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Time Series Analysis of Solar Power Generation Based on Historical Data and Irradiance Using the ARIMA Method

Time Series Analysis Pembangkit Listrik Tenaga Surya Berdasarkan Data Historis dan Iradiansi Menggunakan Metode ARIMA

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Abstract

The demand for renewable energy in Indonesia continues to increase in line with the government's efforts to promote a sustainable energy transition. One of the rapidly growing technologies is On-Grid Solar Power Plants (PLTS), which rely on solar energy as their primary source. However, variations in solar irradiation and environmental factors cause fluctuations in the system's performance, potentially affecting its efficiency and reliability. Therefore, a robust method is needed to accurately predict system performance, supporting maintenance and operational optimization. This study applies the Seasonal Autoregressive Integrated Moving Average (SARIMA) method as a time series analysis approach to predict the Performance Ratio (PR) of PLTS based on historical data and solar irradiation variables. SARIMA was chosen because stationarity tests revealed a significant seasonal pattern that conventional ARIMA models cannot effectively handle. By considering seasonal factors, SARIMA provides a more accurate estimation of PR trends and fluctuations. This research aims to detect potential anomalies early, identify recurring operational patterns, and improve PLTS system monitoring efficiency. Model evaluation results show that SARIMA has higher accuracy than ARIMA in capturing seasonal patterns in PR data. Implementing this model can assist PLTS operators in making more data-driven decisions, optimizing maintenance strategies, and ensuring the reliability of renewable energy systems. These findings contribute to the development of more efficient energy management strategies and support the sustainability of solar energy utilization in Indonesia.

Keywords: *Solar Power Plant, Performance Ratio, SARIMA, Forecasting, Seasonal Analysis*

1. Introduction

With the increasing demand for renewable energy in Indonesia, On-Grid Solar Power Plants (PLTS) have become a key solution for providing a sustainable and environmentally friendly electricity supply. Indonesia has enormous solar energy potential, with an average solar radiation intensity of 4.8 kWh/m² per day in most regions, making it one of the countries with the largest solar energy potential in Southeast Asia (IRENA, 2022) [1]. According to data from the Ministry of Energy and Mineral Resources (ESDM), the installed capacity of PLTS in 2021 reached 207.2 MW and is expected to increase to 6,500 MW by 2025, in line with the National Energy Plan (RUEN) [2][3]. However, a major challenge in the development of On-Grid PLTS is the uncertainty in system performance caused by variations in solar irradiation and environmental conditions. Therefore, it is crucial to conduct accurate performance analysis to optimize the use of this energy source.

The main issue in PLTS operation lies in performance uncertainty due to variability in environmental and technical factors. One of the key indicators for evaluating system efficiency is the Performance Ratio (PR), which reflects the comparison between the electricity generated and the received solar irradiation potential [4][5]. PR values can be used to detect anomalies or system performance degradation; however, traditional approaches often rely on static analysis, which are less effective in capturing long-term changes. Hence, a more advanced analysis approach using historical data, such as Time Series Analysis with the Autoregressive Integrated Moving Average (ARIMA) model, is needed to enable early prediction of potential issues [6]. In this study, the ARIMA method is applied to analyze collected historical data to recognize patterns or trends and detect anomalies that may indicate problems within the system.

Previous research has highlighted the importance of time series-based analysis in monitoring PLTS performance, but most studies have employed simple methods such as Moving Averages or linear regression, which do not account for the complexity of data patterns. For instance, in the study by Murad Al-Omary et al. (2021), only Moving Average was used to analyze PLTS performance over a specific period, which proved less effective in detecting anomalies or non-linear patterns [7][8]. This study aims to address this gap by applying the ARIMA method, which is capable of identifying complex pattern changes in historical data, thus yielding more accurate predictions.

This research is based on various relevant studies to support the analysis and prediction of PLTS performance. Studies [6] and [9] have demonstrated the effectiveness of the ARIMA method in predicting daily total energy in PLTS systems, proving that this approach can capture complex temporal patterns to improve prediction accuracy. Study [10] further integrates feature engineering techniques to enhance the predictive capabilities of models in solar-based microgrid systems, providing a foundation for developing adaptive data-driven systems. In a real-time context, [11] emphasizes the importance of time series-based predictions to improve operational efficiency and enable early detection of potential problems.

The main objective of this study is to apply the ARIMA method to predict potential issues or anomalies in PLTS based on historical and irradiation data. Theoretically, this research is expected to contribute to the development of ARIMA-based historical data analysis methods in the renewable energy sector. Practically, the results can assist PLTS operators in improving system efficiency and supporting the achievement of national renewable energy targets. Moreover, the developed analysis is expected to enhance the reliability and operational efficiency of PLTS, thereby supporting Indonesia's transition toward cleaner and more sustainable energy.

2. Materials and Method

The research begins with a literature review to understand various concepts and methods of ARIMA and SARIMA [1]-[28]. Subsequently, data is collected from a pyranometer and kWh meter as the main sources of information related to solar irradiance and the electrical energy produced. Once the data is gathered, analysis and modeling are carried out using the ARIMA method to identify patterns and trends in the time series data. The results of this analysis are then obtained and further examined to ensure the accuracy of the model.

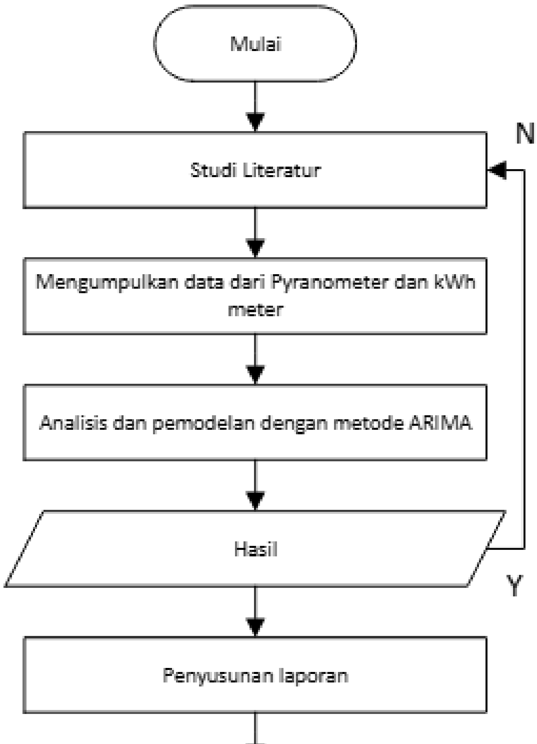


Figure 1. *Research Methodology*

2.1 Solar Power Plant

A Solar Power Plant (PLTS) is a system that converts sunlight into electrical energy using photovoltaic technology. The efficiency and energy output of a PLTS are greatly influenced by the intensity of solar irradiance, temperature, and surrounding weather conditions [11]. The development of PLTS has become increasingly crucial in line with the growing global demand for reliable and environmentally friendly renewable energy sources, in order to reduce dependence on fossil fuels [12].

