Solar Irradiation Prediction Level

GIL-VERA V. D.[1], QUINTERO-LÓPEZ C.[2]
[1]Department of Engineering,
Information Systems and Knowledge Society Research Group,
Luis Amigo Catholic University,
Transversal 51A #67B 90,
COLOMBIA

[2]Basic and Applied Neurosciences Group,
Luis Amigo Catholic University,
Transversal 51A #67B 90,
COLOMBIA

Abstract: - The discipline of Machine Learning (ML), a branch of Artificial Intelligence, enhances the ability to model crucial variables for generating green energy, such as solar radiation. Precise prediction of solar irradiation assists in the strategic placement of solar panels, optimizing energy production, reducing reliance on non-renewable energy sources, and promoting environmental conservation. This research aimed to develop a model for predicting solar irradiation using the Multiple Linear Regression (MLR) technique. The results, while indicating a moderate performance (R^2=0.56, MAE=158.23, MSE=43804.89, and RMSE=209.29), provide a valuable starting point for future studies that seek to improve accuracy with more advanced techniques, such as artificial neural networks (ANN) or hybrid models. This research emphasizes the importance of continuing to investigate more sophisticated models for more accurate prediction and suggests that linear models, while useful for understanding basic relationships, have limitations that can be overcome with more advanced approaches.

Key-Words: - Forecasting, Irradiation, Linear Regression, Machine Learning, Meteorology, Renewable Energy, Sun.

Received: April 12, 2024. Revised: September 5, 2024. Accepted: October 8, 2024. Published: November 7, 2024.

1 Introduction

Solar energy consists of the energy emitted by the sun in the form of electromagnetic radiation. This energy, when harnessed can be in the form of heat and electricity production using different technologies such as solar cells made from silicon which is a better example, [1]. The sun is the principal energy source for our planet, and it has a major influence on many basic phenomena like Earth's surface radiation balance, hydrological cycle regulation or plant photosynthesis as well as extreme weather conditions while not forgetting climatological issues, [2]. As a result, forecasting solar radiance is crucial in the industry of renewable energy and meteorology. It is necessary to predict the generation of electricity as it can help in properly designing photovoltaic systems.

Prediction of solar irradiation is a must for the sizing of the PV power plant as it tells how much electricity will be generated on average. Accurate forecasts allow plant operators to increase their operational efficiencies, perform cost savings, and bring increased effectiveness, [3]. The output of solar power in one location can change with the sky being clear or cloudy and also at morning, afternoon, and dusk. Grid operators can use this to predict the upcoming fluctuations in solar generation and dispatch conventional power supplies such that grid-energy balance is maintained, [4].

Further, it can help energy operators make better decisions about when to buy or sell electricity. The ability to develop a forecast for potential deviations of solar power produced enables them to take appropriate measures in their trading strategies, [5]. Solar irradiance prediction is highly relevant to weather forecasting. It means the weather forecasters can get more accurate sunlight estimates. Furthermore, this is especially immediate in zones where sun-based influence generation is high, [6].

In the scientific literature, several researches have focused on the prediction of solar irradiance. In [7], a short-term solar prediction model was developed with satellite data. In regions with few meteorological observation facilities, such as the deserts in northwest China, they applied Support Vector Machine (SVM) techniques to enhance prediction accuracy. The proposed model proved to be useful as it did not require more meteorological variables and provided better prediction when used along with the satellite data. The most exciting revelation was that the model significantly improved very short-term solar forecasts. That could have a big effect on the large deployment of solar elsewhere in parts of the world that lack extensive meteorological infrastructures.

In [8], only assessed dissemination performance of predicting Solar Irradiation using multiple models for one-hour and short-term global horizontal irradiance (GHI) forecasting. Based on data obtained from a weather station near Erfoud, Morocco which is operated by the German Aerospace Center (DLR) Solar Research Institute and forms part of their enerMENA project they tested ANN framework methods with deep learning models such as Random Forest classifier model (RF), long short-term memory (LSTM). The results of their study indicated that the LSTM model significantly outperformed other models consisting of ANN and Random Forest (RF) for forecasting GHI in advance both in terms of performance and stability.

