ENHANCING SOLAR ENERGY EFFICIENCY: PREDICTIVE MODELING WITH XGBOOST AND LINEAR REGRESSION

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Abstract

Abstract *Improving the reliability of the power grid system and operational efficiency is essential to facing future energy challenges. This study aims to provide added value to the management of the power grid, especially solar photovoltaic power plants (PLTS), by developing a more accurate predictive model for estimating energy output. By utilizing two real-time data sets, namely weather data and PLTS data, as well as machine learning methods, this study compares the performance of the XGBoost and Linear Regression (LR) models. We built the model to overcome high variability in energy output and maintain the stability of the power grid. The results show that XGBoost has a better performance with an MAE value of 38.08 compared to linear regression, which has an MAE of 80.23, indicating the superiority of XGBoost in predicting PLTS energy output. This study also opens up opportunities for further research with a focus on the application of other models such as random forests and neural networks, as well as improving data quality and parameter optimization to further improve prediction reliability and operational efficiency. The best-performing XGBoost model enables more efficient energy utilization and enhances the operational efficiency of PV solar power plants***.**

INTRODUCTION

Many nations have started the transition to environmentally benign alternative energy sources in an effort to address the pressing issues of global climate change and the energy crises brought on by the depletion of fossil fuels (Yang et al., 2024). Photovoltaic (PV) solar energy, which transforms solar radiation into electrical energy, is one of the most promising forms of energy (Sampaio & González, 2017). Only in some high-insolation nations like India and equatorial regions has solar energy seen exceptionally rapid development in the renewable energy market during the last ten years (Hepbasli & Alsuhaibani, 2011). Global solar energy capacity has increased significantly in recent decades, and the International Energy Agency (IEA) research projects that growth will surpass 15 percent annually in the upcoming ten years (Renewables, 2021).

PV technology has shown significant growth and improvement, particularly in terms of increasing the efficiency of solar modules and lowering their manufacturing costs (Tyagi et al., 2013). This would equate to the large-scale (utility-scale) construction of solar power plants, which are already starting to significantly contribute to meeting the world's energy needs. Significant obstacles have, however, also arisen during this expansion, including weather dependence and power generation unpredictability brought on by variations in solar insolation (Assi et al., 2021). The temporal fluctuations in this energy production make it difficult to integrate solar energy into a dynamic power system which is full of sophisticated energy management tools to keep the power grid within operating parameters effectively.

The inability of photovoltaic (PV) solar power systems to produce consistent amounts of electricity is one of their biggest problems, particularly throughout the day when the sun's strength varies according to the weather (Al-Shahri et al., 2021). In the context of power systems, such fluctuation could be troublesome because it makes it difficult to manage the grid effectively, especially when it comes to voltage control and reserve deployment. For instance, the power grid must react quickly and obtain energy from alternative sources to balance the load and prevent blackouts when there is an abrupt cloud cover that blocks the sun and causes solar energy output to drop sharply (Beaudin et al., 2010). This issue is exacerbated in grid systems where there is a high penetration of solar PV systems due to the presence of unpredictable fluctuations which may lead to instability of the grid (Saha et al., 2023).

On top of that, the current limitations in energy storage technology make this problem even worse. Although improvements have been made in battery technology and other energy storage systems, there are still no efficient large-scale storage solutions ready for implementation. Therefore, energy generated by PV plants is often consumed instantaneously, even in the absence of storage facilities (Denholm & Hand, 2011). The inability to buffer this generated energy does not help the operating efficiency of the plants alone, but also adds strain under the management of the grid in relation to load balancing and reserve especially during low insolation periods (Lund et al., 2016).

The research proposed in this study seeks to bring forth a predictive analytics model (Aini et al., 2023; Hastomo et al., 2021; Karno et al., 2023; Yulianto et al., 2023), which will be able to forecast solar PV energy generation output high level of accuracy for available weather and operational data. In this regard, the emergence of machine learning and big data is crucial in modeling the dynamics of the energy output variable of a PV system, which is affected by parameters such as the solar radiation intensity, temperature, and humidity (Antonanzas et al., 2016). The presence of an accurate predictive model takes off the pressure from management of networks since they are able to cope with the variations in energy produced by PV's more easily enhancing the grid's stability and lowering the chances of supply interruptions (Shah et al., 2015).

