JOURNAL OF ENGINEERING SCIENCES

Volume 9, Issue 2 (2022)

*Mbah, O. M., Madueke, C. I., Umunakwe, R., Okafor, C.O. (2022). Machine learning approach for solar irradiance estimation on tilted surfaces in comparison with sky models prediction. Journal of Engineering Sciences, Vol. 9(2), pp. G1-G6, doi: 10.21272/jes.2022.9(2).g1*


# Machine Learning Approach for Solar Irradiance Estimation on Tilted Surfaces in Comparison with Sky Models Prediction

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**Article info:**
Submitted: April 14, 2022
Accepted for publication: August 29, 2022
Available online: September 4, 2022

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**Abstract.** In this study, two supervised machine learning models (Extreme Gradient Boosting and K-nearest Neighbour) and four isotropic sky models (Liu and Jordan, Badescu, Koronakis, and Tian) were employed to estimate global solar radiation on daily data measured for one year period at the National Center for Energy, Research and Development (NCERD) at the University of Nigeria, Nsukka. Two solarimeters were employed to measure solar radiation: one measured solar radiation on a tilted surface at a 15° angle of tilt, facing south, and the other measured global horizontal solar radiation. The measured global horizontal solar radiation and the time and day number were used as input for the prediction process. Python computational software was used for model prediction, and the performance of each model was assessed using statistical methods such as mean bias error (MBE), mean absolute error (MAE), and root mean square error (RMSE) (RMSE). Compared to the measured data, it was discovered that the Extreme Gradient Boosting (XGBoost) algorithm offered the best performance with the least inaccuracy to sky models.

**Keywords:** machine learning, sky models, solar energy, solar radiation, tilted surface.

## 1 Introduction

The sun generates electromagnetic radiation known as solar irradiance, and the quantity of the radiation received in a given area is determined by geographical location, daytime, season, and local weather. The dearth of solar radiation data has necessitated the development of several mathematical models (Isotropic and Anisotropic sky models).

However, it has been observed that mathematical models offer an approximate solution, have high computational cost, and consume time during the solving process. The development of machine and deep learning algorithms is being viewed as a feasible option for estimating solar radiation. This study aims to compare the predicting accuracy of sky models to machine learning models on a tilted surface. Measured solar radiation data on a tilted surface at a 15° angle of tilt, facing south, will be used to train and validate the models.

## 2 Literature Review

Many researchers have utilized several empirical models to estimate global solar irradiance. For example, three isotropic sky models were utilized to estimate global solar irradiance on a tilted surface, and their performance was compared to experimental data using a statistical method [1]. Similarly, two anisotropic empirical models developed by Perez and Hay, Davies, Klucher, and Reindl (HDKR) were utilized to predict solar radiation on tilted surfaces in Sub-Saharan Africa Climate [2]. According to the results, the Perez model fared better regarding statistical measures. Shourehdeli et al. [3] used four empirical models with isentropic coefficients to estimate injector performance in critical mode. In Biskra, Algeria, Chabane et al. [4] established a model for solar irradiance forecasting dependent on the aerosol optical depth between two wavelengths of 550 and 1250 nm.

Machine learning algorithms have also been utilized in forecasting since they allow more data to be incorporated into the forecast. For example, Piryonesis and El-Diraby [5] used a machine learning algorithm to anticipate pavement deterioration and assess long-term pavement performance. With various input data, the Support Vector Machine Regression (SVM-R) model has been effectively utilized to estimate global sun radiation [6-9]. Similarly, the Artificial Neural Network (ANN) approach has been used to forecast and predict historical experimental data [10-14]. In addition, many researchers have employed hybrid models to estimate global solar radiation.

