



Modelling of Solar Power Generation in Malaysia: A Time Series Analysis

Nurul Ain Najwa Zainal Abidin¹, Noor 'Adilah Ibrahim^{1,*}, Neelabja Chatterjee¹

¹ Faculty of Science and Technology, Universiti Sains Islam Malaysia, Bandar Baharu Nilai, 7180 Nilai, Negeri Sembilan, Malaysia

ARTICLE INFO

Article history:

Received 13 April 2025
 Received in revised form 5 June 2025
 Accepted 14 June 2025
 Available online 30 June 2025

Keywords:

Ambient temperature; humidity;
 irradiance; module temperature; solar
 energy production

ABSTRACT

This study explores the dynamics of solar power generation in Malaysia using time series analysis, focusing on key environmental variables such as irradiance, ambient temperature, module temperature, and humidity. Data from a solar installation in Gading Kencana, Melaka, collected between July 2019 and January 2021, underwent stationarity testing, and multiple regression analysis to understand the factors influencing solar energy production. Results reveal that irradiance significantly enhances energy output, while module temperature and humidity negatively impact performance. Ambient temperature shows mixed effects depending on the context. Despite the statistical insignificance of humidity, its multicollinearity with other variables suggests a nuanced impact. The predictive model demonstrates robustness, offering reliable insights into optimizing solar panel efficiency and planning for variability in energy output. The findings aim to support energy managers, policymakers, and solar operators in improving solar power systems, ensuring sustainable energy development amidst Malaysia's climate challenges.

1. Introduction

Solar energy is one of the key factors in the worldwide transition to sustainable energy. Malaysia is a country located at the equator which receives high solar irradiance levels throughout the year. More specifically, Malaysia has an ideal condition for the research and development of solar energy due to its consistent sunlight as well as the climate that supports solar power production. Despite their high potential, the performance of solar power systems is affected by several environmental conditions, such as humidity, irradiance, ambient temperature, and module temperature. In order to optimize the solar power systems, it is important to understand how these variables interact over time.

Table 1 shows the rank of 15 countries with the highest solar power installed recorded by Energy Institute (2024). There are several reasons why these well-developed countries preferred to use solar power energy such as to enhance energy independence and security, technological advancements in their country, to decrease the country's cost and economic benefits. China was written as the highest solar power installed in the world as the country recorded approximately 609 921 MW, since the

* Corresponding author.

E-mail address: nooradilah@usim.edu.my

country is very dominance in solar manufacturing accounted for 83% of the world's solar panel production in 2023 according to an article written by Thibault *et al.*, [20].

Table 1

Rank of the country with the highest solar power installed

Rank	Country	MW of solar power (cumulative)	CAGR (2013-23)
1	China	609,921	42.40%
2	U.S.	139,205	26.50%
3	Japan	87,068	20.40%
4	Germany	81,739	8.30%
5	India	73,109	46.50%
6	Brazil	37,449	122.80%
7	Australia	33,683	22.10%
8	Spain	31,016	16.10%
9	Italy	29,795	5.10%
10	South Korea	27,046	33.10%
11	Netherlands	23,904	43.40%
12	France	20,551	14.60%
13	Vietnam	17,077	127.90%
14	Poland	15,809	141.00%
15	United Kingdom	15,657	18.20%
	World total	1,418,969 MW	25.90%

This study aims to carry out a comprehensive time series analysis of solar power production data collected in Gading Kencana, Melaka, Malaysia by accounting for important environmental variables to address the limitations. The main purpose of this is to examine the significant variables that affect solar energy production. This study aims to forecast the value of the production of solar energy where we consider independent variables such as ambient temperature, environment temperature, irradiance and humidity.

According to International Renewable Energy Agency (IRENA) in 2024, Malaysia's solar energy capacity in 2023, is similar to the previous year that recorded approximately 1933 megawatt. It is also shown a rapid increment compared to last decade which only recorded about 205 MW in 2014. This means that most people in Malaysia are aware of this energy replacement. Figure 1 represents the amount of energy used since 2014 until 2023.

