prediction was for average monthly global sun irradiation. By the artificial neural networks, the maximum mean absolute percentage error is obtained as 6.89% [52, 53]. 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 error in testing and training stage were reported as 0.32 and 0.16 MJ/m^{2}day, respectively [54]. For 4 provinces in Iran, Khorasanizadeh et al. [55, 56] 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%. 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 used. RMSE changed between 8.25 and 4.78 MJ/m^{2}day for the linear model [57]. For Bandar Abass province in Iran, Mohammadi etal. [58] used support vector machine and wavelet transform algorithm. Data for 10 years were 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. RMSE varied between 1.81 and 1.79 MJ/m^{2}day, respectively. 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, opaque sky cover, minimum and maximum temperature, average temperature, relative humidity, daylight temperature, heating and cooling degree days were chosen as parameters [59]. Qin et al. used Levenberg-Marquardt algorithm with inputs including area temperature difference between night and daytime, air pressure rate number of days, vegetation index, mean area temperature, and monthly precipitation. For Tibetan Plateau, data of seven years from twenty two sites are used to train the artificial neural networks [60]. For Shiraz in Iran, Shahaboddin 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. 3 years of data were used for testing. RMSE varied between 0.93 and 0.86 MJ/m^{2}day [61]. 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 for the prediction of average monthly irradiation is proposed. Root mean square error changed from 2.75 and 2.32 MJ/m^{2}day [62]. For Saudi Arabia, Mohamed applied particle swarm optimization for training of the ANN. The longitude, altitude, latitude, sunshine duration, and month of the year were used as inputs. However, 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% [63]. Antonio et al. 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 [64].

Climate, Solar Energy Potential and Electric Production in Usak and Tokat

Equipment limitations and their high maintenance cost, have also limited the number of stations measuring solar radiation, thus meteorological variables are commonly being used in the calculation of solar radiation [65-67]. The land and sunshine period are of great significance for facilities to be established based on solar energy. Thus, comprehensive investigation need to be undertaken about climate, solar energy potential and current facilities. Among many models that have been developed to calculate amount of solar radiation, sunshine hours is the most widely utilized parameter [68].

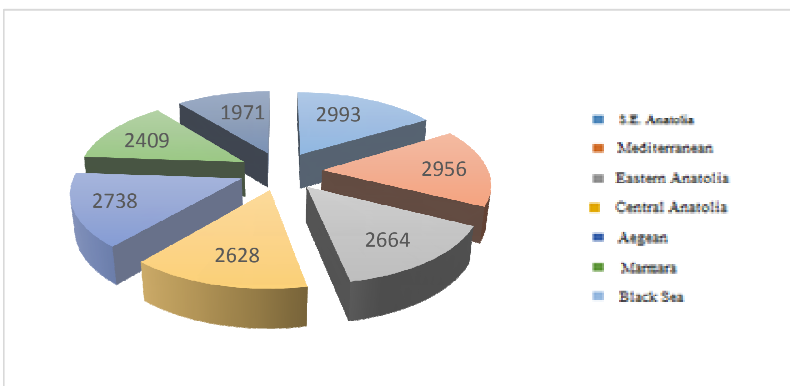


Fig. 4. Annual Total Solar Energy Period (hour-year)

As presented in Figure 4, more than half of Turkey possesses high potential of sunshine. Based on the study of General Directorate of Electrical Power Resources (EIE), average annual sunshine duration of Turkey is reported to be 2640 hours (7.2 hours/day) and average radiation intensity to be 1311 kWh/m²-year (3.6 kWh/m²/day). Solar radiation maps for Usak and Tokat is displayed in Fig. 5.

