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Solar power forecasting using a SARIMA approach for Indonesia's grid integration

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ABSTRACT

Indonesia’s transition toward a renewable energy-dominated power grid is progressing to meet increasing energy demands while reducing dependence on fossil fuels. According to the National Energy General Plan, their goal is to have 23% of the energy mix come from renewables by 2025 and 31% by 2050. Accurate forecasting of photovoltaic (PV) power output is crucial to address the intermittent nature of solar energy and ensure grid stability. A seasonal autoregressive integrated moving average (SARIMA) model was developed to estimate day-ahead photovoltaic power output in Padang City, Indonesia. Using NASA solar irradiance data from March 1-31, 2024, the SARIMA(1,0,1)(4,0,3)24 model achieved high accuracy with an NRMSE of 4.19%. To evaluate its performance, a comparative evaluation was conducted between the SARIMA model and two machine learning methods, namely artificial neural network (ANN) and long short-term memory (LSTM), in which SARIMA achieved the lowest forecasting error. These findings indicate that SARIMA remains an effective and interpretable statistical method for short-term PV forecasting, supporting reliable energy planning and power grid operations towards Indonesia's renewable energy goals.

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1. INTRODUCTION

Indonesia is currently going through a change in its energy sector as it works to meet the increasing demand for energy while reducing its reliance on fuels. The National Energy General Plan of Indonesia has set goals for energy to make up 23 percent of the energy mix by 2025 and 31 percent by 2050 [1], [2]. This transition is important not for the environment but for ensuring a stable energy supply and boosting economic growth as fossil fuel sources shrink [3], [4]. Owing to its geographical advantage, Indonesia possesses abundant solar and wind resources that can significantly contribute to achieving these national energy goals.

However, integrating renewable energy sources into the national grid faces several challenges due to their variable and irregular nature [5]-[7]. Accurate short-term forecasting of renewable energy production, particularly from solar photovoltaic (PV) systems, is critical for maintaining grid reliability and optimizing dispatching operations [7], [8]. Reliable forecasts enable grid operators to anticipate fluctuations in electricity generation, minimize reliance on fossil fuel reserves, and improve system planning efficiency [9], [10]. Recent developments in artificial intelligence and machine learning techniques have significantly enhanced forecasting accuracy and operational efficiency in renewable energy systems [11], [12]. However, many AI-based models require extensive training data and high computational effort, which can limit their application in regions with limited data availability or resources.

The seasonal autoregressive integrated moving average (SARIMA) model represents a practical and transparent approach for daily photovoltaic power forecasting, as it is capable of effectively capturing periodic and seasonal patterns in solar power generation data [13], [14]. Its ability to model recurring fluctuations in solar intensity makes it particularly effective for regions with distinctive climatic variations, such as Indonesia [4], [15].

The SARIMA framework combines seasonal differencing with autoregressive and moving average components to represent these periodic variations accurately [16], [17]. This feature is crucial because several studies have shown that ignoring seasonality can lead to significant forecasting errors in renewable energy applications, including PV systems [18], [19]. By effectively accounting for seasonal effects, SARIMA can deliver more dependable day-ahead forecasts than methods that overlook such dynamics [20], [21]. This study proposes a SARIMA-based framework for day-ahead PV power forecasting to support grid stability and renewable energy integration in Indonesia. Although many studies have investigated PV power forecasting, direct comparisons between SARIMA, artificial neural network (ANN), and long short-term memory (LSTM) using limited irradiance data are still limited. The main contributions of this study are: i) the development of a SARIMA-based daily PV power forecasting model, ii) a comparative evaluation of ANN and LSTM approaches, and iii) validation using actual solar irradiance data from Padang City, Indonesia. The findings of this study are expected to support Indonesia's renewable energy roadmap by improving the accuracy of short-term PV power forecasting and strengthening the reliability of the electricity grid under limited data conditions.

