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Forecasting solar panel using SARIMA integrated with filtering enhancement

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ABSTRACT

This study aims to improve short-term photovoltaic DC power forecasting as a predictive information layer for PV energy management and power electronic applications by integrating the seasonal autoregressive integrated moving average (SARIMA) model with three filtering techniques: the Savitzky–Golay filter (SGF), exponential smoothing filter (ESF), and adaptive Kalman filter (AKF). The SARIMA model was developed as a baseline forecasting approach, while the filtering techniques were applied as post-processing methods to reduce residual fluctuations and improve prediction stability. The dataset was obtained from a photovoltaic system installed at Universitas Negeri Surabaya (UNESA), Indonesia, with DC power measurements recorded at 15-minute intervals over 31 consecutive days. The forecasting performance of the proposed approaches was evaluated using the mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) metrics. The results demonstrate that integrating filtering techniques improves the forecasting performance compared with the baseline SARIMA model. Among the evaluated approaches, the SARIMA-SGF framework achieved the best performance, followed by SARIMA-ESF and SARIMA-AKF, indicating that filtering-based post-processing can effectively enhance SARIMA forecasting accuracy for short-term photovoltaic direct current (DC) power prediction. The findings highlight the potential of combining statistical forecasting models with filtering techniques, particularly for photovoltaic (PV) systems with limited historical data availability.

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1. INTRODUCTION

The increasing integration of renewable energy into modern electrical systems has strengthened the role of photovoltaic (PV) generation as a sustainable source of electrical power. PV systems are increasingly deployed in residential, commercial, and industrial applications because of their modularity, availability, and declining installation costs [1], [2]. However, the effective utilization of PV generation depends not only on energy conversion efficiency but also on the ability of the system to anticipate variations in available power.

Therefore, accurate short-term forecasting of PV direct current (DC) power is important for improving operational planning and power management in photovoltaic energy systems.

Photovoltaic DC power is highly variable because solar irradiance changes with weather conditions and time of day. Short-term environmental disturbances can also introduce rapid fluctuations and noise into measured power data, while the daily operating cycle produces strong seasonal patterns. These characteristics complicate short-term forecasting because a forecasting model must simultaneously represent temporal dependence, seasonality, and irregular fluctuations. Forecast errors during rapid power changes may reduce the usefulness of predicted power for subsequent energy-management decisions. Therefore, a forecasting approach capable of capturing daily seasonality while reducing residual fluctuations is required [3]-[5].

Statistical time-series models such as the seasonal autoregressive integrated moving average (SARIMA) have been widely applied to renewable-energy forecasting because they can represent trend and recurring seasonal components [6]-[9]. Previous studies have shown that SARIMA can provide competitive performance for PV forecasting, particularly when the available dataset exhibits strong periodic behavior. Hybrid approaches combining SARIMA with nonlinear learning methods have also been investigated to improve forecasting capability [10], [11]. However, SARIMA performance remains sensitive to short-term fluctuations and residual noise in the predicted series. Filtering techniques offer a possible solution because they can suppress unwanted variations while maintaining the dominant characteristics of the signal. Among these techniques, the Savitzky-Golay filter (SGF), exponential smoothing filter (ESF), and adaptive Kalman filter (AKF) represent different filtering mechanisms based on local polynomial smoothing, weighted temporal smoothing, and adaptive state estimation, respectively [12], [13].

Despite recent developments in photovoltaic power forecasting, an important research gap remains. SARIMA-based forecasting and filtering techniques have been widely investigated as separate approaches, while the systematic use of filtering as a post-processing stage for SARIMA-based photovoltaic DC power forecasting remains limited. In particular, few studies have directly compared filtering techniques with different operating principles, including polynomial smoothing, adaptive estimation, and exponential smoothing, under the same dataset, forecasting model, and evaluation procedure. Consequently, the relative effectiveness of these filtering strategies in refining residual fluctuations in SARIMA-based PV power forecasts remains insufficiently understood.

The novelty of this study lies in the structured comparative evaluation of three filtering techniques: SGF, AKF, and ESF as post-processing enhancements to a common SARIMA forecasting framework. Rather than proposing a new forecasting algorithm, this study investigates how different filtering mechanisms affect the accuracy and stability of short-term photovoltaic DC power forecasts under consistent experimental conditions. The main contributions are: i) Establishing a seasonal SARIMA baseline for measured PV DC power forecasting; ii) Integrating SGF, AKF, and ESF as post-processing techniques within the same forecasting framework; and iii) Quantitatively comparing their performance using mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), mean absolute percentage error (MAPE), and coefficient of determination (R^2) metrics.

