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Article

Estimation of the hourly solar radiation

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Abstract: Hybrid facility investments from renewable energy sources have increased in recent years. In general, solar power is the secondary energy source in hybrid systems. The reason why solar energy is most commonly used in hybrid power systems is that it is cheaper than other types of renewable energy. Solar-Hydroelectric (SHE) is one of the foremost compatible hybrid energy pairs, as solar and hydroelectric power generation profiles complement one another. Hybrid systems consisting of solar and hydropower have complementary characteristics due to the shared use of infrastructure systems and different periodicities in power generation. Energy management is important for SHE-integrated facilities. Since only a limited amount of energy can be injected into the grid from transformer capacities, energy management in hybrid systems is of great importance. To manage energy in hybrid energy systems, the amount of energy that can be produced each hour must be determined. In hybrid energy plants, there is usually already another renewable energy plant in place, and solar energy is added on top and optimized. Since there are no pyrometers in the existing plants, the daily radiation data from the National Aeronautics and Space Administration (NASA) is used, but the daily energy production amount may be insufficient for accurate energy management. To realize this, it's necessary to reveal the energy generation on an hourly basis. During this study, the quantity of radiation on an hourly basis was determined to calculate solar power generation. Empirical and econometric models utilized in radiation amount determination were performed, and the most appropriate method was clarified by comparing them with one another. Hourly-based radiation is achieved with an empirical method by using National Aeronautics and Space Administration (NASA) daily radiation.

Keywords: SHE (Solar-Hydroelectric); energy management; solar radiation

1. Introduction

Energy management and hybrid energy became the most significant issues to ensure the sustainability of energy production. In general, solar energy is the most renewable energy hybrid. Therefore, it's necessary to work out energy generation amounts on an hourly basis and to confirm energy management. Solar energy may be a style of energy that is easily accessible around the globe. Electricity generation from solar energy is within the sort of function of radiation and temperature. Meteorological measurements are made regionally in many parts of the planet. The radiation amount is obtained from satellites. The NASA official website has daily irradiance data for any coordinate on the planet. However, these data must be obtained on an hourly basis for energy management. The quantity of radiation on an hourly basis is obtained by basically two methods. One of them is the empirical method, and the other is the econometric statistical method. During this study, both approaches were run separately and compared with actual data. The literature reviews are given in the following paragraphs. With the widespread use of hybrid energy, energy management is becoming more important. The main reason is that the capacity that can be fed into the grid does not change, no matter how much the installed power increases. For example, if a wind turbine with an installed capacity of 80 MW, which has the right to inject energy into the grid with an installed capacity of 50 MW, is additionally supported by solar energy with an installed capacity of 100 MW, the amount of energy that the turbine can inject into the grid will not be 180 MW, which is the total installed capacity of the two production facilities, but the amount of electricity injected into the grid will still be 50 MW. Therefore, energy management in hybrid energy systems is critical to the continuity of the system. In hybrid energy, solar energy is mostly used. In hybrid projects using solar energy, the amount of radiation should be determined on an hourly basis to ensure natural and reliable energy management. The amount of radiation is one of the main factors that determines the amount of energy production, as it directly affects the amount of electricity produced by the PV panels. With this study, the solar radiation amounts are accurately and quickly determined every hour and will be used for both efficient power optimization and energy management.

Tırmıkçı used the mathematical models and equations to see the most suitable angle in Sakarya province in her doctoral thesis. During this study, Tırmıkçı revealed a real-time comparison of the two-axis scheme positioned with the sun and therefore the fixed scheme. Tırmıkçı worked on position with the foremost appropriate annual angle [1]. Jacovides et al. stated versatile correlations in determining the hourly solar radiation. During this study, radiation measurements for Cyprus supported the experiment, which was briefly defined empirically by making use of the mathematical models previously stated within the literature studies by other researchers. By calculating the coefficients, hourly radiation is estimated [2]. Iqbal correlated the mean beam with diffuse radiation. Monthly average radiation amounts with the knowledge obtained from the stations for various cities in Canada are calculated [3]. Alsafadi and Başaran Filik used a design algorithm like a machine learning mechanism for hourly solar radiation. Estimated the quantity of radiation on an hourly basis by applying machine learning (ML-machine learning) to empirical models for Eskişehir [4]. Serttaş proposed a brand-new pattern scan-based approach to radiation forecasting [5]. Maleki et al. estimated the global solar radiation on disposed sides. Empirical radiation simulation developed especially within the last ten years for a neighborhood [6]. Chandel and Aggarwal have worked on a one-hour energy model that will provide reliable and accurate finishes up within the western Himalayas. This study has been cited as a reference in many other articles [7].

Khatib and Elmenreich proposed a new approach for obtaining hourly solar radiation. In this study, an artificial neural network is used to generalize daily solar radiation [8]. Berrizbeitia et al. stated an experimental simulation for determining solar radiation. During this study, a review and experimental analysis emphasized that daily radiation amounts are often easily obtained from NASA sources, but it had been emphasized that a model should be developed for the hourly radiation amount obtained on an hourly basis, and empirical coefficients for 19 different regions were tested [9]. Gueymard stated a new estimation approach for solar radiation. During this study, the number of radiations was measured on a monthly and average hourly basis using two new models in line with the information provided by an outsized nation-state and lots of information stations. The empirical coefficients proposed during this study were also utilized in studies conducted by other researchers [10]. Al-Rawahi et al. suggested a new estimation method for Oman. During this study, the amount of radiation is calculated on an hourly basis from the available daily radiation amounts for Oman [11]. Ishola et al. developed a territorial correction factor for the estimation of hourly-based solar irradiance. A comparison was made specific to the estimation model that determined ten regions for radiation amount and also the coefficients determining the regional radiation [12]. Hussein estimated hourly global radiation in Egypt employing a mathematical model. A mathematical model prediction calculates the amount of radiation for Egypt on an hourly basis using meteorological data [13]. Within the studies examined, general and conceptual models were formed by fitting and measurements made in numerous parts of the world and at different times into mathematical models [1–13]. Among these models, mathematical models and experimental coefficients, which are briefly called empirical, were employed within the studies created by Maleki et al. [6], Chandel and Aggarwal [7], Gueymard [10]. In addition to empirical coefficients and prediction models, statistical models are also used when determining the quantity of radiation. When using statistical models, forward-looking estimations are made by using mostly actual data. In regions where data is going to be obtained on an hourly basis, high correlation results are often obtained due to statistical methods. Huang et al. forecasted solar radiation by continuously employing some auto-regressive and space (CARDS) models. During this study, the authors emphasized that the amount of radiation is seriously tormented by weather changes like cloudiness. In this case, the only approaches today are statistics. It's stated that some methods exist in computing networks, and random variables are called stochastically. Within the study, a self-connected (AR-autoregressive) model is used together with a dynamic system model. As a result of the study, it was stated that the proposed system confirmed and improved the predictions by around 30% [14]. Mbaye et al. estimated the solar availability of the Dakar site by using the ARMA model. A self-correlated dynamic average (ARMA-autoregressive moving average) model was used for short-term radiation estimation. Data and validations were obtained from a station located in Dakar. The data represent the period the period between October 2016 and September 2017 and are presented on an hourly basis. As a result of the study, it was emphasized that the ARMA method is reliable [15]. Adejumo and Suleiman estimated solar irradiance by using the ARMA-GARCH approach. A combined self-correlated dynamic mean model (ARMA) and a generalized self-correlated and variable conditions model (GARCH-generalized autoregressive conditional heteroscedasticity) were employed during this study. For the southern element of Nigeria, an estimate was made for the amount of radiation [16]. Ghofrani and Alolayan used statistics for renewable energy forecasting. They stated statistics and connections that will be used for renewable energy and gave information about their general framework [17]. Hassan et al. estimated the daily-based solar radiation of the United Arab Emirates (Al-Ain) by using an econometric statistics model. During this study, statistic connection models (ARIMA) radiation amount estimates, including autoregressive integrated moving averages, were used. 10 years of knowledge were taken (1995–2004), and a two-year estimation (2005–2007) was made within the sunshine of these data. Correlation studies were also performed for the results obtained, and thus the results were compared [18]. Prajapati and Sahay worked on a survey paper on the solar irradiance forecasting method. They used different and reliable statistical methods for the estimation of radiation amounts, and the results were explained [19]. Huang et al. used the ARMA model for estimating the solar energy capability. Short-time radiation estimation was made using the MATLAB program and the ARMA statistical model [20].

