



Predictive Modeling of Renewable Energy Generation Using Environmental and Meteorological Parameters

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Received:- 11/06/2026, Revised:- 19/07/2026, Accepted:- 04/09/2026, Published:- 21/09/2026

ABSTRACT

Accurate prediction of photovoltaic power generation is important for managing the variability associated with solar energy and supporting reliable energy planning. This study evaluated the relationships between environmental conditions and solar power generation and compared data-driven models for predicting AC power output. Generation and weather-sensor records from two photovoltaic plants were integrated, producing 6,416 matched observations. Solar irradiation, ambient temperature, module temperature, temporal characteristics, and plant identity were considered in the analysis. Solar irradiation showed the strongest correlation with AC power ($r = 0.938$), followed by module temperature ($r = 0.903$), whereas ambient temperature demonstrated a moderate association ($r = 0.593$). Predictive Modeling of Renewabl... Multiple Linear Regression, Random Forest, Gradient Boosting, and Extra Trees regression were evaluated using a chronological holdout strategy. Extra Trees achieved the strongest predictive performance, with $R^2 = 0.966$, RMSE = 1,260.682, and MAE = 446.966, outperforming the linear baseline. Predictive Modeling of Renewabl... The findings demonstrate that combining environmental and temporal information with nonlinear ensemble modeling can provide accurate estimates of photovoltaic generation and support data-driven solar energy management.

Keywords: Solar power generation, Photovoltaic systems, Predictive modeling, Solar irradiation, Machine learning

1. Introduction

As countries strive to lessen dependence on fossil fuels and keep up with rising electricity demand, the deployment of renewables has increased in intensity in the shift towards low-carbon energy systems. Solar photovoltaic (PV) technology is a key enabler of this shift, as it is scalable, is seeing its technological and economic barriers continue to fall, and is suitable for both distributed and utility-scale energy generation. Victoria et al. (2021) pointed out that solar photovoltaics have significant potential to help achieve a sustainable energy future, and Haegel and Kurtz (2022) indicated the growing role of solar electricity in global progress towards renewable energy. Recent assessments also reveal that PV deployment continues to grow and so do the penetration of PV generation in electricity systems (Hossain et al., 2024). This growth is a part of the general shift in energy methods towards renewable energy, which is anticipated to play a growing position in decarbonization, energy safety, and sustainable development (Hassan et al., 2024).

However, PV electricity generation has a number of drawbacks: PV power generation is intrinsically tied with environmental and atmospheric conditions, making its output highly variable. The solar irradiation is the main energy input to PV modules, and ambient and module temperatures may affect the PV operating characteristics and PV conversion performance. As a result, large fluctuations in the power output are possible on relatively short time scales in response to changes in the environment. Where solar energy plays a significant role in electricity generation, it is critical to adequately characterize these relationships. This has made the forecasting of irradiance an important topic that has been explored extensively in the context of solar-energy prediction and advanced forecasting techniques have been developed to deal with the temporal variability of irradiance (Abdel-Nasser et al., 2020). Irradiance forecasting method was also found to be important in solar energy prediction by a systematic assessment performed by Sudharshan et al. (2022). Thus, accurate PV power prediction can aid in generation planning, PV system operation, and management under uncertainties (Kumar et al., 2025).

Grid integration of more VREs has also reinforced the demand for forecasting techniques that can assist in balancing the grid and making operation decisions. Forecasts for solar energy can help the electricity systems better anticipate variations in generation and better coordinate energy resources that are available (Sivadarshini et al., 2024). On a more local level, short-term PV generation forecasting can be used to optimise PV self-consumption by aligning the forecasted PV generation with demand (Kut & Pietrucha-Urbanik, 2025). The examples in these applications demonstrate that accurate prediction is not just applicable in the estimation of electricity production in the future, but also in the general management of the energy system. Infrastructure studies with similar sustainability goals have also highlighted the critical role of quantitative design and operating conditions in the efficient management of resources (Garcia-Espinal et al., 2024).