From a power-electronic system perspective, the proposed forecasting framework is intended as a predictive information layer for supervisory PV energy management. Short-term DC power forecasts can potentially support battery scheduling, power allocation, charge-controller operation, and converter reference generation. Although closed-loop converter control and hardware implementation are beyond the scope of the present study, the proposed framework provides a basis for future integration with real-time photovoltaic power-conversion and energy-storage control systems.

2. LITERATURE

The SARIMA method has been widely employed in various studies to forecast power output in PV systems due to its ability to model seasonal patterns in time-series data [14]-[16]. SARIMA can be combined with other modeling approaches to improve forecasting performance. For example, hybrid SARIMA-SVM models have been reported to outperform standalone SARIMA by combining SARIMA's ability to capture linear seasonal patterns with SVM's capability to model nonlinear relationships [17]. Comparative studies involving ARIMA, SARIMA, and LSTM also show that SARIMA remains competitive for renewable energy forecasting, particularly when the data exhibit strong seasonal patterns and the available dataset is relatively limited [18]. However, SARIMA performance depends on data quality, appropriate parameter selection, and the strength of seasonal characteristics. Its limited ability to handle residual noise and random fluctuations motivates the use of additional techniques to improve forecasting accuracy [19].

The SGF is chosen in this study due to its ability to reduce noise without removing the main characteristics of the signal, particularly for data with rapid fluctuations [20]. The DC power output data from PV systems typically exhibits sharp changes in values within short time intervals due to variations in solar radiation and environmental conditions. In such cases, simple smoothing methods like the moving average

often remove important details from the signal, such as peak power values or sudden changes in power levels. The SGF uses a local polynomial approach within a data window, allowing it to preserve the original curve shape despite smoothing [21], [22]. This characteristic makes the method suitable for use in DC power forecasting data, where noise reduction is needed without distorting the main patterns of the forecast results.

Mathematically, SGF works by convolving the original data with filter coefficients obtained through polynomial fitting. This formula is applied to calculate the filtered value at the center of the data window, where the filtered value at position i is computed using (1).

$$\widehat{y_i} = \sum_{j=-m}^{m} c_j y_{i+j} \quad (1)$$

In the SGF formula, the symbol $\widehat{y_i}$ represents the filtered value at position (i), which is computed after smoothing the signal based on the data surrounding that position within a data window. y_{i+j} refers to the original data within the window, encompassing the data points around position i, specifically from (i-j) to (i+j), depending on the size of the window used. Meanwhile, c_j denotes the Savitzky–Golay filter coefficients, which are determined through polynomial fitting of the data within the window. These coefficients assign weights to each data point in the window, enabling the filter to preserve the main characteristics of the signal while reducing noise or random fluctuations present in the data. The AKF was selected in this study due to its ability to estimate optimal values in systems with dynamic, time-varying characteristics [23], [24]. Photovoltaic systems are highly influenced by uncertain environmental conditions, such as fluctuations in solar irradiance and other environmental disturbances. These factors cause the DC power output to be dynamic and contain noise that does not always follow a consistent pattern. The exponential smoothing filter was selected in this study due to its simplicity and its ability to reduce random fluctuations with relatively low computational effort. In energy forecasting applications, simple yet stable methods are often employed as a baseline to evaluate the effectiveness of more complex techniques. Exponential smoothing assigns greater weight to the most recent data, enabling the method to respond to short-term changes without requiring a complex mathematical model [25]-[27].

Additionally, this method was chosen to represent a practical smoothing approach that is straightforward to implement across various forecasting systems. By comparing a complex method such as the adaptive Kalman filter with a simpler technique like exponential smoothing, this study provides a comprehensive perspective on the effectiveness of different levels of filtering complexity in improving the accuracy of DC power predictions in photovoltaic systems. SARIMA has been widely applied to photovoltaic power forecasting because of its ability to capture recurring seasonal patterns. However, its forecasts may still contain short-term fluctuations and residual noise that reduce prediction accuracy. Although filtering techniques have been employed in energy forecasting and signal processing, their systematic use as post-processing methods for SARIMA-based photovoltaic DC power forecasting remains limited. In particular, few studies have directly compared filtering techniques with different operating principles, including polynomial smoothing using the Savitzky–Golay filter, adaptive estimation using the adaptive Kalman filter, and statistical smoothing using the exponential smoothing filter, under the same forecasting framework and evaluation conditions.

