Hourly Solar Radiation Estimation Using Data Mining and Generalized Regression Neural Network Models

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Abstract

Accurate information on solar radiation intensity is essential for the development of solar energy projects. The real-time solar radiation measurement on smaller time intervals is preferred for some precise data. However, since the values are greatly affected by the time and location and the calibration and maintenance work is costly, only professional institutes will perform this type of measurement for short periods. As such, usually properly recorded radiation data are hardly available in most developing countries like Ethiopia. This leads to the requirement of using estimation models established by climatological and geographical parameters of locations. Among various models, hourly solar radiation estimation models are important for much more accurate prediction because of the detailed changes that can be recorded in a day. In this study, Data Mining (DM) and Generalized Regression Neural Network (GRNN) methods were proposed. The correlation coefficients for the models were determined using calculated sun-earth parameters and measured irradiance in Mekelle, Ethiopia. The methods of statistical analysis were used to evaluate and verify the performance of the models. The study showed that the calculated variable coefficients of the DM model and $G_{GRNN} = 0.62 + 0.57\ (G_{mes})$ can predict the nature of hourly solar radiation in the study area. The GRNN method showed better estimation compared to the DM technique. The DM technique also showed a better estimation for clear sky days. The limitations for accurate prediction of the models could be mainly due to the short-term measured average solar radiation values and the outlier input features of the training data space. Hence, further study is recommended for effective predictions, especially for cloudy days.

Keywords: Solar radiation, Estimation models, DM, GRNN, Mekelle

1. Introduction

The solar radiation collected by a surface on earth varies on seasonal (daily or monthly) basis due to the presence of clouds and the Sun position. It also varies on an hourly basis due to the east to the west relative position of the sun (Bekele, 2009). Accurate information on solar radiation intensity is, therefore, essential for the development of solar energy projects as well as long-term performance and economic analysis of solar energy systems at a given location. For some precise researches, the real-time measured solar radiation data recorded on smaller time intervals are preferred. However, the values are greatly affected by the time and location in addition to the costly calibration and maintenance work. Usually, only professional research institutes and universities will perform this type of measurement for short periods (Zhang et al., 2017). Thus, in most developing countries like Ethiopia, properly recorded solar radiation data are hardly available.

Without properly recorded solar radiation data, estimation models are necessary to convert the available climatological and geographical data. Through investigating the literature, a large proportion of studies are to estimate the solar radiation for impending days and hours (Zhang et al., 2017; Lauret et al., 2015; Hocaoğlu et al., 2008). Since an hour is commonly the smallest time interval in the measurements of official meteorological stations, hourly data represents more information and is more useful for different applications (Khatib et al., 2015). Thus, the effective estimations of hourly solar energy capacity through the statistically tested estimation models play an important role in the design and application of solar systems (Duffie, 2013).

Among various models and parameters, Data Mining (DM) models proposed by Liu and Jordan and verified by Collares-Pereira and Rabel formulated using the concept of sun-earth angle, climatological parameters, and geographical parameters have been used to determine hourly solar radiation patterns from daily solar radiation data (Khatib et al., 2015; Bulut et al., 2007; Koussa et al., 2009; Fletcher et al., 2007; Raja, 1994; Trabea et al., 2000;

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Rietveld, 1978; Ravinder Kumar et al., 2005). Many studies have also applied Artificial Neural Networks (ANNs) to estimate solar radiation. The ANNs used to estimate solar radiation have similar configurations and are much more complex than an empirical model in terms of their computational work. Their basic principle is to correlate the input features with the target output in applying different selectable approaches. The variables in an ANN model include the input, the number of layers and neurons, training algorithm, and transfer function. Any modification in the variables can create a new ANN model, so it is necessary to develop appropriate rules to compare these ANN models. Since all of the ANNs have their pros and cons, there is no perfect algorithm for a neural network that can solve all problems. The ANNs algorithm is chosen depending on the task. As such, the Generalized Regression Neural Network (GRNN) was employed in this study. This method is a much more efficient algorism for small datasets and the network uses lazy learning that does not require iterative training but just stores parameters and uses them to make predictions (NeuPy-2019, n.d.; Specht, 1991).