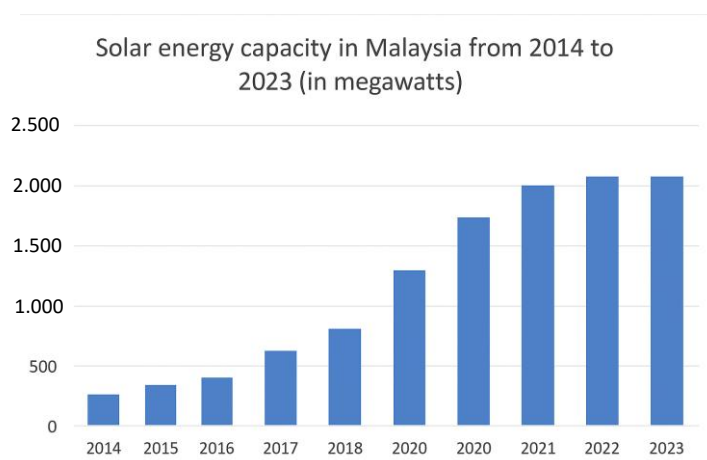


Fig. 1. Solar energy capacity in Malaysia since 2014 to 2023

This study is notable for being able to fill in key knowledge gaps concerning the temporal dynamics of solar power output. This study provides a holistic account of the impact of various factors (humidity, irradiance, ambient temperature and module temperature) on solar power. As a result, this allows the optimization of system performance, energy planning enhancement, and even greater solar power efforts. This can be extremely helpful for energy managers, policymakers as well as solar plant operators. Additionally, this study's insight into the impacts of seasonality and effects of climate change on solar power output can help inform future long-term sustainability plans and adaptive actions for solar power infrastructure. According to a study from Jerez *et al.*, [12] PV power generation in Europe is not expected to be seriously threatened by climate change, especially given expected technological breakthroughs and greater system deployment. On the other hand, a study conducted at Saudi Arabia by Salam *et al.*, [17] stated that Saudi Arabia is investing \$108.9 billion to develop 41 GW of solar energy capacity by 2032 as part of its ambition to transition from oil dependence to renewable energy. Since the country has the large skills of desert areas, obviously the solar radiation intensity is much larger than other countries.

2. Literature Review

2.1 Environment Humidity

There is a clear negative correlation between environmental humidity and solar photovoltaic (PV) system output and efficiency. Research conducted in a variety of places, such as Nigeria, Iraq, and other humid regions, has repeatedly shown that when relative humidity rises, solar panel efficiency significantly decreases. In the comparison of two Nigerian cities from a study conducted by Ettah *et al.*, [8] discovered that Uyo's lower humidity (65%) resulted in greater power efficiency and current output than Port Harcourt, which had higher humidity levels of about 80%. Similarly, Dawood *et al.*, [6] noted that high humidity areas resulted in a 30% decrease in PV efficiency, emphasising the effect on both current and voltage output.

This association is supported by further data from Tijjani *et al.*, [21] who point out that humidity levels above 60% can significantly reduce energy output. Recommendations to lessen the adverse effects of water vapour condensation include the use of cooling techniques and routine panel surface cleaning. The negative impacts of high humidity on PV systems were highlighted by Ayoola *et al.*, [3] who supported these findings with a statistical correlation of -0.826 between humidity and energy generation.

All this research highlight how important local climate factors are in influencing solar energy production. To improve solar panel performance and guarantee energy dependability in humid areas, proactive steps including anti-condensation treatments, optimal panel positioning, and routine maintenance are crucial.

2.2 Irradiance

According to the previous studies, irradiance has a significant impact on solar energy output. According to Li *et al.*, [23] variations in cloud cover and weather have a major influence on the output of solar energy, which is directly related to irradiance levels. In order to sustain efficiency in a variety of situations, adaptive solar energy systems that optimise energy collection under changing irradiance circumstances were emphasised as crucial. Similarly, Huld *et al.*, [11] examined the long-term performance of photovoltaic (PV) systems and found that, although increased irradiance levels improve efficiency, extended exposure can cause solar panel material deterioration. This emphasises

the necessity of cutting-edge materials and upkeep techniques to guarantee solar systems' sustainability.