3. METHOD

The dataset used in this study was obtained from a PV system installed at Universitas Negeri Surabaya (UNESA), Indonesia. The PV system has an installed capacity of 20 Wp, and the generated DC power was measured using a solar charge controller (SCC) with data logging capability. The recorded measurements were stored in CSV format and used as the primary dataset for short-term photovoltaic DC power forecasting. The dataset consists of time-series DC power measurements collected at 15-minute intervals, resulting in 96 observations per day. A total observation period of 31 consecutive days was used in this study. The first 30 days of measurements were used as the training dataset for developing the SARIMA forecasting model, while the measurement data from the 31st day were used as the testing dataset for performance evaluation. The collected PV power data represent daily generation patterns influenced by solar availability and environmental variations. Due to the presence of strong daily periodic characteristics, the dataset is suitable for evaluating seasonal time-series forecasting approaches. Before model development, the dataset was arranged chronologically, and data integrity checks were performed to identify missing or duplicated timestamps. No normalization process was applied because the SARIMA model operates directly on the original time-series values. The overall experimental configuration and forecasting workflow are illustrated in Figure 1.

The forecasting framework consists of four main stages: data preparation, SARIMA model development, filtering-based post-processing, and performance evaluation, as illustrated in Figure 2. The

measured photovoltaic DC power data were first arranged chronologically and divided into training and testing datasets. The training dataset was used exclusively for developing the SARIMA model, while the testing dataset was reserved for evaluating the forecasting performance. Since the data were collected at 15-minute intervals, each day consisted of 96 observations; therefore, the seasonal period was defined as (s=96) to represent the daily PV generation cycle. The SARIMA model was developed by identifying appropriate non-seasonal and seasonal parameters based on the characteristics of the PV power time series. Several SARIMA configurations were evaluated using statistical criteria and forecasting performance metrics. The final SARIMA configuration was selected based on the best forecasting performance among the evaluated models. After generating the SARIMA forecast, SGF, ESF, and AKF were applied as post-processing methods to refine the forecast output. To avoid introducing future information into the forecasting process, the filtering techniques were applied only to the SARIMA forecast output after the prediction stage. The actual measured PV data were used exclusively as reference values for performance evaluation. The performance of the baseline SARIMA model and the filtered forecasting models was then compared using MAE, MSE, RMSE, MAPE, and R^2 metrics.



Figure 1. Experimental setup of the PV DC power

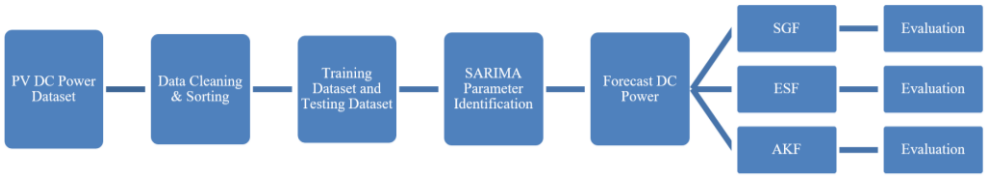

Figure 2. Workflow of SARIMA model development and filtering-based forecasting

4. RESULT AND DISCUSSION

4.1. Identification of SARIMA model performance

The candidate SARIMA models showed similar overall forecasting patterns, although their quantitative performance differed. As presented in Table 1, SARIMA(2,1,1)(1,0,1)_96 achieved the best forecasting performance, with an MAE of 362.63, MSE of 3.4236×10^5, RMSE of 583.64, MAPE of 9.0977%, and R^2 of 0.98123. Although SARIMA(0,1,1)(1,0,2)_96 produced the lowest AIC and BIC values, SARIMA(2,1,1)(1,0,1)_96 was selected as the baseline model because it provided the lowest forecasting errors and the highest R^2 among the evaluated configurations. The selected SARIMA(2,1,1)(1,0,1)_96 model combines second-order autoregressive behavior, first-order differencing, and a first-order moving-average component with seasonal autoregressive and moving-average terms. The seasonal period of 96 observations represents one daily cycle based on the 15-minute sampling interval. This configuration enables the model to capture both short-term temporal variations and recurring daily patterns in photovoltaic DC power and was therefore used as the baseline for subsequent filtering-based post-processing.

Figure 3 presents the ACF and PACF of the photovoltaic DC power series before and after first-order differencing. Before differencing, the ACF exhibits strong and slowly varying correlations across a large number of lags, indicating substantial temporal dependence and non-stationary behavior in the original series. The PACF also shows a dominant correlation at the initial lag, suggesting the presence of short-term autoregressive dependence. To reduce the persistent correlation in the original series, first-order differencing (d=1) was applied. After differencing, the ACF and PACF values decrease substantially and are concentrated around zero for most lags, indicating that the dominant long-range dependence has been reduced. These results support the use of first-order differencing in the SARIMA model and provide diagnostic information for identifying appropriate autoregressive and moving-average components.