The objective of this study is, therefore, to analyze and validate empirical DM and GRNN models for hourly solar radiation estimation using measured irradiance and calculated sun-earth parameters. The study also aims to show the effectiveness of the models for hourly solar radiation estimation. Data was collected permitting direct computerized data recording by automated measurement procedures to obtain more precise results in Mekelle University's main campus, Ethiopia. A description of proposed models was made from literature. This was followed by the determination of the model's unknown coefficients and statistical tests. Computational Microsoft Excel spreadsheets and Python programming language were used for data treatment, conditioning, and analysis. The output of the study appreciates achieving the most appropriate model and will have significant importance in terms of promoting solar energy applications.

2. Materials and Methods

2.1. Sun-Earth Parameters

Location is represented by geographical coordinates in degrees as latitude (φ) and longitude (λ). The solar angle parameters represented as the declination (δ), hour angle (ω), and sunset (ω_s) angles in degrees are used to describe Sun motion. The Earth trajectory around the Sun is an ellipse with the Sun being one of its foci represented by the Sun elevation h and the Sun azimuth ψ in degrees. The relations among the parameters are summarized in Table 1 (Prescott, 1940; Angstrom, 2007; Ulfat et al., 2008; Türkiye Bilimsel ve Teknik Araştırma Kurumu. et al., 2004; Iqbal, 1980; Şen, 2008).

Tab. 1: Sun motion and Earth trajectory Equations

Parameter	Equation	Remark
Sunset hour angle	$\omega_s = \cos^{-1}(-\tan\varphi\tan\delta)$ $\delta = 23.45\sin\ (0.9863 * (248+n_d))$ n_d is the day number	ω_s is the sunshine duration. φ is the angle between the location and the equator. δ is the angle between the sun and the equatorial plane of the earth.
Hour angle	$\omega = 15\ (\mathrm{T}_{Solar} - 12\ \mathrm{hour})$	ω is the angular displacement of the sun from the focal point and it defines the true solar time.
True solar time	$\mathrm{T}_{solar} = \mathrm{T}_{loc} + (\mathrm{EoT} + \left(\frac{\mathrm{Dhg}}{\mathrm{degree}}\right)[(\mathrm{LSMT} - \lambda)])/60$ T_{loc} is the local time (hr) EoT is the Equation of Time (min) D_{hg} is the time difference (advance of 4 min per degree) LSMT is the Local Standard Meridian Time $\mathrm{EoT} = 9.87\sin(2B) - 7.53\cos(B) - 1.5\sin(B)$ $B = (360^0/365)\ (n_d - 81)$ B is a factor $\mathrm{LSMT} = 15^0 * \mathrm{Time\ zone}$	T_{solar} (hr) is given by daily apparent motion of the true or observed sun. It depends on the interval between two successive returns of the sun to the local meridian. EoT is the difference between apparent and mean solar times, both taken at a given longitude for the same real instant of time. LSMT is a reference meridian

		used for a particular time zone. It is similar to the prime meridian used for Greenwich Mean Time (GMT). λ is the angle between the meridian of the location with the standard meridian.
Sun elevation	$h = \sin^{-1}(\sin(\varphi)\sin(\delta) + \cos(\varphi)\cos(\delta)\cos(\omega))$	h is the angle between the horizontal plane with the Sun direction. The value h = 0 is at sunrise and sunset; it varies between 90° (zenith) and 90° (nadir).
Sun azimuth	$\Psi = \sin^{-1}(\cos(\delta)\sin(\omega)/\cos(h))$	ψ is the angle on the horizontal plane, being the projection of the Sun direction with the direction to the south. The azimuth is between -180°≤Ψ≤180°.
Hourly extraterrestrial radiation	$I_o = \frac{12 * 3600 * G_{sc}}{\pi}\left[1 + 0.033 * \cos\left(\frac{360 n_d}{365}\right)\right] * \left[\cos\varphi\cos\delta\sin(\omega_2 - \omega_1) + \frac{\pi(\omega_2 - \omega_1)}{180}\sin\varphi\sin\delta\right]$	G_{sc}, solar constant (i.e 1367W/m^2) is the amount of solar energy per unit time on a unit area at the mean distance of the earth from the sun normal to the direction of propagation of the radiation outside the atmosphere.

2.2. Solar Radiation Data and Processing

The measurement site is located in Mekelle University's main campus, Ethiopia at an altitude of 2208m. The two major seasons in the site are dry and wet. These seasons run from October to May and June to September, respectively. Considering the climate of the site, solar irradiance data were collected at ten minutes interval from March 2018 to October 2019. The solar irradiance data is recorded by the SPN1 sunshine Pyranometer recorder with an accuracy of +/-5%.

