A Performance Comparison of the Extended Kalman Filter and the Unscented Kalman Filter for Photovoltaic Power Output Forecasting

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ABSTRACT

The issue of using renewable energy to replace fossil fuels has become the main focus of all countries worldwide. Fossil energy reserves in the world are no longer as abundant as in previous years. Therefore,

further innovation and development are required to address these problems. Until today, many countries around world are still dependent on fossil fuels for transportation and electricity. The costs and impacts of this are significant. The combustion of fossil fuels can contaminate the environment and endanger human health. Innovation in the field of electricity began with the application of photovoltaic (PV) as a new solar-based energy source. Indonesia is a country with great potential due to its tropical climate and sunshine that lasts all year long. In line with the progress of information technology, the optimization and development of PV power can be implemented optimally to provide sufficient electrical energy that can be distributed equally. In this study, two filtering methods, namely the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), were examined based on their accuracy in forecasting PV power. Both methods are robust in addressing non-linearity issues. Based on the simulation results, the EKF achieved the best Root Mean Squared Error (RMSE) value of 0.09381, and the UKF achieved 0.09041.

Keywords-electricity; estimation; machine learning; photovoltaic

I. INTRODUCTION

Fossil energy is the primary source of electricity and transportation [1]. The extensive consumption of fossil energy can have detrimental effects, triggering an increase in carbon emissions [2]. High levels of carbon emissions are significantly associated with the current issue of climate change and have become a concern for many countries worldwide. The obligation to minimize fossil energy use is stipulated in the Paris Agreement and United Nations Conference of Parties (COP-26) [3]. Therefore, alternative renewable energy and environmentally friendly solutions are required [4]. Solar energy is an alternative energy source that is widely available and can help reduce carbon emissions [5, 6]. However, the application of solar energy is not yet widespread. This is because it depends on the geographical conditions of each country. Photovoltaics (PVs) [7] are very appropriate in southern countries, such as Indonesia, owing to the extended sunlight most of the year and can contribute to economic advancement [8]. Globally, three countries have implemented PV technology: China (36%), the United States (13%), and Japan (11%) [9]. With the current technological advancements in Artificial Intelligence (AI) and Machine Learning (ML), the optimization and efficiency of the power generated by PV can be accurately forecasted. It is useful to anticipate changes in supply and power distribution, and also help to maintain stability [10, 11]. Therefore, this could assist in the future development of PV and obtain more profit from the economic side.

ML is a subfield of AI that can learn from data and has three main approaches: supervised learning, unsupervised learning, and reinforcement learning. This study aims to utilize a supervised learning method supported by two filtering methods, namely the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF), to compare their accuracy and robustness in terms of forecasting of the generated PV power. EKF and UKF are developed from the Kalman Filter (KF) method. The KF was proposed by R.E Kalman and has continued to evolve into a method that can be used for nonlinear models and has been implemented in many fields, such as engineering, healthcare, and economics [12-16]. EKF and UKF are categorized as nonlinear models. The difference between the two methods is that EKF uses adoption from the Taylor expansion, but UKF employs Unscented Transformation (UT) [17].

Several previous studies have shown satisfactory results, but the use of filtering methods remains limited in their application. Therefore, in this study, we applied the filtering methods EKF and UKF as a methodological novelty approach.

II. RESEARCH METHOD

The dataset used in this study was obtained from field research conducted directly by the author from May to September 2024. The dataset consisted of 1600 rows and 5 columns. Table I presents the details of the dataset. Figure 1 presents the weather station used to monitor the weather conditions at the PV site. The specifications of the PV module were 200-watt peak. Table II presents the specifications of the weather station.

TABLE I. DATASET

Trial	Temperature (^{O}C)	Radiation intensity (lux)	Generated power (W)	Duration
1	26.34	118.2	6.52	7
2	27.74	295	25.46	8
3	29.13	578	45.86	9
4	30.52	762	55.17	10
5	30.62	888	63.85	11
6	30.73	877	62.57	12
7	30.84	560	39.65	13
8	30.31	67	1.65	14
9	29.78	67	1.71	15
10	29.25	59	1.37	16
11	28.58	21	0,18	17
...	...	...	...	...
1600	29.73	704	53.75	16

Fig. 1. Weather station.