Ferrari et al. used a statistical model approach for radiation prediction. The climatic data obtained for the town of Milan estimated the amount of radiation within the framework of the numerous statistical models and compared them with each other [21]. Marchesoni-Acland et al. analyzed the performance of the ARMA models. During this study, the quantity of short-term radiation employing a self-repetitive algorithm using satellite data was estimated [22]. Colak et al. carried out ARMA and ARIMA models for determining global solar radiation. The statistical model was constructed comparisons of the ARMA and ARIMA models were made to this model, and radiation amount estimation was made with the best results [23]. Diagne et al. reviewed a global solar radiation prediction model. During this study, they stated that solar energy contains a fluctuating production trend because the amount of radiation changes very rapidly over time, and thus the irradiance amount estimation isn't effective in solar power. Statistical models were used for the quantity of radiation and compared with each other [24]. Alsharif et al. stated that a statistical ARIMA model is utilized for the estimation of solar irradiance. This effort is performed as a case study for Seoul, the Republic of Korea. They used seasonal statistical methods (SARIMA) for the town of Seoul. Connections were established, and comparisons were made employing an information set of roughly 37 years (1981–2017) [25]. Li et al. emphasized that, due to economic and technical restrictions, the daily values of solar radiation were taken into account in most feasibility studies [26]. They improved a graphical solar irridation model by using daily solar irridation values. In this study, they claimed that they got approximately 10% more accuracy than usual methods. Gupta et al. reviewed estimation models of global solar radiation [27]. They emphasized that solar energy is the most important renewable energy for achieving the net zero target by 2050. Hissou et al. examined the machine learning methodology for the prediction of global solar irradiation [28]. They emphasized that the results of the results of this new approach were satiably in accordance with regression models. Guermoui et al. harmonized methodologies like time-varying filters and empirical approach [29]. They stated that the results of this new approach are better than those of classical estimation methods for all studied regions. Fan et al. analyzed empirical and machine learning methodologies for estimating solar irradiation in the various states of China [30]. 12 machine learning models were used in the study. ANFIS, MARS, and XGBoost models were indicated as the most recommended machine learning models. Gürel et al. reviewed various methods for the prediction of solar irradiation [31]. They compared empirical, time-series, artificial intelligence, and hybrid models. They emphasized that each model has advantages and disadvantages in accordance with the targeted zone. They claimed that the hybrid model is a more applicable approach for the prediction of global solar radiation. Yarar et al. emphasized the importance of hourly-based global solar radiation for harmonic analysis of the microgrid connection [32]. Kaysal and Hocaoğlu modelled a new approach using an artificial neural network for the prediction of solar irradiation [33]. They used a two-stage forecasting model and a discrete wavelet transform for their study. Mukhtar et al. integrated conventional and artificial neural networks for the prediction of hourly-based solar irradiation [34]. They emphasized that, in general, developing countries do not have solar pironometers. So, they claimed that the designated method can be used in developing countries, especially African countries. Geetha et al. offered an artificial neural network model for the prediction of global solar radiation [35]. They claimed that, due to this improved model, designing and evaluating the stage of PV installation can be easier without meteorological data collection. In these studies, researchers claimed that hourly solar irradiance data are important for evaluating power plants that are using photovoltaic tools and equipment. They emphasized that the majority of solar irradiance studies and actual measurements are not obtained by daily values due to economic and technical restrictions, especially in developing countries. In their study, they used the identification, classification, clustering, and regression of climate indicators and meteorological data. They compared estimation models and tried to get the best availability.

In the studies conducted by researchers, it was mentioned that more effective results are obtained by using empirical and hybrid methods. In conducting the study, econometric models and empirical modeling approaches were used. As a result of these studies, it was found that empirical models are more useful. Comparing the studies conducted by the researchers, it is found that similar results were obtained, and it is evaluated that the researchers have developed models that contain complex calculations and relationships. The main objective of this study is to provide data for the algorithm to optimize the installed power and energy management of hybrid power plants. The developed algorithm determines the size of the hybrid structure with renewable energy pairs. This algorithm structure consists of four main sections. In the first section, the project characteristics of the renewable energy to be used in the hybrid structure are determined; in the second part, the project characteristics of solar energy; in the third part, the costs; and in the fourth part, the decision mechanism, including the iterative functions, is included. The study carried out aimed to use solar radiation on an hourly basis, which is intended as a data input for the calculation of the amount of energy to be extracted from the solar energy sector. It is expected that the hourly solar radiation is practical and flexible so that it can be used in the algorithm. To meet the requirements of the algorithm, it was preferred to compare models based only on empirical and econometric approaches rather than the complex and mixed structures developed by other researchers. As a result of the comparison, it was found that it is more appropriate to use empirical models because they have high coefficients and can meet the requirements of the algorithm. It has been found that the amount of solar radiation that provides the data input for the developed algorithm can be improved with hybrid or more advanced models. It is assumed that these integrated, developed structures can be used, but in terms of practicality, the use of empirical models is considered sufficient. The designed algorithm is given in **Figure 1**.