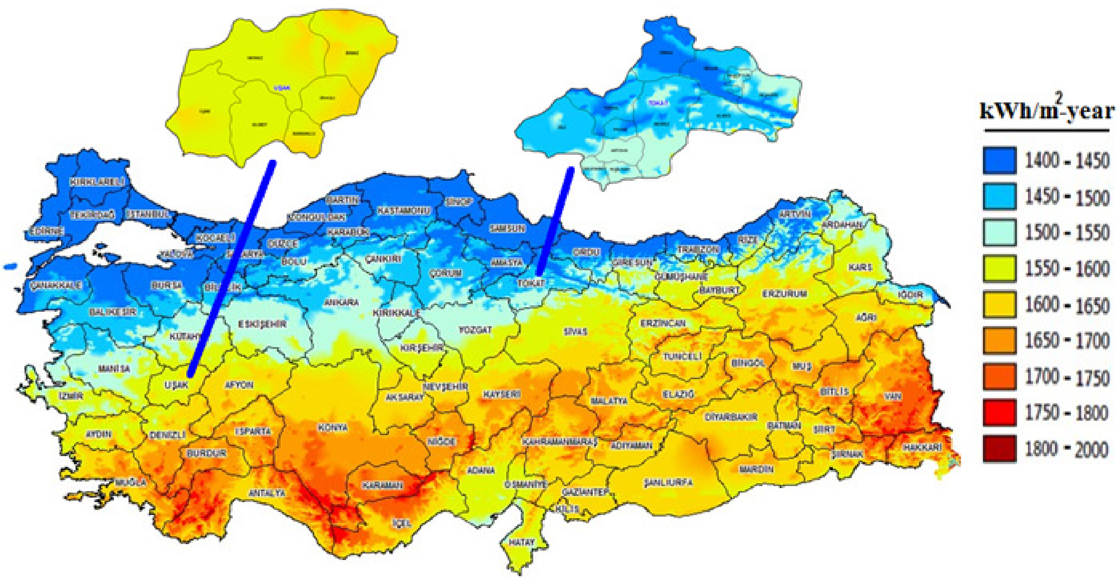


Fig. 5. Solar radiation maps for Uşak and Tokat

In terms of solar energy potential, both cities are placed in the second region. Average solar radiation, radiation function frequency, radiation function phase shift, 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
Usak	11.5	6.15	3.15	38.40
Tokat	12.5	7.76	6.19	40.00

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

2. Solar Radiation Intensity Calculation

Due to the climatic variations and geographic conditions, calculating amount of solar radiation depends on the specific region and requires the selection of the best model among others that are available in the literature. The model developed by Angstrom using radiation data and sunshine duration is the most commonly used one. Vartiainen et al. have proposed a statistical model to estimate the solar radiation amount through the use of data obtained from satellite [69]. Menges et al. provided a statistical comparison of daily total solar radiation on a horizontal surface in a specific city of Turkey with 50 different models in the literature [70]. Katiyar and Pandev have used solar radiation data from five different regions of India between 2001 and 2005 [71]. Consequently, they have developed Angstrom-type first, second, and third degree solar radiation models specific for each region. Monthly total radiation values of the developed model and measured values have also been compared.

2.1. Horizontal Surface

2.1.1. Daily Total Solar Radiation

Total solar radiation on horizontal surfaces on a given day can be calculated through the below equation [72]:

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

where
n: days,
FKI: radiation function phase shift,
FGI: radiation function frequency, and
I_{ort}: annual average of daily total radiation.

2.1.2. Daily Diffuse Solar Radiation

Total daily diffuse solar radiation on horizontal surfaces can be obtained using equation 2 [73].

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

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

2.1.3. Momentary Total Solar Radiation

Momentary total solar radiation on horizontal surfaces can be obtained using equation 2 [74, 75].

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

where;
I_s (W/m^2): solar constant, e: latitude angle; w_s: sunrise hour angle f: solar constant correction factor, d; declination angle can be calculated using the related tables and equations.
Out-of-atmosphere radiation can be calculated using equation 4 [73].

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

where;
A_{ts}: solar radiation and
t_{gi}, : imaginary day length.

2.1.4. Momentary Diffuse and Direct Solar Radiation

Amount of momentary diffuse and direct solar radiation on horizontal surfaces can be obtained using equations 5 and 6 [21, 22] where A_{ys} is function frequency.

$$I_{ys} = A_{ys}C\text{os}\left[\frac{\pi}{t_g}(t-12)\right] \tag{5}$$

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

2.2. Calculating Solar Radiation Intensity on Inclined Surface

2.2.1. Momentary Direct Solar Radiation

Momentary direct solar radiation on inclined surfaces (30°-60°-90° angles) can be calculated using the equation below [75].

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

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

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

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

2.2.2. Momentary Diffuse Solar Radiation

Value of momentary diffuse radiation on inclined surfaces can be obtained using the equation below [22].

$$I_{ye} = R_y I_{ys} \tag{11}$$

Conversion factor R_y for diffuse radiation can be calculated using equation below [75]:

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

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

2.2.3. Reflecting Momentary Solar Radiation

Reflecting radiation on inclined surfaces [75] can be calculated using the equation below:

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

Environment reflection rate is shown with ρ parameter and used with average value of ρ = 0.2 in calculations.