2.2 Historical Data

Historical data refers to a collection of data that records specific events or values that have occurred over a certain period in the past. In the context of Solar Power Plants (PLTS), this data includes solar irradiance, which represents the amount of energy received by solar panels from sunlight over a specific period, as well as environmental temperature and energy production data. All of this information is essential for analyzing system performance and predicting future energy output [13].

2.3 Irradiance Value

Irradiance is the amount of solar radiation energy received on a specific surface area per unit of time, typically measured in watts per square meter (W/m²). In the context of Solar Power Plants (PLTS), irradiance affects how much energy can be generated by solar panels and is influenced by factors such as weather conditions, the position of the sun, time, and panel orientation [14]. The following is the formula used to calculate irradiance value.

$$E = G \times A \times \eta \tag{1}$$

Description :
E = electrical energy produced (kWh)
G = average solar irradiance (W/m²)
A = PV module area (m²)
η = PV module efficiency (%)

2.4 Performance Ratio

The Performance Ratio (PR) is a crucial performance indicator used to evaluate the efficiency of a Solar Power Plant (PLTS). PR measures the system's effectiveness in converting solar energy into electrical energy by comparing the actual amount of energy produced with the maximum possible energy output based on solar irradiance data [15]. The formula to calculate the performance ratio is as follows:

$$PR = \frac{Actual\ kWh}{Expected\ kWh}\ x\ 100\% \tag{2}$$

Description :
Actual kWh : The energy (Total Active Power) generated within a specific time period.
Expected kWh : The energy that should have been generated by the system based on irradiance (solar radiation) data and system capacity.

Rumus Expected kWh

$$ExpectedkWh = WideArea(m^2)\ x\ Cumulative\ Irradiance\ (kWh/m\text{^}2\ )\ x\ Efficiency\ PV\ (\%) \tag{3}$$

Description :
Wide Area (m²) :The total installed surface area of the solar panels (m²).
Cum Irradiance (kWh/m²) :The total amount of solar energy received (kWh/m²).
Efficiency PV (%) : The efficiency of the PV module (%).

2.5 Time Series Analysis

Time Series Analysis is a statistical method used to analyze data observed at specific time intervals, with the aim of understanding historical patterns, trends, seasonality, and fluctuations in the data [16]. In the context of PLTS, time series analysis is essential because solar energy production is influenced by time-based factors such as solar irradiance, ambient temperature, and weather patterns. Seasonal patterns and annual trends can significantly affect the efficiency of PLTS [17]. Time series data often form various data patterns.

2.6 Stasionarity

Data is considered stationary if it does not fluctuate over time. Stationary data has constant mean and variance over time and shows no upward or downward trends. Non-stationary data must undergo transformations to achieve stationarity in terms of mean and variance, in order to minimize modeling errors and ensure the model's effectiveness [18].

2.7 Augmented Dickey Fuller Test

The Augmented Dickey-Fuller (ADF) test is a statistical test used to determine the presence of a unit root in a time series. This test is used to assess whether a time series is stationary or not. The ADF test is represented by the following formula:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \epsilon_t \tag{4}$$

Description :

$\Delta Y_t = Y_t - Y_{t-1}$: Difference between the current and previous value
α : Constant term in the regression equation
βt : Time trend coefficient (used if the data shows a trend)
γY_{t-1} : Coefficient of the lagged dependent variable, indicates presence of unit root (non-stationarity)
$\sum(\delta_i \Delta Y_{t-i})$: Additional lag components to handle autocorrelation
ε_t : Error term assumed to be white noise (random and uncorrelated)

2.8 Autocorrelation Function

The Autocorrelation Function (ACF) is a statistical tool used to measure the degree of correlation between a time series and its own lagged versions at different time intervals [19]. It provides insight into how past values of a dataset relate to current values. The ACF for lag k is calculated as:

$$\rho k = \frac{\sum_{t=k+1}^{n}(Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^{n}(Y_t - \bar{Y})^2} \tag{5}$$

Description :

Y_t : data at time t
$\bar{Y}$: Mean of the entire dataset
n : Total number of observations
k : Number of lags measured

2.9 Partial Autocorrelation Function

The Partial Autocorrelation Function (PACF) is a statistical tool used to measure the correlation between a variable and its own lag, after removing the effects of the intervening lags. PACF gives a clearer picture of the correlation between two time points by eliminating the influence of closer lags. PACF is calculated using the Yule-Walker equations [19], expressed in matrix form as:

$$\begin{bmatrix} 1 & \rho_1 & \rho_2 & \cdots & \rho_{k-1} \\ \rho_1 & 1 & \rho_1 & \cdots & \rho_{k-2} \\ \rho_2 & \rho_1 & 1 & \cdots & \rho_{k-3} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \rho_{k-1} & \rho_{k-2} & \rho_{k-3} & \cdots & 1 \end{bmatrix} \begin{bmatrix} \emptyset_{k,1} \\ \emptyset_{k,2} \\ \emptyset_{k,3} \\ \vdots \\ \emptyset_{k,k} \end{bmatrix} = \begin{bmatrix} \rho_k \\ \rho_{k-1} \\ \rho_{k-2} \\ \vdots \\ \rho_1 \end{bmatrix} \tag{6}$$

Description :

p_k :ACF value at lag k

$\phi_{k,k}$: PACF coefficient for lag k

2.10 Forecasting

Forecasting aims to predict future conditions by analyzing past data as a reference, enabling the estimation of future electricity demand. Accurate load forecasting models play a crucial role in the planning and operation of power systems. This helps understand electricity consumption trends so that future usage can be managed more efficiently [20].

2.11 Research Accuracy

1. Root Mean Square Error

Root Mean Square Error (RMSE) is a statistical metric used to evaluate the accuracy of prediction or estimation models. RMSE calculates the average error between predicted values (ŷ) and actual values

(y) by squaring the differences, averaging them, and then taking the square root. This metric is easy to interpret because the result is in the same scale as the original data [22]. The formula for RMSE is:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\{Yt - \hat{Y}t\}^2} \tag{7}$$

Description:
n = total number of observations
Yt = actual data at time t

2. Mean Square Error

Mean Squared Error (MSE) is a method used to evaluate forecasting accuracy by measuring the errors between predicted and actual values. In MSE, each error is squared, summed, and divided by the number of observations. This method places greater emphasis on larger errors due to the squaring process. The formula for MSE is as follows [17].