Computational Microsoft Excel spreadsheet was employed to process the solar data as required for analysis. The recorded data are checked for errors and inconsistencies. Assessment to correct or remove errors or uncertainty that may lead to biased and misleading of the results were done. Errors resulted from data logger time shifts and missing single data are corrected and all other unnecessary and null data out of the objective were canceled for fast and easy handling of missing values. Then, a computer program using the Python programming language was employed for data analysis. From the raw data set, hourly and daily average statistics were made for the solar irradiance data.

2.3. Solar Radiation Estimation Models

The estimation of average hourly solar radiation was tried based on the parameters and ground recorded data from the measurement site applying DM and GRNN models. These analyses were made using Python programming language.

i. Data Mining (DM) Model

Empirical models are developed for hourly solar radiation data mining using daily solar radiation data. Liu and Jordan proposed (1) for the estimation of hourly solar radiation (Duffie, 2013; Khatib et al., 2015).

$$\frac{G_h}{G_D} = \frac{\left(\frac{\pi}{24}\right)(\cos\omega - \cos\omega_s)}{\sin\omega_s - \left(\frac{2\pi\omega_s}{360}\right)\cos\omega_s} \qquad 1$$

Where G_h is mean hourly solar radiation and G_D is mean daily solar radiation.

Collares-Pereira and Rabel verified the correlation given in (1) and propose (2) for estimating mean hourly solar radiation.

$$\frac{G_h}{G_D} = (a + bCos\,\omega)\frac{\left(\frac{\pi}{24}\right)(\cos\omega - \cos\omega_s)}{\sin\omega_s - \left(\frac{2\pi\omega_s}{360}\right)\cos\omega_s} \qquad 2$$

Where the coefficient a = 0.409 + 0.5016 Sin (ω_s − 60) and b = 0.6609 − 0.4767 Sin (ω_s – 60).

ii. Generalized Regression Neural Network (GRNN)

ANNs are a numerical modeling technique inspired by the biological neural system and is capable of processing non-linear relationship, data sorting, pattern detection, optimization, clustering, and simulation. It is called a "black box" modeling technique because it does not present a physical explanation about the question. The calculation units of ANNs are interconnected neurons in the layers. In terms of configuration, the model usually contains an input layer, a hidden layer, and output layer. In terms of the process of data manipulation, it mainly consists of two stages: training section and testing section. In the training section, the ANNs finish learning and storing the pattern information of the existing database. In the testing section, the ANNs recall the information to produce output based on a particular input database (Zhang et al., 2017). As such, the GRNN was employed to search for a relationship among variables which is one of the most important fields in statistics and machine learning. There are many regression methods available. Linear regression is one of them and is chosen for this task. The parameters for the proposed GRNN model are listed in Table 2 (NeuPy-2019, n.d.; Specht, 1991).

Tab. 2: GRNN model methods

SN	Method	Remark
1	Define input features and target output	T_{solar}, ω, ψ, h, I_o , and G_h
2	Normalization	The network is sensitive when one input feature has higher values than the other one. Input data normalization is required before training.
3	Learning rate	The network is sensitive to the learning rate (Standard deviation [Std]) value. Std should be on the range of input features for good prediction.
4	Training	The network stores all the information about the data (x_train, y_train) for the prediction.
5	Test	The network returns prediction per each sample in the input (x_test).

2.4. Statistical Evaluation Gauges

The corresponding estimated values of the models are compared with measured values using the statistical tests to ensure proper evaluation and check the estimation ability of the proposed models. The performance of the models was compared by Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The coefficient of correlation (R) was used to compare the depth of the correlation between the estimated and ground measured solar radiation (Nguyen et al., 1997).

The MAE defined using (3) yields deviation of the estimated and measured radiation values.

$$MAE = \left(\frac{1}{n}\right)\sum|G_{est} - G_{mes}| \qquad (3)$$

Where n is the number of data considered, G_{est} is the estimated value of mean hourly radiation, and G_{mes} is the measured value of mean hourly radiation.