Almaktar *et al.*, [1] investigated the connection between PV energy production potential and irradiance fluctuation, thus broadening the global perspective. They concluded that while areas with constant irradiance levels are most suited for PV deployment, advanced technologies such as energy storage systems are essential for mitigating the consequences of irradiance fluctuation. As a result, these studies show a significant relationship between irradiance and solar energy output, highlighting the fact that while fluctuation and excessive exposure require material and technical advances, steady and high irradiance levels have a favourable impact on production. For PV system location optimisation and long-term energy efficiency improvements, this relationship is essential.

2.3 Ambient Temperature

There are both positive and negative effects in the relationship between solar energy production and ambient temperature. Higher ambient temperatures increase electron mobility in solar cells, enhancing energy output, as demonstrated by Sanusi *et al.*, [18] who found a clear correlation between temperature and PV performance in Nigeria. Subsequent research has shown that this advantage is constrained by the threshold at which thermal inefficiencies occur.

According to Chandra *et al.*, [5] whereas greater temperatures can increase the production of photocurrent, they also cause thermal losses that lower overall efficiency. By demonstrating the efficacy of adaptive cooling systems, their experimental setup in India increased net energy gains by 7.69%, highlighting the significance of reducing thermal impacts in hot climates. Similar to research by Olabode *et al.*, [14] used simulations to demonstrate that lower ambient temperatures produce the best energy output, hence endorsing the strategic positioning of photovoltaic systems in cooler settings wherever feasible.

This knowledge was further enhanced by Ayoola *et al.*, [3] and Dawood *et al.*, [6]. According to Dawood's research in Kurdistan, excessive heat drastically decreased total energy efficiency, even while temperatures over 55°C maximized current output. Although Ayoola's results in a tropical environment supported the idea that temperature and performance are positively correlated ($R = 0.814$), they also brought attention to the risks of material deterioration at high temperatures.

Thus, these studies indicate that one important factor affecting solar energy generation is ambient temperature. While ambient temperatures are good for energy production, extreme heat requires cooling systems or new materials to reduce thermal inefficiencies and maintain long-term efficiency. In order to optimize PV systems across a variety of climatic regions, this balance is crucial.

2.4 Module Temperature

Module temperature has a major impact on photovoltaic (PV) systems' efficiency and performance. Increased thermal energy from elevated module temperatures affects electron mobility in solar cells, lowering efficiency. Research continuously demonstrates that cooling techniques are crucial for reducing these impacts. A study by Al-Odat *et al.*, [2] showed that in Jordan's hot environment, water cooling improved efficiency by 14% by lowering module temperatures by 20%. According to a review of cooling methods by Rozak *et al.*, [16] hybrid systems might reduce temperatures by as much as 25°C, increasing efficiency by 48.23% in severe situations.

These results are further supported by experimental investigations, such as Bashir *et al.*, [4] which demonstrate an efficiency boost of 13% in monocrystalline cells using back-surface water cooling. Sanusi *et al.*, [18] conducted long-term observations in Nigeria that demonstrated the direct impact

of module temperatures on energy output, underscoring the significance of temperature control in hot climates. Chandra *et al.*, [5] added evidence of active cooling techniques, such as fan-based systems, which stabilise module temperatures and result in notable energy savings.

All of this research supports the idea that the efficiency of solar energy generation is negatively correlated with module temperature. In areas with significant temperature exposure, cooling solutions whether passive, active, or hybrid is essential for maximising the performance of PV systems.

3. Methodology

To achieve the goals, the study will be conducted an average of times from 12 pm until 1 pm. This is due to the sun is at the highest point in the sky which may lead to maximize its irradiance as well as the consistency of the environmental conditions.

3.1 Data Description

Data used for the study were collected from historical data from Gading Kencana Melaka at a specific time and daily from solar panel installation in Melaka. Number of variables in dataset which are important for Solar Panel Performance metrics. The variables are the daily data of environmental humidity (%), solar radiation (W/m²), ambient temperature (°C), module temperature (°C), and solar production. The data has been collected from a set of monitoring systems of the solar panel installation that ensures the measurement precision and continuity of response.