Figure 4 compares the measured PV DC power with the output of the selected SARIMA model. The model captures the overall daily generation profile, including the morning power increase, peak-generation period, and afternoon decline. However, noticeable deviations remain during rapid fluctuations and around peak power, indicating limitations of the baseline SARIMA model in representing short-term variations. Quantitative evaluation further confirms this observation. The baseline SARIMA model achieved an RMSE of 1275.11 mW and an R^2 of 0.86615, indicating that the model captures the general temporal pattern but retains substantial forecasting errors during highly variable periods.

Table 1. SARIMA parameter performance

No.	Model	AIC	BIC	MAE	MSE	RMSE	MAPE (%)	R^2
1	SARIMA(0,1,1)(1,0,1)_96	7176.1	7180.4	362.88	3.4236×10^5	585.11	9.1150	0.98113
2	SARIMA(0,1,1)(1,0,2)_96	7133.1	7138.2	387.84	3.5247×10^5	593.69	9.1397	0.98058
3	SARIMA(1,1,1)(1,0,1)_96	7149.1	7154.2	480.21	4.1158×10^5	641.55	9.3685	0.97732
4	SARIMA(1,1,1)(1,0,2)_96	7133.3	7139.3	387.70	3.5245×10^5	593.67	9.1396	0.98058
5	SARIMA(2,1,1)(1,0,1)_96	7139.7	7145.7	362.63	3.4063×10^5	583.64	9.0977	0.98123
6	SARIMA(2,1,1)(1,0,2)_96	7135.3	7142.2	387.54	3.5243×10^5	593.65	9.1396	0.98058

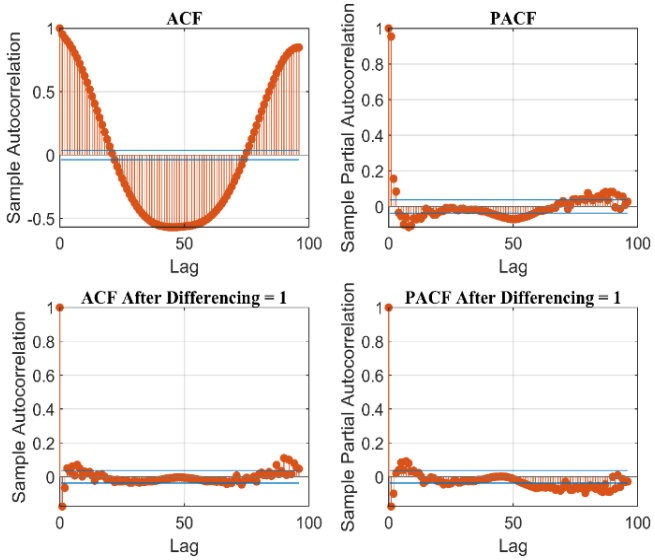

Figure 3. Data processing

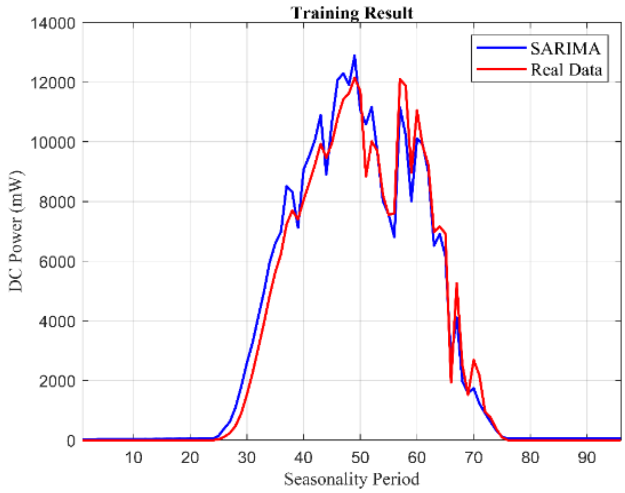

Figure 4. Comparison of measured and SARIMA-forecasted PV DC power during the testing period

Figure 5 compares the measured PV DC power and the baseline SARIMA forecast. As shown in Figure 5(a), the SARIMA-AKF output follows the main trend of the measured PV power while producing a smoother response than the baseline SARIMA forecast. The AKF reduces several short-term deviations; this indicates that the adaptive filtering mechanism can improve the stability of the SARIMA forecast without substantially altering the overall temporal pattern. Figure 5(b) shows the SARIMA-ESF result. The ESF-based output demonstrates closer agreement with the measured data during several parts of the testing period, including the rising and declining portions of the daily generation profile. However, deviations are still visible during abrupt changes in power output. These observations suggest that exponential smoothing is

effective in reducing short-term fluctuations while maintaining the general shape of the forecasted PV power profile. Figure 5(c) presents the SARIMA-SGF result, which shows the closest visual agreement with the measured PV DC power among the three evaluated filtering approaches during the investigated test period. The SGF output follows both the overall generation trend and several short-term variations more closely than the baseline SARIMA forecast. Nevertheless, the exceptionally close agreement observed in this case should be interpreted cautiously and considered together with the quantitative error metrics, since the smoothing characteristics of SGF may strongly influence the resulting forecast trajectory.

