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Hybrid Time-Series Approaches for PV Power Prediction: Evaluating SARIMAX and Generative Model

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Abstract

Forecasting the output power of photovoltaic (PV) systems is crucial in managing renewable energy efficiently and sustainably. The availability of historical data and environmental variables, such as temperature and humidity, greatly influences prediction accuracy. However, in practice, historical data is often incomplete due to technical constraints or limited monitoring infrastructure, which results in decreased prediction quality and system efficiency. To overcome these challenges, this study proposed a comparative approach between two predictive models, namely SARIMAX (Seasonal AutoRegressive Integrated Moving Average with eXogenous variables) as a classical statistical model, and WGAN-GP (Wasserstein Generative Adversarial Network with Gradient Penalty) as a generative deep learning model designed to handle incomplete data and capture nonlinear relationships. The datasets included PV power output from the monitoring system at Universitas Kristen Immanuel (UKRIM) Yogyakarta, along with temperature and humidity data from the Kalitirto weather station in Sleman, Yogyakarta. The research was conducted through several stages, namely: data collection, pre-processing, model training, and evaluation using MAE, MSE, RMSE, and MAPE metrics. The results show that the SARIMAX model using the Time-Series Cross-Validation (TSCV) achieves the best numerical performance (MAE = 0.085; RMSE = 0.145). However, this model fails to represent daily patterns realistically. In contrast, both the standard SARIMAX and WGAN-GP models are more consistent in representing seasonal patterns and daily fluctuations, even though their prediction errors were slightly higher in terms of numerical metrics. The findings advance scientific understanding of hybrid forecasting models and offer practical implications for improving energy reliability and decision-making in data-constrained environments.

Keywords : *Missing data, SARIMAX, Solar energy forecasting, Time-series cross validation, WGAN-GP.*

1. INTRODUCTION

The global transition toward clean energy [1], [2] has driven a significant increase in the utilization of renewable energy sources, particularly solar energy, which offers environmentally friendly and sustainable solutions. Photovoltaic (PV) systems have emerged as a key component in this effort due to their ability to generate electricity from solar radiation[3]. To ensure efficient management and integration of solar energy systems into the electrical grid, accurate forecasting of PV power output is essential[4], [5]. This predictive information supports load scheduling, energy storage management, and real-time power distribution planning. However, a major challenge in PV power forecasting lies in its strong dependence on dynamic weather conditions, as well as limitations in historical data, especially in regions with underdeveloped monitoring infrastructure[6].

Various approaches have been developed to address these challenges, ranging from classical statistical models to deep learning-based methods. One of the most commonly used statistical models is

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the SARIMAX, due to its ability to accommodate seasonal patterns and incorporate exogenous variables, such as weather data[7], [8]. This model is also favored for its long-term stability and interpretability[9]. For example, Kachalla et al.[7] developed a SARIMAX-MLP framework that demonstrated strong performance in forecasting energy output for residential microgrids. Sultana[8] compared the performance of LSTM, NARX, and SARIMAX models and found that LSTM outperformed the others in multi-step forecasting scenarios, particularly in handling complex temporal patterns.

Haider et al. [10]conducted a comparative study involving SARIMAX, Prophet, Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), and LSTM models for forecasting Global Horizontal Irradiance (GHI). The results indicated that SARIMAX performed more reliably for long-term forecasting, whereas LSTM, ANN, and CNN were better suited for short-term prediction. In addition, Kim et al. [6] also utilized ARIMA, SARIMA, SARIMAX, and LSTM approaches to predict photovoltaic energy generation, and found that LSTM produced the least accurate results among the models tested. Further research by Abuzaid et al.[9], emphasized that the combination of statistical models with machine learning techniques can lead to more accurate predictions across different forecasting horizons. For instance, Lee and Cho developed a hybrid model that integrates SARIMAX with ANN, Support Vector Regression (SVR), and LSTM. This combination outperformed standalone SARIMAX in capturing nonlinear patterns and detecting data anomalies that were not detected by ordinary linear models[11].

In the context of incomplete data and complex data distributions, WGAN-GP-based generative approaches have begun to gain significant attention. Liu et al.[12] developed a WGAN model to predict PV output during rainy conditions, where solar radiation variability is particularly high. Park et al.[13] combined an autoencoder with WGAN-GP to generate synthetic PV data, which proved beneficial for improving model training quality. Additionally, this method has also been applied to synthesize wind speed data[14], [15] either independently or in combination with BiLSTM and CNN models[16]. Its application has even been extended to battery-based household energy management systems, as demonstrated by Mansour et al.[17], highlighting the potential of generative models in optimizing energy consumption and load control. Beyond the energy sector, WGAN-GP has been effectively applied in related domains, including battery state-of-charge (SOC) estimation[18] fault detection in solar panels[19], and failure prediction in pumping systems[20]. These developments indicate that generative models offer high flexibility in handling incomplete datasets and enhancing training scenarios in various smart energy applications.