2.2.4. Total Momentary Solar Radiation

Momentary total radiation on inclined surfaces [75] can be obtained using equation below:

$$I_t = I_{de} + I_{ye} + I_{ya} \tag{14}$$

3. Methodology

Figure 6 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 horizontal surfaces. Figure 7 provides 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.

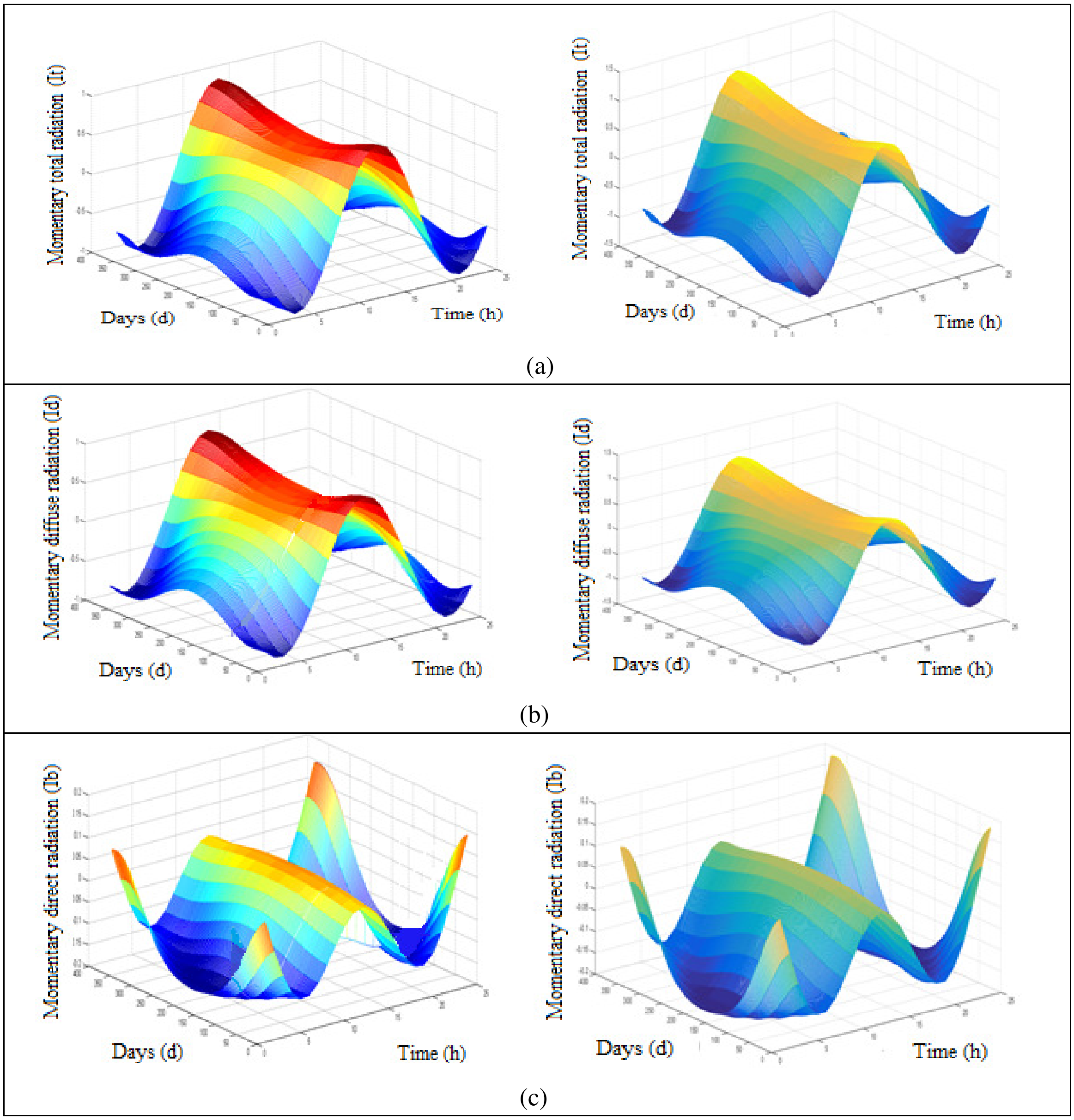
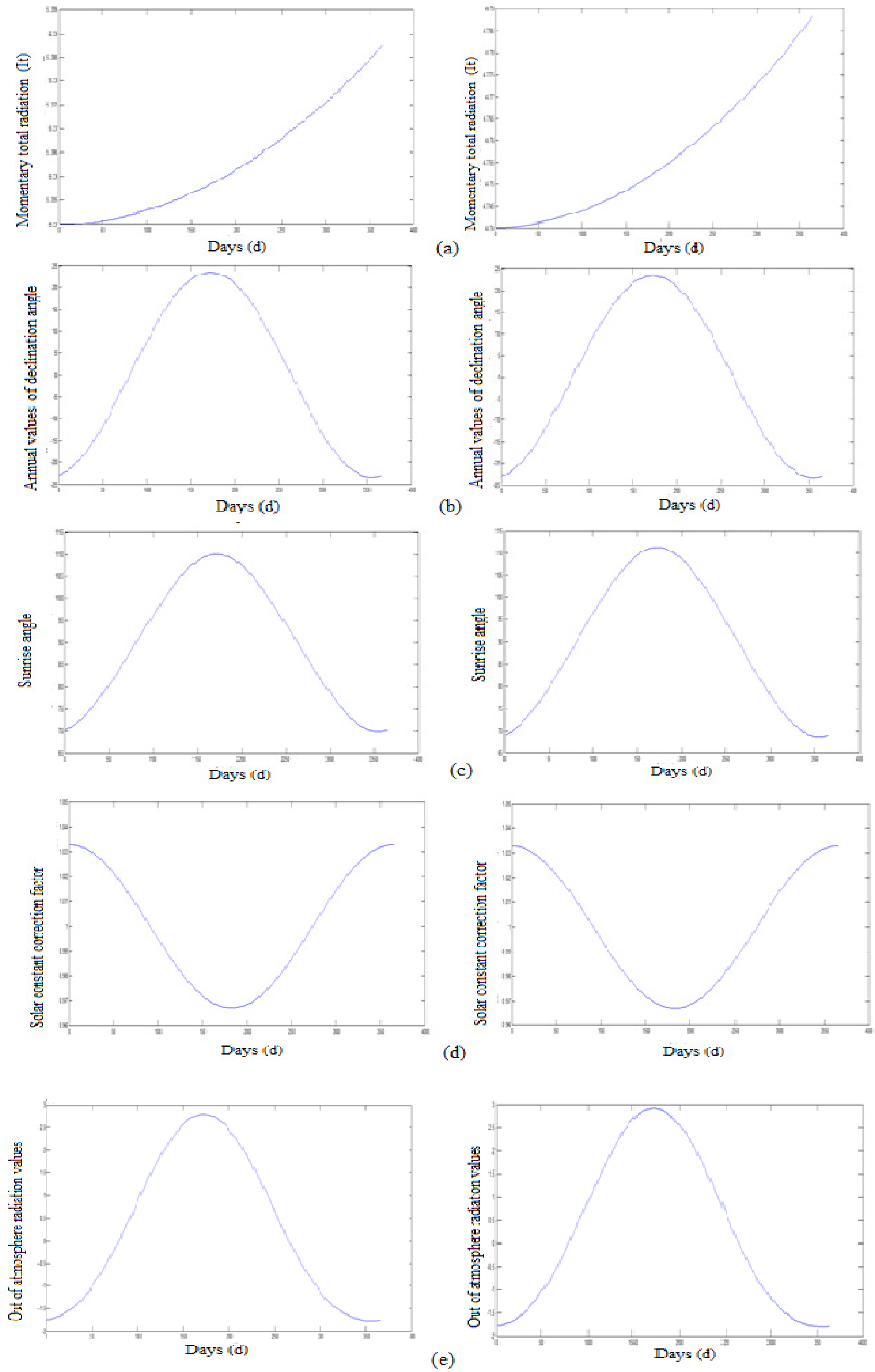