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\{Yt - \hat{Y}t\}^2 \tag{7}$$

Description:
n = total number of observations
Yt = actual data at time t

3. *Mean Absolute Percentage Error*

Mean Absolute Percentage Error (MAPE) is a metric used to evaluate relative error. This method is especially useful when the predicted variable plays a key role in improving forecasting accuracy. In MAPE calculation, the error in each period is divided by the actual value of that period. The average of these percentage errors is then computed. MAPE is widely accessible because it provides clear information on how much the forecasted values deviate from the actual data. The following is the formula for MAPE [22]:

$$MAPE = \frac{1}{N}\sum_{t=1}^{n}\frac{Yt - \hat{Y}}{\hat{Y}} \times 100\% \tag{8}$$

Description:
n = total number of observations
Yt = actual data at time t

There is also an analysis of MAPE values as shown in the table below [23]:

Table 1: Scale of Perform Forecasting [23]

Rentang Nilai MAPE	Arti Nilai
<10%	Very Good Forecasting
10-20%	Good Forecasting
20-50%	Reasonable Forecasting
>50%	Poor Forecasting

Table 1 explains the range of MAPE values obtained from average forecasting calculations. If the MAPE value is less than 10%, the forecast is considered very good and does not require re-forecasting. A MAPE value between 10% and 20% is categorized as good. If the MAPE is between 20% and 50%, the forecasting ability is considered acceptable. However, if the MAPE value exceeds 50%, the forecast is classified as poor, and re-forecasting should be conducted until a lower MAPE value is achieved.

2.12 Arima

ARIMA Method (Autoregressive Integrated Moving Average) is a commonly used technique for forecasting future events. This method was developed by Box and Jenkins [24]. ARIMA combines two different approaches: the Autoregressive (AR) method and the Moving Average (MA) method. According to Box and Jenkins, there are four stages in the ARIMA method: identification through time series plotting, parameter determination using ACF and PACF, model testing, and time series value estimation [19][25].

ARIMA Notation (Autoregressive Integrated Moving Average) is used to describe a statistical model applied in time series analysis. ARIMA models are often used to forecast time series data based on historical patterns. The ARIMA notation is typically written as ARIMA(p, d, q), where:

1. p (*Autoregressive*): The number of lags used in the autoregressive model. It indicates the relationship between current and past values.
2. d (*Integrated*): The degree of differencing needed to make the time series stationary (data with stable fluctuations over time).
3. q (*Moving Average*): The number of lagged forecast errors in the prediction model. This accounts for past noise or errors to improve accuracy.

ARIMA modeling consists of two forms: non-seasonal ARIMA, which is not significantly affected by seasonal factors, and seasonal ARIMA, which is an extension designed to handle time series data with seasonal or periodically recurring patterns. This model captures the seasonal components in data that cannot be explained by a standard ARIMA model. Below is the general form of the non-seasonal ARIMA model expressed in the following equation [26]:

$$(1 - B)(1 - \varphi 1B)Yt = \mu' + (1 - \theta 1B)et \quad (9)$$

Keterangan:
Yt = First ARIMA variable
μ' = Constant
et = Error at time t
B = Variable coefficient
$\varphi 1$, $\theta 1$ = SARIMA parameter

The next ARIMA model is the seasonal ARIMA model, which is an extension of the standard ARIMA model designed to handle time series data with seasonal or periodic patterns. This model captures the seasonal components in data that cannot be explained by a regular ARIMA model. This is commonly referred to as Seasonal ARIMA (SARIMA), and its general form is as follows [26]:

$$Y_t = \mu + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{P} \Phi_k Y_{t-km} + \sum_{l=1}^{Q} \Theta_l \varepsilon_{t-lm} + \varepsilon_t \quad (10)$$

Description :
Yt = Observed value at time t
μ = Process mean
ϕ_i = AR coefficients
θ_j = MA coefficients
Φ_k = Seasonal AR coefficients
Θ_l = Seasonal MA coefficients
et = Error at t

SARIMA is denoted as:

$$SARIMA(p, d, q) \times (P, D, Q, s) \quad (11)$$

Description:
p = autoregressive order (From PACF)
d = order differencing (From stationarity test)
q = moving average order (from ACF)
P,D,Q,s = Seasonal Components

2.13 Python

Python was first developed by Guido van Rossum in 1991. The main goal of Python's development was to create a simple and readable language that supports various programming paradigms, such as object-oriented, functional, and procedural programming [28].

3. Results and Discussion

Irradiance data refers to the solar radiation received by solar panels for conversion into electrical energy. This study uses a PVmet75 sensor to measure irradiance. To determine the Performance Ratio (PR) in this study, solar irradiance values received by the PV panel are used. The reading interval of this irradiance data affects the accuracy of the PR value. Below is the irradiance table for 2024-10-01.

Table 2 Rekapitulation Irradiance 2024-10-01

No	*Datetime*	*Name*	*Irradiance*	No	*Datetime*	*Name*	*Irradiance*
275	2024-10-01 10:01:24	PYN01	688.39	328	2024-10-01 10:54:24	PYN01	888.19
276	2024-10-01 10:02:24	PYN01	682.39	329	2024-10-01 10:55:24	PYN01	931.77
277	2024-10-01 10:03:24	PYN01	689.36	330	2024-10-01 10:56:24	PYN01	952.46
278	2024-10-01 10:04:24	PYN01	715.24	331	2024-10-01 10:57:24	PYN01	945.29
279	2024-10-01 10:05:24	PYN01	716.55	332	2024-10-01 10:58:24	PYN01	944.08
280	2024-10-01 10:06:24	PYN01	715.38	333	2024-10-01 10:59:24	PYN01	941.35
281	2024-10-01 10:07:24	PYN01	702.87	334	2024-10-01 11:00:24	PYN01	906.37

Based on the irradiance data in Table 2, the average irradiance recorded is 800.48 W/m², with a minimum of 513.87 W/m² and a maximum of 952.46 W/m². To calculate the energy produced under average conditions: Given a PV panel area of 8686.121346 m² and PV module efficiency of 21.03%, the generated energy is 14,662.08 W.

This calculation indicates that under average irradiance conditions, the PV system can generate approximately 14,662.08 W. To calculate Performance Ratio (PR), the irradiance value must be in kWh/m², thus the irradiance data in W/m² must first be converted.

After converting irradiance from W/m² to kWh/m², the results are presented in table format to simplify analysis and understanding. These values are used to estimate the Expected kWh, a key component in PR calculation.