The data are taken since July 2019 to January 2021 by considering the factors affecting solar panel performance. The statistical analysis procedures employed here include stationarity test, multicollinearity, correlation analysis, and regression analysis.

3.2 Data Analysis

3.2.1 Stationarity test (ADF test)

In time series analysis, stationarity which denotes that a time series's mean, variance, and autocorrelation are consistent throughout time, is a crucial characteristic. It is important to test and, if necessary, alter the data to meet the stationarity assumption made by many time series models. One popular statistical test for determining if a time series is stationary is the Augmented Dickey-Fuller (ADF) test. In order to justify that the data is stationary, it is necessary to perform hypothesis testing.

$$\text{No constant, no trend: } \Delta y_t = \gamma y_{t-1} + \sum_{s=1}^m \beta_s \Delta y_{t-s} + v_t \quad (1)$$

$$\text{Constant, no trend: } \Delta y_t = \alpha + \gamma y_{t-1} + \sum_{s=1}^m \beta_s \Delta y_{t-s} + v_t \quad (2)$$

$$\text{Constant, trend: } \Delta y_t = \alpha + \gamma y_{t-1} + \delta_t + \sum_{s=1}^m \beta_s \Delta y_{t-s} + v_t \quad (3)$$

where;

y = The value of each explanatory variable

α = Represent the constant on the model

γ = The parameter in AR model

t = The period of time

ρ = The final lag for AR model

s = The number of lags for AR model

Hypothesis:

H_0 = The time series model has a unit root

H_1 = The time series model does not have a unit root

To determine whether the model is stationary or not, the concern is on unit root test. If the time series model has a unit root, the null hypothesis can be rejected. Otherwise, the null hypothesis fails to be rejected. Thus, the model is stationary.

3.2.2 Multicollinearity

When two or more independent variables in a regression model have a strong correlation with one another and give redundant information about the response variable, this is known as multicollinearity. Inflated standard errors and shaky regression coefficient estimations may result from this. A typical tool for detecting multicollinearity is the Variance Inflation Factor (VIF). The following formula is used to get the VIF for an independent variable, X_i :

$$VIF(X_i) = \frac{1}{1-R_i^2} \quad (4)$$

where;

R_i^2 = The coefficient of the determination obtained by regressing X_i

The model can be concluded as higher multicollinearity if the VIF of the model is greater than 10. This may suggest that to remove the variable with the high multicollinearity in order to improve the model's reliability.

3.2.3 Correlation analysis

A correlation analysis checks the force and course of a relationship between two variables. It uses the Pearson correlation coefficient (r), with values from -1 to 1. The range of Pearson correlation varies between -1 (perfect negative linear relation), 0 (no linear association), and +1 (perfect positive linear relation). This study reveals the environmental variables that are most highly correlated with solar panel output, and how variations of these parameters influence performance.

3.2.4 Multiple linear regression

Multiple linear regression is used to model the relationship between the dependent variable (Power MSB 3MW) and the independent variables (humidity, irradiance, ambient temperature, and module temperature). The regression model is specified as follows:

$$SolarPower_t = \beta_0 + \beta_1 humidity_t + \beta_2 irradiance_t + \beta_3 AmbTemp_t + \beta_4 ModTemp_t + \varepsilon_t \quad (5)$$

where;

SolarPower = Daily power output from solar panels

Humidity = Daily environmental humidity

Irradiance = Daily solar irradiance

AmbTemp = Daily ambient temperature

ModTemp = Temperature of solar panel module

ε_t = Error term

β_i = Estimated coefficient where $i = 1, 2, 3, 4$

Hypothesis:

H_0 = There is no significant relationship between solar power output and the independent variables

H_1 = There is a significant relationship between solar power output and independent variables

To determine whether the model is significant or not, the concern is on p-value. If the p-value is less than 0.05, the null hypothesis can be rejected. Otherwise, the null hypothesis fails to be rejected. Thus, there is no significant relationship between the dependent variable and independent variables.