The last but not the least, this paper aims to assess solutions devoted to improvements in operational efficiency of PV plant. One of the key areas of concern is development of predictive strategy for early damage detection of PV modules so that energy losses due to undetected damage are avoided. Implementation of more suitable module cleaning schedules is also an area of focus due to dust and dirt build up reducing the efficiency of solar panels significantly (Bhallamudi et al., 2021). In addition, more positive results are expected from PV power plant operations with better management including land use optimization and regular upkeep of the plant.

Numerous studies on forecasting solar power plant (PV) production are anticipated to support it; nevertheless, the majority of these studies still have limitations, particularly with regard to the accuracy of their forecasts and the applicability of their solutions for grid stability. Since many of the current predictive models are frequently too inaccurate to accurately forecast weather shocks, they are almost useless for grid management. Furthermore, additional research highlighted the disconnect between predictive models and real tactics meant to boost PV power plant efficiency, particularly in terms of how this model might help address present grid stability issues.

The study makes a considerable contribution to the body of knowledge by presenting an innovative idea that combines prediction of photovoltaic (PV) output with practical solutions for grid stability and efficiency of power plant operations. This research aims to develop a more effective model in energy output prediction of PV systems in real life situations, using advanced analytic techniques and big data (Hastomo, 2020; Hastomo et al., 2022), to address the challenges noted in previous works. By employing real-time data and machine learning, this not only increases the accuracy of the predictions but moreover provides practical insights which can be directly put into use for the optimization of grid management.

RESEARCH METHODOLOGY

a. Dataset preparation

There are several steps taken before the data is used in the machine learning process, namely:

1. Standardizing the data format for the "DATE_TIME" feature for the "Plant_Generation_Data.csv" and

"Plant_Weather_Sensor_Data.csv" files in the format "%Y-%m-%d %H: %M".

2. Removing unnecessary data attributes, namely 'PLANT_ID' in the generation file, removing the 'PLANT_ID' and 'SOURCE_KEY' attributes in the weather file.
3. Merging files between Generation_Data and Sensor_Data by binding the same "DATE_TIME" attribute in both files into one new file.
4. Separating time data into new columns, namely "DATE", "TIME", "DAY", "MONTH", "WEEK", "HOURS", and "MINUTES".
5. The result of data checking that the file does not contain Null data, the file contains 67698 rows and 18 columns (Figure 1).
6. Changing the data type for the "SOURCE_KEY" attribute from category to numeric
7. To see the amount of fluctuation, a plot of the amount of ambient temperature data in 34 days was performed (Figure 2)