TABLE II. SPECIFICATIONS OF WEATHER STATION

Specifications	**Description**
Transmission distance in open field	100 m
Frequency	433 MHz
Temperature range	-40-60 ºC
Accuracy	+/- 1 ºC
Resolution	0.1 ºC
Measuring range rel. humidity	10-99%
Accuracy	+/- 5 ºC
Rain volume display	0-9999 m
Accuracy	+/- 10 ºC
Wind speed	0-180 km/h
Accuracy	+/- 1 m/s
Measuring interval thermo-hygro sensor	48 sec
Waterproof level	IPX 3

Figure 2 illustrates the overall research framework employed in this study, beginning with the collection of field measurement data comprising the temperature, solar radiation intensity, relative humidity, and actual PV power output. The collected dataset was then pre-processed to ensure data quality and consistency prior to model implementation. Subsequently, the data were processed using two nonlinear state estimation techniques, namely EKF and UKF, both of which are designed to handle the stochastic and nonlinear characteristics inherent to PV power generation. The final stage involved evaluating the forecasting performance using statistical error metrics, specifically the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), enabling a direct comparison of the accuracy and robustness of the two filtering approaches. This methodological framework ensures a systematic process from raw data acquisition to performance validation, thereby strengthening the reliability of forecasting results.

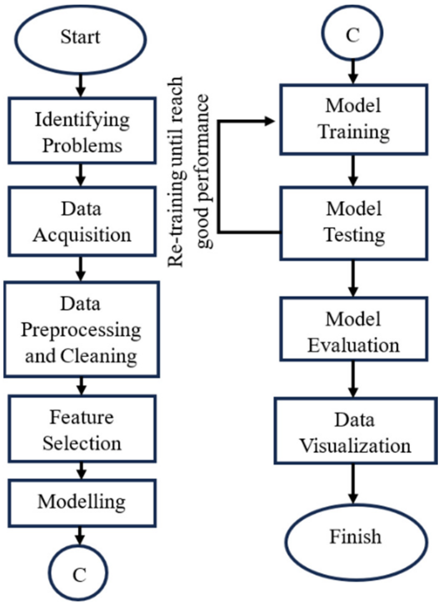

Fig. 2. Research method.

A. *Filtering Methods*

The EKF is an algorithm developed from the KF that can handle nonlinear problems by linearization using the Taylor expansion system [18]. The EKF is derived by modifying the error correction term to accept the nonlinearity of the system [19]. Figure 3 shows the flowchart of the EKF algorithm. Unlike the EKF, the UKF does not require the Jacobian matrix but utilizes a fundamental nonlinear system [20]. This is the reason why UKF can handle complex state equations. Most of the KF family methods are frequently used in the areas of autonomous vehicles and robotics [16].

Figure 3 illustrates the computational flow of the EKF applied in this study for PV power forecasting. The diagram presents the sequential stages of the EKF algorithm, beginning with state initialization and prediction, where the system state vector is advanced using the nonlinear process model $f(\cdot)$, and the associated error covariance is propagated through linearization via the Jacobian matrix. The subsequent step involves the innovation stage, in which the predicted measurement is compared with the actual PV power output to generate the residual error. This residual is then used in the update stage, where the Kalman gain is computed to optimally weight the contribution of model prediction and sensor measurements. The state estimate and error covariance were corrected accordingly, and the cycle was iterated for the entire dataset. Within the context of this study, the EKF effectively integrates environmental variables, such as temperature and radiation intensity, captured by the weather station with the nonlinear dynamics of PV power generation. By leveraging local linearization, the EKF achieves computational efficiency while maintaining sufficient accuracy, enabling reliable short-term PV forecasting under stochastic and nonlinear conditions.

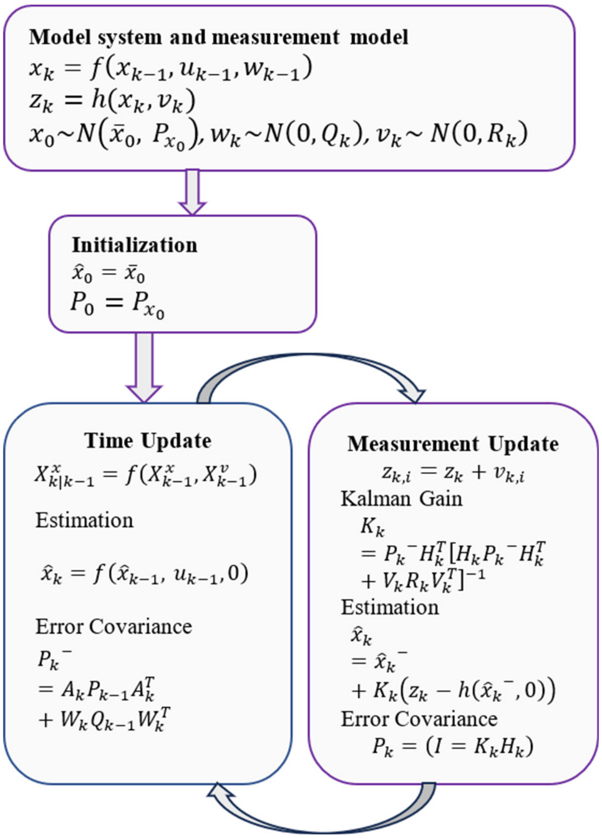

Fig. 3. Computational flow of EKF.