However, there is a gap in the existing literature. Most studies still focus primarily on short-term numerical accuracy without thoroughly evaluating the models, ability to reconstruct seasonal patterns and realistic fluctuations. Studies that combine statistical analysis, such as SARIMAX, with generative models such as WGAN-GP for PV forecasting under conditions of missing data are still very limited. Therefore, this study aims to address this gap through an evaluative approach that considers both numerical prediction accuracy and the fidelity of seasonal pattern reconstruction in the forecast results.

This research seeks to evaluate and compare the performance of SARIMAX and WGAN-GP models in forecasting PV power output under conditions of incomplete historical data and limited local weather variables. The case study was conducted on the PV system at UKRIM, which experienced data loss between December 2023 and February 2024. The researchers used weather data from the Kalitirto station as an exogenous input. The main contributions of this study include: (1) the integration of statistical and generative methods within a limited data scenario, and (2) an empirical analysis of the predictive capabilities and temporal pattern reconstruction of both models.

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2. METHOD

This study aims to develop a predictive framework for forecasting photovoltaic (PV) system power output based on statistical and deep learning approaches. The primary focus lies in the application and comparison of two methods with distinct yet complementary characteristics, namely SARIMAX, representing a classical statistical approach, and WGAN-GP, representing a generative deep learning method. The proposed framework consists of five main stages: (1) data collection, (2) data preprocessing, (3) model development, (4) performance evaluation, and (5) result validation as shown in the Figure 1.

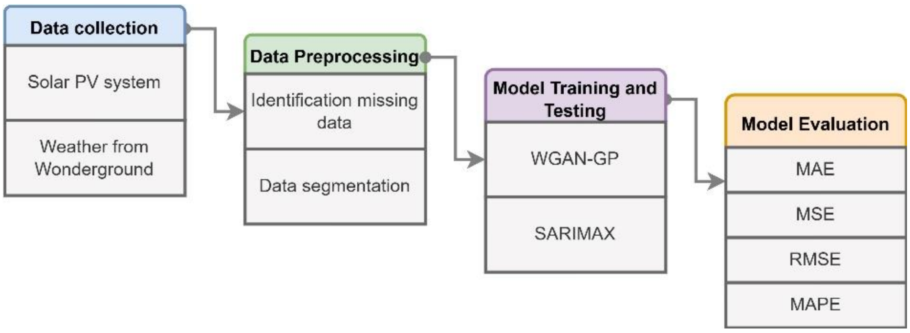

Figure 1. The stages of research

2.1. Data Collection.

The first stage of this study involved collecting data from two primary sources. Energy output data from the solar panel system was obtained via the Huawei Fusion Solar platform, which was used to monitor energy production from the PV system installed at Universitas Kristen Immanuel (UKRIM). The second source was weather data retrieved from the Wunderground application, specifically from the Kalitirto Sleman station, Yogyakarta (https://www.wunderground.com/weather/id/sleman/ISLEMA43).

The dataset spanned the period from May 18, 2023, to September 6, 2024. From the Fusion platform, daily electricity production data were collected in kilowatt-hours (kWh). Meanwhile, from Wunderground, temperature and humidity data were obtained and used as exogenous variables in the prediction models.

2.2. Data Pre-processing

Missing data identification was a significant step in this stage. It was performed by visualizing the dataset using time series plots to detect anomalies or data gaps. Following this, the data were segmented into two parts, namely pre-gap (before the missing data period) and post-gap (after the missing data period). This segmentation was crucial to ensure that model training and evaluation were conducted appropriately according to the temporal structure of the dataset.

2.3. Model Development of SARIMAX and WGAN-GP

2.3.1. SARIMAX Model

The development of the SARIMAX model is carried out in several stages. First, the optimal combination of hyperparameters is determined, specifically (p, d, q) for the ARIMA component [21]and (P, D, Q, s) for the seasonal component. The selection is performed using a minimization approach based on the Akaike Information Criterion (AIC)[22], as shown in Equation (1):

$$AIC = 2k - 2ln(L) \quad (1)$$

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where:
k is the number of parameters in the model,
L is the likelihood of the estimated model.

Once the optimal parameter combination is obtained, the model is trained using the pre-gap data. Validation is performed using the TSCV approach without shuffling to preserve the temporal structure of the data[23].

2.3.2. WGAN-GP Model

To overcome the challenges posed by incomplete data and enhance the variability of input data, the WGAN-GP generative deep learning model is employed. This model is designed to generate realistic synthetic data that closely approximates the distribution of the original data. This model employs the loss function in the training stage as shown in Equation (2):

$$L(D) = -E_{x\sim Pdata}D(x) + E_{z\sim Pz}D(G(z)) + \lambda E_{\hat{x}\sim P\hat{x}}(\|\nabla D(\hat{x}\|_2 - 1)^2 \quad (2)$$

where:
$E_{x\sim Pdata}D(x)$ is real data score
$E_{z\sim Pz}D(G(z))$ is fake data score
$\lambda E_{\hat{x}\sim P\hat{x}}(\|\nabla D(\hat{x}\|_2 - 1)^2$ is gradient penalty

The core architecture of the WGAN-GP model consists of two neural networks, namely a generator and a discriminator. The generator produces new data samples, while the discriminator evaluates whether these samples resemble real data. The model is trained iteratively by adding a gradient penalty term to ensure training stability and prevent mode collapse.