2. METHOD

This study focuses on forecasting solar irradiance data using the SARIMA model based on time series analysis. The electrical power generated by PV units is highly dependent on the level of solar irradiance received by the PV modules, as stated in (1) [22].

$$P_{PV}(S) = \begin{cases} P_{pvn}\frac{S^2}{S_{stc}R_c}\ for\ S < R_c \\ P_{pvn}\frac{S}{S_{stc}}\ for\ S \geq R_c \end{cases} \tag{1}$$

P_{Pvn} is the nominal power output of the PV unit. S refers to the solar irradiance incident on the PV module. S_{stc} is the solar irradiance under standard testing conditions, and R_c is a particular irradiance point. The connected solar PV generator has a rated power of 25 megawatts. The standard test condition for solar irradiance (S_{stc}) is set to 1000 w/m^2, and the specific irradiance point (R_c) is set to 120 w/m^2.

The data used in this study were obtained from NASA's historical records of solar radiation in the city of Padang, located at coordinates Latitude –0.8983 and Longitude 100.3495, as shown in Figure 1. Hourly solar radiation data (24 data points per day) were collected from March 1 to March 31, 2024. The data set has been verified to contain no missing or abnormal values, ensuring consistency and reliability throughout the observation period.

Figure 1. Solar radiation map of Padang City as the study area [23]

Using (1), historical PV output power was calculated and presented in Figure 2. The observed pattern shows clear daily and seasonal characteristics, with solar radiation intensity increasing after sunrise, peaking at midday, and decreasing towards sunset. These characteristics justify the application of the SARIMA model for day-ahead PV power forecasting. A summary of the dataset characteristics and PV system configuration is given in Table 1.

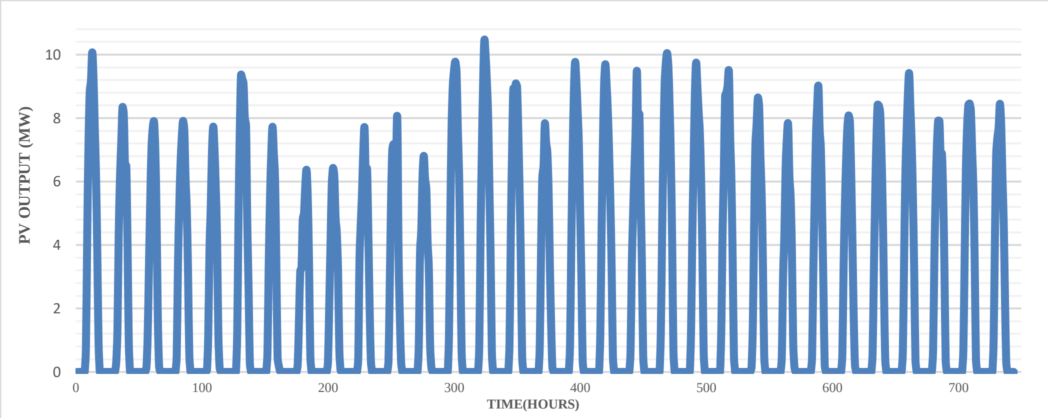

Figure 2. Historical data PV power output

Table 1. Dataset characteristics and PV system configuration

Parameter	Value
Location	Padang City, Indonesia
Latitude	–0.8983º
Longitude	100.3495º
Period	March 1–31, 2024
Sampling interval	1 hour
Installed PV capacity	25 MWp

The SARIMA model uses an autoregressive approach to forecast future values based on past observations. By incorporating seasonal components, this model extends the ARIMA framework and becomes well-suited for time series data with recurring patterns and periodic fluctuations. This capability is particularly important for applications such as load demand, weather, and renewable energy forecasting, where seasonal variations strongly affect system dynamics [24], [25]. The SARIMA model in mathematical formulation is given by (2).

$$\phi_p(B)\phi_P(B^S)(1-B)^d(1-B^S)^D y_t = \theta_{q(B)}\Theta_Q(B^S)\varepsilon_t \quad (2)$$

Where: Φ is AR parameter order p, θ is the MA order q, and Θ is the seasonal MA order q. Forecasting using seasonal ARIMA can be obtained from four main stages: identification, estimation, diagnostic checking, and forecasting. Steps for applying the seasonal ARIMA method to day-ahead forecasting for PV power output are shown in Figure 3.