3.2.5 T-test

A t-test is used to compare the means of two groups to determine whether they are significantly different from each other. There are three types of t-tests which are one-sample t-test which is used to compare the mean of a single sample to a known value or population mean, independent t-test which includes two sample is used to compare the means of the two independent groups and a paired t-test that compares the means of two related groups for example the measurement of before and after on the same subjects.

$$\text{One sample t-test: } t = \frac{\bar{X}_1 - \mu}{\frac{s}{\sqrt{n}}} \quad (6)$$

$$\text{Two sample t-tests: } t = \frac{(\bar{X}_1 - \bar{X}_2)}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}} \quad (7)$$

where;

$\bar{X}_n$ = Observed mean of the sample

μ = Assumed mean

s_n = Standard deviation of the sample ($n = 1$ and 2)

n = Sample size

Hypothesis:

H_0 = The means of the groups are equal ($\mu_1 = \mu_2$)

H_1 = The means of the groups are equal ($\mu_1 \neq \mu_2$)

To determine whether the model is significant or not, the concern is on p-value. If the p-value is less than 0.05, the null hypothesis can be rejected. Otherwise, the null hypothesis fails to be rejected. Thus, there is no significant relationship between the dependent variable and independent variables.

3.2.6 R^2

R^2 measures the goodness of fit of a model. In regression, if the R^2 coefficient is close to 1, it shows that the regression predictions perfectly fit for the data. R^2 represents the proportion of the variance in the dependent variable that is explained by the independent variables in the model.

$$R^2 = 1 - \frac{SSR}{SST} \quad (8)$$

where;

SSR = Sum squared residuals (unexplained variance)

SST = Total sum squared (total variance)

Hypothesis:

H_0 = The independent variables do not collectively explain any variability in the dependent variable ($R^2 = 0$)

H_1 = At least one independent variable contributes to explaining the variability in the dependent variable ($R^2 > 0$)

3.2.7 F-test

The F-test is a statistical test used to determine whether there is a significant relationship between variables in a regression model or to compare the variances of two populations. It evaluates the overall significance of the model and whether the independent variables collectively explain the variation in the dependent variable.

$$\text{For regression: } F = \frac{MS_{\text{regression}}}{MS_{\text{residual}}} \quad (9)$$

where;

$$MS_{\text{regression}} = \frac{SS_{\text{regression}}}{df_{\text{regression}}}$$

$$MS_{\text{residual}} = \frac{SS_{\text{residual}}}{df_{\text{residual}}}$$

df = degree of freedom

Hypothesis:

$H_0 = p \leq \alpha$: indicating the model is significant

$H_1 = p > \alpha$: indicating the model may not be significant

To determine whether the regression model is significant or not, the concern is on p-value. If the p-value is less than 0.05, the null hypothesis can be rejected. Otherwise, the null hypothesis fails to be rejected. Thus, the regression model is not significant.

4. Results

Before analyzing the data, we filled up all the missing data (4.114%) using linear interpolation. In Table 2, we demonstrate the descriptive statistics of the data. It shows that all variables are

negatively skewed except environment humidity. Meanwhile, all variables are found to be leptokurtic since the kurtosis are all greater than 0.

Table 2
Descriptive statistics of the data

	Variables				
	Solar Production	Environment Humidity	Irradiance	Ambient Temperature	Module Temperature
Mean	0.772452	-0.01203	0.340968947	-0.00417	0.004255
Standard error	14.22306	0.358285	10.32069189	0.082838	0.357077
Standard deviation	347.5203	8.754179	252.1714864	2.02403	8.724675
Sample variance	120770.3	76.63565	63590.45855	4.096697	76.11995
Kurtosis	1.776079	2.352706	0.518062811	3.291423	1.593094
Skewness	-0.16422	0.290384	-0.122092067	-0.3337	-0.19416

4.1 Stationary Test (Augmented Dickey-Fuller Test)

In regression analysis, it is important to make sure all the variables are in a stationary state. This is because once the data is stationary, the mean, variance, and autocorrelation structure are in a constant state. It helps the series to not exhibit trends, seasonality, or changing variability over time.