Data-driven approaches can offer a powerful way of analyzing complex relationships between environmental conditions and energy-system behavior. In the field of power systems, AI and ML techniques are being used more and more, as they can recognize nonlinear relationships, interactions, and temporal patterns that may not be fully captured using traditional linear techniques. According to Alhamrouni et al. (2024), AI is increasingly contributing to the fields of power-system stability, control, and protection. Machine-learning techniques have also proven useful in other energy forecasting scenarios, such as forecasting electricity prices for energy-management systems (Yousaf et al., 2021) and short-term electricity-load forecasting with support vector machine and extreme learning machine (Ahmad et al., 2020). Amidst the latest research, there has been exploration into algorithms like XGBoost for data-driven forecasting in smart-energy systems and gridstability applications (Rekha & Bhumika, 2025). Together, these technologies all signal the promise of predictive analytics to enable a more and more data-dependent electricity system.

In PV applications, the ability to predict correctly, however, relies on the proper representation of the physical and environmental characteristics related to PV generation. Observed irradiation, ambient temperature, module temperature and temporal characteristics offer the opportunity for models to relate a measurable operating condition to the actual electrical output. Comparing the conventional and ensemble regression methods can further help to validate whether nonlinear algorithms are useful over baseline statistical methods or not. These comparisons are useful as they should be understood in the context of the environmental structure of PV generation. Predictive methods have shown great potential for supporting solar generation planning under uncertainty using data-driven approaches (Kumar et al., 2025), and the advancements in solar forecasting continue to highlight the significance of incorporating meteorological data with computational methods (Kut & Pietrucha-Urbanik, 2025). This study therefore examined environmental impacts on PV generation and compared several prediction algorithms based on measurements from two PV power plants, both operational and from weather sensors. This study was designed to

achieve the following goals:

- To characterize temporal and environmental patterns in solar power generation.
- To quantify associations between irradiation, temperature, and AC power output.
- To develop and compare machine-learning models for predicting solar power generation.

2. Materials and Methods

2.1 Dataset and Study Design

The data of the power generation from the solar PV plant and weather data from the weather sensor were taken from two solar PV plants' data from 15 May 2020 to 17 June 2020. Generation data such as AC power, DC power, daily yield and total yield and environmental data such as solar irradiation, ambient temperature and module temperature were measured (Kannal, 2020). The main prediction outcome was chosen to be AC power.

2.2 Data Preprocessing

These generation records were compared with the weather records and matched up by their time and date, and then separated by plant and combined for the final dataset. Power measurements were aggregated from inverter level to get plant level generation. Checks for missing data, duplication of data, and unusual observations. Post integration, there were 6416 complete observations. For predictive modelling purposes, hour of day information was converted into cyclic temporal information.

2.3 Statistical and Environmental Analysis

Generation and environmental variables were subjected to descriptive statistics such as mean, standard deviation, median, minimum and maximum. Diurnal variations of the AC power were analyzed on the observation period. Association between the AC power output and the solar irradiation, the module temperature and ambient temperature were quantified using correlation analysis.

2.4 Predictive Modeling

The regression models such as Multiple Linear Regression, Random Forest, Gradient Boosting, Extra Trees were developed to predict the AC power. Predictors included irradiation, ambient temperature, module temperature, temporal features and plant identity. Observations were split chronologically with the earliest observations used to develop the model, and the last ~20% used for independent testing.

2.5 Statistical Analysis and Model Evaluation

Python programming language was used for all the analyses with pandas, NumPy, scikit-learn, and Matplotlib. The coefficient of determination (R^2), root mean squared error (RMSE) and mean absolute error (MAE) were used to assess the model performance. However, it was also evaluated graphically, by comparing the observed and predicted values, for prediction agreement and error patterns.