Table 3 shows the irradiance conversion at several specific time points, providing an overview of solar energy intensity variations over time.

Table 3 irradiance conversion

No	*Datetime*	*Name*	solrad	Δ_t	*Irradiance*
500	2024-10-01 08:21:24	PYN01	534.4		
501	2024-10-01 08:22:24	PYN01	537.29	0.016667	0.0089548333625227700
502	2024-10-01 08:23:24	PYN01	551.2	0.016667	0.0091866666966117900
503	2024-10-01 08:24:24	PYN01	558.41	0.016667	0.0093068332661589400
504	2024-10-01 08:25:24	PYN01	559.48	0.016667	0.0093246666970616200
505	2024-10-01 08:26:24	PYN01	565.67	0.016667	0.0094278333640645700
506	2024-10-01 08:27:24	PYN01	561.61	0.016667	0.0093601665991073300
507	2024-10-01 08:28:24	PYN01	576.76	0.016667	0.0096126666980003900
508	2024-10-01 08:29:24	PYN01	581.45	0.016667	0.0096908333649218600
509	2024-10-01 08:30:24	PYN01	589.6	0.016667	0.0098266665957402400
510	2024-10-01 08:31:24	PYN01	596.03	0.016667	0.0099338333657139400
511	2024-10-01 08:32:24	PYN01	590.44	0.016667	0.0098406666987435900

After obtaining the irradiance values in kWh/m², the next step is to calculate the total Cumulative Irradiance by summing all irradiance values from 2024-10-01 10:01:24 to 11:00:24, resulting in a total of 5.057545 kWh/m². The cumulative irradiance value, derived from the sum of irradiance readings during that period, is then used to calculate the Expected kWh, which is a key component in the Performance Ratio (PR) formula.
Below is the Actual kWh data, which will be used in the calculation of the performance ratio.

Table 4 *Actual data* kWh

No	*Datetime*	*Name*	*kwh_eexp*	No	*Datetime*	*Name*	*kwh_eexp*
1	2024-10-01 00:00:24	KWH0 1	820.465026 9	3078	2024-10-01 23:56:25	KWH0 1	822.362976 1
2	2024-10-01 00:00:24	KWH0 3	991.956970 2	3079	2024-10-01 23:56:25	KWH0 3	993.809021
3	2024-10-01 00:01:24	KWH0 3	991.960022	3080	2024-10-01 23:56:25	KWH0 3	993.809021
4	2024-10-01 00:01:24	KWH0 1	820.466003 4	3081	2024-10-01 23:57:25	KWH0 3	993.812011 7
5	2024-10-01 00:02:24	KWH0 1	820.468017 6	3082	2024-10-01 23:57:25	KWH0 3	993.812011 7

The Actual kWh values mentioned above represent part of the total energy received. To obtain the daily energy, it is calculated as: energy_end − energy_start, resulting in a total energy of 6617 kWh for KWH01 and KWH03 on that day. Before proceeding with the Performance Ratio (PR) calculation, the Expected kWh must be determined. Based on the calculations, the expected energy output from the PV system is 9238.57 kWh. This value is essential for evaluating the system's efficiency.

Once the required values for calculating the PR are obtained, the next step is to compute the daily PR, as this study uses a per-day interval for PR analysis. Based on the calculation results, the Performance Ratio (PR) of the PV system is 71.62%. This indicates the system's efficiency in converting solar energy into usable electricity. Factors such as temperature, dust, inverter power loss, and weather conditions can affect the PR value.

This research uses a data sample covering four months, from October 1, 2025, to January 31, 2025, with a total of 123 PR data entries. Below are several sample performance ratio data points collected over the four-month period.

Table 5 Sample Data *Performance Ratio*

No	***Date***	***Actual Production (kWh)***	***Expected Production (kWh)***	***Performance Ratio (%)***
1	01 October 2024	6677	9238.57279	72.01471103
2	02 October 2024	6954.6	9558.389246	72.75912103
3	03 October 2024	7194.47	9827.710992	73.20595819
29	29 October 2024	7344.98	10030.30477	73.22788461
30	30 October 2024	6719.25	9182.387235	73.17541537
31	31 October 2024	6054.49	8184.435333	73.97565933
32	01 November 2024	6449.51	8680.123759	74.3020512
33	02 November 2024	5013.27	7043.527544	71.17555754
34	03 November 2024	4319.61	5698.528651	75.80219851
42	11 November 2024	4738.03	6531.473171	72.54152128
44	13 November 2024	6153.55	8940.505885	68.82776075
60	29 November 2024	7062.26	9684.11549	72.92622653
61	30 November 2024	6359.38	8381.913673	75.87026361
62	01 December 2024	7091.87	9810.208788	72.29071423
63	02 December 2024	5532.66	7267.344092	76.13042578
64	03 December 2024	2983.53	3783.250772	78.86154474
65	04 December 2024	3625.61	4572.889752	79.28487666
66	05 December 2024	4248.25	5428.961644	78.25161198
67	06 December 2024	2992.33	3763.228475	79.51497018
90	29 December 2024	5212.7	6965.096437	74.84031337
91	30 December 2024	6551.59	8952.929928	73.17816684
92	31 December 2024	5327.73	7008.374953	76.01947721

No	*Date*	*Actual Production (kWh)*	*Expected Production (kWh)*	*Performance Ratio (%)*
93	01 January 2025	5981.65	8266.018624	72.36434216
94	02 January 2025	7560.07	10259.91085	73.68553302
95	03 January 2025	5902.1	7841.407676	75.26837328
121	29 January 2025	3030.35	3941.098218	76.89100428
122	30 January 2025	5128.01	6819.656292	75.19455205
123	31 January 2025	5215.28	7157.086119	72.8687613

From the sample table, it can be analyzed that the average PR is stable but shows fluctuations, ranging between 68.82% to 79.51%, with most values between 72% and 76%. Higher PR values occurred on specific days, especially in December. The lowest PR was recorded on November 13, 2024 (68.82%), possibly due to technical issues or bad weather. Lower PRs were also observed in early October and mid-November. In contrast, December saw higher PRs, peaking at 79.51% (December 6), with several days near 78%-79%, possibly due to system improvements, better weather, or operational factors. Actual vs. Expected Production Pattern: On several days, actual production was close to expected, but most days showed actual production falling short. For example, on November 11, 2024, the PR was just 68.82%, indicating suboptimal system performance.

After collecting the PR sample data, it is plotted to observe patterns. Below is the performance ratio curve chart based on the collected data.