Figure 4 illustrates the computational flow of the UKF, which extends the classical KF framework to nonlinear systems by employing an unscented transformation. The process begins with the initialization stage, where the initial state estimates $\hat{x}_0$ and its error covariance P_{x0} are defined. Within the model system and measurement model block, the system dynamics are described by a nonlinear process model $x_k = f(x_{k-1}, u_k) + w_k$, whereas the measurement equation $z_k = h(x_k) + u_k$ incorporates sensor noise. The next stage, Time Update (prediction), generates a set of sigma points that capture the mean and covariance of the state distribution, propagates them through the nonlinear process model, and computes the predicted state estimate $\hat{x}_{k\,|k-1}$ along with the corresponding covariance $P_{xk|k-1}$. In the Measurement Update stage, the predicted measurements are compared with the actual sensor observations to obtain the innovation. The Kalman gain K_k is then calculated to optimally combine model predictions and sensor data, followed by an update of the state estimate and error covariance. This iterative cycle of prediction and update enables the UKF to maintain higher accuracy and stability than the EKF when addressing strongly nonlinear and stochastic PV power generation processes.

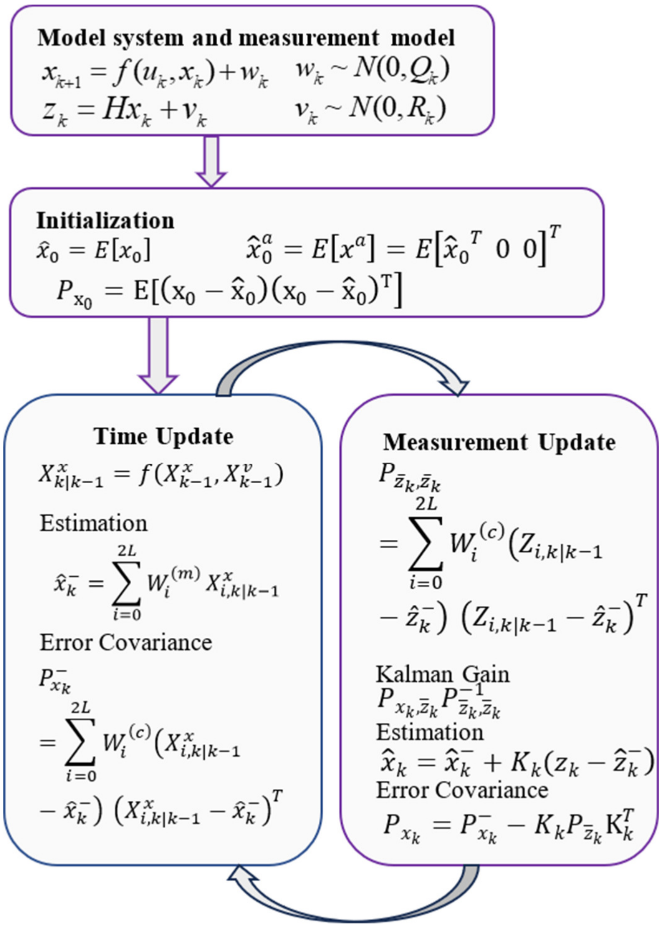

Fig. 4. Computational flow of UKF.

B. Evaluation Metrics

In several studies on forecasting, assessment, or evaluation of model performance are often performed by estimating the Mean Squared Error (MSE) and Root Mean Squared Error (RMSE), which are given by the following equations:

$$MSE = \sum_{i=1}^{n} \frac{(X_i - F_i)^2}{n} \tag{1}$$

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(X_i - F_i)^2}{n}} \tag{2}$$

III. RESULTS AND DISCUSSION

From a number of trials that have been conducted, several important points have been raised regarding the power generated by PV. It is known that the power generated by PV is affected by radiation intensity. Figures 5 and 6 show plots of the radiation intensity and PV power generated, respectively.

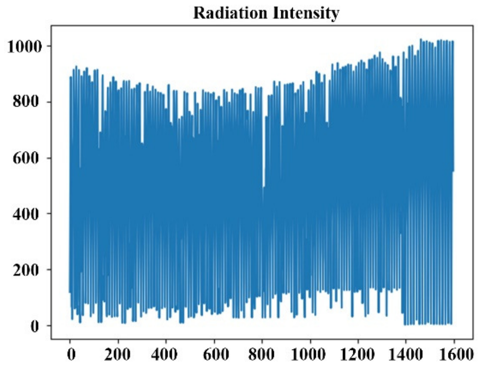

Fig. 5. Plot of the radiation intensity.