In our study, we found that all variables are stationary at the first difference with p-values below than 0.05 significance level. This aligns with the hypothesis that fails to reject the null hypothesis if the time series model does not have a unit which means they are stationary.

4.2 Multicollinearity

Multicollinearity occurs when two or more independents are highly correlated which may affect the reliability of regression coefficients. In order to detect multicollinearity in a multiple regression model, the Variance Inflation Factor (VIF) was used. VIF measures the extent to which the variance of a regression coefficient is inflated as a result of multicollinearity.

Based on Table 3, all the variables are getting the VIF near to the threshold value of 10 except irradiance with 4.34. This happens due to there is more than one highly correlated between independent variables in the model. The variables recorded the highest VIF are environment humidity and ambient temperature with 8.74 and 9.14 respectively. However, these variables may need corrective action in order to lower the correlation between other variables. Irradiance in the other hand, recorded the lowest multicollinearity suggests its coefficient in the regression model is reliable and interpretable.

The variable with higher multicollinearity should be considered to be removed or combined with other variables for example ambient and module temperature, if one is less critical for interpretation.

Table 3
Multicollinearity test of the variables

Variable	VIF
Humidity	8.74
Irradiance	4.34
AmbTemp	9.14
ModTemp	7.75

4.3 Correlation

The correlation of data being tested to prove the relationship between dependent variable and independent variables. This may help to identify potential predictors that are strongly associated with solar energy production. The table below shows the correlation matrices among all variables.

Based on Table 4, it is clearly shown that there is an inverse relationship between solar production and environment humidity as stated in the studies by Ettah *et al.*, [8], Tijjani *et al.*, [21] and Ayoola *et al.*, [3] which recorded -0.6643. Higher humidity will reduce solar efficiency which is caused by an increase in atmospheric scattering of sunlight and solar irradiance decreased. On the other hand, irradiance and solar production showed a strong positive correlation indicated by 0.9206.

Table 4

The correlation between variables

	Solar production	Environment Humidity	Irradiance	Ambient Temperature	Module Temperature
Solar production	1				
Environment Humidity	-0.6643	1			
Irradiance	0.9206	-0.6805	1		
Ambient Temperature	0.6527	-0.9370	0.6658	1	
Module Temperature	0.7867	-0.8229	0.8715	0.8271	1

4.4 Multiple Linear Regression Model

The multiple linear regression model provides insights of the factors influencing solar energy production. The equation below shows the contribution of the independent variables which are environment humidity, irradiance, ambient temperature and temperature.

$$\text{SolarPower}_t = 0.41 - 2.44\text{humidity}_t + 1.402\text{irradiance}_t + 22.99\text{AmbTemp}_t - 10.41\text{ModTemp}_t + \varepsilon_t$$

The intercept value equal to 0.41, acts as the baseline of the regression analysis where when all the independent variables are zero, the dependent variable will equal 0.41 unit. Based on the Table 5, it is proven that irradiance has a strong positive on solar power production. This is due to the coefficient for irradiance being 1.402 which represents that for every 1 W/m² increase in irradiance, solar power production increases by 1.402 units. The p-value presents as 0.000, which is less than a significant level of 5% affirms that the relationship between irradiance and solar energy production is statistically significant. In addition, ambient temperature also positively impacts on solar efficiency where a 1°C rise in ambient temperature, solar energy production increases by 22.99 units. Given its p-value is 0.004 which is less than a significant level of 5% indicates that the relationship between ambient temperature and solar energy production is statistically significant.

Table 5

The regression analysis

	Coefficient	t-stat	p-value
Intercept	0.405	0.076	0.94
Humidity	-2.44	-1.348	0.178
Irradiance	1.402	31.653	0.000
AmbTemp	22.99	2.871	0.004
ModTemp	-10.41	-6.084	0.000

On the other hand, environment humidity negatively affects solar power production, with the coefficient of -2.44 showing that with every 1% increase in humidity, solar energy production will be lost by 2.44 units suggesting that higher humidity levels decrease solar power. This variable is also not statistically significant because the p-value of 0.178 is higher than the significant level of 5%, indicating that rather than a regular pattern, the observed impact can be the result of random variation. Meanwhile, module temperature as well, negatively impacts solar energy production. The value of coefficient -10.41, implies that every 1% increase in module temperature can lower the solar energy production by 10.41 units. Likewise, module temperature is statistically significant where the p-value is less than 5%, which is 0.000, aligns with the known thermal efficiency losses in photovoltaic systems.