For example, Torabi et al. [15] proposed a Cluster-Based Approach (CBA) that estimates daily global solar radiation on the horizontal surface using a support vector machine and an Artificial Neural Network. The results demonstrate that the hybrid model outperformed the separate models in terms of mean absolute percentage error. Similarly, Gala et al. [16] used three hybrid models to forecast global solar radiation in seven different sites in Spain: support vector machine, gradient boosted regression, and random forest. The outcome demonstrates that the hybrid model is extremely effective. Achour et al. [17] utilized a hybrid mode to estimate Southern Algeria's solar radiation. Furthermore, Herath et al. [18] developed a mathematical model for daily global solar radiation forecast and compared its performance to that of artificial neural network prediction.

Some international findings on the use of machine learning algorithms in forecasting horizontal solar radiation have been published.

Quej et al. [19] assessed the performance of an "adaptive neuro-fuzzy inference system (ANFIS), an artificial neural network (ANN), and a support vector machine (SVM) in calculating daily global horizontal solar radiation from collected data in Mexico". SVM fared better, according to the results. Similarly, Marzo et al. [20] forecasted daily solar radiation data from deserts in Chile, Israel, Saudi Arabia, South Africa, and Australia using an artificial neural network (ANN) model trained on daily minimum and maximum temperatures as well as extraterrestrial radiation. The model was tested using a statistical tool and data. ANN produced an average relative root mean square derivation (RRMSD) of 0.13 and a correlative coefficient of 0.8. In Turkey, Augbulut et al. [21] employed four different machine learning methods (Support Vector Machine (SVM), Artificial Neural Network (ANN), Kernel and Nearest-Neighbor (KNN), and Deep Learning (DL)) to forecast power output system. In addition, the four machine learning approaches were used to predict daily global solar radiation in four Turkish districts. (Kirklareli, Tokat, Nevsehir and Karamam) [22]. The result indicated that ANN has a higher prediction than other models. Haciouglu Rifat [23] built a linear and gaussian regression model for solar irradiance estimation in Turkey's Zonguldak province. The input parameters were wind speed, temperature, pressure, and humidity; statistically, the gaussian model performed better. Various machine learning algorithms based on linear and nonlinear regression approaches were also examined [24-28].

In addition, multiple empirical models for estimating solar radiation were examined using the average monthly mean value of solar radiation in Bhopal, India [29].

However, several researchers have observed that empirical models do not accurately forecast solar radiation data because they do not capture the complicated and nonlinear relationship between the response and the covariate variable in humid regions [30-32].

## 3 Research Methodology

### 3.1 Site and measurement

The solar radiation data were measured at the National Center for Energy Research and Development (NCERD) in the University of Nigeria, Nsukka. Nsukka is a town and Local Government Area in South East Nigeria in Enugu State with latitude 6°51′28″ North and longitude 7°23′44″ East. Nsukka has a tropical savanna climate with the highest average temperature of 36° in February and 28° lowest in July. Two solarimeters were used to measure solar radiation data for one year (Febrary2017 - January 2018). One solarimeter monitored hourly global solar radiation on a horizontal surface, whereas the other measured it on a tilted surface with a 15° inclination heading south.

### 3.2 Description of machine learning models

Machine learning is an aspect of artificial intelligence that uses algorithms to build a model from data. They are employed in the estimation of the target function to predict the output variable given the input variables. The following is a brief description of the two machine learning algorithms used.

#### 3.2.1 Extreme gradient boosting (XGBoost)

Extreme gradient boosting is a machine learning approach that describes the gradient and how the loss function can be minimized using second partial derivatives of the loss function. It is a technique used for regression and classification which produces a prediction model in the form of a decision tree. The XGBoost model on prediction of *i*-th instance at the *t*-th iteration is given as

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, y_i^{\wedge(t-1)} + f_t(X_i)\right) + \Omega(f_t) \qquad (1)$$

where l is the loss function, $f_t$ is the $t'^{th}$ tree output; $\Omega$ – the regularization and $y_i^{\wedge(t)}$ – the prediction of the *i*-th instance at the *t*-th iteration. XGBoot loss function approximation with Taylor expansion is given as

$$L^{(t)} = \sum_{i=1}^{n} l\left(y_i, y_i^{\wedge(t-1)}\right) + g_t f_t(X_i) + \frac{1}{2} h_i f_t^2(X_i) + \\ +\Omega(f_t) \qquad (2)$$

where $g_i$ and $h_i$ – the first and second derivatives of the loss function.