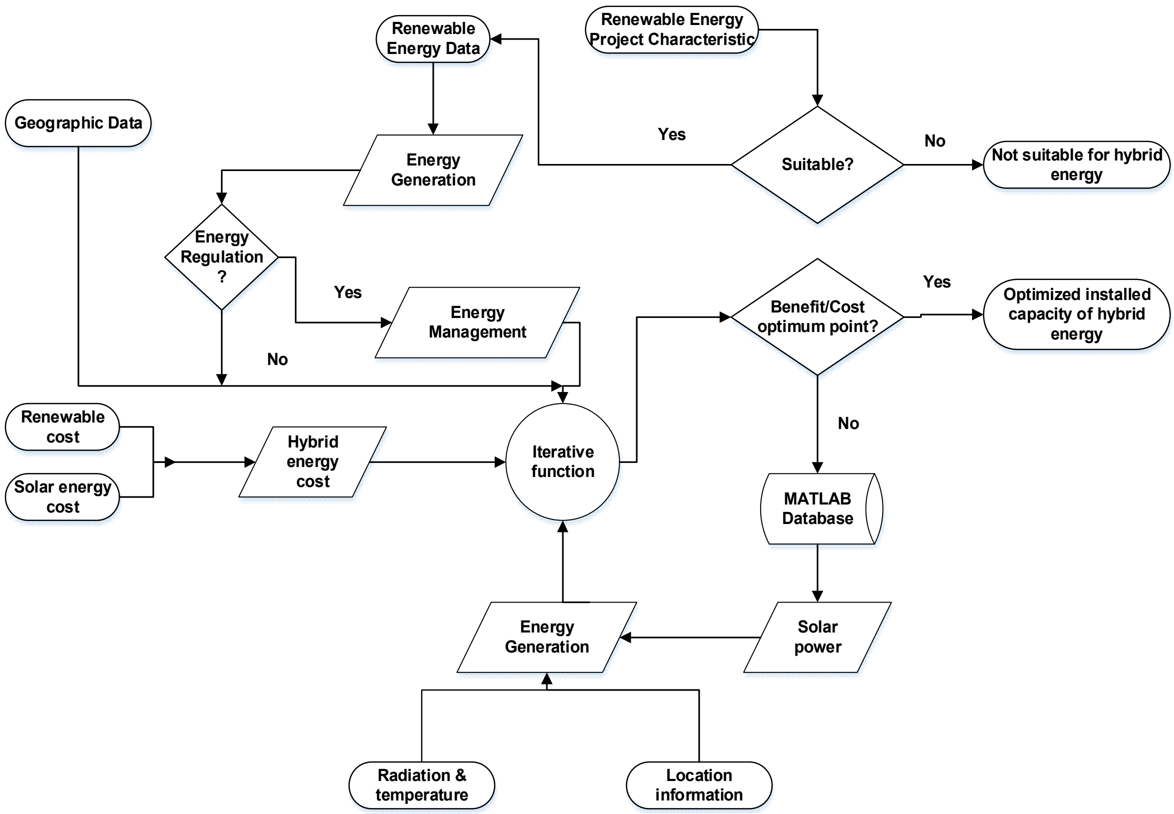

Figure 1. The algorithm of installed capacity for solar energy in integrated hybrid renewable structure.

Thanks to the developed algorithm, the installed capacity of solar energy to be engaged in hybrid energy systems is determined and optimized. The algorithm has a simple but effective decision mechanism and basically works considering the generation profiles and characteristics of the energy management of renewable energy plants in the hybrid structure. In this study, the amount of solar radiation data was estimated to feed into the algorithm and determine the amount of solar energy production. Since energy management is done on an hourly basis, the predictions aim to determine the amount of solar radiation on an hourly basis.

2. Mathematical model

The ratio of the amount of solar energy on an empirical hourly basis to the amount of solar energy daily is calculated by Equation (1) given below.

$$\frac{G_h}{G_d} = \frac{\left(\frac{\pi}{24}\right).(\cos w - \cos w_s)}{\sin w_s - (\frac{2\pi w_s}{360}).(\cos w_s)} \tag{1}$$

In Equation (1), G_h represents the hourly-based solar irradiance (kWh/m^2), G_d represents the daily-based solar irradiance (kWh/m^2), w_s represents the hour angle at sunrise (° degrees). w represents the hour angle (° degrees) which the displacement of the sun concerning a defined zone of the world and can be found by Equation (2) below.

$$w = \left(\frac{360}{24}\right).(AST - 12) \tag{2}$$

The AST (apparent solar time) specified in Equation (2) represents the observed or actual solar time. AST is calculated by Equation (3) given below;

$$AST = LST + EoT + \left(4\frac{\text{minute}}{\text{degree}}\right)[(LSMT - LOD)] \tag{3}$$

LST (local standard time) specified in Equation (3) represents the time of local standard, LOD represents the longitude, $LSMT$ (local standard meridian time) represents the meridian time of local standard, and EoT (equation of time) represents the imbalance of visible and mean solar time. $LSMT$ and EoT are found by Equations (4) and (5) given below.

$$LSMT = 15°.(Zone\ of\ GMT) \tag{4}$$

$$EoT = 9.87.\sin(2B) - 7.53.\cos(B) - 1.5.\sin(B) \tag{5}$$

The *GMT* (Greenwich Mean Time Zone) specified in Equation (4) represents the time intervals arranged according to the city of Greenwich. B is a coefficient and is found as stated in Equation (6) below;

$$B = \frac{360°}{365}.(n - 81) \tag{6}$$

The n specified in Equation (6) represents the number corresponding to the day in the calendar year. For example, while the number of n for January 1 is 1, the number n for February 1 is 32.

w_s specified in Equation (1) is found by Equation (7);

$$w_s = \cos^{-1}(-\tan\emptyset\tan\delta) \tag{7}$$

The w_s specified in Equation (7) represents the sunrise angle. In this equation $\emptyset$ represents the angle of latitude (°C), and δ represents the slope (°C). δ is calculated by Equation (8) given below.

$$\delta = 23.45.\sin\left[\frac{360(284 + n)}{365}\right] \tag{8}$$

The angle δ varies between +23.45°/–23.45°. The following **Figure 2** shows the change in the angle during the year;

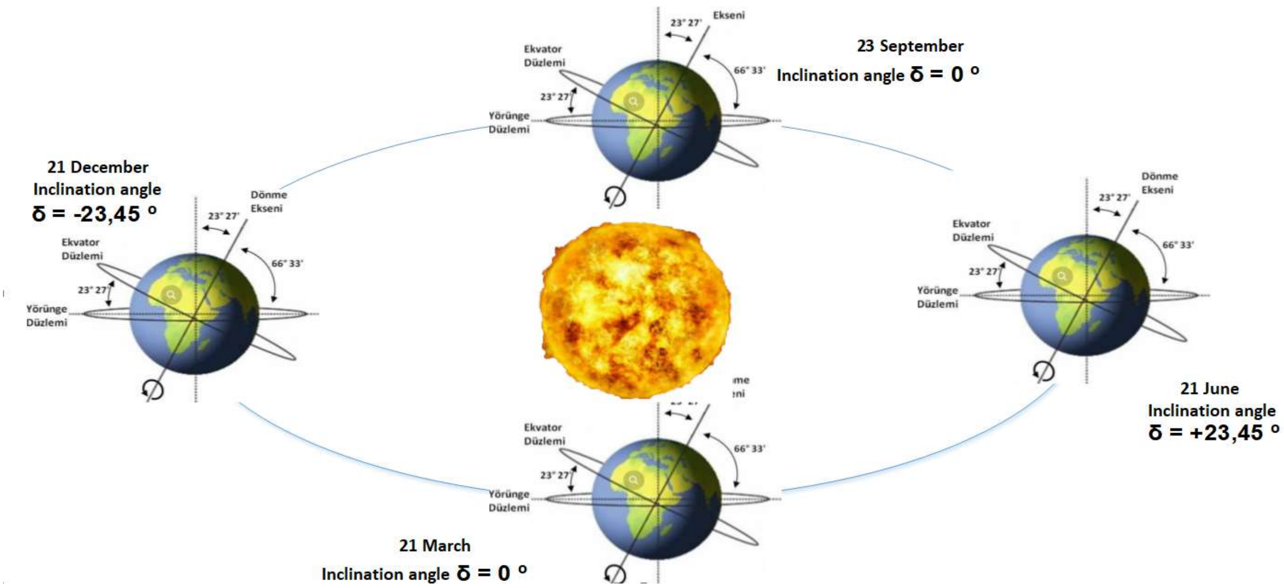

Figure 2. Angle of inclination and change over the year [6].