The RMSE defined using (4) yields the same idea of deviation between estimated and measured radiation values.

$$RMSE = \sqrt{\frac{\sum(G_{est} - G_{mes})^2}{n}} \qquad (4)$$

The R is defined using the statistical formula in (5):

$$R = \frac{\sum(G_{est} - \bar{G}_{est})(G_{mes} - \bar{G}_{mes})}{\sqrt{\sum(G_{est} - \bar{G}_{est})^2\sum(G_{mes} - \bar{G}_{mes})^2}} \qquad (5)$$

The MAE values can be negative or positive for under and overestimations, respectively. Errors are added up neglecting the signs to obtain the mean. Thus, the long-term performance of the correlations is determined by allowing a comparison of the actual deviation term by term. This is useful to care for outliers in the data. The RMSE values are always positive and zero in the ideal case. It gives a short-term performance of the correlations by allowing a term by term comparison of the actual deviation. This is useful to care for unexpected values in the data. The R values are always less than one and one in the ideal case. It is useful to measure if the model is good or not.

3. Results and Discussion

3.1. Solar Data and Models Parameters

The geographical and astronomical parameters of the measurement site are summarized in Table 3.

Tab. 3: Geographical and astronomical parameters of the measurement site

Parameter	Value
Latitude (φ) in degrees	13.33
Longitude (λ) in degrees	39.30
Local time (T_{loc}) in hours	00:00 - 23:00
Time zone in hours	GMT + 3
Number of days (n_d)	Between 1 for 1st of January and 365 for 31st of December

The statistics of the collected data are summarized in Table 4.

Tab. 4: Measured data statistics

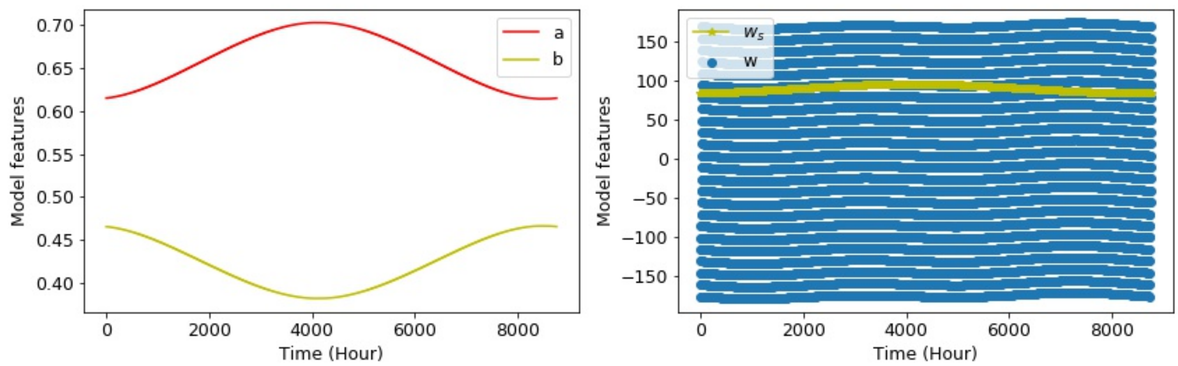
Indicator	Global Irradiance (Wm^{-2})
Count	76616.00
Mean	253.49
Std	347.55
Max	1408.07
Min	1.05

The processed measured data for the analysis using the selected GRNN model are summarized in Table 5.

Tab. 5: Processed GRNN model data

Parameter	Description
Training data	70%
Test data	30%
Range of normalized input features	[-4, 3]
Range of Std	[0.1, 1.1]

The model empirical relations were used to calculate the DM model features of the measurement site shown in Figure 1 (a and b).



(a) (b)

Fig. 1: DM model feature values (a) Coefficients a and b, (b) W and W_s

The Python code was run to train the network for different learning rates by varying the standard deviation (Std) using the normalized input features. The Mean Square Error (MSE) that minimized the actual test target and network output was used to compare the performance of the GRNN method as can be seen from Figure 2.