In [9], they have proposed a novel mechanism for solar irradiation prediction by integrating ANN, support vector regression (SVR), and convolutional neural network (CNN) models. Data from several weather stations were employed to enhance the accuracy of forecasted solar irradiation. The most important result of this study is that the solar irradiation forecasting model, using hybrid SVR+CNN models, provides a very effective prediction and outperforms existing methodologies. This result endorses the suitability of a neighbor data-based strategy for more accurate solar irradiation prediction and indicates that this approach may be a practical instrument in field deployment.

In [10], they proposed a new system called AOHDL-SRP to ensure true prediction of solar irradiation based on deep learning technique (i.e., the fusion between Attention-based Long Short-Term Memory Network models (ALSTMs) and Convolutional Neural Networks (CNNs) as well as hyperparameter optimization by using Particle Swarm Optimization algorithms, namely ALSTM-PSO. They have experimented on a large scale and with different data sets, the results obtained from experimental analysis of the AOHDL-SRP model show a maximum R^2=100%, which is better than some contemporary models in terms of accuracy. This result points to the potential for AOHDL-SRP as a valuable tool in improving solar irradiation forecasting, with notable implications for renewable energy systems programming and control.

In [11], 78 existing models were tested and 4 new ones were derived with observations at each of the weather stations available (105) for daily solar irradiation prediction in a temperature difference (ΔT, zonal approach over five zones. These models were utilized to assess their performances, and generalized coefficients for the superior model (N1-4) were derived as it showed higher accuracies at individual ΔT zones along with a combined ΔT zone.

The most pertinent discovery was the fact that the N1-4 model, along with its generalized coefficients at national and zonal levels have a reasonable level of accuracy to indirectly forecast daily solar irradiation for long-term high ΔT zones or intermittently low ΔT sunny days which has valuable implications in photovoltaic /solar thermal systems design as well as agricultural, ecological and climatic investigations. They argue that the importance of sophisticated solar energy forecasting models will rise increasingly in coming years to maximize wind power plant operation and control. Moreover, the performance of advanced models needs to be compared with those of traditional statistical models to substantiate the justification for having a more sophisticated forecasting model.

In [12], a hybrid model that integrates radiative transfer with ML techniques for estimating diffuse solar irradiation at different observation sites in China was analyzed. Moreover, the accuracy of several RTM-RF (RTM model based on RF), RTMXGBoost, RTMMultilayer perceptron (MLP), ResNet50-Deep neural network (RTM mask holder DNN), and Residual Convolutional Neural Network (RCNN) modeling methods were assessed by comparing with ground-based reference observations. The results showed that the meta-hybrid models RTM-RF and RTM-XGBoost obtained considerably more accurate estimates than RNN, LSTM, or MLPs. This conclusion indicates that using the radiative transfer model and ML is competent in any domain lacking ground-based observation for attaining credible indirect normal solar irradiance values. In summary, all the above require solar irradiation forecasting to efficiently and effectively operate these plants successfully allowing grid system strength stability as well assist in energy trading decisions. Solar irradiation affects the extremes of weather phenomena and temperature, along with global mean sea level so it is crucial to appropriately investigate geography-based (spatial) and time-varying trends in solar radiative climate.

2 Multiple Linear Regression (MLR)

MLR is a supervised learning algorithm used in ML and statistics to model the relationship between a dependent scalar variable "*Y*" with one or more explanatory variables *X(1),…,X(n).* A MLR model is represented by Eq. (1):

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \quad (1)$$

Y is the output, *Xi* are independent variables or input parameters, and is a cut-off point with the coordinate of *y*-axis. The error is evaluated as the function of location points along with their corresponding actual output *Y*-value in this ML model. Learning this algorithm tries to minimize the cost of a quadratic error function and these coefficients are equivalent to the line which should be optimal. Datasets of the construction RLM model in this work are disclosed in [13].

Several works found in the review of the scientific literature have used this technique in topics related to solar energy. In [14], compared the performance of the ANFIS method and the MLR method in forecasting solar irradiation intensity. The findings indicate that the ANFIS method outperformed the MLR method in predicting solar irradiation intensity, with better RMSE and MAE values. The results show that the ANFIS method provided a more accurate solar irradiation intensity prediction than the MLR method.