In the study carried out by Chandel and Aggarwal [7] the relationship between daily and hourly solar radiation is given in Equation (9) below;

$$r_t = \frac{G_h}{G_d} \tag{9}$$

The r_t term specified in Equation (9) represents the conversion rate between hourly and daily solar radiation. The r_t ratio is obtained by Equation (10) given below;

$$r_t = \frac{r_o.\left[1 + q.\left(\frac{a_2}{a_1}\right).k.A(w_s).r_0\right]}{\left[1 + q.\left(\frac{a_2}{a_1}\right).B(w_s)/A(w_s)\right]} \tag{10}$$

The r_o given in Equation (10) represents the ratio of the earth outside hourly based solar irradiance to the daily irradiance. This ratio is calculated by Equation (11) given below. The coefficients, k, $A(w_s)$ and $B(w_s)$ are given in Equations (12)–(14).

$$r_o = (\cos w - \cos w_s)/k.A(w_s) \tag{11}$$

$$k = \frac{24}{\pi} \tag{12}$$

$$A(w_s) = \sin w_s - w_s.cosw_s \tag{13}$$

$$B(w_s) = w_s.(0.5 + \cos^2 w_s) - 0.75 . \sin 2w_s \tag{14}$$

The coefficients, a_2 and a_1 specified in Equation (10) are empirical coefficients. These coefficients are calculated by Equation (15) below;

$$\begin{aligned} a_1 &= 0.41341.K_t + 0.61197.{K_t}^2 - 0.01886.K_t.S_0 + 0.00759.S_0 \\ a_2 &= \mathrm{Max}(0.054; 0.28116 + 2.2475.K_t - 1.76118.{K_t}^2 - 1.84535\sin h_0 \\ &\quad + 1.6811.\sin^3 h_0 \end{aligned} \tag{15}$$

K_t in Equation (15) represents the measured radiation ratio of earth's face to the calculated irradiance at the highest point of the atmosphere. In this study, ratio is accepted as 0.61 [10].

Given in Equation (10), q is the incidence angle of the beam, h_0 is the sun height of the atmosphere, S_0 is the daytime duration. The corresponding Equations (16)–(18) are given below to calculate the relevant parameters;

$$q = \cos\emptyset.\cos\delta \tag{16}$$

$$\sin h_0 = \frac{q.A(w_s)}{w_s} \tag{17}$$

$$S_0 = k.w_s \tag{18}$$

In addition to empirical methods, the amount of solar radiation can be determined by using econometric statistical methods. If hourly data is available for the studied site, hourly solar radiation data can be obtained, which is likely to occur prospectively. The most commonly used models in the literature and their explanations are given below. Time series lead to statistical data. These models, which are especially used for the sun and wind, produce new predictions in line with the actual data. One of the most used models is the self-connection (AR-autoregressive) model. The AR model is calculated as given in Equation (19);

$$x_t = \sum_{i=1}^{m} \phi_i.x_{t-i} + w_t = \phi_1.x_{t-1} + \phi_2.x_{t-2} + \cdots + \phi_m.x_{t-m} + w_t \tag{19}$$

In Equation (19), x_t represents time series value, w_t represents noise amounts, ϕ = ($\phi_1, \phi_2, \ldots, \phi_m$) vectors of model coefficients, m represents positive integer.

Another model is the moving average (MA-moving average) model. In this model, unlike the AR model, time series are created by using weighted total values in this model. The MA model is calculated as given in Equation (20);

$$x_t = \sum_{j=0}^{n} \theta_j . w_{t-j} = w_t + \theta_1 . x_{t-1} + \theta_2 . x_{t-2} + \cdots + \theta_n . x_{t-n} \tag{20}$$

Equation (20), x_t represents the time series value, w_t represents the noise amounts, $\theta = (\theta_1, \theta_2, \ldots, \theta_n)$ is the vector coefficients of the model, n represents the positive integer. θ_0 is accepted as $\theta_0 = 1$.

Another model is the self-correlated moving average (ARMA) model. This model has emerged by using AR and MA models together. It is calculated by Equation (21) given below.

$$x_t = \sum_{i=1}^{m} \phi_i . x_{t-i} + \sum_{j=0}^{n} \theta_j . w_{t-j} \tag{21}$$

In Equation (21), x_t is time series value, w_t is the amount of noise, $\theta = (\theta_1, \theta_2, \ldots, \theta_n)$ is the vector of moving average model coefficients, $\phi = (\phi_1, \phi_2, \ldots, \phi_m)$ is the vector of self-correlated model coefficients, m and n represent a positive integer. θ_0 is accepted as $\theta_0 = 1$.

Another model is the self-related and external variable moving average (ARMAX). This model has emerged by using AR and MA models together, as well as expanding the overall scope by using variables. It is calculated by Equation (22) given below.

$$x_t = \sum_{i=1}^{m} \phi_i . x_{t-i} + \sum_{j=0}^{n} \theta_j . w_{t-j} + \sum_{k=1}^{p} \lambda_k . e_{t-k} \tag{22}$$

In Equation (22), x_t is time series value, w_t is noise amount, $\theta = (\theta_1, \theta_2, \ldots, \theta_n)$ is the vector of moving average model coefficients, $\phi = (\phi_1, \phi_2, \ldots, \phi_m)$ is the vector of the self-correlated model coefficients, $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_p)$ is the external variable coefficient, m, n and p represent a positive integer. θ_0 is accepted as $\theta_0 = 1$.

Another model is the self-correlated and integrated moving average (ARIMA) model. This model is achieved by using AR and MA models together, as well as evaluating non-stationary variables. It is calculated by Equation (23) given below.

$$x_t = \sum_{i=1}^{m} \phi_i . S^d . x_{t-i} + \sum_{j=0}^{n} \theta_j . w_{t-j} \tag{23}$$

In Equation (23), x_t is the time series value, w_t is the amount of noise, $\theta = (\theta_1, \theta_2, \ldots, \theta_n)$ is the vectors of moving average model coefficients, $\phi = (\phi_1, \phi_2, \ldots, \phi_m)$ is the vectors of self-correlated model coefficients, m and n represent a positive integer. θ_0 is accepted as $\theta_0 = 1$. The expressions $S = 1 - q - 1$ and $\phi_m(q)$, represent the stationarity and translatability expressions of the AR (m) operator.

3. A case study

The second method employed in obtaining the quantity of radiation is the approach that features econometric and statistical methods. The most widely used econometric models within the literature are autoregressive integrated moving average (ARIMA), autoregressive moving average (ARMA), autoregressive moving average model with exogenous variables (ARMAX), autoregressive (AR), and moving average (MA) models. Additionally, an artificial neural network (ANN) model was used as a synthetic intelligence element. Econometric models were created using the

"R" modeling program and MATLAB. The models used were compared with one another, and therefore the best-suited one was chosen. In the first place, a one-day forecast was made for the AR and MA models, which are econometric models. Econometric models are fed from the data set from a solar energy plant that is found in Denizli province, Acıpayam district of Turkey. A seven-day real data set was used to predict one-day radiation. The MATLAB program is employed for this prediction. The demonstration of the model is given in **Figure 3**.

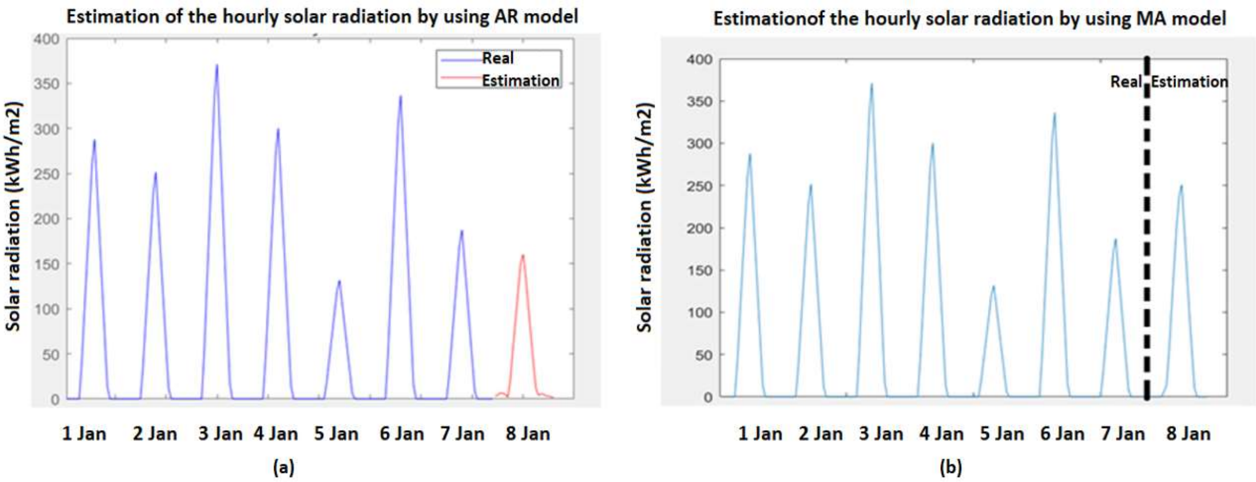

Figure 3. Estimation of the hourly solar radiation by **(a)** AR model; and **(b)** MA model.