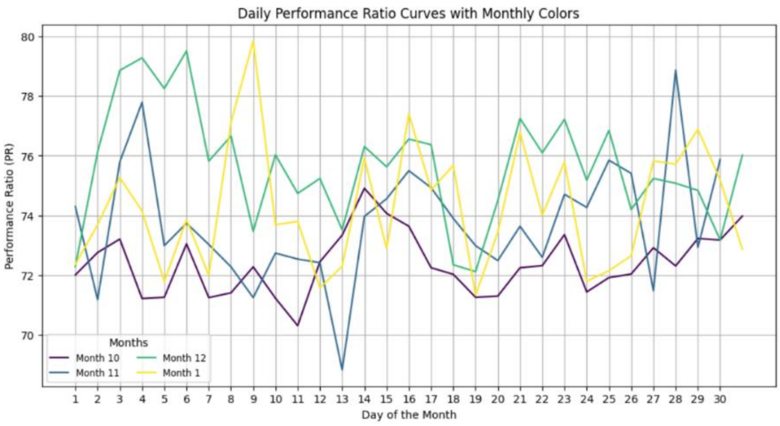


Figure 1 Monthly Curva PR

From the curve, it can be seen that daily PR fluctuates significantly each month. October shows a more stable pattern with minor changes, while November and January show sharper variations with significant peaks and drops. Although December also shows fluctuations, the trend appears higher compared to other months. Notable spikes occur in early and late December and mid-January, while sharp drops are seen in mid-November and early January. Overall, October and November have lower and more stable PRs, while December and January show improvement with more varied patterns.

From the sample PR curve above, the stationarity of the PR data is then tested using the Augmented Dickey-Fuller (ADF) method. Below is the plot of the ADF test.

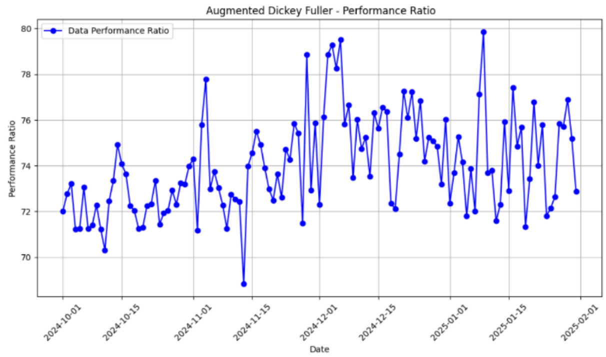


Figure 2 Plot ADF test

The **Augmented Dickey-Fuller (ADF) test** results on the **Performance Ratio (PR)** data of the solar power system indicate that:

Table 6 Result ADF

ADF Static	:	-4.66948	Critical Values	:	
p-value	:	0.000096	1%	:	3.48559
Total Lags	:	1	5%	:	2.88574
Observation	:	121	10%	:	2.57968
Information Criterion	:	397.0978			

After conducting the ADF test and confirming that the Performance Ratio data is stationary, the next step is to determine the optimal model parameters using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis to identify suitable values for AR (p), MA (q), and differencing (d). ACF measures the correlation between a data point and its previous lags. Below is the ACF and PACF analysis plot:

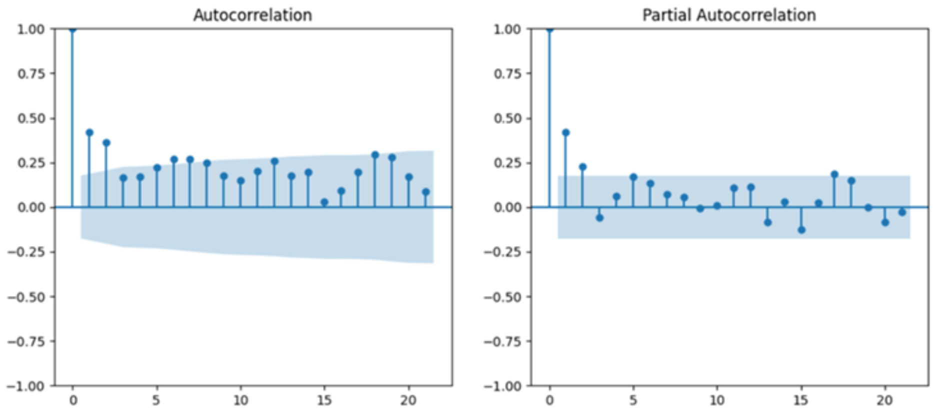


Figure 3 ACF and PACF analysis plot

The figure above shows the ACF and PACF plots of the analyzed data. ACF illustrates the correlation between a current observation and its lagged values across various lags and PACF shows the direct correlation between an observation and its lag, after removing the influence of intermediate lags.

From the ACF plot, it is evident that autocorrelation values remain significant at several initial lags, indicating a seasonal pattern in the data. This suggests that a Moving Average (MA) component should be included in the SARIMA model, with an appropriate order q. Based on the provided data, ACF values are significant at lags 1, 2, and 3, which indicates that a MA model with q = 2 or 3 could be appropriate.

Meanwhile, the PACF plot shows a sharp decline in correlation after a certain lag, suggesting the need for an Autoregressive (AR) component, where the order p is determined by the point where PACF first drops close to zero.PACF measures the direct relationship between an observation and its lag by eliminating the effects of intervening lags. Since PACF is significant at lag 1 and 2, but then drops sharply, this suggests that an AR model with p = 1 or 2 could be used. Below are the detailed results:

Table 7 ACF and PACF Analisys

Lags	*ACF Value*	*PACF Value*	Lags	*ACF Value*	*PACF Value*
0	1	1	11	0.2018547	0.120563087
1	0.418492774	0.421923042	12	0.257824068	0.132490964
2	0.363883955	0.233435475	13	0.17375838	-0.091415296
3	0.165811089	-0.061982557	14	0.194032984	0.034739546
4	0.168673994	0.063684092	15	0.031580764	-0.142042097
5	0.2246085	0.179241635	16	0.092158586	0.02683557
6	0.270509959	0.144628761	17	0.197782762	0.221422227
7	0.271265704	0.077997161	18	0.297219931	0.189573252
8	0.247383683	0.060567314	19	0.279879878	0.007096955
9	0.173756812	-0.007320581	20	0.172647613	-0.109343192
10	0.149673748	0.011842763			

Table 7 shows the values of the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) at various lags. From the analysis results, it can be observed that the ACF values gradually decrease and remain significant at several early lags, indicating the presence of a Moving Average (MA) pattern in the data. Meanwhile, the PACF values show a cutoff after the first few lags, suggesting an Autoregressive (AR) pattern in the data.