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 67698 entries, 0 to 67697
Data columns (total 18 columns):
 #   Column               Non-Null Count  Dtype      #   Column              Non-Null Count  Dtype
---  ------               --------------  -----     ---  ------              --------------  -----
 0   DATE_TIME            67698 non-null  object     10  TIME                67698 non-null  object
 1   SOURCE_KEY           67698 non-null  object     11  DAY                 67698 non-null  int32
 2   DC_POWER             67698 non-null  float64    12  MONTH               67698 non-null  int32
 3   AC_POWER             67698 non-null  float64    13  WEEK                67698 non-null  UInt32
 4   DAILY_YIELD          67698 non-null  float64    14  HOURS               67698 non-null  object
 5   TOTAL_YIELD          67698 non-null  float64    15  MINUTES             67698 non-null  int32
 6   AMBIENT_TEMPERATURE  67698 non-null  float64    16  TOTAL MINUTES PASS  67698 non-null  int32
 7   MODULE_TEMPERATURE   67698 non-null  float64    17  DATE_STRING         67698 non-null  object
 8   IRRADIATION          67698 non-null  float64   dtypes: UInt32(1), float64(7), int32(4), object(6)
 9   DATE                 67698 non-null  object    memory usage: 8.1+ MB
```

Figure 1. Null data checking

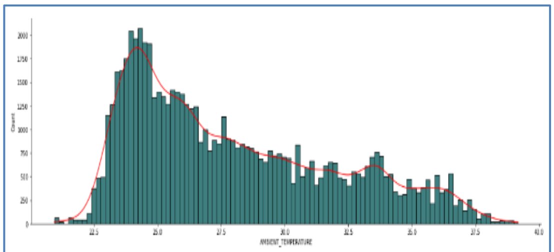

Figure 2. Visualization of count data based on AMBIENT_TEMPERATURE

b. Linier Regression

One of the most popular machine learning techniques for predicting the most basic numerical values is linear regression (Kinaneva et al., 2021), which is also utilized in this work since it predicts the energy production of solar power plants. The way the algorithm operates is by establishing a linear relationship between the dependent variable the value to be predicted, or energy output and independent variables features or factors impacting energy output, such weather data. Fitting a linear equation to observed data is the process of modeling the relationship between a dependent variable and one or more independent variables. This process is known as linear regression, and it can be expressed as follows:

$$y = b_0 + b_1 x + \epsilon \qquad (1)$$

$y =$ dependent variable (output / prediction)
$x =$ independent variable (input)
b_o= intercept (the value of y when x = 0)
$b_1 =$ slope/gradient (the steepness of the line, indicating how much y changes for every one-unit change in x)
$\epsilon =$ error term (the difference between the observed value and the predicted value).

c. XGBoost

XGBoost combines models sequentially, that is every new model addresses the errors made by the previous model (Shehadeh et al., 2021). Its main technique is to take many weak learners generally decision trees and fit them in an ensemble model to create a strong model.

The selection of XGBoost for this study stems from its fundamental ability to observe and forecast energy output with a high degree of accuracy, particularly in very complex and multi-factor data scenarios. The authors of the well-known book XGBoost: A Scalable Tree Boosting System, (Chen & Guestrin, 2016), claim that XGBoost is a good fit for a number of large-scale predictive and data analytic activities, including forecasting renewable energy. Furthermore, research by (Asselman et al., 2023) in the publication Machine Learning with XGBoost: A Review states that the algorithm is best suited for these kinds of jobs because the data is typically highly diverse and characterized by outliers, which is the situation with forecasts of solar power generation.

HASIL DAN PEMBAHASAN

This section explains from the beginning with the data used in this study to several data analyses that can provide much broader insights and are very useful for increasing the electrical energy generated from solar power plants.

The dataset was obtained from www.kaggle.com , consisting of 2 files in CSV format from solar power plants for 34 days (2020-02-15 to 2020-06-17). Plant_Generation_Data.csv, with column attribute names DATE_TIME, PLANT_ID, DC_Power, AC_POWER, DAILY_YIELD, and TOTAL_YIELD (Figure 3). Plant_Weather_Sensor_Data.csv, with column attribute names DATE_TIME, PLANT_ID, SOURCE_KEY, AMBIENT_TEMPERATURE, MODULE_TEMPERATURE, and IRRADIATION (Figure 4).