The study was distributed with the "R" modeling program for ARIMA and ANN models. Six days of information acquisition are employed for 1 day and 6 days following estimations. The study results and existing condition comparisons are demonstrated within the graphs below. The details of the study are given in **Figures 4** and **5**.

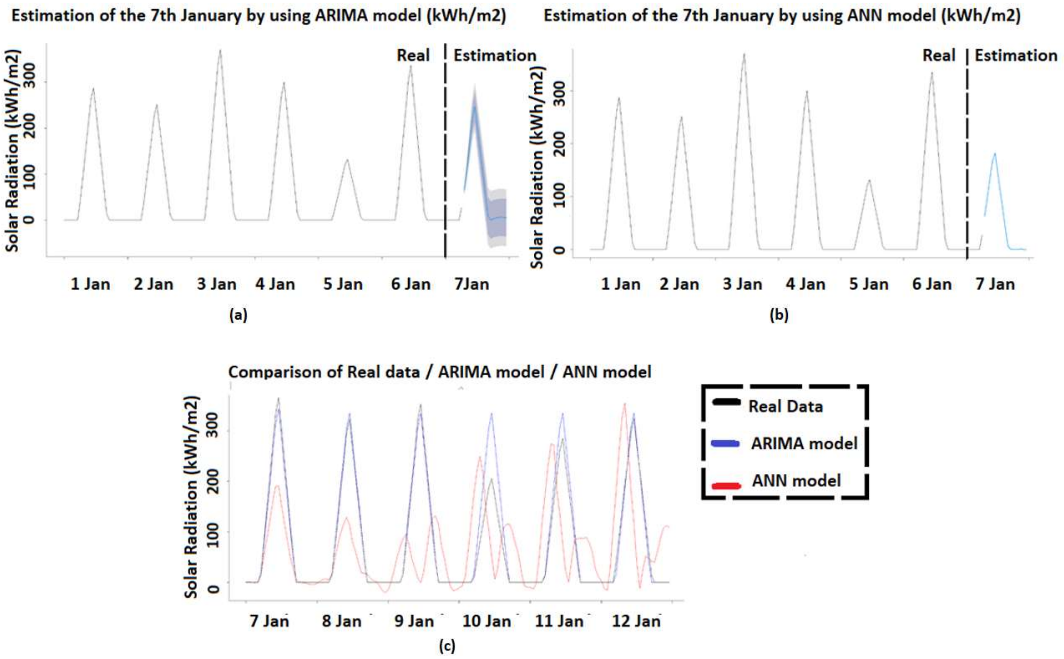

Figure 4. Models comparison **(a)** ARIMA model; **(b)** ANN model; **(c)** ARIMA/ANN models.

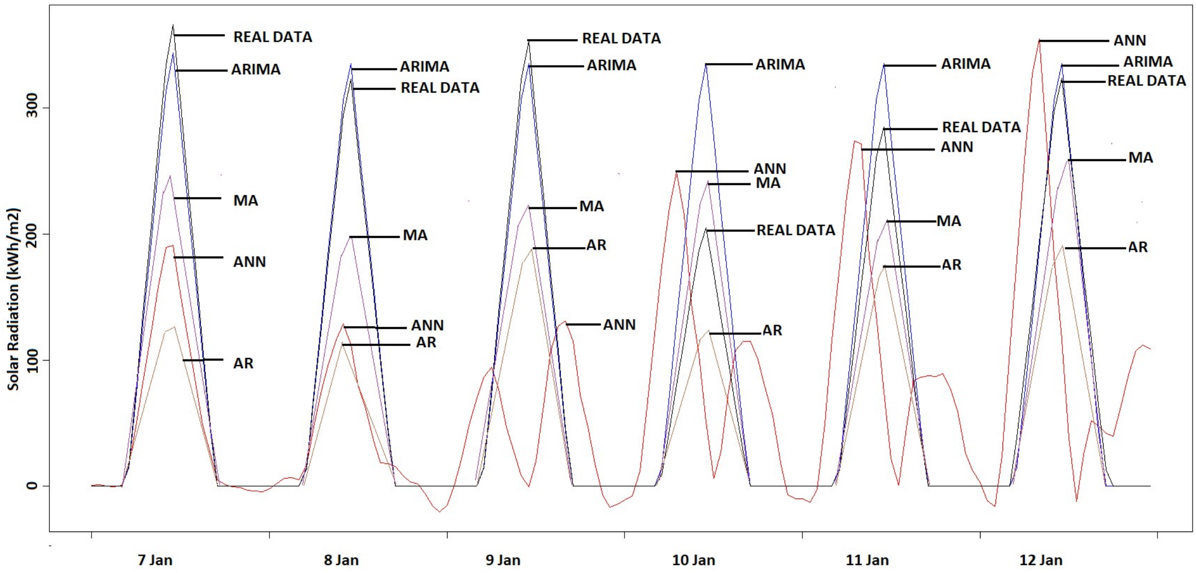

Figure 5. Comparison of the econometric models.

Looking at the comparative figure, it is clear that the econometric models differ from the actual data. Taken on its own, it can be said that the ARIMA model produces results that are relatively similar to the original data. Although the ARIMA model consists of the integration of other AR and MA models, it is a more advanced econometric model. Finally, using the data within the first 2 months of the year—January and February—radiation amount predictions were made for the primary six days of March. The subsequent chart shows the relevant studies and their results. Estimates obtained with AR and MA models produced very different results from the particular data. Within the more advanced ARIMA and ANN models, estimations were made using only a two-day data set. Additionally, "R" modeling, which is an econometric program that has more precise results for these models, was used. First, the ARIMA model was run. The quantity of estimation that offers the foremost optimum solution in step with the determined number of steps has been revealed. The blue drawing within the graph below gives the optimum ARIMA line. Other gray areas reflect the framework of others and sensibility (**Figure 6**).