In [15], different methods have been applied to estimate solar irradiation, where empirical equations, ANN, and MLR are the examined prediction techniques. These results indicate that the models are consistent with those presented in review articles, and include specific variables associated with increased diagnostic performance. The comparison between ANN and MLR models is observed to be consistent.

In [16], a regression model was built to provide short-term prediction on solar irradiance; another functional relationship between solar and air temperature/humidity would be able also established, got three equations were presented for relating the trend concerning temperature.

In [17], performed a vast comparison between regression model and ANN forecasting models for predicting global solar irradiation. Results revealed that ANN models produced lower mean absolute percent error values and higher R values than regression models. Results reveal the best performance of ANN in predicting global solar radiation.

In [18], a new methodology for estimating solar irradiation was recommended. From the meteorological data by the Hargreaves method and linear regression there are some missing data in these records. The results compared and analyzed the observed solar insolation with predicted or modeled values in terms of statistical measures such as CRM, RMSE, NSE values, and percent errors. These results reveal that the proposed method has good performance, it can be used successfully because of CRM near zero, RMSE low values NSE close to unit, and less percentage error.

In [19], compared various ML models in predicting solar irradiation. The results confirmed that the proposed GBT model has a better capability to predict solar radiation and can be used successfully for short-term prediction of solar irradiation using only meteorological parameters as input. Several ML algorithms were used for predicting global horizontal solar irradiation in [20]. Results show that the root mean square error of MLP models was less than those encountered using regression-based models, but worse compared to ANFIS and SVM for global irradiation interpolated over a distance. In addition, it assesses the performance of decision trees in solar irradiation modeling temperature and day number-based models depict similar $R^2 > 85\%$, especially when no sunshine records are at hand.

3 Method

This work aimed to build a predictive model for solar irradiation based on historical data, including solar irradiation measurements and various meteorological variables such as wind direction (°), temperature (°F), barometric pressure (Hg), humidity (%) and wind speed (Mi/h). The multiple linear regression (MLR) technique was employed for this purpose. The historical data set comprised measurements of solar irradiation (W/m²) and meteorological variables (Table 1).

The MLR technique was used, adjusting hyperparameters and performing cross-validation. Python programming language and libraries such as LinearRegression, Pandas, Numpy, Matplotlib, and Seaborn were utilized to build the model. The code is available in [21]. The final model was evaluated using test data not involved in the training process.

The ability of the model to generalize to new and unseen data was analyzed, and its performance was compared to traditional solar irradiation prediction methods.

An accurate predictive model for solar irradiation can significantly impact various sectors, including solar energy management, agriculture, urban planning, and climatology. A reliable model enhances the efficiency and sustainability of solar energy usage, aiding in informed decision-making in sectors influenced by solar irradiation.

Table 1. Database description

Nomenclature	***Variable***	***Description***
Y	Solar irradiation	Watts per square meter (W/m²)
V1	Temperature	Degrees Fahrenheit (°F)
V2	Humidity	Percentage (%)
V3	Barometric pressure	mmHg
V4	Wind direction	Degrees °
V5	Wind speed	Miles per hour (Mi/h)

4 Results

Table 2 presents the correlation matrix. This indicated that irradiation has a positive correlation with temperature (0.73), pressure (0.12), and wind speed (0.074), and a negative correlation with humidity (-0.23) and wind direction (-0.23).

Table 2. Correlation matrix

	Y	***V1***	***V2***	***V3***	***V4***	***V5***
Y	1	0.73	0.12	-0.23	-0.23	0.074
V1	0.73	1	0.31	-0.29	-0.26	-0.031
V2	0.12	0.31	1	-0.22	-0.23	-0.084
V3	-0.23	-0.29	-0.22	1	-0.0018	-0.21
V4	-0.23	-0.26	-0.23	-0.0018	1	0.073
V5	0.074	-0.031	-0.084	-0.21	0.073	1

The distribution diagram (Figure 1) showed a bell-shaped (normal distribution) pattern, suggesting good model predictions.