A general overview of the WGAN-GP architecture [24] is illustrated in Figure 2.

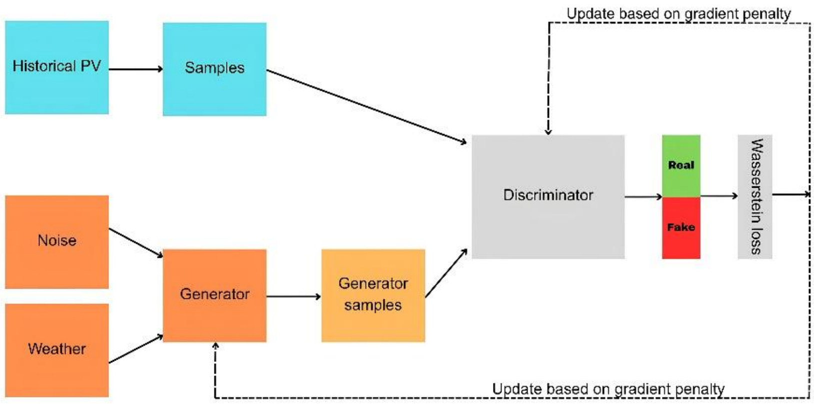

Figure 2. The architecture of the WGAN-GP Model

2.4. Model Performance Evaluation

The predictive performance of both models were evaluated using four common metrics in time series analysis: MAE (Mean Absolute Error) as in (2), MSE (Mean Squared Error) as in (3), RMSE (Root Mean Squared Error) as in (4), and MAPE as in (5) [25]. These metrics are calculated using the Equation (3), (4), (5), and (6):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (3)$$

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$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (4)$$

$$RMSE = \sqrt{MSE} \quad (5)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100\% \quad (6)$$

Description:

n = number of data,
y_i = actual value,
$\hat{y}_i$ = predictive value.

2.5. Validation and interpretation

In addition to evaluation based on numerical metrics, researchers also conducted visual validation of the distribution of predicted results. The distribution of prediction results regarding SARIMAX and SARIMAX with TSCV, WGAN-GP were compared with actual data using time-series plot. For synthetic data from WGAN-GP, this approach aims to determine the extent to which the generative model can mimic the real distribution pattern of the PV system output data. In addition, differences in daily and seasonal patterns were also analysed to assess the accuracy of the temporal structure of the predicted results.

3. RESULT AND ANALYSIS

This section presents the results of experiments conducted using two modeling approaches, namely SARIMAX and WGAN-GP, in predicting the power output of PV systems under data loss conditions. Analysis was conducted to evaluate the effectiveness of each model based on metrics of accuracy, prediction stability, and the ability to reconstruct missing data. In addition, visual and numerical comparisons between actual data and predicted results were also presented, in order to assess how well the model is able to capture seasonal patterns and the influence of exogenous variables.

3.1. PV and Weather Data

The daily data on solar panel energy production from 18 May 2023 to 6 September 2024 is shown in Figure 3, in kWh, which illustrates the pattern of actual energy output throughout that time span.

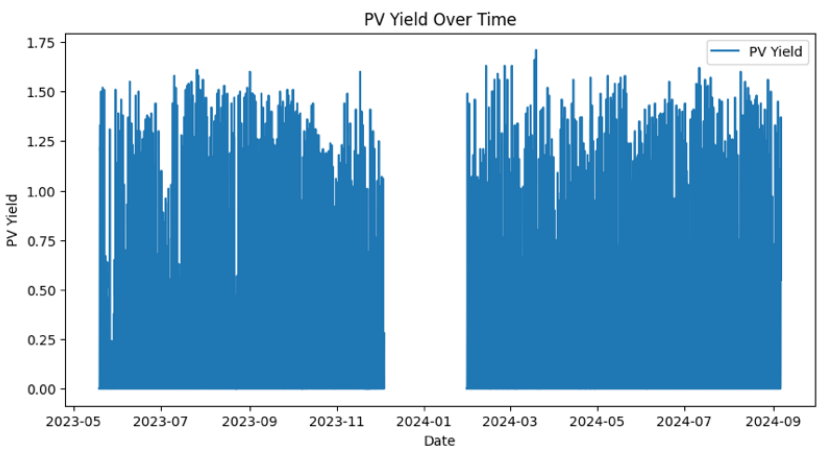

Figure 3. Dataset of daily records of energy production

Figure 3 shows a seasonal trend where energy production tends to be higher in the middle of the year, which coincides with the dry season in Yogyakarta. The graph also shows a significant data gap

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between December 2023 and February 2024, indicating data loss due to logging system constraints. After that period, the system recorded data consistently until September 2024. Sharp fluctuations in daily data reflect the influence of atmospheric conditions such as clouds, rain, or high humidity that inhibit the intensity of solar radiation.