3. Results

3.1 Dataset Characteristics and Environmental Conditions

After integration to the timestamp level, generation and weather-sensormark data, a total of 6,416 observations was matched, with 3,157 observations from Plant 1 and 3,259 observations from Plant 2. It covered the period from 15 May to 17 June 2020, with no missing values for the analytical variables. Descriptive characteristics of solar generation and environmental parameters are given in Table 1. The mean AC power generation was 5,844.95 with significant fluctuations over time ($SD = 7,576.96$) and a highest power generation of 29,150.21. Average values of mean solar irradiation, ambient temperature and module temperature were 0.231, 26.84°C and 31.99°C, respectively. The range of module temperature was significantly higher than ambient temperature, with the highest reading recorded at 66.64°C, whilst median AC power was significantly lower than the mean, which is expected as there are few observations during non-daylight times and those that are made during such periods have low or zero

generation.

Table 1. Descriptive Characteristics of Solar Power Generation and Environmental Parameters

Variable	Mean	SD	Median	Minimum	Maximum
AC Power	5,844.946	7,576.958	638.474	0.000	29,150.212
DC Power	36,338.094	69,582.971	1,264.466	0.000	298,937.786
Ambient Temperature (°C)	26.835	3.934	25.974	20.399	39.182
Module Temperature (°C)	31.987	11.836	26.478	18.140	66.636
Solar Irradiation	0.231	0.307	0.024	0.000	1.222

Note: SD = standard deviation; AC = alternating current; DC = direct current.

3.2 Temporal Variation in Solar Power Generation

PV generation clearly exhibited a diurnal behavior during the period of study. It can be seen in figure 1 that the mean AC power had stayed near to zero during the night hours, rose quickly after about 06:00, and peaked at the maximum mean value at around midday. The highest mean diurnal AC output was around 12:15 and was around 17,359. From there on, generation fell through the afternoon, and hit close to zero in the early evening. The resulting aggregated profile shows a smooth ramp-up and ramp-down, with significant dependence of the PV generation on the daily PV cycle, while the fluctuations around the peak midday PV generation suggest that other factors, such as environmental conditions and operational differences at the plant level, also influenced PV generation.