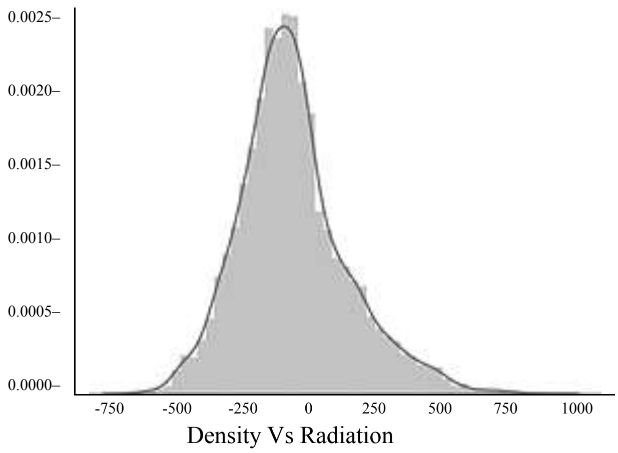

Fig. 1: Distribution diagram

The model's performance was evaluated using several regression metrics. Among these, the coefficient of determination (R²) stands out as it measures the proportion of variance in the dependent variable that the independent variables account for, as outlined in Eq. (2):

$$R^2 = \frac{\left(\sum_{t=1}^{n}(yo_t - \overline{yo})\,(ym_t - \overline{ym})\right)^2}{\sum_{t=1}^{n}(yo_t - \overline{yo}\,)^2 . \sum_{t=1}^{n}(ym_t - \overline{ym}\,)^2} \quad (2)$$

Additionally, the performance was evaluated using the Mean Absolute Error (MAE), which reflects the average magnitude of prediction errors, as detailed in Eq. (3):

$$MAE \; = \frac{1}{n}\sum_{t=1}^{n} ||yo_t - \; ym_t|| \quad (3)$$

The Mean Squared Error (MSE) was also utilized, offering insight into the average of the squared differences between predicted and actual values, as indicated in Eq. (4):

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(y_t - \; \overline{y_t}\,)^2 \quad (4)$$

Lastly, the Root Mean Squared Error (RMSE) was considered, which represents the square root of the average squared discrepancies between the observed and predicted values, Eq. (5):

$$RMSE = \; \sqrt{\frac{1}{n}\sum_{t=1}^{n}(yo_t - \; ym_t)^2} \quad (5)$$

In Eq. (2) to (5), n is the number of data points, *ym_t* and *yo_t* respectively for predicted and observed solar irradiation. The former is denoted as $\overline{ym}$ and the latter by $\overline{yo}$. The value of R² is interpreted as a correlation between the observed and predicted values. What more you get with RMSE and MAE is that a closer value to 0 indicates better, in other words, the prediction values have been predicted as it was found. Multiple performance measures (RMSE, MAE) should be used to get the full vision of how well your model is performing.

Table 3 presents the R², MAE, MSE, and RMSE metrics, showing an R²=0.56, MAE=158.23, MSE=43804.89, and RMSE=209.29. These metrics indicate that the MLR model explains a moderate percentage of the variability in solar irradiation but still has considerable error.

Table 3. Results of the MLR model

Metric	*Value*
R^2	0.56
MAE	158.23
MSE	43804.89
RMSE	209.29

An R^2 of 0.56 means that approximately 56% of the variability in solar irradiation can be explained by the linear regression model. An MAE of 158.23 indicates that, on average, the model predictions have an absolute error of approximately 158.23 units of the solar irradiation measurement. An MSE of 43804.89 indicates that the average of the squares of the prediction errors is approximately 43804.89 units of the solar irradiation measure.

An RMSE of 209.29 indicates that, on average, the model predictions have an error of approximately 209.29 units of the solar irradiation measure. These statistics indicate that the MRLM explains a moderate percentage of the variability in solar irradiation, but the model predictions still have considerable error, as evidenced by the relatively high MAE, MSE, and RMSE. Table 4 presents the coefficients of the MLR model.