	DATE_TIME	PLANT_ID	SOURCE_KEY	DC_POWER	AC_POWER	DAILY_YIELD	TOTAL_YIELD
0	2020-05-15 00:00:00	4136001	4UPUqMRk7TRMgml	0.0	0.0	9425.000000	2.429011e+06
1	2020-05-15 00:00:00	4136001	81aHJ1q11NBPMrL	0.0	0.0	0.000000	1.215279e+09
2	2020-05-15 00:00:00	4136001	9kRcWv60rDACzjR	0.0	0.0	3075.333333	2.247720e+09
...	...	...	...	...	...	...	...
67695	2020-06-17 23:45:00	4136001	vOuJvMaM2sgwLmb	0.0	0.0	4322.000000	2.427691e+06
67696	2020-06-17 23:45:00	4136001	xMbIugepa2P7lBB	0.0	0.0	4218.000000	1.068964e+08
67697	2020-06-17 23:45:00	4136001	xoJJ8DcxJEcupym	0.0	0.0	4316.000000	2.093357e+08

67698 rows × 7 columns

Figure 3. Plant_Generation_Data.csv

	DATE_TIME	PLANT_ID	SOURCE_KEY	AMBIENT_TEMPERATURE	MODULE_TEMPERATURE	IRRADIATION
0	2020-05-15 00:00:00	4136001	iq8k7ZNt4Mwm3w0	27.004764	25.060789	0.0
1	2020-05-15 00:15:00	4136001	iq8k7ZNt4Mwm3w0	26.880811	24.421869	0.0
2	2020-05-15 00:30:00	4136001	iq8k7ZNt4Mwm3w0	26.682055	24.427290	0.0
...	...	...	...	...	...	...
3256	2020-06-17 23:15:00	4136001	iq8k7ZNt4Mwm3w0	23.354743	22.492245	0.0
3257	2020-06-17 23:30:00	4136001	iq8k7ZNt4Mwm3w0	23.291048	22.373909	0.0
3258	2020-06-17 23:45:00	4136001	iq8k7ZNt4Mwm3w0	23.202871	22.535908	0.0

3259 rows × 6 columns

Figure 4. Plant_Weather_Sensor Data.csv

Peak sun hours (PSH): The term "peak sun hours" (PSH) usually refers to the daily irradiance. The total PSH for the day is the total number of hours during which 1 kW/m2 of energy would be needed to produce the same amount of energy as the total for the day. Peak sunlight and peak sun hours are synonymous words. The total amount of solar energy incident on a unit area over a specific period of time, such as a day, a month, or a year, is known as irradiance. An alternative term for irradiance is insolation. the quantity of solar radiation that strikes a surface in a given period of time. Peak Sun Hour (kWh/m2/day) is the daily measurement of insolation. Irradiance: Solar radiation incident to a surface at a given time, in W/m2 (Figure 5).

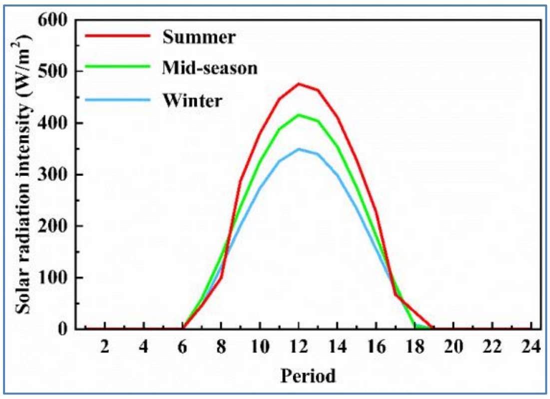

Figure 5. Shows the 24-hour total solar energy per unit area

Based on the angle of the sun to the panel, this shape (Figure 5) was created. When the sun is still up in the morning, it is essentially at its lowest point in the sky. Sunlight must travel through the atmosphere as much as possible in order to reach the panel at this moment. Because solar energy is lost to the atmosphere, it is important to remember this. This implies that less solar energy is available for the panel to convert the thicker the atmosphere. Sunlight does not have to travel through much of the atmosphere when it is directly overhead in the middle of the day. As a result, more rays of the sun will be captured by the panel during this period. The same lens is also at risk of falling on snow. But it is not valid for the brighter and sunnier days of winter. This can be simply explained by the sun being lower in the sky than it is during the summer.

Disturbance & Abnormality Detection in Solar Power Plants Abnormality in DC_POWER generation can be seen from the graph of DC_POWER generation per day, it is found that every day there is a fluctuation in power generation. Less fluctuation in DC_POWER generation is observed on the days: 2020-05-15, 2020-05-18, 2020-05-22, 2020-05-23, 2020-05-24, 2020-05-25, 2020-05-26. High Fluctuation in DC_POWER generation was observed on the days: 2020-05-19, 2020-05-28, 2020-05-29, 2020-06-02, 2020-06-03, 2020-06-04, 2020-06-13, 2020-06-14, 2020-06-17. Very High Fluctuation & Reduction in DC_POWER generation was observed on the days: 2020-06-03, 2020-06-11, 2020-06-12, 2020-06-15. The reason for very high Fluctuation & Reduction in DC_POWER generation is due to a glitch in the system or may be weather fluctuation or due to cloud cover.

The average power generation per day is visible from the DC_POWER generation per day.