To assess forecasting accuracy, the SARIMA model was benchmarked against ANN and LSTM under limited data conditions using three performance metrics: mean absolute error (MAE), root mean square error (RMSE), and normalized root mean square error (NRMSE), defined as (3)-(5) [26].

$$MAE(t) = \frac{1}{n}\sum_{t=1}^{n}|P_{dev}(t)| \quad (3)$$

$$RMSE(t) = \sqrt{\left(\frac{1}{n}\sum_{t=1}^{n}|P_{dev}^2(t)|\right)} \quad (4)$$

$$NRMSE = \frac{RMSE}{P_{Max}-P_{min}} \times 100\% \quad (5)$$

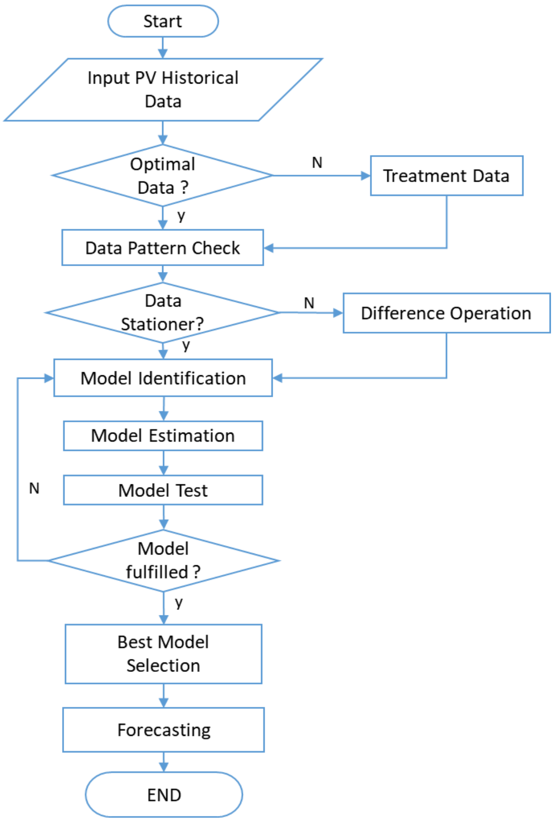

Figure 3. Workflow of the SARIMA model illustrating the steps for day-ahead PV power forecasting

3. RESULTS AND DISCUSSION
3.1. Stationarity and model identification
From Figure 2, it can be observed that the PV power output data shows a clear and recurring daily seasonal pattern at a fixed 24-hour interval. Therefore, the ARIMA model applied in this study uses a Seasonal ARIMA (SARIMA) structure. The development of a SARIMA forecasting model begins with an analysis of the time series characteristics to assess data stationarity, where statistical properties such as the mean, variance, and autocorrelation remain constant over time. This property is crucial for ensuring that the SARIMA model produces reliable forecasts and avoids incorrect regression results.

Stationarity was evaluated using the augmented Dickey–Fuller (ADF) test applied to the PV power output data. As reported in Table 2, the p-value is below 0.05, and the test statistic is lower than the critical value, indicating that the series is stationary and appropriate for subsequent modeling.

The autocorrelation function (ACF) and partial autocorrelation function (PACF) were subsequently examined to determine the appropriate model orders, as illustrated in Figures 4 and 5, respectively. These graphs show a clear seasonal pattern with a 24-hour period, consistent with the daily solar radiation cycle. Based on these observations, a seasonal ARIMA model is considered suitable for capturing both the trend and the recurring daily seasonality in the PV power output data.