Table 4. Coefficients of the MLR model

Variable	*Description*	*Coefficient*
V1	Temperature	38.22
V2	Pressure	-749.95
V3	Humidity	-0.28
V4	Wind direction (Degrees)	-0.27
V5	Speed	8.44

Eq. (6) predicts solar irradiation (Y) as a function of the variables temperature($V1$), pressure($V2$), humidity($V3$), wind direction($V4$), and wind speed($V5$).

$$Y = 21076.34 + 38.22\,\mathrm{V1} - 749.95\,\mathrm{V2} - 0.28\,\mathrm{V3} - 0.27\,\mathrm{V4} + 8.44\,\mathrm{V5} \tag{6}$$

A one-unit temperature increase is related to a 38.22-unit increase in solar irradiation, holding all other model variables constant. A one-unit increase in pressure is related to a 749.95-unit decrease in solar irradiation, holding all other model variables constant. A one-unit increase in humidity is related to a 0.28-unit decrease in solar irradiation, holding all other model variables constant. A one-unit increase in wind direction is related to a 0.27-unit decrease in solar irradiation, holding all other model variables constant. A one-unit increase in wind speed is related to an 8.44-unit increase in solar irradiation, holding all other model variables constant.

Higher temperature and wind speed tend to be related to higher solar irradiation, while higher atmospheric pressure and humidity tend to be associated with lower solar irradiation. Wind direction has a negative, but weaker influence compared to the other variables, in other words, although wind direction negatively affects solar irradiance, its impact is minor compared to the other factors analyzed.

5 Discussion

Using the MLR method, an R^2 of 0.56 is moderate for forecasting solar irradiance in this study. These values are consistent with previous studies that have implemented regression models to correct solar insolation such that coefficients of determination were also in the mid-range. On the other hand, modern methods like deep neural networks and hybrid learning can achieve huge improvements in predicting solar irradiance by achieving R^2 values close to or higher than 0.85 considering new research outputs (As compared with only 82% from older methods) structures are shown, [22]. Although MLR is a valuable tool for entry-level modeling and explaining the relationships among variables, this also indicates that more advanced techniques could greatly enhance predictive capability.

Although it was a very useful tool, the linear nature of this study's MLR model also limits its applicability. The MLR model fits a linear relationship between the independent variables i.e., temperature, humidity (absolute), barometric pressure, wind direction, and wind speed with the dependent variable of solar irradiance. This assumption of linear relation in meteorological data is likely an oversimplification, as nonlinear relationships between weather variables can be complex. In addition, the model performance (MAE=158.23, MSE=43804.89, and RMSE=209.29) suggests significant scope for improvement in the accuracy of models as well. ML models that capture nonlinearity and interaction between variables like the ANN-based model or tree-based model can give a better image of contributing factors to solar irradiance.

The analysis performed in this study allowed the identification of relationships between solar irradiance and meteorological variables, which contributes to improving solar energy management and photovoltaic system planning. The main contribution of this study lies in the detailed evaluation of how these meteorological variables influence solar irradiance and in the validation of the model with a historical data set.

This research underscores the need for further research into advanced modeling techniques for solar irradiance prediction. The development of more accurate models will not only contribute to the optimization of solar power generation but will also enable better planning and management of energy resources. In particular, future research could focus on the integration of hybrid techniques that combine the robustness of traditional models with the learning capabilities of modern artificial intelligence methods. In addition, the improvement in the quality and quantity of meteorological data, together with the use of advanced ML algorithms, can lead to a deeper understanding of climate dynamics and better utilization of renewable energies at a global level.

6 Conclusion

Based on the evaluation results, this study shows that the MLR method is an effective approach for solar irradiation prediction by meteorological variables. Although it has medium performance metrics, the MLR model can give us meaningful information about the relationships between solar irradiation and some factors like temperature, humidity, atmospheric pressure wind direction, or average speed of air. The research underlines the need to consider these ML techniques for solar energy resources to be handled efficiently. It also proposes that innovative models must be explored further to increase both the precision and robustness of predictions involved with solar irradiation.

Through the use of ML models, solar energy utilization can become more efficient and sustainable with less dependence on non-renewable resources which ultimately helps to reduce global carbon footprint. These results illustrate that solar irradiation forecasting has come a considerable way, but faces many challenges regarding prediction reliability. The MLR model seemed to be promising, but more extensive research is needed to investigate advanced ML methods such as deep-learning models and ensemble techniques that have achieved better performances in the studies. Furthermore, it is necessary for the improvement of data collection methodologies and validation techniques that could lead to an increment in solar irradiation prediction accuracy which can increase overall reliability to expand the properties of renewable energy sources across a larger portion of the global energy portfolio.