Thus, the model highlights the importance of managing irradiance, ambient temperature, and module temperature to enhance solar power production, while having environment humidity as a variation may reduce the production.

5. Conclusion

This study created a forecasting model by analyzing the variables that affect solar energy production to predict energy output. Data preprocessing guaranteed correctness by filling in missing values; interpolation only affected 4.114% of the dataset. The variables' eligibility for regression analysis was validated by stationarity testing.

Based on our analysis, we discovered that the most important factor, irradiance, had a large positive effect on solar energy output. Ambient temperature also had a beneficial effect on efficiency. Environment humidity had a negative but statistically negligible influence, while module temperature had a negative effect that was consistent with thermal efficiency losses. High VIF readings indicated multicollinearity among a few factors, most notably humidity and ambient temperature. Irradiance's low multicollinearity supported its accuracy as a predictor. Taking multicollinearity into account could improve model accuracy. Solar energy production was accurately predicted by the predictive model, with prediction intervals controlling for variability and confidence intervals capturing the mean output. Despite the fact that small increases in prediction intervals were a reflection of uncertainty, the model consistently offered trustworthy and consistent insights for making decisions.

In conclusion, optimizing solar energy output requires careful control of irradiance, ambient temperature, and module temperature. Although the model works well, it can be made even more reliable by tackling multicollinearity and improving variable selection.

Acknowledgment

This research was not funded by any grant.

References

- [1] Jereb, Borut. "Solar Irradiance Stability Factors." *Energies* 17, no. 18 (2024): 4549. <https://doi.org/10.3390/en17184549>
- [2] Al-Odat, Mohammed Qassim. "Experimental study of temperature influence on the performance of PV/T cell under Jordan climate conditions." *Journal of Ecological Engineering* 23, no. 10 (2022). <https://doi.org/10.12911/22998993/152283>
- [3] Ayoola, R. O. "Performance analysis of solar photovoltaic modules in tropical climates." *Renewable Energy Reports*, 6(3), 215–230 (2024).
- [4] Bashir, Muhammad A., Hafiz M. Ali, Khuram P. Amber, Muhammad W. Bashir, Hassan Ali, Shahid Imran, and Muhammad S. Kamran. "Performance investigation of photovoltaic modules by back surface water cooling." *Thermal Science* 22, no. 6 Part A (2018): 2401–2411. <https://doi.org/10.2298/TSCI160215290B>