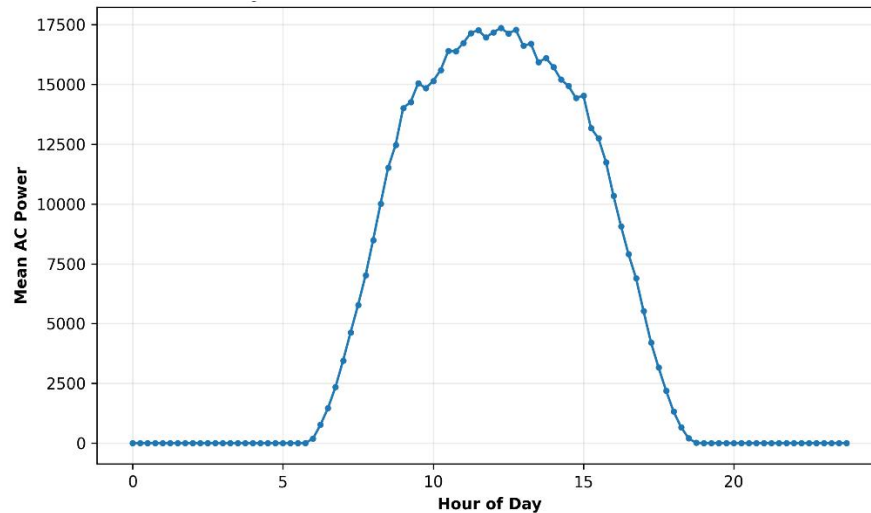


Figure 1. Diurnal Pattern of Solar AC Power Generation

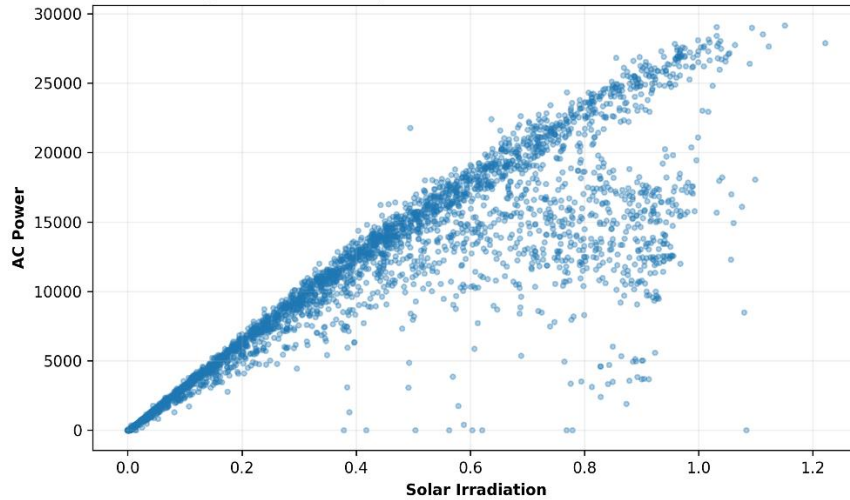
3.3 Relationships Between Environmental Parameters and Solar Generation

The results of the correlation analysis revealed good correlation between solar generation and the environmental conditions measured. As can be seen from Table 2, irradiation had the highest positive correlation with AC power ($r = 0.938$) and the module temperature had the next highest positive correlation with AC power ($r = 0.903$). The ambient temperature moderately correlated with AC power ($r = 0.593$). The strong correlation between irradiation and module temperature ($r = 0.951$) was observed, and between ambient and module temperatures ($r = 0.818$) was observed. These results show that instantaneous solar exposure was the environmental variable most closely related to the electricity production and module temperature was a good proxy for the solar loading at the same time.

Table 2. Correlation Matrix of Solar Generation and Environmental Parameters

Variable	AC Power	Irradiation	Ambient Temperature	Module Temperature
AC Power	1.000	0.938	0.593	0.903
Irradiation	0.938	1.000	0.655	0.951
Ambient Temperature	0.593	0.655	1.000	0.818
Module Temperature	0.903	0.951	0.818	1.000

The relationship between irradiation and AC power are shown in figure 2. In general, the degree of irradiation was seen to correspond with the power output, the relationship being essentially linear at lower to moderate irradiation. However, under high irradiation, there was a greater spread indicating that the same level of irradiation did not always yield the same electrical output. These variations are part of the rationale for considering, in addition to irradiation, other variables such as temperature, temporal data and the identity of the plants in the prediction models.

**Figure 2. Relationship Between Solar Irradiation and AC Power Generation**

3.4 Predictive Model Performance

A chronological holdout design was used to assess predictive performance, with the first observations being used to build the models and the last ~20% observations being used to evaluate the models. Predictors were environmental variables, cyclical time-of-day features and plant identity. The overall results in Table 3 indicate that all the nonlinear ensemble models were significantly better than the conventional linear regression. Linear regression achieved an R^2 of 0.900, RMSE of 2,170.525, and MAE of 1,505.409. Random Forest was able to increase R^2 to 0.965 and Gradient Boosting was able to achieve a similar R^2 of 0.964. The R^2 of the Extra Trees model was 0.966, the RMSE was 1260.682 and the MAE was 446.966, the best results of the test set. This was a significant decrease in absolute and squared prediction error compared to linear regression.

Table 3. Comparative Performance of Solar Power Generation Prediction Models

Predictive Model	R^2	RMSE	MAE
Linear Regression	0.900	2,170.525	1,505.409

Random Forest Regression	0.965	1,289.933	456.625
Gradient Boosting Regression	0.964	1,305.733	498.457
Extra Trees Regression	0.966	1,260.682	446.966

Note: R^2 = coefficient of determination; RMSE = root mean squared error; MAE = mean absolute error. Lower RMSE and MAE indicate lower prediction error.