Fig. 6. Change of annual solar radiation values for 24-hour period on horizontal surfaces


Momentary total radiation (It)
Days (d)
(a)
Annual values of declination angle
(b)
Sunrise angle
(c)
Solar constant correction factor
(d)
Out of atmosphere radiation values
(e)

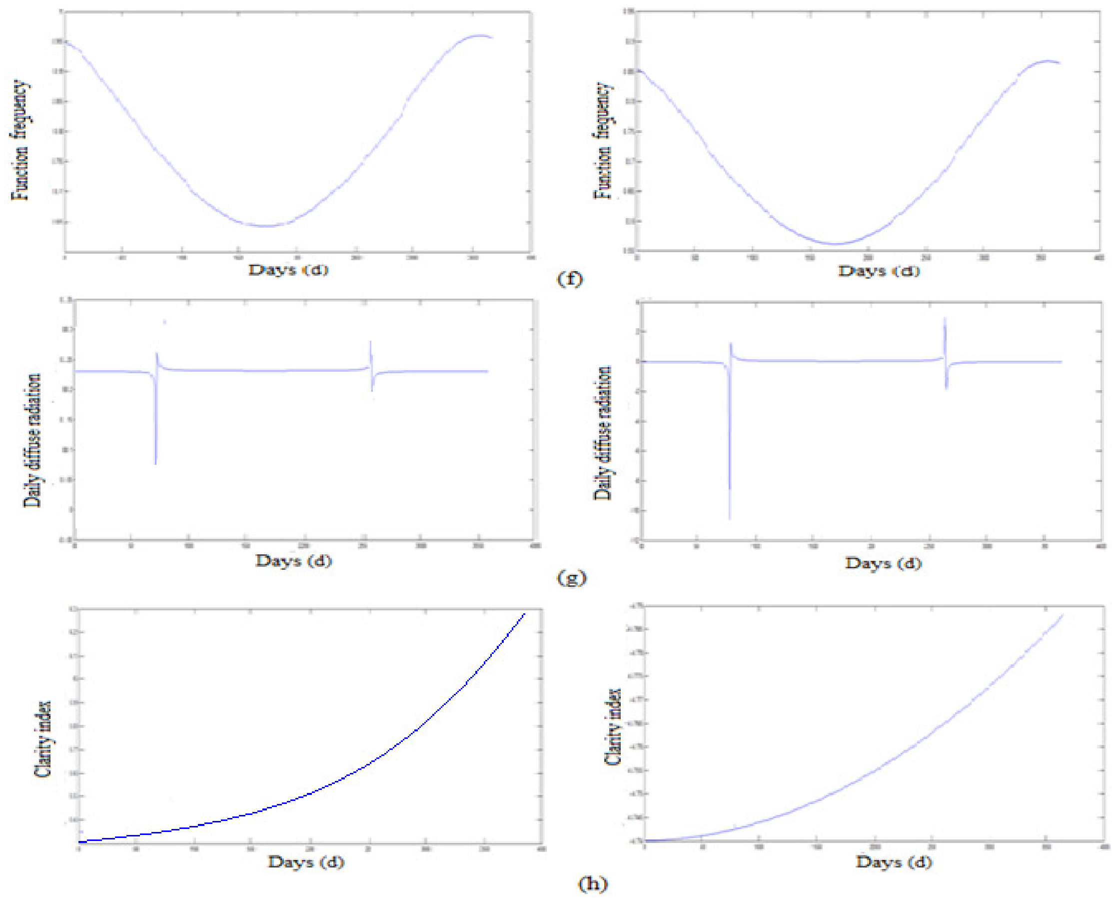
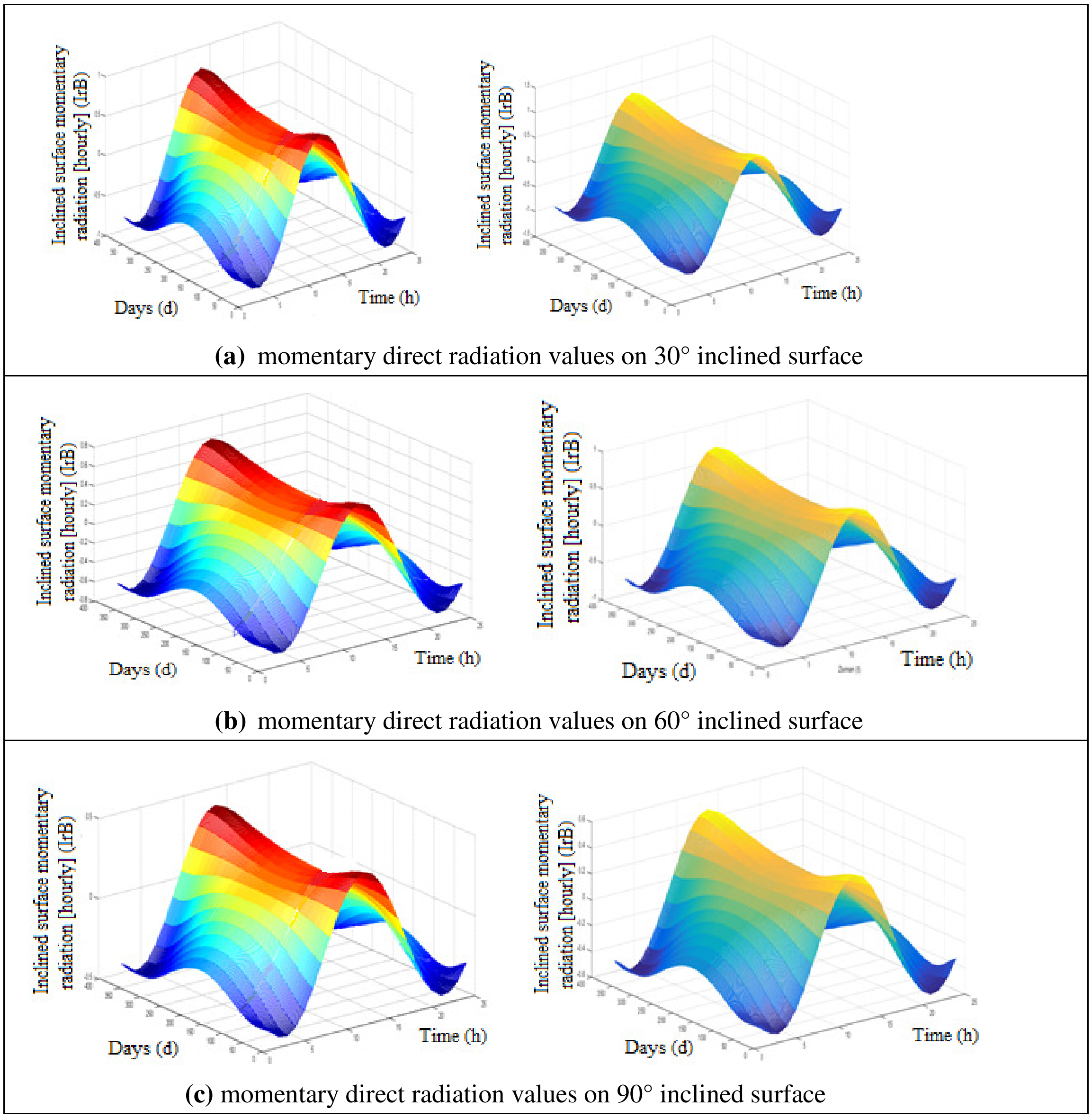