The monitoring system at UKRIM does not record weather data directly, hence no meteorological information is available to analyse the relationship between weather conditions and energy production. To overcome these limitations, this study uses external weather data obtained through engineering web scraping from the Wunderground app. The data was taken from the nearest weather station, namely Kali Tirto station, Sleman, Yogyakarta, which is about 3 km from UKRIM. The data time range covered the period 18 May 2023 to 6 September 2024. The dataset is visualized in Figure 4.

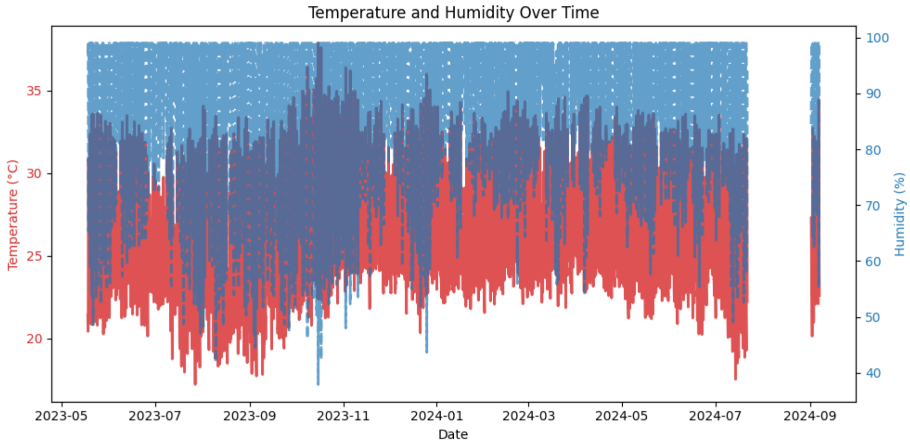

Figure 4. Plot of Temperature and Humidity Time Series from Wunderground Station

Figure 4 shows the fluctuations in temperature (in °C) and air humidity (in %) from May 2023 to September 2024. The daily temperature ranges 20-36°C with a gradually decreasing pattern from mid-2023 to mid-2024, while the humidity ranges from 40-100% and tends to increase in the rainy season (around late 2023 to early 2024). Both variables show high daily variability, which reflects the dynamics of tropical weather in Yogyakarta. The pattern of the relationship between temperature and humidity is inverse in general, where an increase in humidity is usually accompanied by a decrease in temperature, especially during the rainy season.

3.2. Experiment

3.2.1. Training and testing of SARIMAX model

SARIMAX Model is used in this study to predict the output power of solar panels (PV yield) by considering historical patterns and the influence of external variables such as temperature and humidity. At the initial stage, the process of selecting hyperparameters was carried out to explore various combinations of model parameters. The selection of the best combination was based on the minimization of the AIC value, which measured the balance between the complexity of the model and its predictive capabilities. Optimization results produce the best parameters as follows: (p, d, q) = (2, 0, 0) and (P, D, Q, s) = (1, 1, 1), with an AIC value of -4804.9959. Furthermore, SARIMAX models with these parameters were trained using pre-defined training data. After the training was completed, the model was tested using test data to evaluate its performance in predicting PV power. The results of the comparison between the predicted value and the actual data are shown in Figure 5 to assess the extent to which the model can represent the actual time pattern.

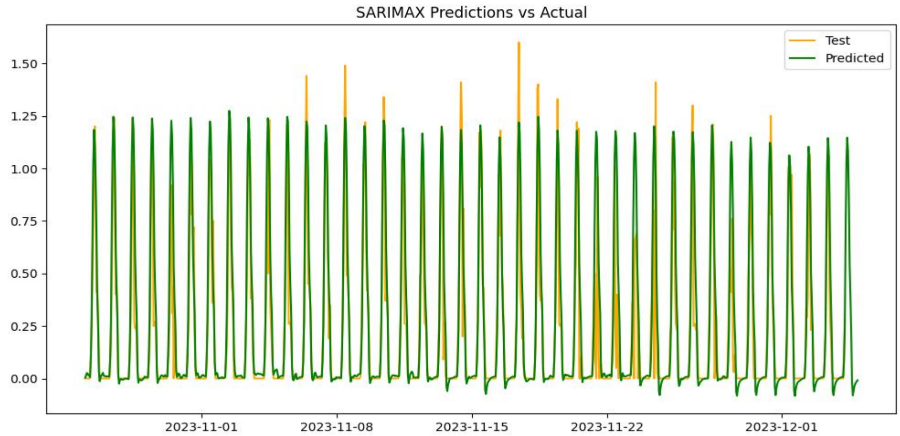

Figure 5. Prediction Results with SARIMAX

Figure 5 shows the predicted results PV yield using the SARIMAX model (green line) compared to the actual test data (yellow line) during the observation period between early November to early December 2023. The Model utilizes historical data as well as external variables such as temperature and humidity as additional predictors.