3.5 Observed and Predicted Solar Power Generation

Another evidence of the predictive capacity of the Extra Trees model was obtained from the correspondence between the measured and the model-estimated generation. As seen in Figure 3, the bulk of the predicted observations were clustered near the 1:1 reference line, and in the low to intermediate generations. Some observations had great deviations at a high level of generation, otherwise agreement was generally good at higher output levels. The test-set R^2 is found to be 0.966 which means that around 96.6% of test set AC power observations is explained by the model. Results of the performance show that the combination of irradiation, ambient temperature, module temperature, temporal characteristics and plant information offered significantly improved predictive accuracy when compared to a linear specification alone.

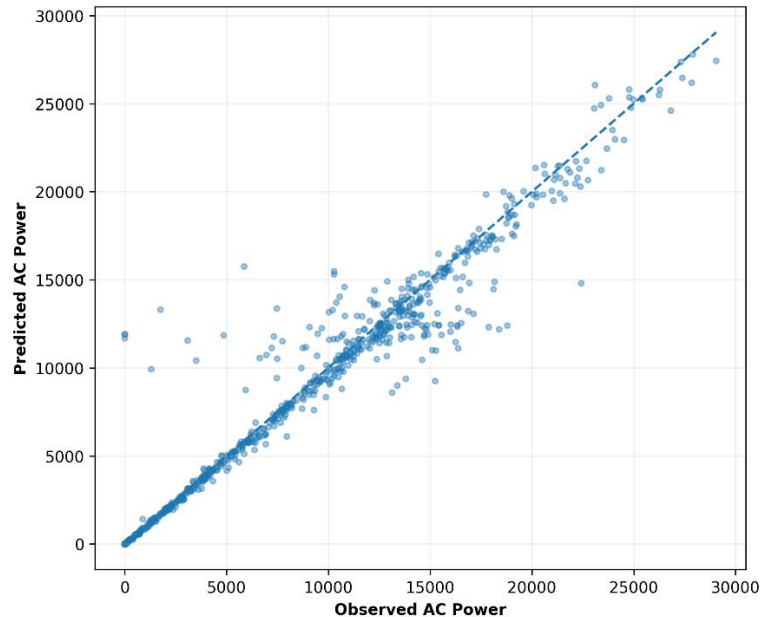


Figure 3. Observed Versus Predicted AC Power Generation Using the Extra Trees Model

As a whole, the results showed an empirical relationship of the PV generation with environment conditions that remained constant. Irradiation was the variable most highly correlated with the AC output, with the high correlation with module temperature also showing the thermal response of PV modules to the sun. The comparative modeling results also indicated that the nonlinear ensemble methods were more effective in capturing these relationships than linear regression, thus enabling them to be used to model solar power for short-term prediction.

4. Discussion

They show that the environmental conditions were a strong control on solar photovoltaic generation and that generation was clearly diurnal. AC power grew quickly after sunrise, peaked at midday on average and then fell towards the evening. This temporal profile is related to the availability of the incident solar energy and reflect the dependence of the PV output and the irradiation. Benchrif et al. (2023) also showed that changes in irradiation have an impact on PVs behaviour and maximum power generation. Present results are the extension of this relation

with the use of operational plant data, with the highest correlation being achieved with AC power ($r = 0.938$). Previous experimental results also showed that variation of the solar irradiation conditions can significantly affect the outside performance of photovoltaic modules (Parretta et al., 1998). The relationship between the observed irradiation and power thus represents a physical response, as well as a statistical association.

The module temperature was also highly correlated with AC power ($r = 0.903$), and moderately correlated with ambient temperature ($r = 0.593$). In an important note, such positive relations should not be understood as being proof that a higher temperature is per se good for the PV conversion efficiency. In general, high module temperature was observed at the same time as high solar exposure, as indicated by the high correlation between irradiation and module temperature ($r = 0.951$). PV cells' electrical properties and efficiency can also be directly impacted by temperature conditions, especially when used under high temperatures (Sun et al., 2022). Similarly, Jo et al. (2024) revealed that the performance of photovoltaic generation is the product of the interaction of environmental and system-level factors. It is reasonable that the greater association is found for module temperature versus ambient temperature since module temperature represents a more direct measure of the thermal condition of the PVs' surface where the electricity is generated.