Based on the evaluation of performance metrics in Table 2 for DC power forecasting in the photovoltaic system using various filtering techniques, it can be concluded that the application of filtering methods significantly enhances prediction accuracy compared to the baseline SARIMA model. The SARIMA model without filtering showed reasonably good performance, with a MAE of 689.16 mW, MSE of 1,625,894.77 mW², and RMSE of 1,275.11 mW. However, the predictions were still imperfect, with a MAPE of 6.26% and R^2 of 0.866, indicating that the model explained only about 86.6% of the data variability.

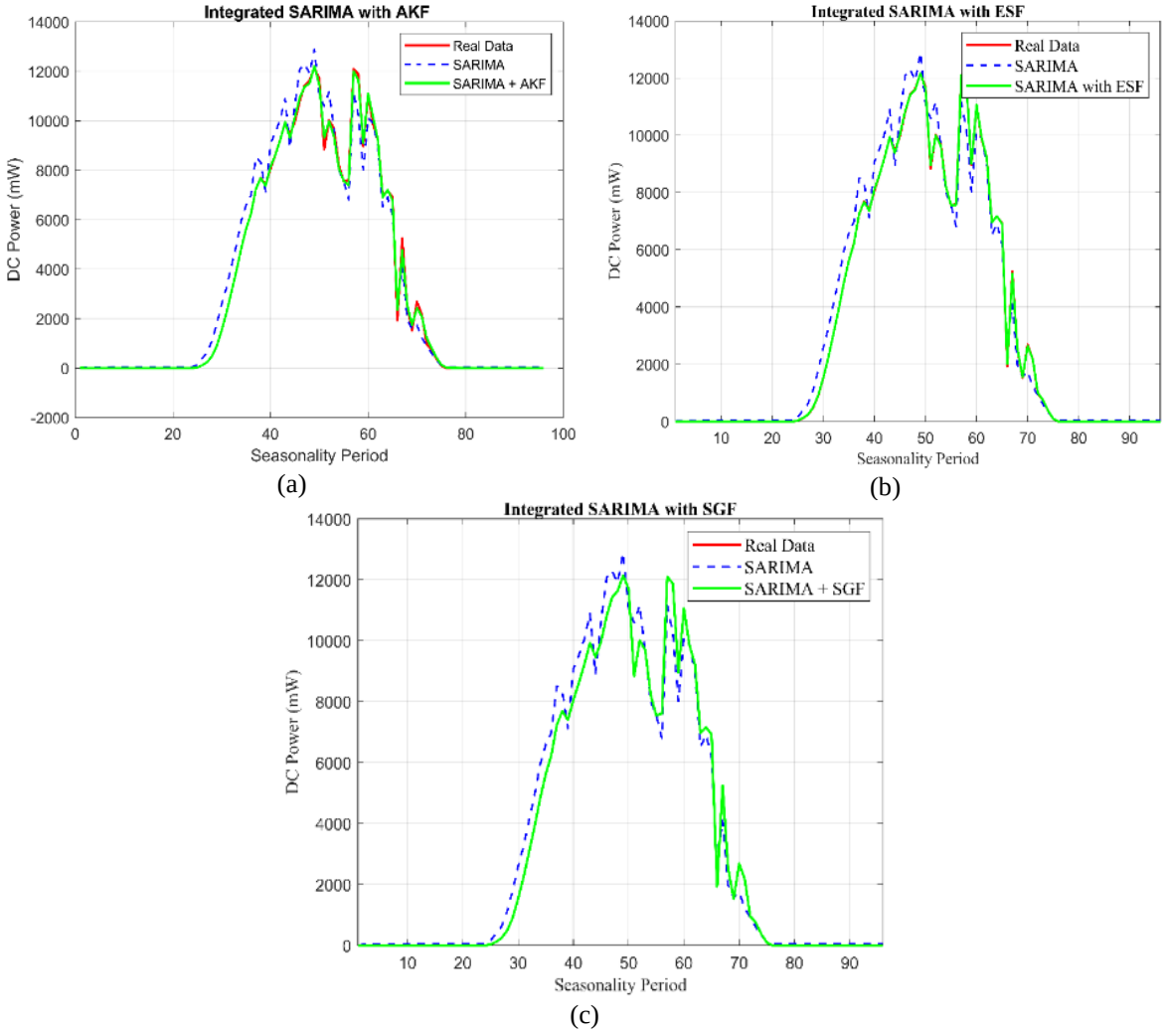

Figure 5. SARIMA with filter comparison results: (a) AKF, (b) ESF, and (c) SGF

Table 2. Evaluation metrics model result

Model	MAE (mW)	MSE (mW^2)	RMSE (mW)	MAPE (%)	R^2
SARIMA	689.1558	1625894.7747	1275.1058	6.2571	0.86615
SARIMA_ESF	14.053	736.42	27.137	1.1684	0.99996
SARIMA_AKF	56.2192	736.4165	120.2876	3.7948	0.99920
SARIMA_SGF	3.7738e-14	9.7146e-27	9.8563e-14	1.2336e-14	1