1. 2020-05-15 was the day with the highest average DC_POWER generation.
2. On 2020-06-11, the average DC power generation was at its lowest.

Weather-related variations or system failures are to blame for this significant variance in DC_POWER generation. On the other hand, we can determine which day produced the most and least DC_POWER from this bar chart.

The IRRADIATION graph pattern looks very similar to the daily DC_POWER generation. In solar power plants, DC_POWER or output power is largely dependent on IRRADIATION. Or it is not wrong to say that it is directly proportional. Similar to DC_POWER generation, the highest and lowest average IRRADIATION generation also occurred on: 2020-05-15 and 2020-06-11.

Daily Ambient Temperature Graph showing the daily ambient temperature changes during the period of May 15, 2020 to June 10, 2020 to provide an overview of temperature fluctuations throughout the day. The general trends that can be observed from the graph include an increase in temperature in the morning to noon due to heating by sunlight, followed by a decrease in temperature in the afternoon to evening when solar energy decreases. The pattern of this graph is often influenced by factors such as weather conditions, seasons, and geographic location, which can cause daily temperature variations.

a. Comparison of the Best and Worst Solar Power Plants

1. The primary environmental conditions that impact the production of solar power include.
2. One aspect that influences the solar panels' ability to absorb sunlight is cloud cover. Another thing to be aware of in the winter is the increased layer of cloud cover. Thick clouds make it harder for sunlight to reach the sun, which will reduce the solar power system's production.
3. Even during the day, there are additional aspects to take into account when the system is not operating at its best, even though the sun's position can have an impact on output.
4. Solar power generation is directly dependent on solar radiation;
5. The temperature of the solar panels is the main cause of solar power systems not operating at their best.

The DC_POWER and IRRADIATION graphs both resemble the ideal graphs previously described. Because of the minimal differences in IRRADIATION, solar panel temperature, and ambient temperature, the weather appears to be excellent and there are no clouds in the sky.

b. Calculating the Inverter Efficiency of Solar Power Plants

Since heat loss occurs during this conversion, the inverter efficiency describes the amount of dc power that will be converted to ac power. Only the inverter's power mode is maintained by the standby power used. It is also known as the inverter's power usage when there is no load. Therefore, the inverter efficiency = pac/pdc, where pac refers to the ac output power in watts and pdc refers to the dc input power in watts (Figure 6).

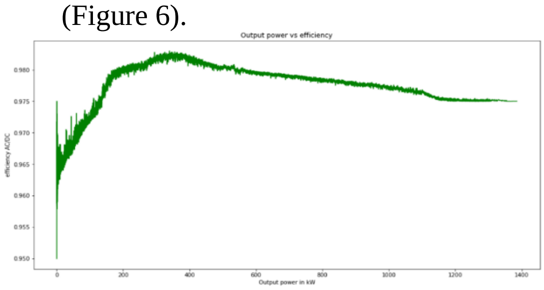

Figure 6. AC/DC efficiency graph from this study

A high-quality pure sine wave inverter's normal efficiency is from 90% to 95%, whereas a low-quality modified sine wave inverter's typical efficiency ranges from 75% to 85% for the two primary types of inverters available on the market. Because efficiency rises and can reach its maximum value at a higher load power capacity compared to a lower load power capacity, and provided the inverter output power capacity is not exceeded, the efficiency value of these power inverters is dependent on variations in the inverter load power capacity. Generally speaking, the efficiency will be fairly poor below 15% of the inverter load. As a result, a good matching between the inverter capacity and its load capacity will allow for greater efficiency, which means greater inverter ac output power for the same dc input power (Figure 7).

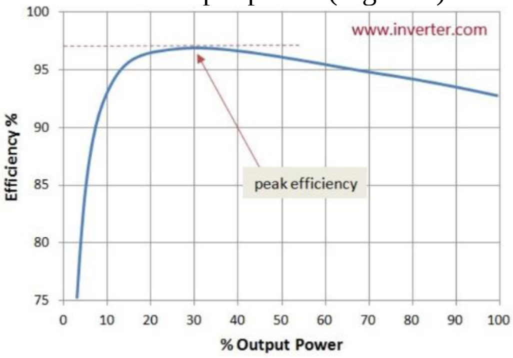

Figure 7. AC/DC efficiency graph

c. Correlation