The predictive results of the SARIMAX model show the suitability of seasonal patterns and daily fluctuations are quite good against the actual data. The peak values consistently follow the shape of the actual curve, which shows that the model successfully captures the main trends and seasonal cycles of solar panel energy output.

However, there are some significant deviations on certain days, where the actual value is much higher than the predicted result. This is most likely due to weather anomalies such as cloudy clouds or rain causing extreme fluctuations, or sudden yield peaks due to unexpected sun exposure.

To assess the performance of the SARIMAX model in predicting the output power of solar panels, a quantitative evaluation was carried out using four main metrics, namely MAE, MSE, RMSE, and MAPE. The evaluation results are shown in Table 1.

Table 1. Evaluation of SARIMAX prediction

Model	MAE	MSE	RMSE	MAPE
SARIMAX	0.094	0.038	0.196	9.25

The results of the evaluation of sporadically occurring error patterns are also consistent with the high MAPE values shown in Table 1, which indicates that although the model is generally trend-accurate, there are inaccuracies at some extreme points. In addition, it appears that the SARIMAX model is quite stable in replicating repetitive daily patterns, which indicates its ability to understand the periodic cycle (seasonality) of PV yield data. This deemed SARIMAX suitable for use as a short-to medium-term predictive tool, especially for solar energy planning and monitoring needs. In addition, the performance of the SARIMAX model showed a fairly low prediction error rate on MAE and RMSE metrics, with values of 0.094 and 0.196, respectively. This shows that on average the absolute error of PV yield prediction is still within acceptable limits for data-driven energy monitoring or prediction system applications.

3.2.2. SARIMAX with TSCV

After obtaining the initial results, further optimization was carried out with TSCV to overcome potential bias in data sharing. The technique used is Expanding Window Validation. This approach helps

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the model become more robust to changes in trends in historical data, as well as more adaptive in the face of fluctuations in solar energy production due to external factors. Figure 6 shows the results of SARIMAX predictions by the method TSCV, which is compared with actual data to see how the model captures energy production patterns over time.

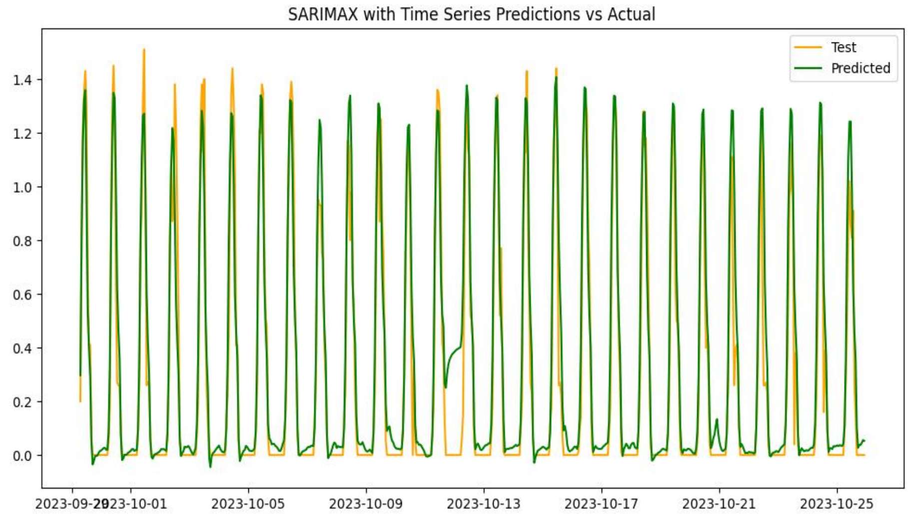

Figure 6 shows the prediction results PV yield using SARIMAX model with pure time series data integration without external variables.

The SARIMAX TSCV Model can mimic the daily pattern of PV yield quite accurately. It appears that the model's predictions follow a strong daily energy up-and-down pattern, indicating the model’s ability to study and replicate seasonal trends as well as daily cycles of solar energy. However, at some specific points, such as around 9-11 October, there were deviations in predictions from actual values, which were most likely caused by sudden changes in the weather or interruptions in observational data. Table 2 presents the results of the performance evaluation of the SARIMAX with TSCV model based on four evaluation metrics, namely MAE, MSE, RMSE, and MAPE. The use of TSCV aims to test the resilience of the model to new data not seen before, which reflects the ability of generalization in predicting PV yield more realistically.