#### 3.2.2 K-nearest neighbor (KNN)

K-nearest neighbor is a supervised machine learning algorithm to solve classification and regression problems.

It locates the k-nearest neighbor to the test data and performs classification with the class label. The average nearest neighbor ratio is given as:

$$ANN = \frac{\overline{D_o}}{\overline{D_E}} \tag{3}$$

where $\overline{D_o}$ – the observed mean distance between each feature and its nearest neighbor is given as:

$$\overline{D_o} = \frac{\sum_{i=1}^{n} d_i}{n} \tag{4}$$

and $\overline{D_E}$ – the expected mean distance for the features given in a random pattern.

$$\overline{D_E} = \frac{0.5}{\sqrt{\frac{n}{A}}} \tag{5}$$

in the above equations, $d_i$ – the distance between feature $i$ and its nearest neighboring feature, $n$ corresponds to the total number of features; $A$ – the area of the minimum enclosing rectangle around all features.

### 3.3 Solar radiation on the horizontal surface

Horizontal solar radiation (global irradiance) is the summation of direct(beam) and diffuse(scattered) irradiance. Direct irradiance comes directly from the sun to the earth's surface, while diffused irradiance is the scattered solar radiation that reaches the earth's surface.

$$I_H = I_{H,b} + I_{H,d} \tag{6}$$

where $I_{H,b}$ – the beam(direct) irradiance; $I_{H,d}$ – the diffuse irradiance and $I_H$ – horizontal solar radiation.

### 3.4 Solar radiation on the tilted surface

The incident solar radiation on a tilted surface is composed of three components (direct irradiance, diffuse irradiance, and ground reflectance):

$$I_T = I_{T,b} + I_{T,d} + I_{T,r} \tag{7}$$

where $I_{T,b}$ is the beam irradiance (tilted surface); $I_{T,d}$ is the diffuse irradiance (tilted surface); $I_{T,r}$ – the ground reflectance and $I_T$ – solar radiation on the tilted surface.

### 3.5 Isotropic models that are commonly utilized are described

To estimate solar irradiance on a tilted surface, isotropic and anisotropic sky models are utilized. Four isotropic sky models were utilized in this investigation, and their findings were compared to machine learning models. The isotropic sky models are described briefly below.

#### 3.5.1 Badescu model

Badescu model has a view factor of $F = \left(\frac{3+\cos\beta}{4}\right)$ and can be expressed as

$$I_T = I_{H,b}R_b + I_{H,d}\left(\frac{3+\cos\beta}{4}\right) + I_{H,\rho}\left(\frac{1-\cos\beta}{2}\right) \tag{8}$$

#### 3.5.2 Tian model

This model evaluated three components of solar radiation on a slanted surface (beam, diffuse, and ground reflectance):

$$I_T = I_{H,b}R_b + I_{H,d}\left(1 - \frac{\beta}{180}\right) + I_{H,\rho}\left(\frac{1-\cos\beta}{2}\right) \tag{9}$$

#### 3.5.3 Koronakis model

Koronakis model incorporated the circumsolar and horizontal brightening and proposed the slope $\beta = 90^0$ and is proposed to be

$$I_T = I_{H,b}R_b + I_{H,d}\left(\frac{2+\cos\beta}{3}\right) + I_{H,\rho}\left(\frac{1-\cos\beta}{2}\right) \tag{10}$$

#### 3.5.4 Liu-Jordan model

This model assumes that circumsolar and horizon brightening are both zero and that diffuse radiation is exclusively isotropic:

$$I_T = I_{H,b}R_b + I_{H,d}\left(\frac{1+\cos\beta}{2}\right) + I_{H,\rho}\left(\frac{1-\cos\beta}{2}\right) \tag{11}$$

### 3.6 Methods of models evaluation

In this work, the prediction of machine learning models and isotropic sky models was compared to the experimental data using three statistical tests: Mean Absolute Error (MAE), Mean Bias Error (MBE), and Root Mean Square Error (RMSE) (RMSE).