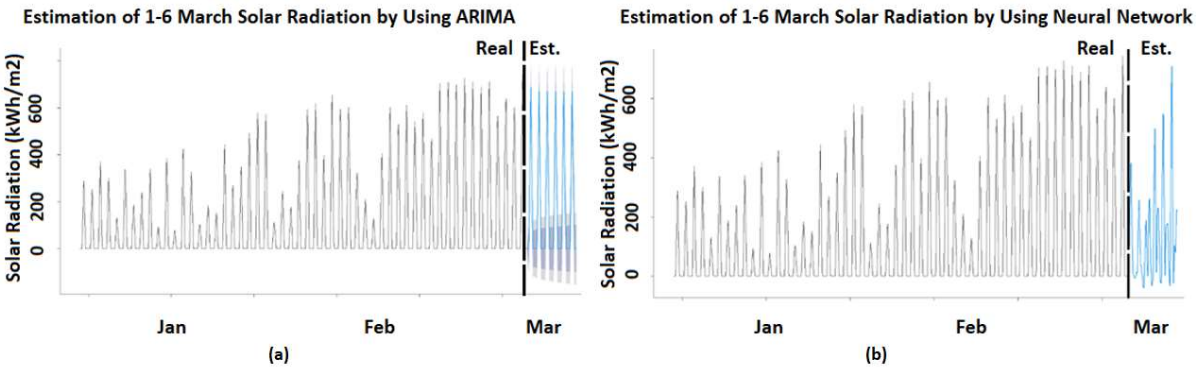

Figure 6. Prediction of the solar radiation of 1–6 March by using **(a)** ARIMA; and **(b)** ANN.

Using econometric models can provide reasonable results if the information is as detailed and long as possible. It's not always easy to achieve these detailed, supported coordinates in radiation estimations. An empirical model comes into play in these circumstances. The daily radiation amounts are often reached at supported coordinates on the official NASA website. When the empirical model compares with the artificial neural network and ARIMA models,

- It doesn't need one-to-one hourly radiation. It is often obtained on an hourly basis using daily radiation.
- While the amount of radiation at any point in the world is obtained daily from public sources, it's too difficult to access hourly radiation amount data supported by coordinates.
- High correlation with real values.
- Does not need long-term data entry like ARIMA and ANN.
- Obtaining realistic predictions not only in short-term forecasts like ARIMA and ANN but also in long-term forecasts.

Due to its prominent features, it's been decided to use an empirical model for radiation predictions. Based on the results obtained, using the MATLAB GUI program, an interface has been created to display the quantity of radiation within the day, month, year, or any desired period. Changes in the amount of radiation throughout the year and the start and end times are often determined within the interface and may be obtained at desired month, day, and hour intervals.

So, an empirical model is chosen for hourly-based estimation. The radiation amounts of the coordinates of the solar energy plant located in Denizli province, Acıpayam district, which are used for empirical models, were obtained daily from the NASA website [36]. By making use of the equations described within the mathematical model section, hourly radiation amounts were obtained in daily radiation amounts. Additionally, the study was enriched with the MATLAB GUI program. By using the MATLAB GUI, it's possible to draw graphs of the quantity of radiation on an hourly basis at any time during the year. While designing the MATLAB GUI graphic area, radiation amounts were graphed in line with the beginning and end times. The timeline relies on months, days, and hours. Desired graphs are drawn by entering the periods to be seen in these boxes. An 8760-hour-based radiation dataset was created to hide the entire year. The MATLAB GUI chart below shows the 24 h radiation amounts for 31 March, 30 June, 30 September, and 31 December. This demonstration is given in **Figure 7**.

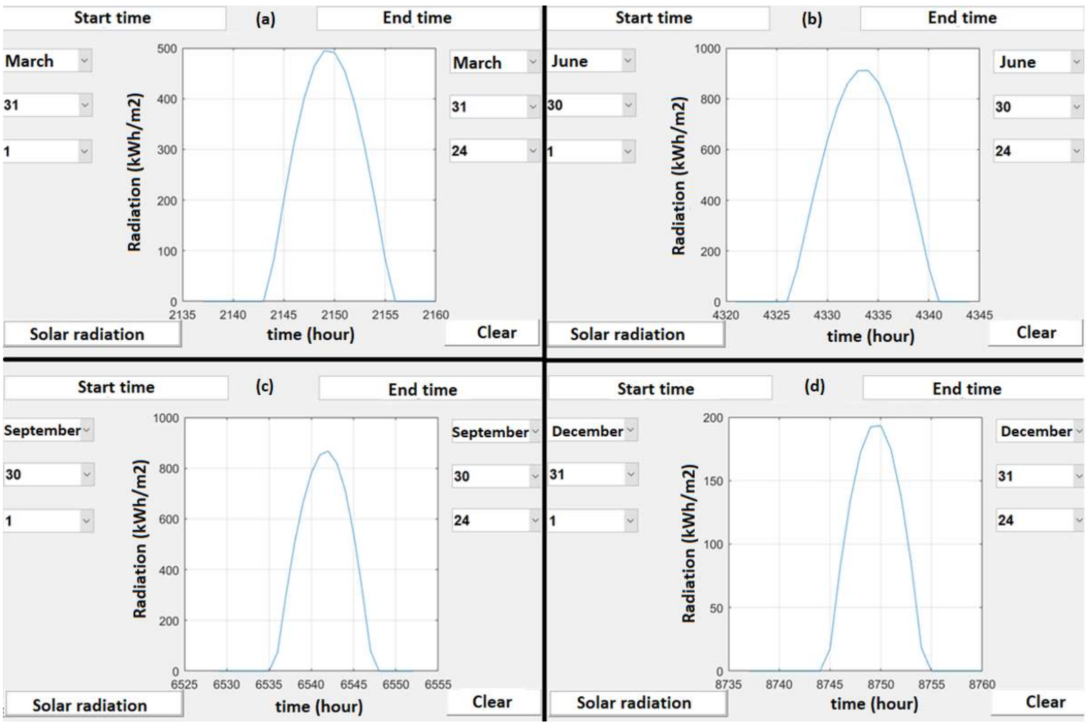

Figure 7. Estimation of the hourly based solar radiation by using the empirical model in MATLAB GUI **(a)** 31 March; **(b)** 30 June; **(c)** 30 September; and **(d)** 31 December.

The daily radiation amounts were taken from the NASA website for the solar energy plant located within the Acıpayam district of Denizli province. This original dataset is given in **Figure 8**.

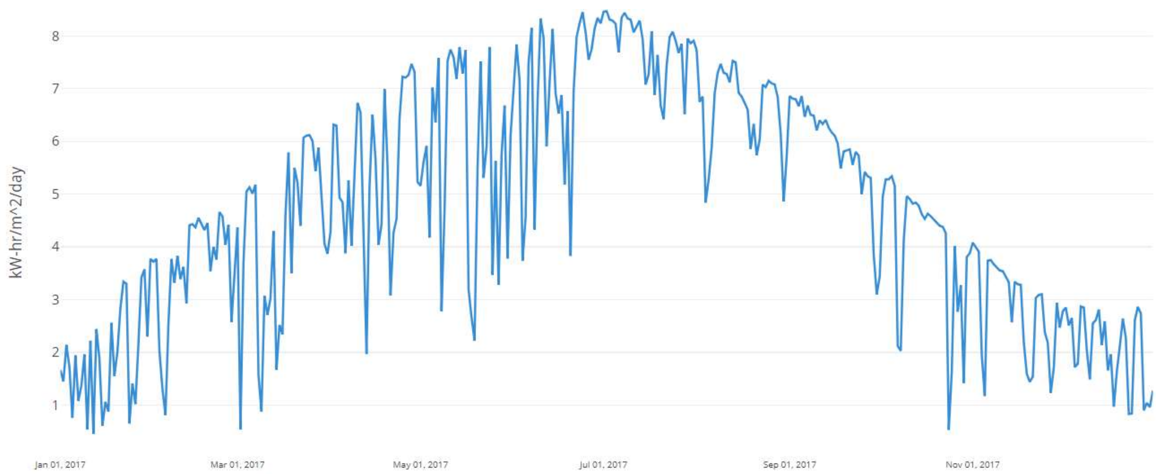

Figure 8. The daily solar radiation obtained from the NASA website (365 days) [26].