DC_POWER and IRRADIATION of 0.93 have a strong link, as seen in the correlation map (Figure 8). In order to obtain the same scale, we multiply IRRADIATION by 1000 in order to further validate this link. Combining the two graphs (DC_POWER and IRRADIATION) in Figure 9 reveals that the patterns in the graphs' fluctuations are the same. Given the strong correlation between DC output power and IRRADIATION, any model's predictive potential will be rather high.

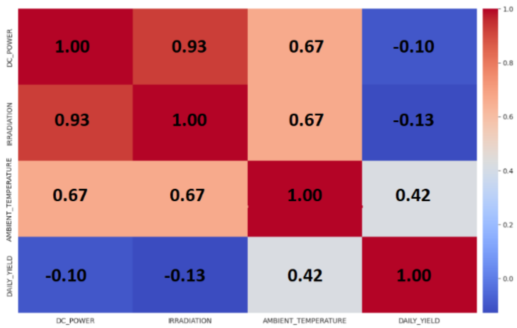

Figure 8. Correlation map

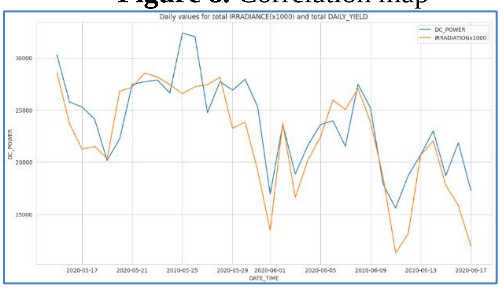

Figure 9. Combining the two graphs (DC_POWER and IRRADIATION)

d. Performance parameter MAE

One of the evaluation metrics that is frequently used to evaluate the effectiveness of regression models, including the forecasts of energy output from solar plants, is Mean Absolute Error (MAE). The mean absolute error (MAE) measures the discrepancy between a model's anticipated and actual results. The following formula is used to determine the MAE in terms of math.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (2)$$

Where:

1. y_i is the actual value (for example, the actual power produced by the solar panel).
2. $\hat{y}_i$ is the predicted value of the model
   n is the total number of predictions

e. Solar Power Prediction

Several algorithmic techniques are applied in this study in order to determine which model yields the greatest outcomes. Using previously provided data, each model's error rate was measured using the MAE after the training procedure was completed. The XGBoost algorithm had MAE values of 38.07622434301755, respectively. In reference to the Linear Regression technique, the values of MAE and 80.22835981583654, in that order. Plotting of the prediction results is limited to XGBoost (Figure 10) and Linear Regression (Figure 11) in order to save writing pages. The results of error measurements for all algorithms used in this study are collected in one table (table 1).

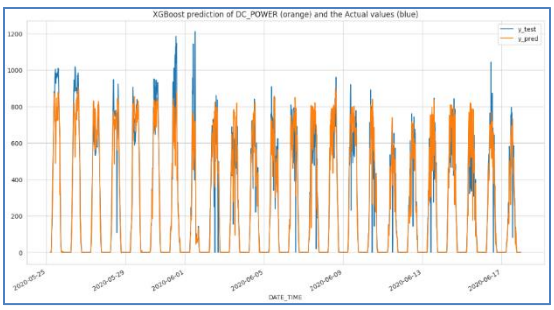

Figure 10. Plot of prediction results using XGBoost

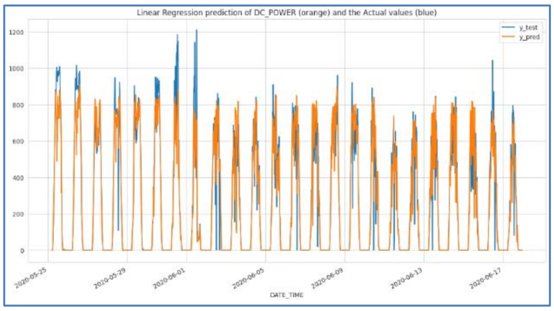

Figure 11. Plot of prediction results using Linear Regression

Table 1. The results of error measurements

Performance parameter	XGBoost	Linear Regression
MAE	38.08	80.23

Based on the comparison of MAE (mean absolute error) results between XGBoost and linear regression, it can be seen that XGBoost has much better performance in predicting data, with an MAE of 38.8 compared to linear regression, which has an MAE of 80.23. The lower MAE in XGBoost indicates that this model is more accurate in predicting the actual value because the average error produced is smaller. XGBoost's ability to handle higher data complexity makes it more effective in understanding non-linear patterns that simpler linear regression models may not capture.

CONSLUSION

With the help of operational and meteorological data, this research is successful in creating a predictive model that can estimate solar power plants' energy output with accuracy. two machine learning algorithms XGBoost and Linear Regression were used to achieve this. The findings showed that a higher level of prediction may be achieved by utilizing real-time data and advanced analytics in addition to historical data. Additionally, a notable boost in power producing plants can be accomplished by implementing doable strategies like corrective maintenance for PV modules and scheduling cleaning appropriately. The superior performance of the XGBoost model enables more efficient energy management, minimizes the risk of resource waste, and enhances the operational effectiveness of PV solar power plants.

For future studies, research can be focused on exploring other machine learning models such as random forest or neural networks to compare performance with XGBoost and linear regression. In addition, testing with variations in parameters and important features (feature engineering) can be done to optimize the prediction model. Improving data quality and adding relevant external data can also be a focus so that the model is more robust in facing real-world scenarios. Performance evaluation using other metrics, such as RMSE or R2, can also provide a broader perspective on model accuracy.

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