#### 3.6.1 Mean bias error (MBE)

The mean bias error evaluates the whole bias and detects if the model is producing overestimation ($MBA > 0$) or underestimation when ($MBA < 0$). Mean bias error is given as

$$MBE = \frac{1}{n}\sum_{i=1}^{n}(Hpi - H_{mi}) \tag{12}$$

where $H_{pi}$ – the predicted value; $H_{mi}$ – the measured value; *n* – the number of observations.

#### 3.6.2 Mean absolute error (MAE)

Mean absolute error is a measure of model evaluation metric used with regression models and can be expressed as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(\left(\frac{H_{pi}-H_{mi}}{n}\right) \tag{13}$$

where *n* is the number of data points.

#### 3.6.3 Root mean square error (RMSE)

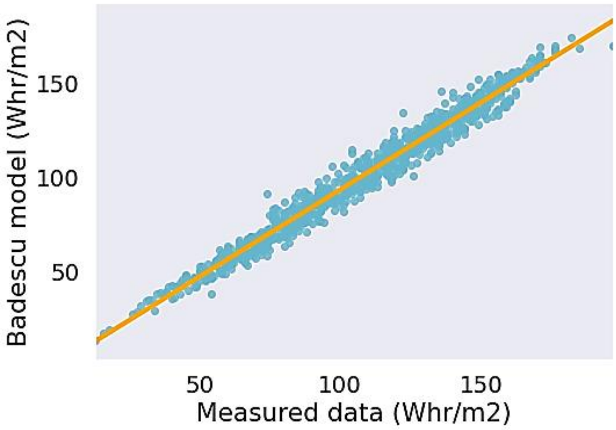
The fluctuation of the anticipated values around the observed data is quantified by the root mean square error. It is computed using the following equation:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(H_{pi} - H_{mi})^2} \tag{14}$$

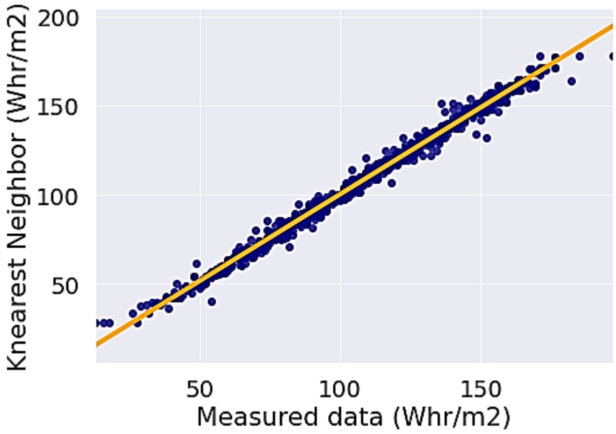
where $H_{pi}$ – the predicted value; $H_{mi}$ – the measured value; *n* – the number of observations.

## 4 Results

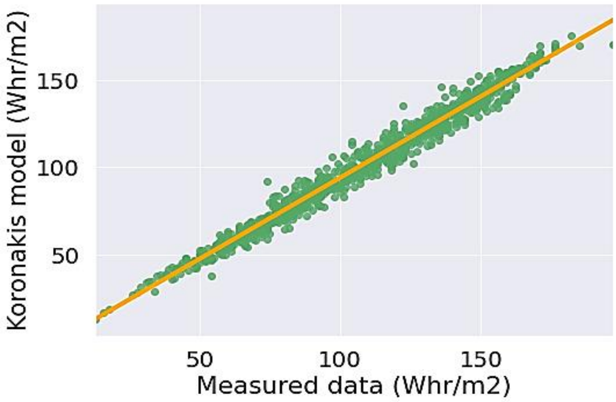
Figure 1 depicts the correlation between the models and the measured solar radiation data on a tilted surface using scattered plots. The greater the association between the models and the measured data, the closer the data points are to the line of best fit. The models and the measured data have a high, positive, linear correlation. By offering a tighter grouping of data points, the Extreme gradient boosting (Xgboost) model provided the most significant correlation among the models, followed by K-nearest neighbor, Badescu, Koronakis, Tian and Liu, and Jordan models, in that order.