The amount of solar energy produced may be calculated by using the panel data. To check the operation of the approach, a dataset of a SPP that is located at a distance of 2 km was taken. Daily NASA data for the identical region were correlated hourly within the light of the original data using the equations above. The parametric statistic obtained as a result of 86% gives a robust concept whose acceptance is usable for solar radiation. The daily NASA data are converted to the hourly irradiance shown in the figure below. The correlation graph of the study is given in **Figure 9**.

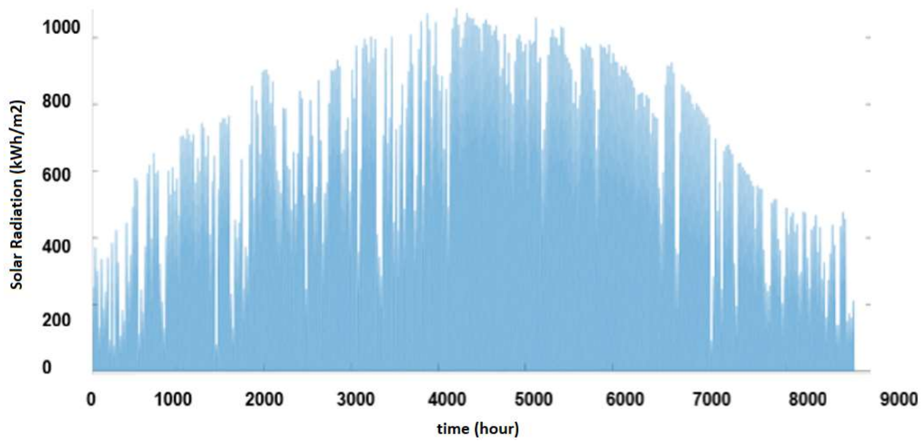

Figure 9. The hourly based solar irradiance obtained from the daily solar irradiance dataset (8760 h = 24 h/day × 365 day).

The energy generation amount was estimated by using the empirically obtained radiation amount and panel/inverter data of a solar energy plant located within the Acıpayam district of Denizli province. The particular production of this existing facility has been compared with the energy generation amounts prepared using the radiation amounts obtained on an hourly basis. *X* variable references the time, *Y* is that the radiation. The coefficient of correlation is obtained as 0.8625. The result is given in **Figure 10.**

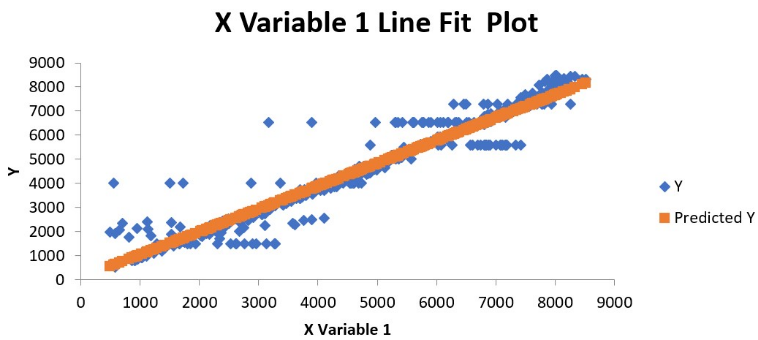

Figure 10. Predicted and real solar radiation correlation plot.

With the assistance of the designed interface, analyses may be made for specified periods, and changes in radiation amounts may be observed. After determining the quantity of radiation, the quantity of energy to be obtained from the sun was determined. After obtaining the amount of radiation, the amount of energy that will be obtained from the sun was calculated following the mathematical model and algorithm explained within the above sections. Before calculating the quantity of radiation, the energy production figures of an SPP facility located in Denizli province/Acpayam district were compared with the energy amount obtained by the proposed method, and the technical specifications of the panels utilized in the prevailing SPP facility were taken as a basis. Within the current SPP facility, Yingli Solar-branded 250-watt polycrystalline PV panels are used. Within the manuals (data sheet) containing the technical specifications of the PV panels, the measurement results under the quality test (STC-standard test condition) and nominal operating cell (NOCT) conditions are included.

The amount of power that can be obtained from PV panels depends on radiation and temperature. The graph below shows the I-V and power curves of the PV panels embedded in MATLAB. Technical specifications also include changes in current and voltage due to a natural process. After entering the NOCT values of the chosen PV panel, the values to be obtained and the voltage were determined by using the hourly data obtained from the meteorology station for Acıpayam district. The quantity of energy that may be obtained from the solar power system was calculated by multiplying the determined current and voltage values with one another. Since a high production forecast of roughly 91% can be obtained in comparison to the particular electricity generation. It's been accepted that the said approach is employed in other regions similarly. Accordingly, the calculation was made by using the tactic described above within the determination of the number of radiations in the related HEPP facility area.

4. Conclusion

The summarized results of this study are given below.

In recent years, worldwide applications and research have been disbursed for SHE plants, which is one of the hybrid renewable energy systems. One of the foremost issues for these integrated facilities is the management of the amount of energy generated from solar and hydroelectricity. To confirm reliable energy management, hourly electricity generation must be obtained. Electricity generation from solar energy may be a function that depends on the quantity of radiation and temperature. To see the amount of solar energy on an hourly basis, the amount of radiation must be determined. While it's easy to access the daily radiation data on a coordinated basis, this data isn't disclosed to the public on an hourly basis.

There are two basic methods employed in the literature to get the quantity of radiation on an hourly basis. One of them is the empirical method, and the other is the econometric method. In this study, the quantity of radiation was determined by using both methods. As a result of the studies, the quantity of radiation on an hourly basis was obtained from the daily radiation data, while more realistic results were obtained with the empirical method. The biggest difference during this comparison is the requirement of longer-term and more detailed data for econometric statistical models to get an affordable result. By using the empirical model, the quantity of radiation on an hourly basis was obtained from the daily radiation. These data are often easily employed in the energy management of renewable hybrid energy systems like solar hydroelectric facilities. The suggested hourly-based global solar radiation, which is obtained by an empirical model, can be used in the developed algorithm of a hybrid renewable energy system. It is a simple and practical way to estimate the amount of solar energy. The existing results are adequate; in addition to this, the study can be improved by using advanced artificial intelligence methods.

Conflict of interest: The author declares no conflict of interest.