The model built in this work, by providing accurate estimates of solar irradiance, allows for better planning and management of solar energy systems, helping operators to optimize the location of solar panels, adjust energy production according to climatic conditions, and reduce dependence on non-renewable energy sources such as fossil fuels. By improving energy efficiency, the need to resort to polluting energy sources is reduced, which in turn helps mitigate environmental impact, reducing greenhouse gas emissions and promoting more sustainable development. These models therefore play a key role in the transition to a cleaner and more environmentally friendly energy future.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the authors used ChatGPT 4.0 to improve the manuscript's readability and language. After using ChatGPT 4.0, the authors reviewed and edited the content as needed and took full responsibility for the publication's content.

References:

[1] M. Sengupta, Y. Xie, A. Lopez, A. Habte, G. Maclaurin, and J. Shelby, “The National Solar Radiation Data Base (NSRDB),” *Renewable and Sustainable Energy Reviews*, vol. 89, pp. 51–60, 2018. doi: 10.1016/j.rser.2018.03.003.

[2] M. Guermoui, F. Melgani, K. Gairaa, and M. L. Mekhalfi, “A comprehensive review of hybrid models for solar radiation forecasting,” *Journal of Cleaner Production*, vol. 258, pp. 719–733, 2020. doi: 10.1016/j.jclepro.2020.120357.

[3] G. Narvaez, L. F. Giraldo, M. Bressan, and A. Pantoja, “Machine learning for site-adaptation and solar radiation forecasting,” *Renewable Energy*, vol. 167, pp. 333–342, 2021. doi: 10.1016/j.renene.2020.11.089.

[4] M. Aslam, J.-M. Lee, H.-S. Kim, S.-J. Lee, and S. Hong, “Deep Learning Models for Long-Term Solar Radiation Forecasting Considering Microgrid Installation: A Comparative Study,” *Energies (Basel)*, vol. 13, no. 1, pp. 1–15, 2020. doi: 10.3390/en13010147.

[5] S. Sun, S. Wang, G. Zhang, and J. Zheng, “A decomposition-clustering-ensemble learning approach for solar radiation forecasting,” *Solar Energy*, vol. 163, pp. 189–199, 2018. doi: 10.1016/j.solener.2018.02.006.

[6] H. Acikgoz, “A novel approach based on integration of convolutional neural networks and deep feature selection for short-term solar

radiation forecasting," *Applied Energy*, vol. 305, pp. 1-23, 2022. doi: 10.1016/j.apenergy.2021.117912.

[7] L. Yang, X. Gao, Z. Li, and D. Jia, "Intra-day solar irradiation forecast using machine learning with satellite data," *Sustainable Energy, Grids and Networks*, vol. 36, pp. 1-12, 2023. doi: 10.1016/j.segan.2023.101212.

[8] Z. Bounoua and A. Mechaqrane, "Hourly and sub-hourly ahead global horizontal solar irradiation forecasting via a novel deep learning approach: A case study," *Sustainable Materials and Technologies*, vol. 36, pp. 1-17, 2023. doi: 10.1016/j.susmat.2023.e00599.

[9] Y. Y. Hong and J. J. F. Martinez, "Forecasting solar irradiation using convolutional long short-term memory and feature selection of data from neighboring locations," *Sustainable Energy, Grids and Networks*, vol. 38, pp. 1-13, 2024. doi: 10.1016/j.segan.2023.101271.

[10] K. Irshad, N. Islam, A. A. Gari, S. Algarni, T. Alqahtani, and B. Imteyaz, "Arithmetic optimization with hybrid deep learning algorithm based solar radiation prediction model," *Sustainable Energy Technologies and Assessments*, vol. 57, pp. 1-8, 2023. doi: 10.1016/j.seta.2023.103165.