Fig. 7. Solar radiation on horizontal surfaces

Momentary direct radiation values with three different angles (30^0, 60^0 and 90^0) for 24-hour time period are provided in Figure 8. The highest values for all three angles are obtained on the 355th day at 12:00, while the lowest values are obtained on the same day at 03:00.

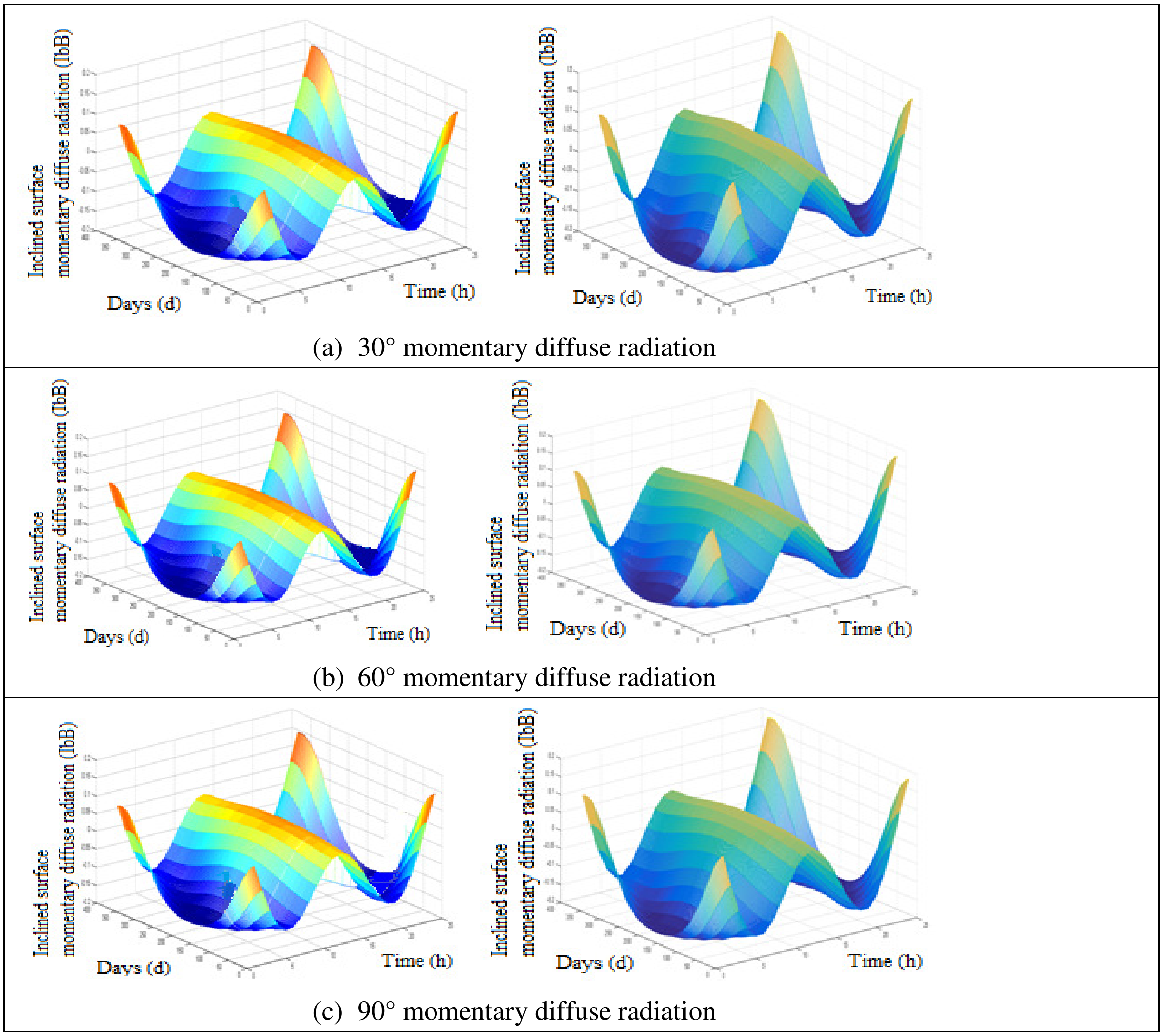


(a) momentary direct radiation values on 30° inclined surface

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

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

Fig. 8. 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

Fig. 9. Annual momentary diffuse radiation values for inclined surfaces

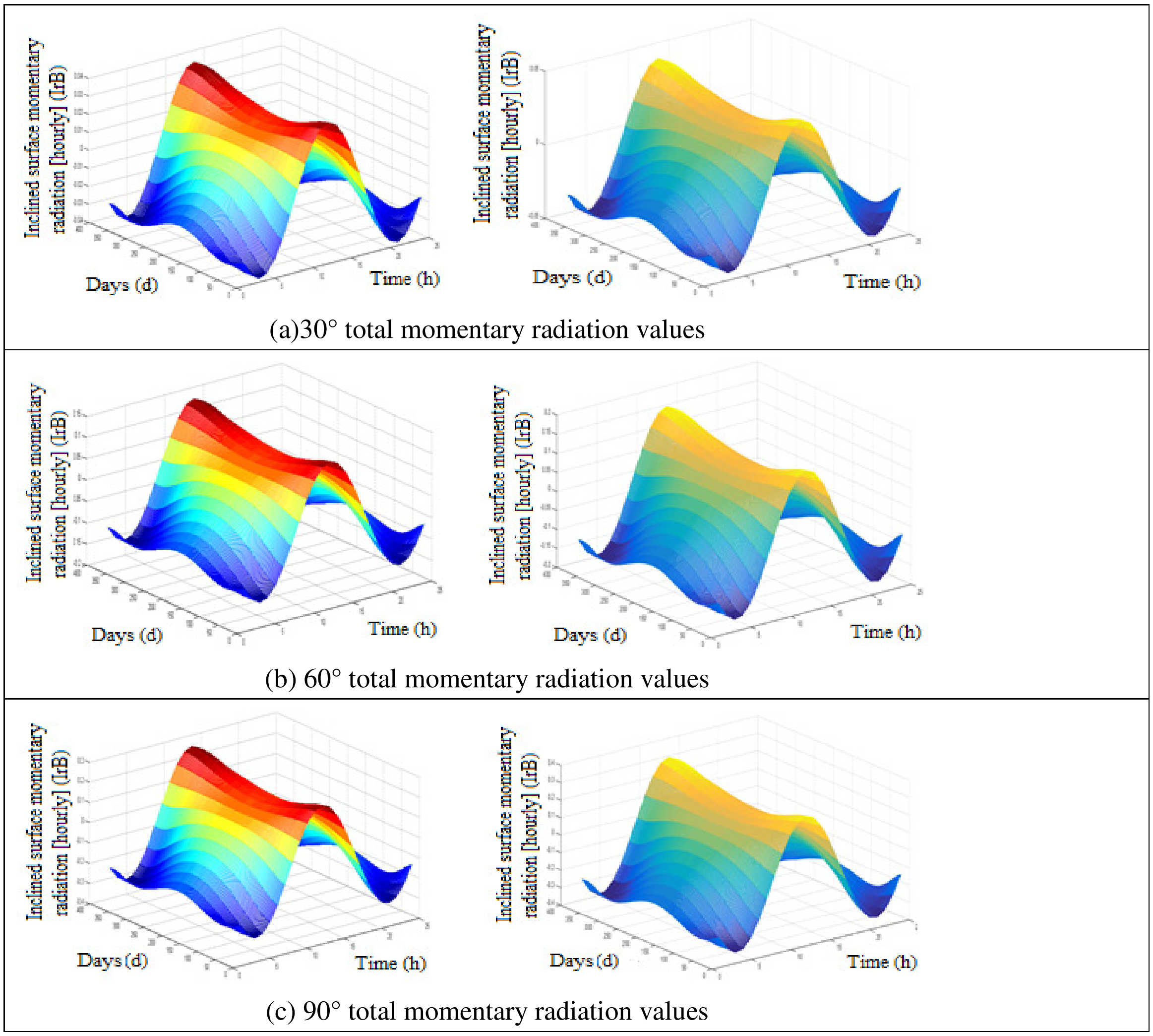


Fig. 10. Annual total momentary radiation values for inclined surface

Annual momentary diffuse radiation values for three angles (30^0, 60^0 and 90^0) are provided in Figure 9. Annual values of total momentary solar radiation for 24-hour periods are provided in Figure 10.

4. Findings and Results

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		Usak	Tokat
Total radiation	Imax W/m2	5.3881	4.7858
	Imin W/m2	5.3500	4.7400
Declination angle	dmax	23.6798	23.4488
	dmin	-23.7398	-23.4468
Sunrise hour angle	wmax	112.1015	112.9271
	wmin	70.9865	69.8123
Out-of-Atmosphere Radiation	Io(max) W/m2	281010	299215
	Io(min) W/m2	-177450	-189100
Transp. Index	Bmax	0.3330	0.3567
	Bmin	-0.0011	-0.0111
Total diffuse radiation	Iy(max) W/m2	6.2822	4.7881
	Iy(min) W/m2	5.1800	4.7400
Function freq.	Ats(max)	0.9500	0.8612