Table 2. Augmented Dickey-Fuller (ADF) result

p-value	Test Statistic	Critical value	Conclusion
0.001	-4.2204	-1.9413	stationer

3.2. SARIMA model estimation and forecast result
After confirming the stationarity of the dataset, several candidate SARIMA configurations were tested to determine the most suitable model for PV power forecasting. The model identification process involved evaluating different combinations of parameters in the form of SARIMA(p,d,q)(P,D,Q)s, where s=24 represents the hourly seasonal period.

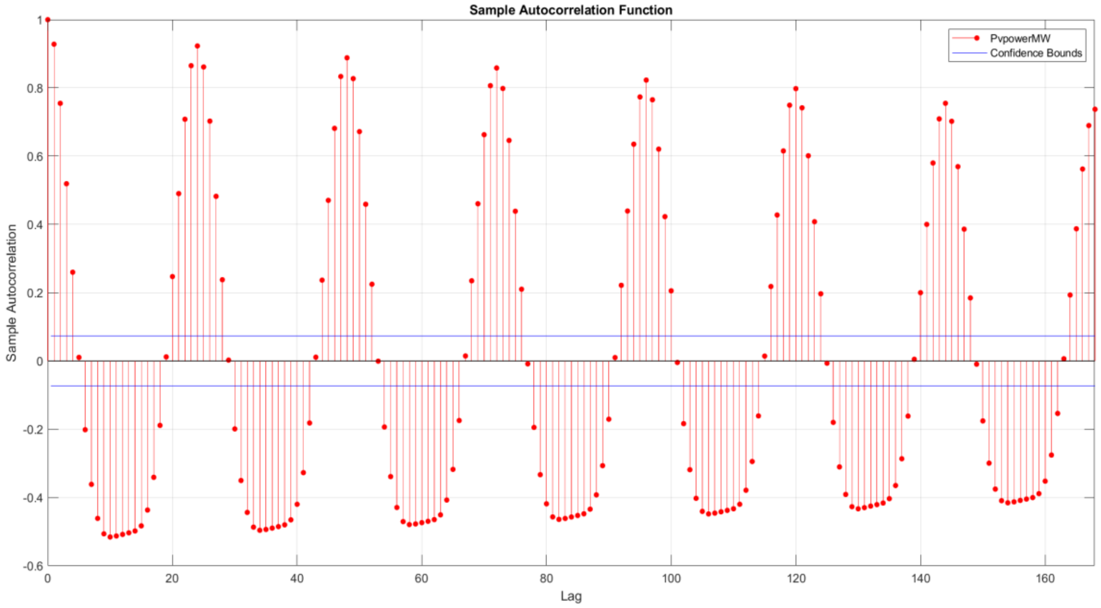

Figure 4. Autocorrection function

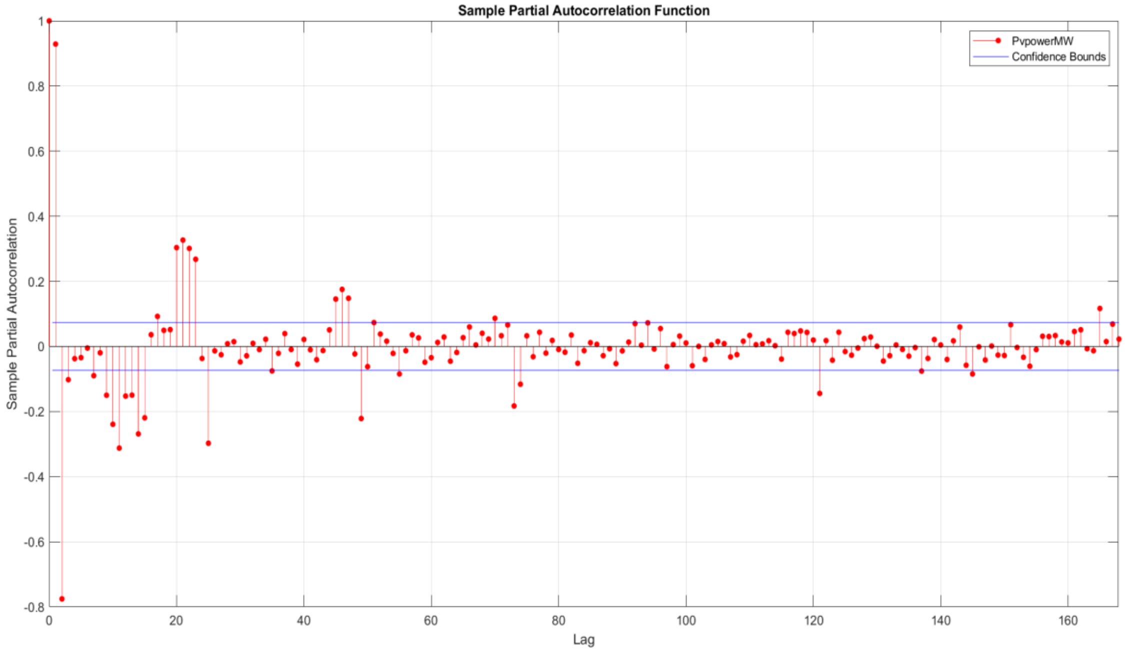

Figure 5. Partial autocorrection function

The optimal model was selected using the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), where lower values indicate a better balance between goodness of fit and model complexity. The analysis of the autocorrection function and partial autocorrection function indicates the potential for model development and testing, as illustrated in Table 3.

Based on the model comparison, the SARIMA(1,0,1)(4,0,3)$_{24}$ configuration was chosen as the optimal model due to its lowest AIC and BIC values. The estimated model parameters are summarized as follows:

- Non-seasonal AR (p=1): 0.788
- Non-seasonal MA (q=1): 0.073
- Seasonal AR (P=4): {-1.237, -0.833, -0.052, -0.047}
- Seasonal MA (Q=3): {0.438, -0.175, -0.650}

These parameters indicate a strong influence of seasonal autoregressive and moving average components, consistent with the 24-hour periodic behavior of solar radiation. Figure 6 shows the results of the model fitting, demonstrating a good fit between the historical PV power data and the adjusted values. The SARIMA model accurately tracks daily variations in solar irradiance and captures peak and off-peak behavior with minimal deviation.