Based on these results, the selection of parameters p and q in the SARIMA model is carried out by observing the point where PACF experiences a cutoff (to determine p) and where ACF shows significant decay (to determine q). Additionally, if there is a significant seasonal pattern, the values of P, D, and Q in the SARIMA model are also determined by considering the ACF and PACF patterns in data with specific periodicity.

Based on the observed patterns in the plots, the combination of p and q values for the SARIMA model can be determined by identifying the point where the ACF and PACF plots show cutoffs or significant decays. This information is then used in the parameter search process using the Grid Search method. After obtaining the simplified model equation, the next step is to evaluate the accuracy of the model by testing it using Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). This evaluation aims to assess how well the model can represent historical data and predict future values. In addition, residual analysis will also be conducted to ensure that the model errors behave as white noise, which means there is no systematic pattern left in the residuals. If the test results show that the model still has large errors or non-random residuals, then the model needs to be refined by adjusting the parameters (p,d,q) × (P,D,Q,s) or trying other optimization techniques.

The first evaluation is conducted by calculating the RMSE, which measures the average deviation between actual and predicted values in the same units as the original data. The smaller the RMSE value, the better the model is at predicting data. Then, MSE (Mean Squared Error) is calculated. MSE is often used in model optimization processes as it provides an indication of how large the average squared forecasting errors are. Additionally, MAPE (Mean Absolute Percentage Error) is used to evaluate forecasting errors as a percentage of actual values.

After obtaining the forecasting results, the predictions are then compared to the actual data using Mean Squared Error (MSE), which is square-rooted to obtain RMSE. If the resulting RMSE is smaller than the previous best_score, the parameters are stored as the best parameters.

If a certain parameter combination fails to execute, an error message will appear detailing the cause of the failure. After all combinations are tested, the system prints out the best parameter combination along with its RMSE value. Finally, the SARIMA model is retrained using the best parameters found. This model can then be used for forecasting new data. The results of the evaluation show that:
Best PDQ: (0, 0, 2, 0, 1, 1, 12) → RMSE: 2.064
Where:
RMSE:2.064
MAPE:2.42%
MSE: 4.262

The results of the forecasting model evaluation using SARIMA indicate that the prediction error is relatively small, with a Root Mean Squared Error (RMSE) of 2.064, showing that the average deviation between actual and predicted values is not large. The Mean Squared Error (MSE) of 4.262 indicates that there are some larger errors, but overall they are within acceptable limits. Meanwhile, the Mean Absolute Percentage

Error (MAPE) of 2.42% shows that the level of prediction error is relatively low compared to the actual values, indicating that the model is quite good at forecasting. Below is the result of the actual performance ratio versus the forecast.

Table 8 the actual performance ratio versus the forecast.

Date	*Forcasted PR*	*Actual PR*	*PR (Filled)*	*Error*	*Error %*
2/1/2025	74.730715	76.075704	76.075704	1.344989	1.767961
2/2/2025	76.384306	77.271025	77.271025	0.886718	1.147543
2/3/2025	74.512522	77.130778	77.130778	2.618255	3.394566
2/4/2025	74.446813	75.98166	75.98166	1.534848	2.020024
2/5/2025	72.854381	71.952241	71.952241	0.90214	1.253804
2/6/2025	73.000716	79.067572	79.067572	6.066856	7.673001
2/7/2025	74.099126	77.99095	77.99095	3.891824	4.990097
2/8/2025	75.201548	78.038493	78.038493	2.836944	3.635314
2/9/2025	75.514893	75.879831	75.879831	0.364939	0.480943
2/10/2025	74.967427	78.454825	78.454825	3.487399	4.445104
2/11/2025	74.765946	76.447017	76.447017	1.681072	2.199003
2/12/2025	72.950854	0	72.950854	72.95085	inf
2/13/2025	74.891104	0	74.891104	74.8911	inf
2/14/2025	76.575125	0	76.575125	76.57513	inf
2/15/2025	74.512522	0	74.512522	74.51252	inf
2/16/2025	74.446813	0	74.446813	74.44681	inf
2/17/2025	72.854381	0	72.854381	72.85438	inf
2/18/2025	73.000716	0	73.000716	73.00072	inf
2/19/2025	74.099126	73.994518	73.994518	0.104608	0.141372
2/20/2025	75.201548	72.550359	72.550359	2.651189	3.654274
2/21/2025	75.514893	73.433616	73.433616	2.081277	2.834229
2/22/2025	74.967427	76.604335	76.604335	1.636908	2.136835
2/23/2025	74.765946	77.194106	77.194106	2.42816	3.145526
2/24/2025	72.950854	71.890505	71.890505	1.060349	1.47495
2/25/2025	74.891104	71.191291	71.191291	3.699813	5.197003
2/26/2025	76.575125	75.654656	75.654656	0.920469	1.216672
2/27/2025	74.512522	69.928154	69.928154	4.584368	6.555826
2/28/2025	74.446813	69.856359	69.856359	4.590454	6.571275

Based on the results of the SARIMA model evaluation using MSE, RMSE, and MAPE metrics, it is evident that the model has a fairly good level of accuracy in predicting the Performance Ratio (PR). From the table comparing the Forecasted PR and Actual PR values, the model errors vary, with the largest prediction error occurring on February 6, 2025, where the error reached 7.67%. Meanwhile, most errors fall within the 1%–5% range, indicating that the model performs quite well, although there are still some significant deviations. In addition, there are several days where the Actual PR value equals 0, which causes the MAPE value to become infinite (inf) due to division by zero. Therefore, to objectively assess the model's accuracy, the MAPE calculation must exclude data with Actual PR = 0.

Although RMSE and MAPE values are relatively low, the next important step is to perform residual testing to ensure that the model errors behave as white noise, meaning they have no specific pattern and are randomly distributed. This is essential to confirm that the model has captured all existing patterns in the data and has not left any unmodeled structure. If the residuals are random and patternless, the model is considered to have captured all available information in the data. The following is the residual visualization.