In contrast, applying the ESF to the SARIMA model led to a substantial improvement. The SARIMA + ESF model achieved a reduction in MAE to 14.05 mW, MSE to 736.42 mW², and RMSE to 27.14 mW, demonstrating the effective error reduction provided by ESF. The MAPE decreased to 1.17%, and R^2 increased dramatically to 0.99996, indicating that this model nearly fully explains the variability in the data. The SARIMA + AKF model also showed significant improvement over the baseline SARIMA. With a MAE of 56.22 mW, MSE of 736.42 mW², and RMSE of 120.29 mW, the AKF-enhanced model achieved good error reduction, although not as pronounced as the ESF-based model. The MAPE was 3.79%, with R^2 of 0.99920, still reflecting very high accuracy, albeit slightly lower than that of SARIMA + ESF. The SARIMA-SGF configuration achieved the lowest error values among the evaluated methods, with metrics approaching zero during the test period. Due to this unusually high performance for measured photovoltaic power data, the results were re-examined by considering data separation, forecast filtering, array alignment, and metric calculation. Therefore, the reported values indicate strong agreement under the current experimental setup and should not be considered as evidence of universally near-perfect forecasting performance.

5. DISCUSSION

The findings of this study are consistent with previous research indicating that filtering techniques can significantly enhance the performance of forecasting models for time-series data characterized by high fluctuations and noise. Similarly, in the context of smoothing variable power series, studies have shown that the Savitzky–Golay filter can effectively reduce high-frequency fluctuations in solar PV output data, outperforming simple moving average and low-pass filters [28]. Hybrid forecasting models employing SG filter preprocessing have also been shown to enhance prediction performance by reducing noise and highlighting essential patterns in input time series data [29]. Previous research has demonstrated that applying filtering techniques such as the Kalman filter to photovoltaic power forecasting can significantly reduce prediction errors and improve model accuracy by dynamically correcting forecast deviations [30]. These observations align with the results of the present study, SGF produced the lowest numerical forecasting errors among the three post-processing techniques. However, the exceptionally small error values require cautious interpretation because they were obtained from a limited test period and may be influenced by the smoothing characteristics and implementation settings of the filter. Further evaluation using multiple forecasting windows and longer datasets is therefore required before drawing broader conclusions regarding the superiority of SGF.

The limited dataset duration is an important limitation of this study. The proposed framework was evaluated using measurements from a single photovoltaic installation during a short observation period. Therefore, the results indicate the effectiveness of the SARIMA-based filtering framework under the tested conditions rather than representing all photovoltaic systems. Factors such as seasonal variation, geographical differences, weather uncertainty, and PV characteristics may affect forecasting performance. Future studies should evaluate the proposed approach using longer-term datasets from different seasons, PV capacities and geographical locations to improve model robustness and generalizability. Another limitation is the use of a single train-test partition for validation. Future research should apply rolling-origin evaluation with multiple forecasting horizons and extended datasets to provide a more comprehensive assessment of model performance.

From the perspective of power electronic applications, the proposed forecasting framework can provide predictive information for higher-level control systems in photovoltaic installations. Although converter control and hardware implementation are outside the scope of this study, the obtained forecasting information can potentially be utilized for adaptive power management, converter reference adjustment, and energy storage coordination. Future work will integrate the forecasting framework with photovoltaic power converters and real-time control strategies to evaluate its practical implementation.

6. CONCLUSION

This study developed a SARIMA-based forecasting framework integrated with three filtering techniques, namely SGF, ESF, and AKF, to improve short-term DC power forecasting accuracy in photovoltaic systems. The proposed approach addresses SARIMA limitations in handling residual noise and short-term fluctuations by applying filtering methods as post-processing stages within the same forecasting framework. The results show that filtering techniques improve forecasting performance compared with the baseline SARIMA model. Among the evaluated methods, SARIMA-SGF achieved the highest accuracy, while SARIMA-ESF and SARIMA-AKF also reduced forecasting errors significantly. These findings demonstrate the effectiveness of different filtering strategies for enhancing SARIMA-based photovoltaic DC power forecasting.