The residual analysis indicates that the SARIMA residuals are randomly distributed around zero with no evident pattern, suggesting that the model adequately captures the underlying temporal structure of the PV power series. The residual variance remains approximately constant, indicating homoscedasticity, and the symmetric distribution around zero implies the absence of systematic bias. These results confirm the suitability of the SARIMA model for short-term PV power forecasting.

Table 3. Test result estimated the seasonal Arima model

Model	Test result	Akaike information criterion (AIC)	Bayesian information criterion (BIC)
$(1,0,1)(4,0,3)_{24}$	P: 121 D: 0 Q: 73 Constant: 0.00191057 AR: {0.788084} at lag [1] SAR: {-1.23696 -0.833146 -0.0519581 -0.0469967} at lags [24 48 72 96] MA: {0.073504} at lag [1] SMA: {0.437898 -0.174916 -0.649917} at lags [24 48 72] Seasonality: 24 Variance: 0.178295	850.4916	899.2717
$(1,0,1)(3,0,2)_{24}$	P: 97 D: 0 Q: 49 Constant: -0.00112977 AR: {0.790112} at lag [1] SAR: {-0.798565 -0.10543 -0.00526306} at lags [24 48 72] MA: {0.0744015} at lag [1] SMA: {-0.0416654 -0.53733} at lags [24 48] Seasonality: 24 Variance: 0.195327	914.3702	954.6213
$(1,0,1)(2,0,1)_{24}$	P: 73 D: 0 Q: 25 Constant: -0.00245291 AR: {0.799728} at lag [1] SAR: {-0.153214 -0.110092} at lags [24 48] MA: {0.0837639} at lag [1] SMA: {-0.699712} at lag [24] Seasonality: 24 Variance: 0.200336	929.2080	960.7694
$(1,0,1)(1,0,1)_{24}$	P: 49 D: 0 Q: 25 Constant: -0.00203189 AR: {0.801619} at lag [1] SAR: {-0.0799361} at lag [24] MA: {0.0802372} at lag [1] SMA: {-0.768562} at lag [24] Seasonality: 24 Variance: 0.201554	929.0535	956.5206