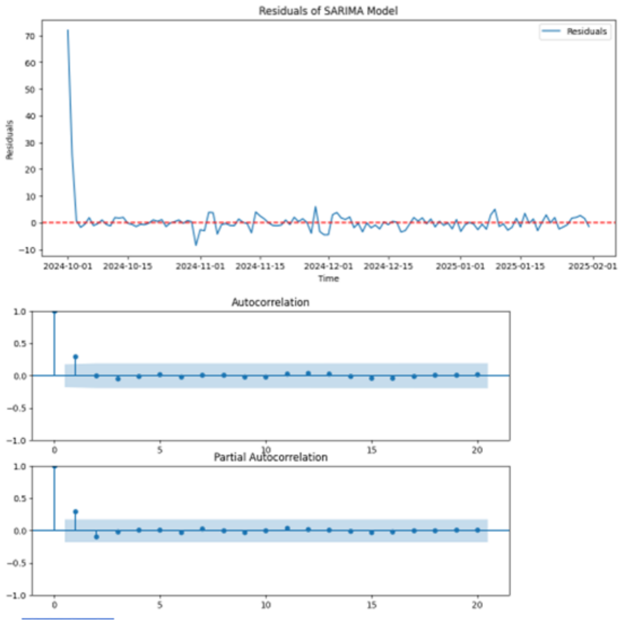


Figure 4 residual visualization

With the results of the Ljung-Box and Jarque-Bera tests shown in the table below:

Table 9 Hasil Uji *Ljung-Box* dan *Jarque-Bera*

Ljung-Box	Jarque-Bera
p-value = 0.32025 > 0.05	(p-value = 0.0 < 0.05)

Based on the residual analysis, the SARIMA model used demonstrates reasonably good performance in capturing historical data patterns. This is evident from the residual plot, where most residuals are randomly scattered around the zero line, and from the Ljung-Box test result, which indicates that the residuals do not exhibit significant autocorrelation (p-value = 0.32025 > 0.05). This means the model errors do not show remaining patterns and behave as white noise, which is a strong indication that the model has effectively captured the structure in the data. However, the Jarque-Bera test result shows that the residuals are not normally distributed (p-value = 0.0 < 0.05), which may indicate the presence of some outliers or structures not fully explained by the model. Despite this, the model remains suitable for forecasting purposes, although further improvements—such as additional data transformations or reevaluation of model parameters—may be beneficial.

After the SARIMA model is evaluated and its residuals meet the white noise assumption (random and patternless), the model can be used for future forecasting. The forecasting process is based on the validated SARIMA model equation, where the predicted value Y_{t+h} is calculated through a combination of autoregressive (AR), moving average (MA), and seasonal components from the historical data. Based on the forecasting results and comparison between Forecasted PR and Actual PR for February 2025, prediction accuracy varies throughout the month, with errors ranging from 0.14% to 7.67%.

1. February 1–9, 2025: Model Relatively Accurate
   1) Errors ranged from 0.48% to 4.99%, indicating fairly good prediction accuracy.
   2) A significant anomaly occurred on February 6, 2025, with an error of 7.67%.
   3) Possible cause: actual PR was higher than predicted (79.07% vs 73.00%), suggesting a sudden increase in data not captured by the model.
2. Period February 12–18, 2025: No Data (*Error* Inf)
   1) *Actual* PR = 0, resulting in infinite error (inf).
   2) Possible cause: data recording failure or monitoring system disruption.
   3) Solution: use filled PR values as alternative inputs.
3. February 19–28, 2025: Stable Model, but with Overestimation
   1) The smallest error occurred on February 19, 2025 (0.14%), indicating an almost perfect prediction.
   2) The highest errors occurred on February 27–28, 2025 (6.55% and 6.57%), indicating model overestimation.
   3) Possible cause: external factors such as poor weather or system degradation not accounted for in the SARIMA model.

Overall, the SARIMA model successfully captures the historical data patterns with most prediction errors falling within reasonable limits. These forecasting results can serve as a basis for short-term predictions of the Performance Ratio (PR) for February 2025. However, a few anomalies and external factors caused deviations in predictions, particularly on February 6 and February 27–28. Therefore, while the model can be relied on for forward-looking predictions, further adjustment for external variables may be necessary to improve forecast accuracy.

Table 10 below presents the SARIMA model's PR forecasting results for February 2025. In this table, the Forecasted PR represents the predicted value, while the Lower Bound and Upper Bound indicate the prediction range based on the confidence interval, reflecting the potential variability of PR values for each day.

Table 10 Result of *Forecasting* SARIMA February 2025

Date	*Forcasted PR*	*Lower Bound*	*Upper Bound*
2/1/2025	74.730715	70.576168	78.885262
2/2/2025	76.384306	72.087758	80.680855
2/3/2025	74.512522	69.998126	79.026918
2/4/2025	74.446813	69.932417	78.961209
2/5/2025	72.854381	68.339985	77.368777
2/6/2025	73.000716	68.48632	77.515112
2/7/2025	74.099126	69.58473	78.613522
2/8/2025	75.201548	70.687153	79.715944
2/9/2025	75.514893	71.000497	80.029289
2/10/2025	74.967427	70.453031	79.481823
2/11/2025	74.765946	70.251591	79.2803
2/12/2025	72.950854	68.436526	77.465183
2/13/2025	74.891104	70.205038	79.577171
2/14/2025	76.575125	71.877327	81.272924
2/15/2025	74.512522	69.79602	79.229025
2/16/2025	74.446813	69.73031	79.163316
2/17/2025	72.854381	68.137878	77.570884
2/18/2025	73.000716	68.284213	77.717219
2/19/2025	74.099126	69.382623	78.815629
2/20/2025	75.201548	70.485046	79.918051
2/21/2025	75.514893	70.79839	80.231396
2/22/2025	74.967427	70.250924	79.68393
2/23/2025	74.765946	70.049483	79.482409
2/24/2025	72.950854	68.234416	77.667292
2/25/2025	74.891104	70.010034	79.772175
2/26/2025	76.575125	71.68279	81.46746
2/27/2025	74.512522	69.602224	79.42282
2/28/2025	74.446813	69.536515	79.357111

From the forecasting results presented in Table 10, the PR values are predicted to fluctuate between 72% and 76% throughout February 2025. The highest predicted PR is expected on February 14, 2025, with a value of 76.58%, while the lowest point is predicted on February 17, 2025, at 72.85%. Overall, the PR values are expected to remain stable within a reasonable range, despite some daily fluctuations.