The predictive study also indicated that the nonlinear ensemble techniques were superior in modelling these relationships among the environment. The R^2 for the Linear Regression was 0.900 while that of Random Forest, Gradient Boosting and Extra Trees was 0.965, 0.964 and 0.966 respectively. The Extra Trees model also produced the lowest RMSE (1,260.682) and MAE (446.966). These enhancements indicate that the PV power generation was nonlinear and interactive and thus could not be adequately described by one linear specification. As noted by Valli and Sujatha (2024), there are algorithms that have varying abilities to model complex data structures, and comparative predictive modeling is useful in these situations. Advanced computational methods have also demonstrated good predictive abilities in other renewable-energy applications, such as predictive and diagnostic modeling of grid-integrated wind-energy systems (Behara & Saha, 2025).

The close agreement between the observed and predicted AC power comes as further proof of the validity of the environmental and temporal predictors chosen. However, the accuracy of prediction without considering the transparency of the model should not be. For scientific purposes, it is necessary to know if the prediction behavior is consistent with plausible relationships in the system being modeled. Interpretable models were highlighted to be important where machine learning is used for scientific extrapolation and where models may see conditions outside the models' training domain (Muckley et al., 2023). The term "interpretability" can mean various things depending on the analysis goal and the use that is intended (Iooss et al., 2022). The significant empirical correlations of irradiation, module temperature, and generation in the present study give a physically meaningful insight into the reasons for the environmental predictors to model performance.

This is especially relevant as machine learning techniques are introduced to the study of the environment and energy. However, Jiang et al. (2024) proposed that interpretable machine learning can also help to better understand the processes represented by complex environmental data, in addition to prediction. In the same vein, Fan et al. (2021) pointed out the general need for interpretability when using more complex computational models. Enabling the prediction of PV generation with a coherent understanding of the environment-meteorology relationship may thus be more useful for PV forecasting than using an algorithm as a pure forecasting tool. The present results suggest that irradiation is the most important observable environmental factor, and that temperature and temporal information is also useful to understand output variations.

There are a number of caveats. The temporal coverage of the dataset was relatively short, and the number of PV plants was only two, which did not represent the variability in the season and geographical distribution. The only meteorological data available were irradiation and temperature; other possibly important ones such as cloud cover, humidity, wind speed, precipitation and atmospheric pressure were not available. Further, the strong inter-correlation between the different factors (irradiation, module temperature, generation) must be taken into account when assigning independent influences to the different predictors. The models should then be tested in the future for longer durations, in different climatic zones and for independent PV installations. The use of wider meteorological observations and explicit model-interpretability techniques could help to further identify the role of the environment in generation, and to assess the robustness of the high predictive performance seen here against varying operating conditions.

5. Conclusion

The results of this study clearly showed the utility of combining environmental, temporal and plant level information as a basis for data-driven prediction of PV based power generation. Sixty-four hundred and sixteen matched observations revealed a marked diurnal generation; the highest production being around midday. Solar irradiation had the highest correlation value with AC power ($r = 0.938$), and module temperature with a correlation value of ($r = 0.903$); ambient temperature had a moderate correlation value ($r = 0.593$). Predictive Modeling of Renewabl... Also, the predictive analysis showed the benefits of employing a nonlinear ensemble method over traditional linear regression. Extra Trees showed the best predictive performance with R^2 of 0.966, RMSE of 1,260.682 and MAE of 446.966 among all the approaches evaluated. Predictive Modeling of Renewabl... All of these results suggest that measurements of the environment and temporal characteristics can reliably estimate the short term solar power output. The methodology can be used for PV generation planning and energy management for operation. These models need to be validated with longer time series, geographically distributed PV installations and more meteorological parameters in future studies to make them more robust for other environmental and seasonal conditions.

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