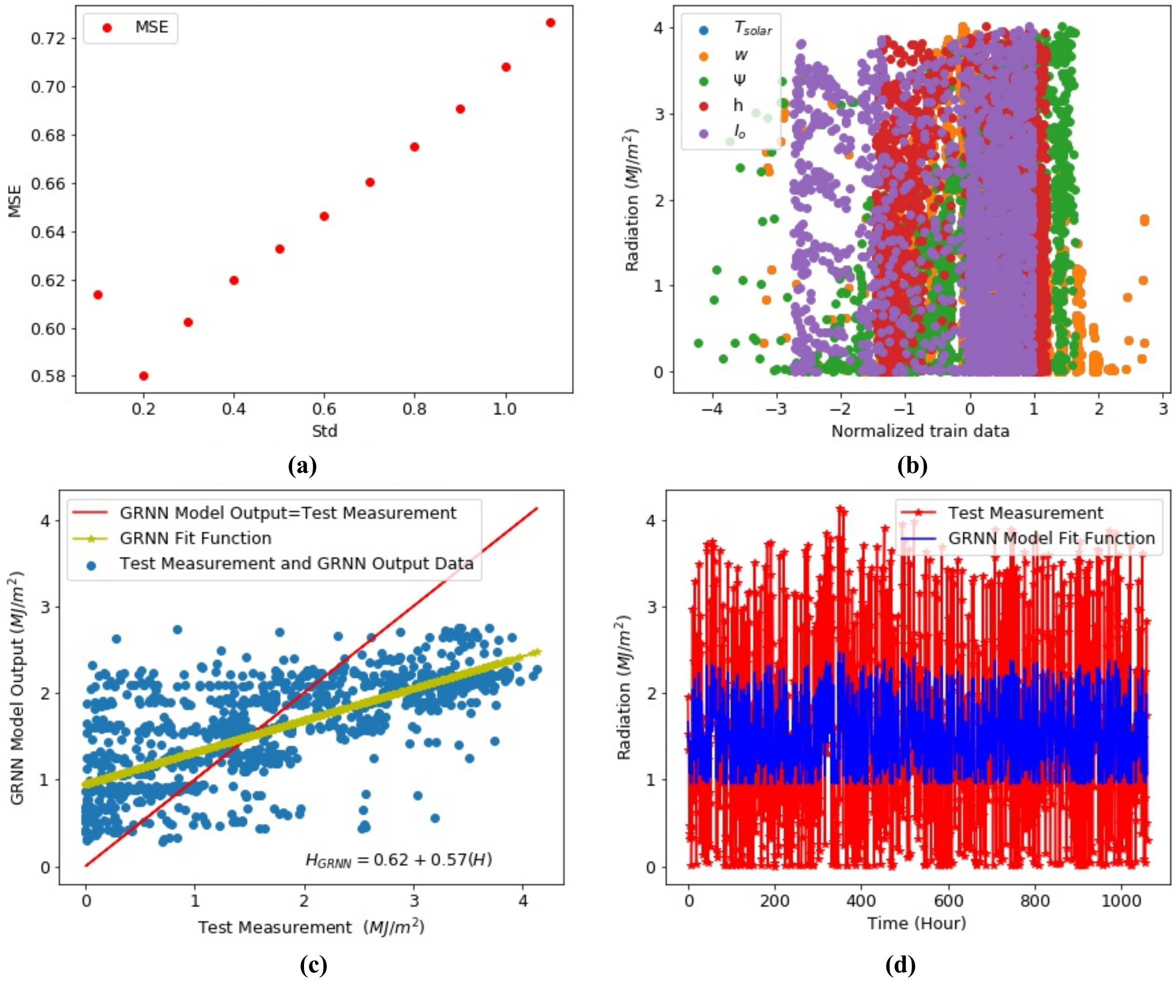


Fig. 2: GRNN learning and test (a) MSE, (b) Training data, (c) Network correlation factor, (d) Test data

From Figure 2a, the MSE subsequently receded to a lower value as the Std become 0.2 to show superior performance. As a result, the measured solar radiation can be related to the final trained neural network output after a test data in Figure 2d by $G_{GRNN} = 0.62 + 0.57\ (G_{mes})$. From Figure 2c, it is possible to see that the estimation match is acceptable, although not perfect for a wide range of solar radiation values. Some points on the lower and higher radiation measurements seem to diverge from the regressed line. This might arise due to the presence of data points far from other training points which are not representative of all input space. Analysis of the scatter plot for the training data in Figure 2b clearly shows the case.

3.2. Solar Radiation and Statistical Tests

The calculated extraterrestrial solar radiation and the re-sampled measured solar radiation data from the Python script file written for the analysis are shown in Figure 3.