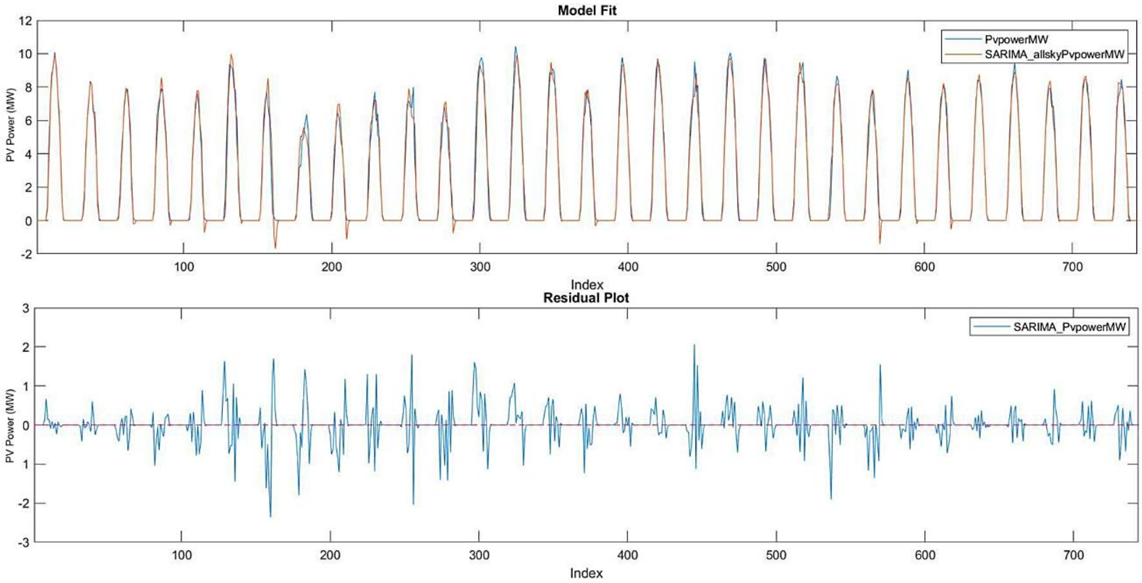

Figure 6. Estimated best seasonal ARIMA model

The day-ahead PV power forecast for April 1, 2024, is presented in Table 4 and visualized in Figure 7. The forecast indicates a characteristic diurnal pattern: power production begins to increase after sunrise (around 06:00), reaches its peak at midday, and gradually declines in the afternoon. The predicted maximum power output is 8.55 MW at 12:00 noon, corresponding to the highest solar radiation of the day.

Table 4. Day-ahead forecast result

Hours	0	1	2	3	4	5	6	7	8	9	10	11
PV power (MW)	0.003	0.005	0.007	0.009	0.010	0.011	0.019	0.750	3.512	5.894	7.373	8.188
Hours	12	13	14	15	16	17	18	19	20	21	22	23
PV power (MW)	8.550	7.876	6.797	5.194	2.823	0.374	0.015	0.014	0.014	0.014	0.014	0.014