Table 2. Sarimax Prediction Evaluation with TSCV

Model	MAE	MSE	RMSE	MAPE
SARIMAX with TSCV	0.085	0.021	0.145	9.63

The MAE value of 0.085 indicates that the average absolute error between the predicted result and the actual value is low, indicating a good prediction accuracy. The MSE value of 0.021 and RMSE of 0.145 are also quite small, indicating that the squared error that occurs in the prediction is relatively minimal and consistent. In addition, the MAPE value of 9.63% indicates that the prediction error in percentage terms to the actual value is below 10%, which in practice is considered to be very good accuracy for renewable energy forecasting models. Overall, the results show that the usage of TSCV in SARIMAX model training has successfully increased the reliability and prediction accuracy by minimizing overfitting to seasonal and temporal patterns in historical data.

3.2.3. Predictions of WGAN-GP

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After completing the training process, WGAN-GP was evaluated using testing dataset consisting of actual solar panel energy output (PV yield) data, along with relevant weather features, such as temperature and humidity. This evaluation aimed to assess the model's ability to predict the PV score based on the prior studied pattern. The prediction results were directly compared with the actual data to examine the accuracy level. Four common evaluation metrics in time series analysis, MAE, MSE, RMSE, and MAPE, were employed to quantitatively assess the model's performance. Figure 7 illustrates the visualization prediction result which shows that the model predictions (the green line) closely follow the actual values (yellow line) across most time points. In addition, the model is also able to capture seasonal patterns effectively, particularly during periods of high energy fluctuations. However, there are some deviations in certain segments, such as between indices 600 to 800, where the model struggles to track abrupt changes or noise in the actual data. This suggests that while WGAN-GP is proficient in reconstructing general patterns, it still encounters challenges when dealing with extreme dynamics or sudden perturbations in historical data.

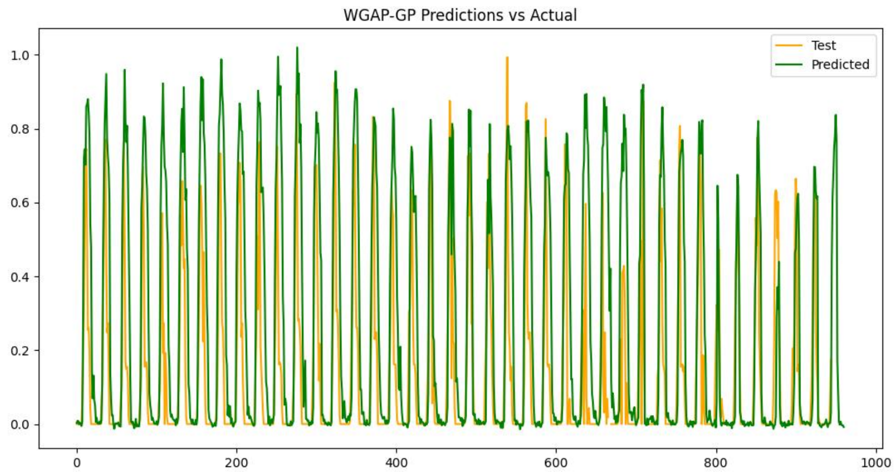

Figure 7 Performance of WGAN-GP model in predicting PV yield value against actual data

After the WGAN-GP model was trained, it was evaluated using a testing dataset comprising actual PV output data and relevant weather variables. A performance evaluation was then conducted to assess the model's accuracy, with the results presented in Table 3 below.

Table 3. Prediction Evaluation WGAN-GP

Model	MAE	MSE	RMSE	MAPE
WGAN-GP	0.161	0.071	0.267	1.79

The MAE value of 0.161 indicates that the average absolute error between the predicted and actual values is moderate, higher than the previous SARIMAX model. The MSE value of 0.071 and RMSE of 0.267 indicate that statistically, the squared error and root mean square error of the prediction are at an acceptable level. However, the MAPE value of 1.79% is very low and indicates that in percentage terms, the model prediction is very close to the actual value. This shows that although the absolute error is higher than SARIMAX, the WGAN-GP model is more stable in the context of relative error. The advantage of WGAN-GP lies in its ability to capture the structure seasonal patterns and daily fluctuation effectively, as well as reconstructing missing data realistically. These results shows that even though WGAN-GP model is not the best in terms of absolute numerical error, this model is very competitive in representing the general pattern of PV energy production. Thus, WGAN-GP is superior in scenarios with limited data or when pattern interpretation is the main priority, not just numerical accuracy.

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3.2.4. Forecast on missing period data

Figure 8 shows the daily forecast results for the missing data period using the SARIMAX, SARIMAX TSCV, and WGAN-GP methods. From the plot results, it can be seen that the SARIMAX and WGAN-GP methods show a more realistic pattern, where PV Yield production tends to be low in the morning, increases during the day, and decreases again in the afternoon, in accordance with the characteristics of solar energy production. However, the results obtained from SARIMAX TSCV show the opposite pattern, where PV Yield production is high in the morning and actually decreases during the day. This pattern contradicts the fact that sunlight intensity is usually maximum during the day, so energy production should also peak at that time. This indicates that the SARIMAX TSCV method fails to capture the daily pattern of PV Yield production well on a smaller time scale.