- [5] Chandra, Subhash, Sanjay Agrawal, and D. S. Chauhan. "Effect of ambient temperature and wind speed on performance ratio of polycrystalline solar photovoltaic module: An experimental analysis." *International Energy Journal* 18, no. 2 (2018).
- [6] Dawood, Tareq Aziz, Ramzi Raphael Ibraheem Barwari, and Abdulrazzak Akroot. "Solar Energy and Factors Affecting the Efficiency and Performance of Panels in Erbil/Kurdistan." *International Journal of Heat & Technology* 41, no. 2 (2023). <https://doi.org/10.18280/ijht.410203>
- [7] Energy Institute, "The Energy Institute," *Energy Institute*, n.d.
- [8] Ettah, E., P. Ushie, J. Obiefuna, and N. Nwachukwu. "Comparative study of the effects of relative humidity on solar electricity generation in UYO and Port-Harcourt, Nigeria." *International Journal of Mathematics and Physical Sciences Research* 3, no. 2 (2015): 66-70.
- [9] Faiz, Faizan Ul Hassan, Rabia Shakoor, Abdur Raheem, Farhana Umer, Nadia Rasheed, and Muhammad Farhan. "Modeling and analysis of 3 MW solar photovoltaic plant using PVSyst at Islamia University of Bahawalpur, Pakistan." *International journal of Photoenergy* 2021, no. 1 (2021): 6673448. <https://doi.org/10.1155/2021/6673448>
- [10] Gading Kencana Sdn. Bhd., "Gading Kencana - Malaysia's Renewable Energy Service Provider," *Gading Kencana*, August 27, 2024.
- [11] Huld, Thomas, Richard Müller, and Attilio Gambardella. "A new solar radiation database for estimating PV performance in Europe and Africa." *Solar energy* 86, no. 6 (2012): 1803-1815. <https://doi.org/10.1016/j.solener.2012.03.006>
- [12] Jerez, Sonia, Isabelle Tobin, Robert Vautard, Juan Pedro Montávez, Jose María López-Romero, Françoise Thais, Blanka Bartok et al. "The impact of climate change on photovoltaic power generation in Europe." *Nature communications* 6, no. 1 (2015): 10014. <https://doi.org/10.1038/ncomms10014>
- [13] Larasati, Nadyanti, Amien Rahardjo, Hanindito Titah Prameswara, and Faiz Husnayain. "Interconnection Study of a 3 MWp Solar Farm on 20 kV Distribution System Considering Power Flow and Short Circuit." *ELKHA: Jurnal Teknik Elektro* 12, no. 2 (2020): 84-91. <https://doi.org/10.26418/elkha.v12i2.41598>
- [14] Olabode, Olakunle Elijah, Ignatius Kema Okakwu, Daniel Oluwaseun Akinyele, Titus Oluwasuji Ajewole, Seun Oyelami, and Oluwatobi Vincent Olisa. "Effect of Ambient Temperature and Solar Irradiance on Photovoltaic Modules' Performance." *Iranica Journal of Energy & Environment* 15, no. 4 (2024): 402-420. <https://doi.org/10.5829/ijee.2024.15.04.08>
- [15] IRENA (2024), Renewable energy statistics 2024, International Renewable Energy Agency, Abu Dhabi.
- [16] Rozak, OJAK ABDUL, MUHAMAD ZALANI Daud, S. Y. A. I. F. U. L. Bakhri, and MOHD ZAMRI Ibrahim. "Review of the impact of tropical climate on solar photovoltaic modules performances using the combination of cooling systems." *Journal of Sustainability Science and Management* 18, no. 1 (2023): 228-236. <https://doi.org/10.46754/jssm.2023.01.014>
- [17] Salam, Mohammad Asif, and Sami A. Khan. "Transition towards sustainable energy production—A review of the progress for solar energy in Saudi Arabia." *Energy Exploration & Exploitation* 36, no. 1 (2018): 3-27. <https://doi.org/10.1177/0144598717737442>
- [18] Sanusi, Y. K., G. R. Fajinmi, and E. B. Babatunde. "Effects of ambient temperature on the performance of a photovoltaic solar system in a tropical area." *The Pacific Journal of Science and Technology* 12, no. 2 (2011): 176-180.
- [19] Shrestha, Arun Kumar, Arati Thapa, and Hima Gautam. "Solar radiation, air temperature, relative humidity, and dew point study: Damak, Jhapa, Nepal." *International Journal of Photoenergy* 2019, no. 1 (2019): 8369231. <https://doi.org/10.1155/2019/8369231>
- [20] Harold Thibault. "China's Paradox: The World's Biggest Polluter and a Leader in the Environmental Transition." *Le Monde.Fr*, October 12, 2024.
- [21] Tijjani, B., Abubakar, H., and Bello. "Impact of environmental conditions on photovoltaic system efficiency: A study of relative humidity and ambient temperature." *Nigerian Journal of Solar Energy* 29, no. 1 (2020): 57–64.
- [22] "UNRWA 3MW Solar PV Power Project, Environmental and Social Impact." *UNRWA*, n.d.
- [23] Li, Tong, Ting Su, Jiang Wang, Suiyi Zhu, Yuxin Zhang, Zhi Geng, Xianze Wang, and Yidi Gao. "Simultaneous removal of sulfate and nitrate from real high-salt flue gas wastewater concentrate via a waste heat crystallization route." *Journal of Cleaner Production* 382 (2023): 135262.