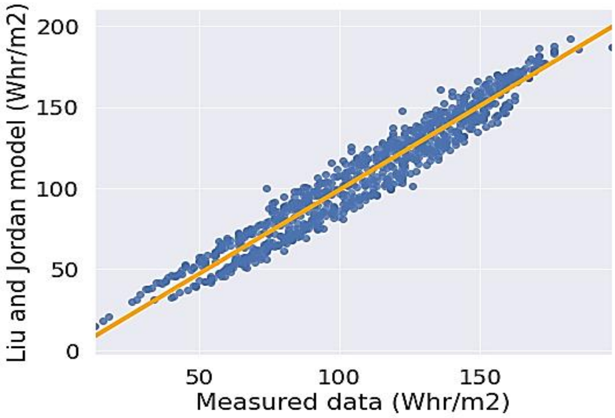

a



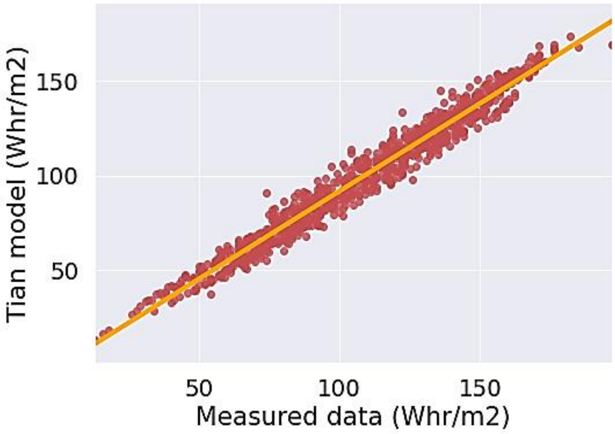

b



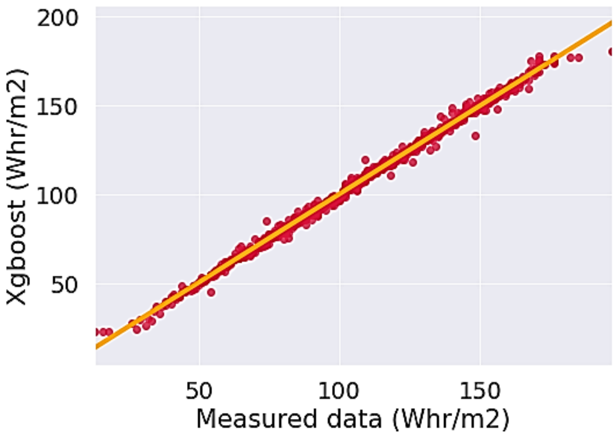

c




d




e




f

Figure – Predicted versus measured solar radiation data on titled surfaces for the six models, W·hr / m$^2$: a – Badescu model; b – K-nearest neighbor; c – Koronakis model; d – Liu-Jordan model; e – Tian model; f – XGBoost

Figure 2 compares each model forecast with the measured solar radiation data on day 329 with the most significant clearness index. The graph demonstrates that the two machine learning models (Extreme gradient boosting and K-nearest neighbor) provided nearly identical results closer to the measured solar radiation data, while the Liu and Jordan model produced the highest projected values across all models.