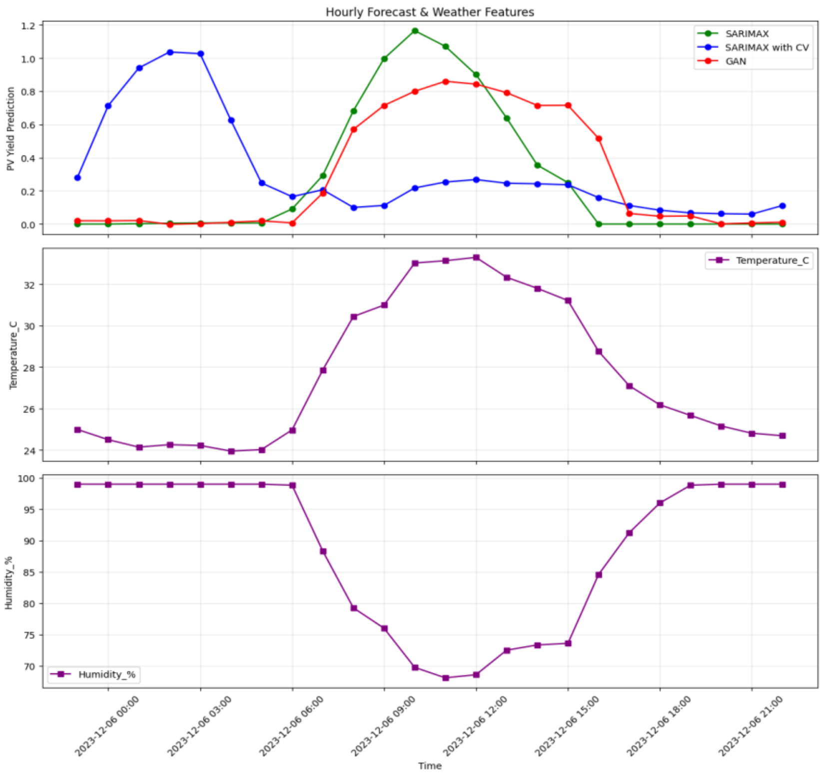

Figure 8 Daily forecast result graph of the model

4. DISCUSSIONS

4.1. Performance Comparison between Models

Comparison between three approaches, SARIMAX, SARIMAX with TSCV, and WGAN-GP, in this study was done to get more comprehensive understanding about each model performance in predicting photovoltaic system output power. Each model was evaluated using the same metrixes which are MAE, MSE, RMSE, and MAPE. This comparison aimed to highlight the relative advantage of each approach, both in terms of numerical accuracy and consistency of predictions against actual patterns. Table 4 and Figure 9 below present the model performance comparison.

Table 4. Model performance comparison

Model	MAE	MSE	RMSE	MAPE
SARIMAX	0.094	0.038	0.196	9.25
SARIMAX with TSCV	0.085	0.021	0.145	9.63
WGAN-GP	0.161	0.071	0.267	1.79

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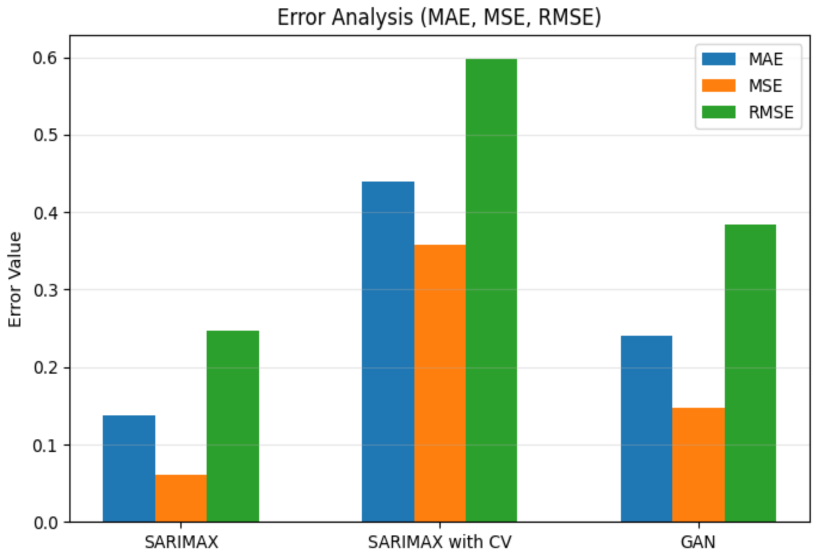

Figure 9 Performance comparison chart between models

SARIMAX produces MAE of 0.094, MSE of 0.038, and RMSE of 0.196. This shows that this model is quite good at minimizing absolute and squared errors in prediction. The resulting MAPE of 9.25% indicates that on average, SARIMAX predictions deviate by about 9% from the actual value, which is still in the moderate accuracy category for energy applications.