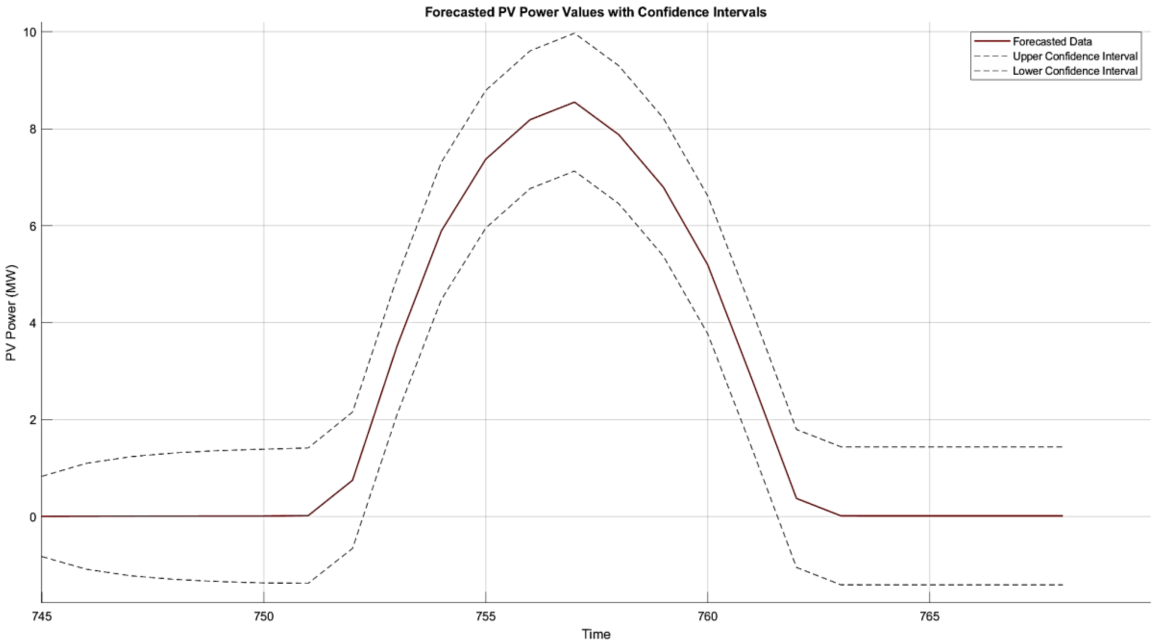

Figure 7. Forecast PV power output from the best model of seasonal ARIMA

3.3. Forecasting model evaluation and comparison

The SARIMA model parameters were selected based on the lowest AIC and BIC values, resulting in the optimal SARIMA configuration (1,0,1) $(4,0,3)_{24}$. This study employs a hold-out validation approach, where the SARIMA model is trained using solar irradiance data from March 1 to 30, 2024, and then tested using actual PV power data on March 31, 2024. This approach serves as a one-step-ahead forecasting validation equivalent to the first fold of a rolling cross-validation scheme. To further assess the robustness of the SARIMA model, two machine learning approaches, namely ANN and LSTM, were implemented using the same dataset. The ANN was designed as a feedforward network with two hidden layers of 50 and 25 neurons, while the LSTM architecture comprised a sequence input layer, an LSTM layer with 200 hidden units, a fully connected layer, and a regression output layer. Model performance was evaluated using MAE, RMSE, and NRMSE metrics.

A comparison of the actual PV power generated on March 31, 2024, with the forecasted results from SARIMA, ANN, and LSTM models is illustrated in Figure 8. Actual data shows a clear daily pattern, where electricity generation starts around 7:00 a.m., peaks around midday, and gradually declines to zero at night. All three models are able to capture this general trend, albeit with varying degrees of accuracy. The SARIMA model yields results that are remarkably close to the actual values, particularly during the morning increase and the evening decrease, demonstrating its ability to represent seasonal patterns accurately. The ANN model provides slightly higher estimates during peak periods, but still follows the actual pattern relatively well, demonstrating its ability to model nonlinear characteristics even with limited data. In contrast, the LSTM model exhibits a tendency to overestimate PV output during daytime hours, particularly between 07:00 and 14:00, with deviations exceeding 4–6 MW. This behavior is consistent with the quantitative results reported in Table 5.