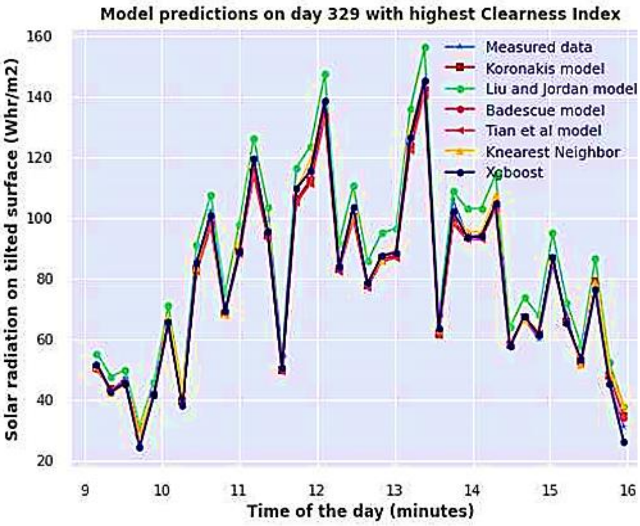



Figure 2 – Comparison of different models' estimation with measured data

In addition, the Koronakis model had the lowest predicted values of all the isotropic sky models.

## 5 Discussion

The Root Mean Square Error quantifies the volatility of expected values around the measured data (RMSE). The model's performance improves as the value decreases. Extreme gradient boosting (XGBoost) had the lowest RMSE of 2.11 W·hr/m$^{2,}$ and the Tian model had the highest RMSE of 11.20 W·hr/m$^2$. Other models, such as Koronakis, Liu and Jordan, Badescu, and K-nearest Neighbor, achieved RMSEs of 8.71 W·hr/m$^2$, 9.23 W·hr/m$^2$, 9.46 W·hr/m$^2$, and 3.35 W·hr/m$^2$.

Mean Absolute Error (MAE) is a model evaluation metric. The XGBoost model had the lowest MAE of 1.37 W·hr/m$^2$, followed by the K-nearest neighbor at 2.34 W·hr/m$^2$, and the Koronakis, Liu-Jordan, and Badescu models had an MAE of 7.22 W hr/m$^2$, 8.06 W·hr/m$^2$, and 7.90 W·hr/m$^2$, respectively. The Tian model had the highest MAE of 9.44 W·hr/m$^2$.

Mean Bias Error (MBE) provides information on the models' long-term performance. It tells whether the model is over or underestimating. When MBE is more than zero, the model overestimates. When MBE is less than zero, the model underestimates.

XGBoost and K-nearest neighbor models had a positive MBE of 0.00647Whr/m$^2$ and 0.16430W hr/m$^2$, respectively. Other models, such as Koronakis, Liu-Jordan, Badescu, and Tian, have negative values of MBE errors: –6.51 W·hr/m$^2$, –0.71 W·hr/m$^2$, –7.26 W·hr/m$^2$ and –8.95 W·hr/m$^2$, respectively.

## 6 Conclusions

The efficiency of sky models and machine learning models for estimating solar radiation on a tilted surface was compared to observed solar radiation data on a tilted surface. The findings are based on comparing four isotropic sky models and two machine learning models.

The statistical analysis found that extreme gradient boosting (XGBoost) had the lowest RMSE (2.11 W·hr/m$^2$), MAE (1.37 W·hr/m$^2$), and MBE (0.01 W·hr/m$^2$) among the six models, whereas Tian had the greatest RMSE (11.20 W·hr/m$^2$), MAE (9.44 W·hr/m$^2$), and MBE (–8.95 W·hr/m$^2$).

The two machine learning models (Extreme gradient boosting and K-nearest neighbor) outperformed the isotropic sky models in terms of RMSE, MAE, and MBE.

Extreme gradient boosting (XGBoost) and the K-nearest neighbor model can estimate global solar radiation on a tilted surface, where observed data is scarce.

## 7 Acknowledgments

The authors appreciate the National Centre for Energy, Research and Development (NCERD), University of Nigeria, Nsukka, where the solar radiation data was measured.

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