SARIMAX equipped with Time-Series Cross-Validation technique shows improved performance. MAE decreases to 0.085, MSE to 0.021, and RMSE to 0.145. This decrease reflects the improvement in accuracy and stability of the model in recognizing time and seasonal patterns. However, MAPE increases slightly to 9.63%, which is likely due to larger prediction errors at points with low actual values, thus having a proportional impact on the error percentage. Nevertheless, overall, SARIMAX with TSCV provides superior results in terms of numerical metrics, making it a good choice for scenarios that require high precision in predicted values.

Unlike the two previous models, WGAN-GP shows unique evaluation characteristics. MAE of 0.161, MSE of 0.071, and RMSE of 0.267 indicate that this model has higher absolute and squared error rates. However, the MAPE value of only 1.79% is very surprising and indicates that the prediction error relative to the actual value is very small. This shows that although WGAN-GP tends to have a larger absolute deviation, the model's prediction is proportionally very close to the actual data, especially at large PV values. WGAN-GP is also known to excel in representing daily and seasonal fluctuation patterns and in handling missing data.

These differences in characteristics indicate that each model has its own strengths. SARIMAX with TSCV excels in absolute value accuracy and is suitable for use in forecasting contexts with high numerical precision demands, such as energy capacity planning or daily load management. WGAN-GP excels in maintaining the stability of error patterns and proportions, making it ideal for scenarios where representation of data shape and long-term trends is more important than numerical precision. Standard SARIMAX still performs quite well and can be used in complete data conditions without special cross-validation.

To evaluate the effectiveness and relevance of the proposed approach, a performance comparison was conducted against several existing studies that applied different modeling techniques. Table 5 presents a summary of model performance metrics, including Root Mean Square Error (RMSE), Mean Absolute Error (MAE), error rate, and coefficient of determination (R^2), as reported in prior research.

Table 5. Model performance comparison with previous studies

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References	Performances	Values
Kachala et al.[7]	RMSE	0.153
	MAE	0.091
Kim et al.[6]	Error rate	7.12
Haider et al.[10]	RMSE	63.54
	MAE	35.23
Abuzaid et al.[9]	R^2	0.9174
This study	RMSE	0.196
	MAE	0.094

From the comparison, it can be observed that the model proposed in this study achieves an RMSE of 0.196 and MAE of 0.094. Although slightly higher than the RMSE and MAE reported by Kachala et al. (0.153 and 0.091, respectively), the values remain within a competitive range, indicating a reasonably accurate performance. Kim et al. reported an error rate of 7.12, which, although not directly comparable due to the difference in metric, provides a useful reference point in terms of prediction accuracy.

In contrast, the significantly higher RMSE and MAE reported by Haider et al. (63.54 and 35.23, respectively) suggest that the proposed model in this study offers a major improvement in terms of error minimization. Additionally, while Abuzaid et al. reported a high R^2 value of 0.9174, which indicates strong predictive power, the different nature of the metric limits direct comparison.

This research plays an important role in helping scientists and engineers better understand how to predict the power output of photovoltaic (PV) systems. By comparing three different forecasting models—SARIMAX, SARIMAX with time-series cross-validation, and WGAN-GP—the study shows that no single method is best for every situation. Instead, each model offers its own strengths: SARIMAX with TSCV works well when accuracy in numbers is needed, while WGAN-GP does a great job capturing overall trends and patterns, even when data is missing or incomplete.

5. CONCLUSION

This study has reviewed and compared the performance of SARIMAX, SARIMAX with Time-Series Cross-Validation (TSCV), and WGAN-GP models in forecasting the output power of photovoltaic (PV) systems under data loss conditions for a certain period. The SARIMAX model shows good performance in capturing seasonal patterns and daily fluctuations of PV yield data, with an MAE value of 0.094 and an RMSE of 0.196. This model can represent the main trend of solar energy production even though there are deviations in unexpected extreme conditions. The use of the TSCV approach on SARIMAX resulted in improved predictive performance, with an MAE of 0.085 and an RMSE of 0.145. This indicates that time series validation can improve the generalization ability of the model, making it more robust to changes in data patterns and seasonal fluctuations. However, when applied to the missing data period, the SARIMAX model with TSCV showed an unrealistic daily pattern, indicating the model's weakness in accurately capturing the daily time distribution. On the other hand, the WGAN-GP model showed quite promising ability in learning the distribution of PV yield data and producing predictions that resembled the actual data. Despite having higher MAE and RMSE values (0.161 and 0.267), this model was able to follow the main patterns, including seasonal fluctuations, well. However, the predictive performance of WGAN-GP decreased in very low or highly fluctuating data conditions and showed a high MAPE value due to sensitivity to small values.

Overall, the comparison results show that SARIMAX with TSCV is superior in numerical accuracy, but standard SARIMAX and WGAN-GP are more stable in pattern in daily prediction. Therefore, for practical application in solar energy forecasting in future research, model selection will consider specific needs such as medium-term numerical accuracy or daily pattern realism and data distribution flexibility.

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CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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