[11] R. Qiu, L. Li, Li. Wu, E. Agathokleous, C. Liu, B. Zhang, Y. Luo, and S. Sun, "Modeling daily global solar radiation using only temperature data: Past, development, and future," *Renewable and Sustainable Energy Reviews*, vol. 163, pp. 1-16, 2022. doi: 10.1016/j.rser.2022.112511.

[12] Y. Lu, R. Zhang, L. Wang, X. Su, M. Zhang, H. Li, S. Li, and J. Zhou, "Prediction of diffuse solar radiation by integrating radiative transfer model and machine-learning techniques," *Science of the Total Environment*, vol. 859, pp. 1-19, 2023. doi: 10.1016/j.scitotenv.2022.160269.

[13] V. D. Gil-Vera, Solar Radiation Dataset, 2024, [Online]. https://raw.githubusercontent.com/victorgil777/SOLAR_IRRADIATION/main/Solar_Irradiation.csv (Accessed Date: October 1, 2024).

[14] V. Z. Antonopoulos, D. M. Papamichail, V. G. Aschonitis, and A. V. Antonopoulos, "Solar radiation estimation methods using ANN and empirical models," *Computers and Electronics in Agriculture*, vol. 160, pp. 160–167, 2019. doi: 10.1016/j.compag.2019.03.022.

[15] H. Suyono, R. N. Hasanah, R. A. Setyawan, P. Mudjirahardjo, A. Wijoyo, and I. Musirin, "Comparison of solar radiation intensity forecasting using ANFIS and multiple linear regression methods," *Bulletin of Electrical Engineering and Informatics*, vol. 7, no. 2, pp. 191–198, 2018.

[16] U. Nalina, V. Prema, K. Smitha, and K. U. Rao, "Multivariate regression for prediction of solar irradiance," in *Proc. 2014 International Conference on Data Science & Engineering (ICDSE)*, Cochin, India, pp. 177–181, 2014. doi: 10.1109/ICDSE.2014.6974633.

[17] R. Kumar, R. K. Aggarwal, and J. D. Sharma, "Comparison of regression and artificial neural network models for estimation of global solar radiations," *Renewable and Sustainable Energy Reviews*, vol. 52, pp. 1294–1299, 2015. doi: 10.1016/j.rser.2015.08.021.

[18] M. R. Rietveld, "A new method for estimating the regression coefficients in the formula relating solar radiation to sunshine," *Agricultural Meteorology*, vol. 19, no. 2, pp. 243–252, 1978. doi: 10.1016/0002-1571(78)90014-6.

[19] I. Daut, M. Irwanto, Y. M. Irwan, N. Gomesh, and N. S. Ahmad, "Combination of Hargreaves method and linear regression as a new method to estimate solar radiation in Perlis, Northern Malaysia," *Solar Energy*, vol. 85, no. 11, pp. 2871–2880, 2011. doi: 10.1016/j.solener.2011.08.026.

[20] M. A. Hassan, A. Khalil, S. Kaseb, and M. A. Kassem, "Potential of four different machine-learning algorithms in modeling daily global solar radiation," *Renewable Energy*, vol. 111, pp. 52–62, 2017. doi: 10.1016/j.renene.2017.03.083.

[21] V. D. Gil-Vera, Python code of the research Solar Radiation Prediction Level, 2024, [Online]. https://github.com/victorgil777/Irradiation/blob/main/Predicting_the_value_of_solar_radiation.ipynb (Accessed Date: October 1, 2024).

[22] G. Etxegarai, A. López, N. Aginako, and F. Rodríguez, "An analysis of different deep learning neural networks for intra-hour solar irradiation forecasting to compute solar photovoltaic generators' energy production," Energy for Sustainable Development, vol. 68, pp. 1–17, Jun. 2022. doi: 10.1016/j.esd.2022.02.002.

Contribution of Individual Authors to the Creation of a Scientific Article

- Gil-Vera, V. D. carried out the development of the model, implemented the Python libraries, has organized and executed the statistical analysis.
- Quintero-López, C. assisted in the writing, editing, and interpretation of the results.

Sources of Funding
This work was funded by Luis Amigó Catholic University - Cost Center [0502020965].

Conflict of Interest
The authors have no conflicts of interest to declare.