Figure 8 and Table 5 show that the SARIMA model achieves superior short-term forecasting accuracy compared with ANN and LSTM, particularly under limited data conditions. While ANN attains moderate performance, LSTM exhibits lower accuracy, indicating its dependence on large training datasets. These results directly address the research gap identified in the Introduction by confirming that classical statistical models such as SARIMA can outperform more complex neural architectures for short-term PV power forecasting in data-constrained environments. Although most recent studies in Indonesia focus on machine learning-based PV forecasting, the results of this study show that statistical models with explicit seasonal structures, such as SARIMA, remain highly relevant for short-term forecasting tasks, especially when historical data availability is limited. Based on the forecasting results obtained, the SARIMA-based framework can support network operators in improving daily dispatching planning, reducing reserve margins, and minimizing dependence on fossil fuel-based power plants. This capability is highly relevant to the Indonesian power system, where enhanced accuracy in PV forecasting is essential for sustaining grid reliability amid increasing renewable energy penetration.

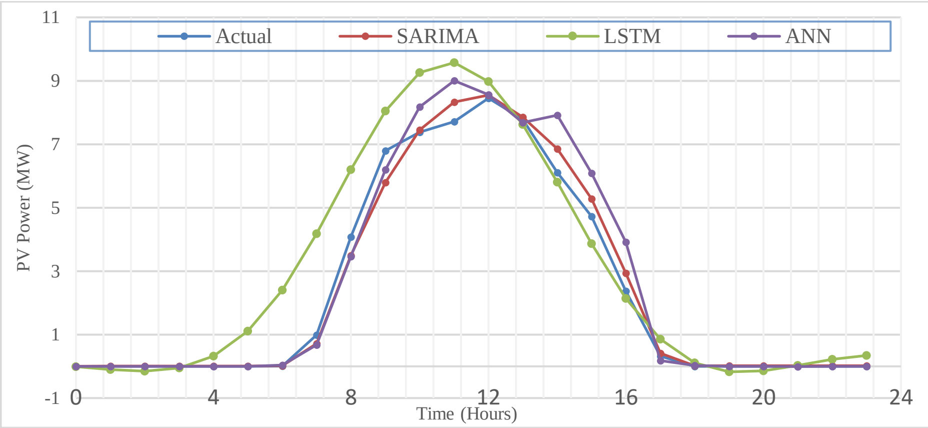

Figure 8. Comparison of actual and forecasted PV power output using SARIMA, ANN, and LSTM models under limited data conditions

Table 5. Comparison of forecasting accuracy metrics

Model	MAE (MW)	RMSE (MW)	NRMSE (%)
SARIMA(1,0,1)(4,0,3)$_{24}$	0.2016	0.3544	4.1925
ANN	0.3645	0.6669	7.8897
LSTM	0.7533	1.1552	13.6657

4. CONCLUSION

This study developed a SARIMA-based model for forecasting PV solar power one day in advance in the city of Padang. The optimal SARIMA model (1,0,1) (4,0,3)$_{24}$ configuration effectively captures seasonal variations in solar irradiance using data from Padang City and demonstrates high forecasting accuracy. The proposed model achieved an NRMSE of 4.19%, outperforming the ANN and LSTM models, which recorded NRMSE values of 7.89% and 13.67%, respectively. These results confirm that SARIMA provides a more consistent and stable forecasting performance under limited data conditions, offering a practical and transparent solution for short-term PV power prediction in support of renewable energy integration. Despite these promising results, the SARIMA model is inherently linear, and this study relies on one month of historical data, which may limit generalizability. Future work will extend the analysis to multiple Indonesian regions, incorporate longer datasets, and investigate hybrid SARIMA–machine learning models with uncertainty quantification to further enhance forecasting reliability and grid operation support.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Syafii		✓	✓			✓		✓	✓	✓	✓	✓	✓	✓
Aulia	✓		✓	✓			✓			✓			✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [S], upon reasonable request.

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