	Ats(min)	0.6418	0.5695
Mom. Tot. Rad.	It(max)	1.7555	1.0011
	It(min)	-0.9844	-1.1044
Mom. Dif. Rad.	$(Ays)_{max}$	0.8991	0.8112
	$(Ays)_{min}$	0.5799	0.5
	Id(max)	1.7853	0.9851
	Id(min)	-0.5865	-0.9956
Mom. direct rad.	Ib(max)	0.0465	0.1854
	Ib(min)	-0.1546	-0.1881

Attributes		Usak	Tokat
Mom. dir. Rad.	Idbmax(30°)	0.8678	0.8933
	Idbmin(30°)	-0.9670	-0.9721
	Idbmax(60°)	0.6190	0.7807
	Idbmin(60°)	-0.7824	-0.8923
	Idbmax(90°)	0.0397	0.4992
	Idbmin(90°)	-0.4182	-0.5882
Mom. Dif. rad.	IbBmax(30°)	0.0395	0.1714
	IbBmin(30°)	-0.1512	-0.1715
	IbBmax(60°)	0.0489	0.1898
	IbBmin(60°)	-0.1549	-0.1872
	IbBmax(90°)	0.0458	0.1911
	IbBmin(90°)	-0.1645	-0.1876
Mom. reflecting rad.	IrBmax(30°)	0.0378	0.0486
	IrBmin(30°)	-0.0400	-0.0485
	IrBmax(60°)	0.1191	0.1499
	IrBmin(60°)	-0.1521	-0.1673
	IrBmax(90°)	0.2781	0.3001
	IrBmin(90°)	-0.2921	-0.3258

Solar radiation values on inclined and horizontal surfaces are calculated through MATLAB software. Based on the calculations, the values of the indicators show that potential for photovoltaic systems in both cities correspond to expected levels. 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 study is aims to establish a reference for choosing the most efficient solar panel by relying on the real solar radiation values obtained for the most efficient photovoltaic system design. The solar radiation levels are evaluated to be at acceptable efficiency levels to design a photovoltaic system.

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