To evaluate the accuracy of the model, the forecasting results are compared to the actual Performance Ratio (Actual PR). The following table presents a comparison between the predicted and actual values, including the calculation of absolute error and percentage error to assess how accurately the model can predict the PR.Table 11 presents the comparison between Forecasted PR and Actual PR for February 2025. In this table:

Table 11 *Actual Performance Ratio VS Forecasting*

Date	Forcasted PR	Actual PR	PR (Filled)	Error	Error %
2/1/2025	74.730715	76.075704	76.075704	1.344989	1.767961
2/2/2025	76.384306	77.271025	77.271025	0.886718	1.147543
2/3/2025	74.512522	77.130778	77.130778	2.618255	3.394566
2/4/2025	74.446813	75.98166	75.98166	1.534848	2.020024
2/5/2025	72.854381	71.952241	71.952241	0.90214	1.253804
2/6/2025	73.000716	79.067572	79.067572	6.066856	7.673001
2/7/2025	74.099126	77.99095	77.99095	3.891824	4.990097
2/8/2025	75.201548	78.038493	78.038493	2.836944	3.635314
2/9/2025	75.514893	75.879831	75.879831	0.364939	0.480943
2/10/2025	74.967427	78.454825	78.454825	3.487399	4.445104
2/11/2025	74.765946	76.447017	76.447017	1.681072	2.199003
2/12/2025	72.950854	0	72.950854	72.95085	inf
2/13/2025	74.891104	0	74.891104	74.8911	inf
2/14/2025	76.575125	0	76.575125	76.57513	inf
2/15/2025	74.512522	0	74.512522	74.51252	inf
2/16/2025	74.446813	0	74.446813	74.44681	inf
2/17/2025	72.854381	0	72.854381	72.85438	inf
2/18/2025	73.000716	0	73.000716	73.00072	inf
2/19/2025	74.099126	73.994518	73.994518	0.104608	0.141372
2/20/2025	75.201548	72.550359	72.550359	2.651189	3.654274
2/21/2025	75.514893	73.433616	73.433616	2.081277	2.834229
2/22/2025	74.967427	76.604335	76.604335	1.636908	2.136835
2/23/2025	74.765946	77.194106	77.194106	2.42816	3.145526
2/24/2025	72.950854	71.890505	71.890505	1.060349	1.47495
2/25/2025	74.891104	71.191291	71.191291	3.699813	5.197003
2/26/2025	76.575125	75.654656	75.654656	0.920469	1.216672
2/27/2025	74.512522	69.928154	69.928154	4.584368	6.555826
2/28/2025	74.446813	69.856359	69.856359	4.590454	6.571275

Based on the comparison results in Table 11, the SARIMA model is capable of delivering fairly accurate predictions, with errors ranging from 0.14% to 7.67%.

1. The smallest error occurred on February 19, 2025 (0.14%), indicating that the model was almost perfect in predicting the PR on that day.
2. The largest error occurred on February 6, 2025 (7.67%), where the actual PR was significantly higher than the forecast (79.07% vs 73.00%).
3. During the period February 12–18, 2025, Actual PR values were unavailable, resulting in infinite (inf) errors. In this situation, Filled PR values were used to replace the missing data.
4. At the end of the month (**February 27–28, 2025**), the model tended to overestimate predictions, with errors of **6.55%** and **6.57%**, respectively.

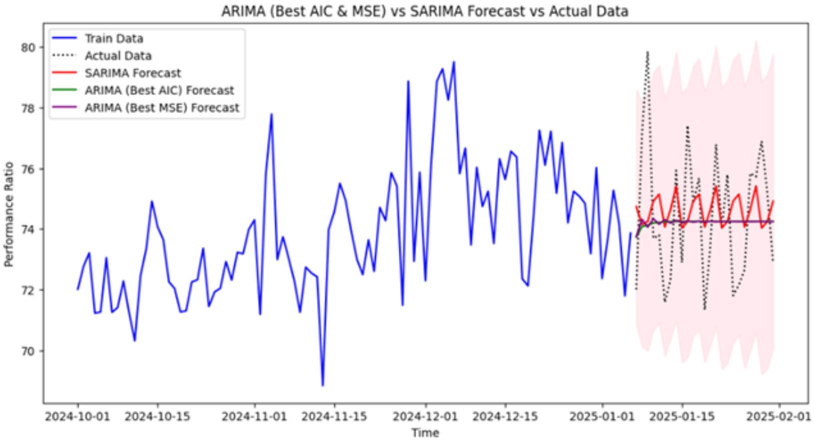
In addition, to ensure that the method used is optimal, a comparison of the prediction accuracy between the ARIMA and SARIMA models was conducted, based on MSE, RMSE, and MAPE, as shown in Table 12 below.

Table 12 Hasil Evaluasi ARIMA vs SARIMA

Model	MSE	RMSE	MAPE
ARIMA	4.753	2.180	2.48%
ARIMA	4.727	2.174	2.47%
SARIMA	4.928	2.220	2.46%

The evaluation results show that the ARIMA model has MSE values of 4.753 and 4.727, with corresponding RMSE values of 2.180 and 2.174. Meanwhile, the SARIMA model has an MSE of 4.928 and an RMSE of 2.220. Based on RMSE and MSE alone, ARIMA appears to perform better.
However, the MAPE of SARIMA is lower (2.46%) compared to ARIMA (2.48% and 2.47%), indicating that SARIMA has a smaller relative error in predicting PR values.

Figure 5 Visualisasi Hasil ARIMA dan SARIMA



This aligns with the results shown in Figure 5, which illustrates that ARIMA is not as effective as SARIMA in capturing seasonal patterns. Therefore, although ARIMA has slightly lower RMSE and MSE, SARIMA is still selected in this study because it better captures the seasonal patterns in the PR data and has lower relative error on a percentage scale. Even though the SARIMA model has produced reasonably good predictions, there are still anomalies and overestimations on certain days. This suggests that while the model can be used for short-term forecasting, there is still room for further optimization to improve its accuracy, particularly in handling external factors that influence PR.

4. Conclusion

Based on the analysis, the average Performance Ratio (PR) ranges between 72–75%, with some days reaching over 77%, especially in early to mid-December. Despite daily fluctuations, the PR trend shows an increase in December, although actual production tends to be lower than expected due to weather factors, system efficiency, or operational disturbances. The Augmented Dickey-Fuller test confirmed that the data is stationary without requiring additional transformation. Forecasting results using the SARIMA model show that predicted PR values range from 72.85 to 76.57, with a moderate uncertainty margin of approximately ±4–5 units. The model effectively captures seasonal patterns and historical trends, producing relatively small errors (0.14%–7.67%) and the highest accuracy on February 19, 2025, with an error of only 0.14%. Evaluation metrics such as MAE, RMSE, and MAPE were used to measure model performance. Although SARIMA is effective in predicting PR, the model does not account for external factors such as weather and environmental conditions that may affect solar power system performance. Therefore, ARIMA-based methods are more suitable for short- to medium-term forecasting, especially if the PR pattern is relatively stable and not significantly influenced by unpredictable external factors.

To improve accuracy and understanding of seasonal patterns, it is recommended to use a larger sample size, ideally covering a 2–5 year period. Furthermore, integrating forecasting methods with other techniques such as Random Forest (RF) or Support Vector Regression (SVR) may yield more robust results. Lastly, data visualization using Power BI will facilitate better interpretation and effective presentation of forecasting results.

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