References

1. Tırmıkçı CA. Real-time Comparison of a Two-Axis Sun-Tracking Moving Solar System and a Fixed Solar System Positioned at an Optimal Annual Inclination Angle (Turkish) [PhD thesis]. Sakarya Üniversitesi; 2018. pp. 1-110.
2. Jacovides CP, Tymvios FS, Assimakopoulos VD, et al. Comparative study of various correlations in estimating hourly diffuse fraction of global solar radiation. Renewable Energy. 2006, 31(15): 2492-2504. doi: 10.1016/j.renene.2005.11.009
3. Iqbal M. Correlation of average diffuse and beam radiation with hours of bright sunshine. Solar Energy. 1979, 23(2): 169-173. doi: 10.1016/0038-092x(79)90118-x
4. Alsafadi M, Başaran Filik Ü. Hourly global solar radiation estimation based on machine learning methods In Eskisehir. Eskişehir Technical University Journal of Science and Technology A—Applied Sciences and Engineering. 2020, 21(2): 294-313. doi: 10.18038/estubtda.650497
5. Serttaş F. A New Approach to Solar Irradiance Forecasting Based on Pattern Scanning (Turkish) [Master's thesis]. Afyon Kocatepe Üniversitesi; 2015. pp. 1-67.
6. Maleki MS, Hizam H, Gomes C. Estimation of hourly, daily and monthly global solar radiation on inclined surfaces: Models re-visited. Energies. 2017, 10(1): 134. doi: 10.3390/en10010134
7. Chandel SS, Aggarwal RK. Estimation of hourly solar radiation on horizontal and inclined surfaces in western Himalayas. Smart Grid and Renewable Energy. 2011, 2(1): 45-55. doi: 10.4236/sgre.2011.21006
8. Khatib T, Elmenreich W. A model for hourly solar radiation data generation from daily solar radiation data using a generalized regression artificial neural network. International Journal of Photoenergy. 2015, 2015: 1-13. doi: 10.1155/2015/968024
9. Berrizbeitia SE, Jadraque Gago E, Muneer T. Empirical models for the estimation of solar sky-diffuse radiation. A review and experimental analysis. Energies. 2020, 13(3): 701. doi: 10.3390/en13030701
10. Gueymard C. Prediction and performance assessment of mean hourly global radiation. Solar Energy. 2000, 68(3): 285-303. doi: 10.1016/s0038-092x(99)00070-5
11. Al-Rawahi NZ, Zurigat YH, Al-Azri NA. Prediction of hourly solar radiation on horizontal and inclined surfaces for Muscat/Oman. The Journal of Engineering Research [TJER]. 2011, 8(2): 19. doi: 10.24200/tjer.vol8iss2pp19-31
12. Ishola KA, Fealy R, Mills G, et al. Developing regional calibration coefficients for estimation of hourly global solar radiation in Ireland. International Journal of Sustainable Energy. 2018, pp.1-15.
13. Hussein TAT. Estimation of hourly global solar radiation in egypt using mathematical model. International Journal Latest Trends Agriculture Food Science. 2012, 2(2): 74-82.
14. Huang J, Korolkiewicz M, Agrawal M, et al. Forecasting solar radiation on an hourly time scale using a coupled autoregressive and dynamical system (CARDS) model. Solar Energy. 2013, 87: 136-149. doi: 10.1016/j.solener.2012.10.012
15. Mbaye A, Ndiaye ML, Ndione DM, et al. ARMA model for short-term forecasting of solar potential: Application to a horizontal surface of Dakar site. OAJ Materials and Devices. 2019, 4(1). doi: 10.23647/ca.md20191103
16. Adejumo AO, Suleiman EA. Application of ARMA-GARCH models on solar radiation for South Southern Region of Nigeria. Journal of Informatics and Mathematical Science. 2017, 9(2): 405-416.
17. Ghofrani M, Alolayan M. Time series and renewable energy forecasting. Time Series Analysis and Application. 2018, 77-92. doi: 10.5772/intechopen.70845
18. Hejase HAN, Assi AH. Time-series regression model for prediction of mean daily global solar radiation in Al-Ain, UAE. ISRN Renewable Energy. 2012, 2012: 1-11. doi: 10.5402/2012/412471
19. Prajapati SK, Sahay KB. A survey paper on solar irradiance forecasting method. International Journal of Engineering Research & Technology (IJERT). 2016, 5(3): 536-541. doi: 10.17577/ijertv5is030469
20. Huang R, Huang T, Gad R. Solar generation prediction using the ARMA model in a laboratory-level micro-grid. In: Proceedings of the 2012 IEEE Third International Conference on Smart Grid Communications (SmartGridComm); 5-8 November 2012; Tainan, Taiwan. pp. 1-6. doi: 10.1109/SmartGridComm.2012.6486039
21. Ferrari S, Lazzaroni M, Piuri V, et al. Statistical models approach for solar radiation prediction. In: Proceedings of the 2013 IEEE International Instrumentation and Measurement Technology Conference (I2MTC); 6-9 May 2013; Minneapolis, MN, USA. pp. 1-6. doi: 10.1109/I2MTC.2013.6555712

22. Marchesoni-Acland F, Lauret P, Gomez A, et al. Analysis of ARMA solar forecasting models using ground measurements and satellite image. In: Proceedings of the 2019 IEEE 46th Photovoltaic Specialists Conference (PVSC), 16-21 June 2019; Chicago, USA. pp. 1-7. doi: 10.1109/PVSC40753.2019.8980821
23. Colak I, Yesilbudak M, Genc N, et al. Multi-period prediction of solar radiation using ARMA and ARIMA models. In: Proceedings of the 2015 IEEE 14th International Conference on Machine Learning and Applications, 9-11 December 2015, Miami, Florida, USA. pp. 1045-1049. doi: 10.1109/ICMLA.2015.33
24. Diagne M, David M, Lauret P, et al. Review of solar irradiance forecasting methods and a proposition for small-scale insular grids. Renewable and Sustainable Energy Reviews. 2013, 27: 65-76. doi: 10.1016/j.rser.2013.06.042
25. Alsharif M, Younes M, Kim J. Time series ARIMA model for prediction of daily and monthly average global solar radiation: The case study of Seoul, South Korea. Symmetry. 2019, 11(2): 240. doi: 10.3390/sym11020240
26. Li Y, Wang Y, Yao W, et al. Graphical decomposition model to estimate hourly global solar radiation considering weather stochasticity. Energy Conversion and Management. 2023, 286: 116719. doi: 10.1016/j.enconman.2023.116719
27. Gupta S, Singh AK, Mishra S, et al. Estimation of solar radiation with consideration of terrestrial losses at a selected location—A review. Sustainability. 2023, 15(13): 9962. doi: 10.3390/su15139962
28. Hissou H, Benkirane S, Guezzaz A, et al. A novel machine learning approach for solar radiation estimation. Sustainability. 2023, 15(13): 10609. doi: 10.3390/su151310609
29. Guermoui M, Gairaa K, Ferkous K, et al. Potential assessment of the TVF-EMD algorithm in forecasting hourly global solar radiation: Review and case studies. Journal of Cleaner Production. 2023, 385: 135680. doi: 10.1016/j.jclepro.2022.135680
30. Fan J, Wu L, Zhang F, et al. Empirical and machine learning models for predicting daily global solar radiation from sunshine duration: A review and case study in China. Renewable and Sustainable Energy Reviews. 2019, 100: 186-212. doi: 10.1016/j.rser.2018.10.018
31. Gürel AE, Ağbulut Ü, Bakır H, et al. A state of art review on estimation of solar radiation with various models. Heliyon. 2023, 9(2): e13167. doi: 10.1016/j.heliyon.2023.e13167
32. Yarar N, Yagci M, Bahceci S, et al. Artificial neural networks based harmonics estimation for real university microgrids using hourly solar irradiation and temperature data. Energy Nexus. 2023, 9: 100172. doi: 10.1016/j.nexus.2023.100172
33. Kaysal K, Hocaoğlu FO. Modelling of different mother wavelet transforms with artificial neural networks for estimation of solar radiation. Eskişehir Technical University Journal of Science and Technology A—Applied Sciences and Engineering. 2023, 24(2): 141-154. doi: 10.18038/estubtda.1184918
34. Mukhtar M, Oluwasanmi A, Yimen N, et al. Development and comparison of two novel hybrid neural network models for hourly solar radiation prediction. Applied Sciences. 2022, 12(3): 1435. doi: 10.3390/app12031435
35. Geetha A, Santhakumar J, Sundaram KM, et al. Prediction of hourly solar radiation in Tamil Nadu using ANN model with different learning algorithms. Energy Reports. 2022, 8: 664-671. doi: 10.1016/j.egyr.2021.11.190
36. NASA Prediction of Worldwide Energy Resources. The power project. Available online: https://power.larc.nasa.gov/ (accessed on 22 November 2023).