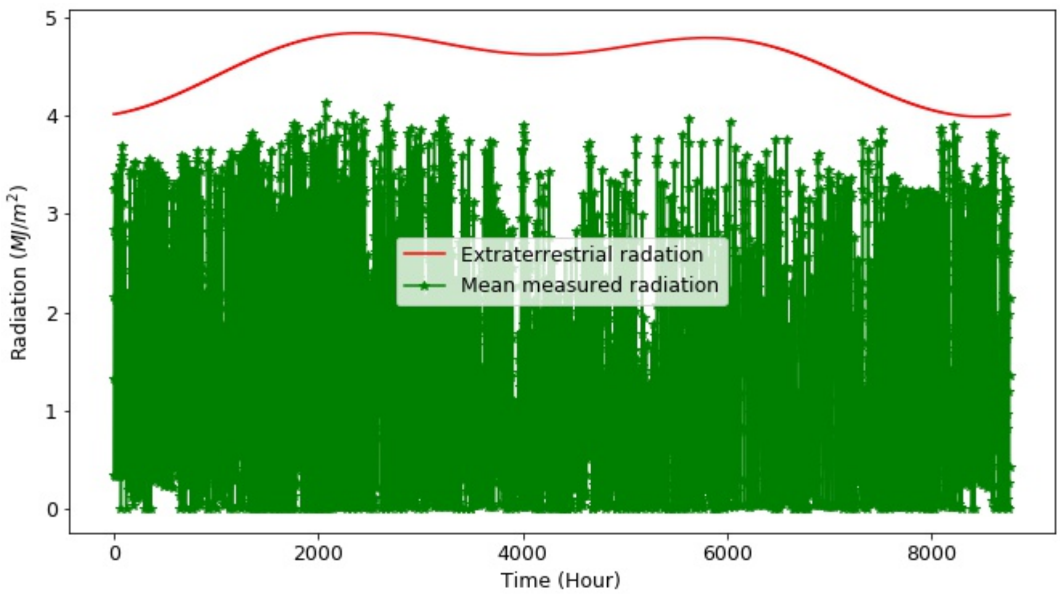


Fig. 3: Hourly extraterrestrial and measured radiation

The average hourly solar radiation from the DM model and corresponding variable feature values, the parallel measured values, and the corresponding difference (delta) values are shown in Figure 4.

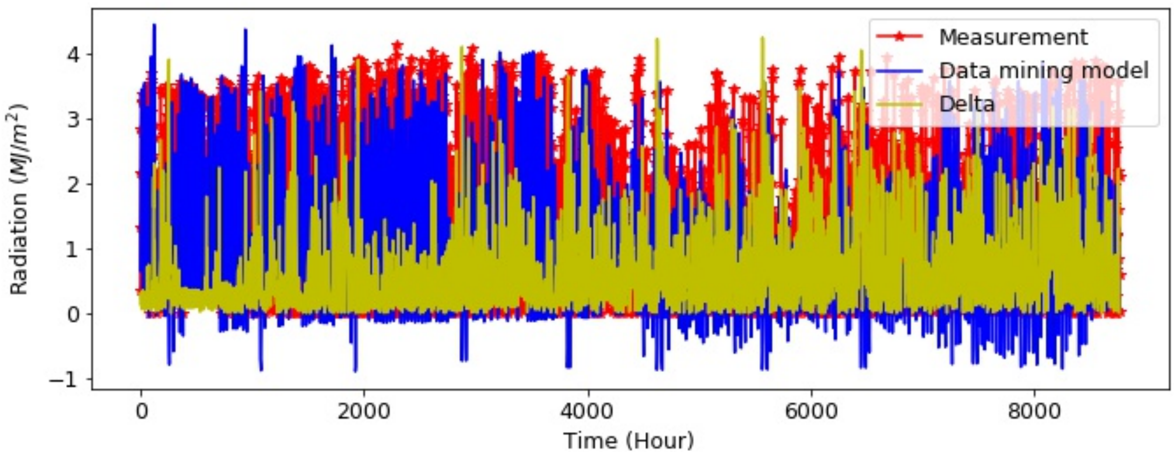


Fig. 4: Measured and DM extracted hourly solar radiation

The average hourly solar radiation from the GRNN model, the parallel measured values, and the corresponding difference (delta) values are given in Figure 5.