This study has several limitations. The evaluation was conducted using a relatively short dataset collected from a single photovoltaic system, and external influencing factors such as solar irradiance, temperature, and weather conditions were not included in the forecasting model. These limitations may affect the generalizability of the proposed approach for different PV operating conditions. Future research should consider longer observation periods, multi-location photovoltaic datasets, and additional environmental variables to improve model robustness. Furthermore, combining filtering techniques with advanced machine learning or deep learning approaches may provide opportunities to develop more adaptive and accurate photovoltaic power forecasting models.

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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.

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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 upon reasonable request.

REFERENCES

[1] T. S. Kishore, P. U. Kumar, and V. Ippili, "Review of global sustainable solar energy policies: Significance and impact," *Innovation and Green Development*, vol. 4, no. 2, Apr. 2025, doi: 10.1016/j.igd.2025.100224.
[2] S. Al-Ali, A. G. Olabi, and M. Mahmoud, "A review of solar photovoltaic technologies: developments, challenges, and future perspectives," *Energy Conversion and Management: X*, vol. 27, Jul. 2025, doi: 10.1016/j.ecmx.2025.101057.
[3] K. J. Iheanetu, "Solar photovoltaic power forecasting: a review," *Sustainability*, vol. 14, no. 24, Dec. 2022, doi: 10.3390/su142417005.
[4] T. AlSkaif, S. Dev, L. Visser, M. Hossari, and W. van Sark, "A systematic analysis of meteorological variables for PV output power estimation," *Renewable Energy*, vol. 153, pp. 12–22, Jun. 2020, doi: 10.1016/j.renene.2020.01.150.
[5] M. Alrashidi and S. Rahman, "Short-term photovoltaic power production forecasting based on novel hybrid data-driven models," *Journal of Big Data*, vol. 10, no. 1, Mar. 2023, doi: 10.1186/s40537-023-00706-7.
[6] V. Mohanasundaram and B. Rangaswamy, "Photovoltaic solar energy prediction using the seasonal-trend decomposition layer and ASOA optimized LSTM neural network model," *Scientific Reports*, vol. 15, no. 1, 2025, doi: 10.1038/s41598-025-87625-0.
[7] J. Ramirez-Vergara, L. B. Bosman, E. Wollega, and W. D. Leon-Salas, "Review of forecasting methods to support photovoltaic predictive maintenance," *Cleaner Engineering and Technology*, vol. 8, Jun. 2022, doi: 10.1016/j.clet.2022.100460.