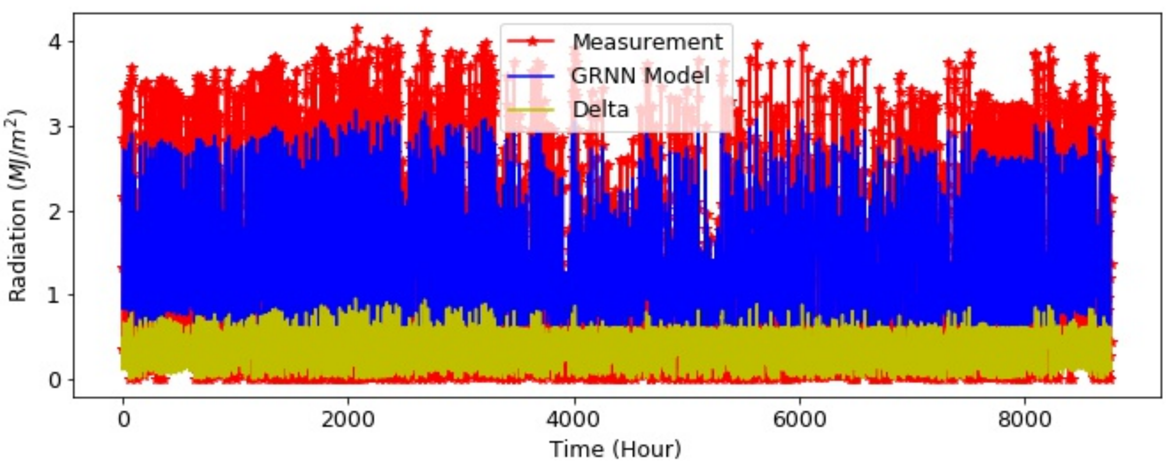


Fig. 5: Measured and GRNN predicted hourly solar radiation

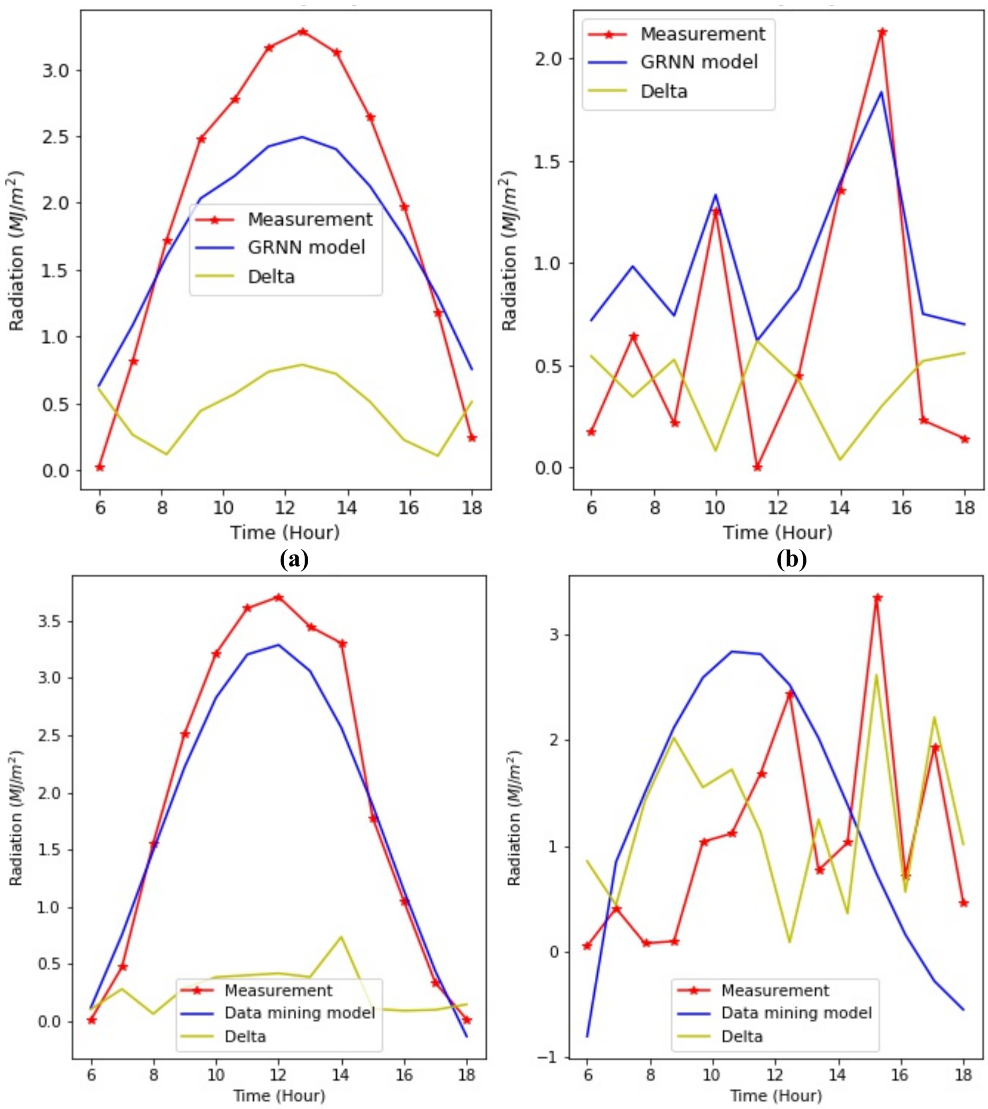
The statistical tests (MAE, RMSE, and R) for comparison of estimations were determined and the results are summarized in Tables 6.