[8] R. Maulana, S. Syafii, and A. Aulia, "Solar power forecasting using a SARIMA approach for Indonesia's grid integration," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 17, no. 1, Mar. 2026, doi: 10.11591/ijpeds.v17.i1.pp293-302.
[9] K. Bano, V. Suresh, F. Montana, and P. Janik, "Comparative evaluation of deep-learning and SARIMA models for short-term residential PV power forecasting," *Energies*, vol. 19, no. 8, Apr. 2026, doi: 10.3390/en19081991.
[10] S. Cantillo-Luna, R. Moreno-Chuquen, D. Celeita, and G. Anders, "Deep and machine learning models to forecast photovoltaic power generation," *Energies*, vol. 16, no. 10, May 2023, doi: 10.3390/en16104097.
[11] J. Sharma *et al.*, "A novel long term solar photovoltaic power forecasting approach using LSTM with Nadam optimizer: A case study of India," *Energy Science & Engineering*, vol. 10, no. 8, pp. 2909–2929, Aug. 2022, doi: 10.1002/ese3.1178.
[12] J. Che, S. Ye, Z. Wang, and X. Lv, "Power prediction algorithm for wind solar integration into DC power grid under trend analysis," *Engineering Research Express*, vol. 8, no. 5, Mar. 2026, doi: 10.1088/2631-8695/ae3f77.
[13] M. S. ElMenshawy and A. M. Massoud, "Short-term load forecasting in active distribution networks using forgetting factor adaptive extended Kalman filter," *IEEE Access*, vol. 11, pp. 103916–103924, 2023, doi: 10.1109/ACCESS.2023.3315591.
[14] E. Arellanos-Tafur, J. Villalba-Castro-Cuba, J. R. Sole, J. C. Jara, J. O. Marquez, and M. Damas-Niño, "Solar power forecasting and uncertainty quantification using SARIMA: case study of Tacna solar plant, Peru," in *2025 IEEE XXXII International Conference on Electronics, Electrical Engineering and Computing (INTERCON)*, IEEE, Aug. 2025, pp. 1–8, doi: 10.1109/INTERCON67304.2025.11244666.
[15] N. Mbuli, "Exponential smoothing forecasting techniques in power systems: a systematic literature review of recent applications (2018–2024)," *International Transactions on Electrical Energy Systems*, vol. 2026, no. 1, Jan. 2026, doi: 10.1155/etep/8833254.
[16] J. A. Ibañez, I. B. Benitez, J. M. Cañete, J. C. Magadia, and J. A. Principe, "Accuracy assessment of satellite-based and reanalysis solar irradiance data for solar PV output forecasting using SARIMAX," *Journal of Renewable and Sustainable Energy*, vol. 15, no. 6, Nov. 2023, doi: 10.1063/5.0160488.
[17] M. Bouzerdoum, A. Mellit, and A. Massi Pavan, "A hybrid model (SARIMA–SVM) for short-term power forecasting of a small-scale grid-connected photovoltaic plant," *Solar Energy*, vol. 98, pp. 226–235, Dec. 2013, doi: 10.1016/j.solener.2013.10.002.
[18] M. L. Hossain, S. M. N. Shams, and S. M. Ullah, "Time-series and deep learning approaches for renewable energy forecasting in Dhaka: a comparative study of ARIMA, SARIMA, and LSTM models," *Discover Sustainability*, vol. 6, no. 1, Aug. 2025, doi: 10.1007/s43621-025-01733-5.
[19] C. Prakash, B. Dhyani, A. Chauhan, and A. Sayal, "ARIMA based forecasting of solar and hydro energy consumption with implications for grid stability and renewable policy," *Discover Sustainability*, vol. 6, no. 1, Jul. 2025, doi: 10.1007/s43621-025-01536-8.
[20] M. J. Niedźwiecki, M. Ciołek, A. Gańcza, and P. Kaczmarek, "Application of regularized Savitzky–Golay filters to identification of time-varying systems," *Automatica*, vol. 133, Nov. 2021, doi: 10.1016/j.automatica.2021.109865.
[21] M. J. Nasero, H. Samet, B. Zaker, and M. A. Jarrahi, "Implementing enhanced fault detection and classification in DC microgrids with Savitzky-Golay Filter," *IET Renewable Power Generation*, vol. 19, no. 1, Jan. 2025, doi: 10.1049/rpg2.70150.
[22] A. J. Kałka and A. M. Turek, "Searching for alternatives to the Savitzky–Golay filter in the spectral processing domain," *Applied Spectroscopy*, vol. 77, no. 4, pp. 426–432, Apr. 2023, doi: 10.1177/00037028231154278.
[23] H. Lee, N.-W. Kim, J.-G. Lee, and B.-T. Lee, "Kalman filter-based adaptive forecasting of PV power output," in *2020 International Conference on Information and Communication Technology Convergence (ICTC)*, IEEE, Oct. 2020, pp. 1342–1347, doi: 10.1109/ICTC49870.2020.9289532.
[24] Y. Yang, T. Yu, W. Zhao, and X. Zhu, "Kalman filter photovoltaic power prediction model based on forecasting experience," *Frontiers in Energy Research*, vol. 9, Sep. 2021, doi: 10.3389/fenrg.2021.682852.
[25] D. Matushkin, A. Zaporozhets, V. Babak, M. Kulyk, and V. Denysov, "Hourly photovoltaic power forecasting using exponential smoothing: a comparative study based on operational data," *Solar*, vol. 5, no. 4, Oct. 2025, doi: 10.3390/solar5040048.
[26] F. E. Sapnken *et al.*, "A whale optimization algorithm-based multivariate exponential smoothing grey-holt model for electricity price forecasting," *Expert Systems with Applications*, vol. 255, Dec. 2024, doi: 10.1016/j.eswa.2024.124663.
[27] K. Shejul, R. Harikrishnan, and H. Gupta, "The improved integrated exponential smoothing based CNN-LSTM algorithm to forecast the day ahead electricity price," *MethodsX*, vol. 13, Dec. 2024, doi: 10.1016/j.mex.2024.102923.
[28] A. Atif and M. Khalid, "Saviztky–Golay filtering for solar power smoothing and ramp rate reduction based on controlled battery energy storage," *IEEE Access*, vol. 8, pp. 33806–33817, 2020, doi: 10.1109/ACCESS.2020.2973036.
[29] S. Liu, T. Xu, X. Du, Y. Zhang, and J. Wu, "A hybrid deep learning model based on parallel architecture TCN-LSTM with Savitzky-Golay filter for wind power prediction," *Energy Conversion and Management*, vol. 302, Feb. 2024, doi: 10.1016/j.enconman.2024.118122.
[30] R. A. Sinulingga *et al.*, "A performance comparison of the extended Kalman filter and the unscented Kalman filter for photovoltaic power output forecasting," *Engineering, Technology & Applied Science Research*, vol. 16, no. 1, pp. 30745–30750, Feb. 2026, doi: 10.48084/etasr.13866.

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