Tab. 6: The statistical test results of estimations

Indicator	DM	GRNN
MAE	0.74	0.42
RMSE	1.03	0.50
R	0.77	0.83

From the results of the statistical tests, it is clear that the GRNN model predicted the hourly solar radiation more successfully. This is in line with the large number of studies that had applied ANN to estimate solar radiation that concluded ANN models were more accurate than empirical models (Rajesh Kumar et al., 2015; Yadav et al., 2014; Qazi et al., 2015). However, it is possible to see that the estimation matches are not perfect. This could be because of the needs to consider the scattering, absorption, and reflection of the atmospheric components in detail becomes more difficult for the process of accurate hourly solar radiation estimation.

Looking in to further details in Figure 6, the prediction accuracy of the proposed GRNN model (Figure 6a and Figure 6b) is low for the lower and higher solar radiation measurements of both clear sky and cloudy days. Hourly solar radiation for clear sky days (Figure 6c) is predicted well by the DM model. However, a bad prediction is observed for cloudy days (Figure 6d) using the DM model.



(a) (b) (c) (d)

Fig. 6: Typical hourly solar radiation (a) GRNN clear sky, (b) GRNN cloudy (c) DM clear sky, (d) DM cloudy

The prediction accuracy of the proposed GRNN model is affected by the uneven distribution of the input features on the training data space. The prediction accuracy of the DM model is affected due to the mean daily solar radiation value of the measured data. This could be mainly due to unstable solar radiation levels caused by the difference in cloud formation and atmospheric conditions at different times.

The variation in estimation is usually solved by adding shifting constants to the models. Moreover, to improve the generalization capability of the proposed neural network and the accuracy of the GRNN model, only points that span the whole training data space could be considered. Since ground measured data recorded for a short period cannot provide valuable information, the variation is usually solved using long-term average data. Estimation results improved in this way could become more acceptable.

4. Conclusions

The study aims at evaluating the appropriateness and effectiveness of DM and GRNN models for the prediction of hourly solar radiation collected at the earth's surface. To select the most appropriate model for Mekelle University's main campus solar measurement site, estimation models have been collected from the literature. Measured irradiance and calculated sun-earth parameters of the site were used for the analysis. The performance of the employed models was evaluated and compared based on the statistical gauges MAE, RMSE, and R. According to the results, the models can predict the nature of the hourly solar radiation with reasonable accuracy using variable DM model coefficients and $G_{GRNN} = 0.62 + 0.57\ (G_{mes})$. The estimation matchs are not perfect because of the need to consider the scattering, absorption, and reflection of the atmospheric components. The GRNN model shows better prediction compared to DM. The proposed hourly DM model also showed acceptable prediction for clear sky days as compared to cloudy sky days. The limitations for accurate prediction of the models are the outlier input features of the training data space and the daily average solar radiation of the measured data. This could be mainly due to the short-term average values of the measured solar radiation. These limitations could be solved by removing outlier data from the training data space and adding shifting constants to the models. Furthermore, the limitations could be improved by using long-term average solar radiation measurements. As such, further study is recommended for a thorough treatment of the models to consolidate with this study for effective estimation of hourly solar radiation in the study area and elsewhere with comparable climatic conditions.

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