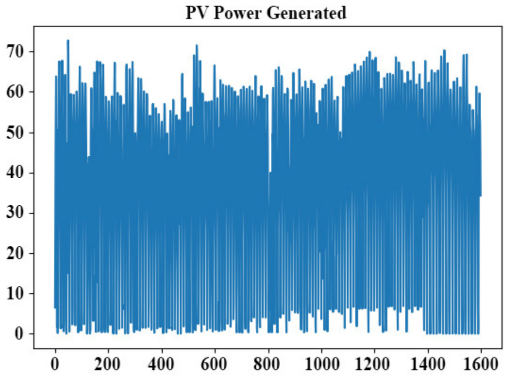

Fig. 6. Plot of the power generated by the PV.

Figures 5 and 6 show that there are similarities in the patterns for both variables. So, it can be concluded that the PV can work effectively and with great potential in the dry season of Indonesia which lasts for 6 months. The next step was to simulate forecasting on existing data based on PV power generation and simulate 100 days forward using EKF and UKF. The results of the simulations are shown in Figures 7 and 8.

Figure 7 illustrates the forecasting results of the power generated from the PV 100 days forward in time using EKF and UKF and setting the noise parameter R to 0.03. Both methods were able to follow the actual data, although the actual values exhibited dynamic fluctuations. The results from the EKF are shown by the green line, and the UKF results are shown by the black line. Furthermore, both methods have a slight difference in the error value and are within reasonable limits. The EKF achieved an MSE value of 0.00881 and an RMSE value of 0.09386. The UKF achieved the best MSE and RMSE values of 0.00817 and 0.09041, respectively.

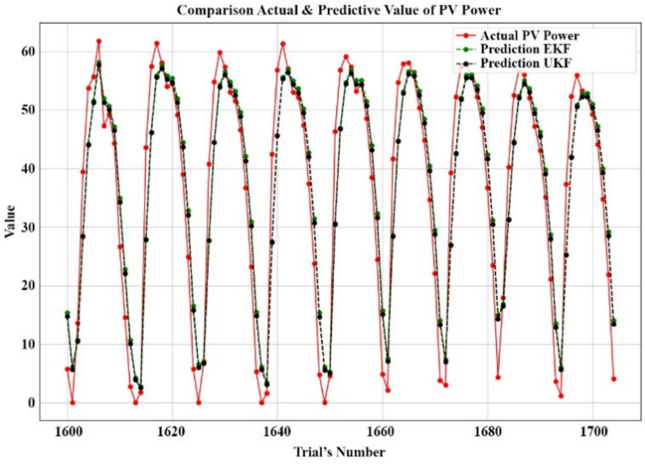

Fig. 7. Simulation data of EKF and UKF using R of 0.03 compared to actual data.

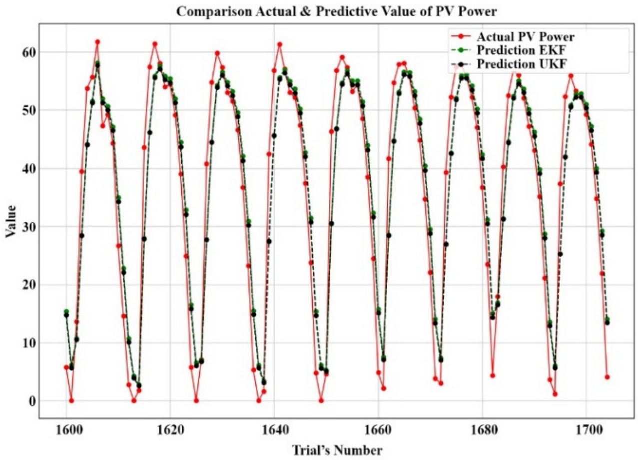

Fig. 8. Simulation data of EKF and UKF using R of 0.01 compared to actual data.

The plot shown in Figure 8 shows the forecasting results of the power generated by the PV 100 days forward using EKF and UKF and setting the R parameter to 0.01. Both methods are able to follow the line of the actual values, where the condition of the actual values appears dynamic with a sharp pattern of fluctuation. The EKF results are shown by the green line, and the UKF results are shown by the black line. Both methods have a slight difference in the error value and are within reasonable limits. EKF achieved an MSE value of 0.00880 and an RMSE value of 0.09381. The UKF achieved the best MSE and RMSE values of 0.00817 and 0.09041, respectively. The forecasting results of the second simulation were not significantly different from those of the first simulation.

Table III presents a comparison between the actual PV power output and the forecasting results obtained using the EKF and UKF under two different measurement noise parameter settings (R=0.03 and R=0.01). The results demonstrate that both the EKF and UKF can closely track the actual PV power values with relatively small deviations. In several trial points, the forecasted values of both methods exhibit strong agreement with the measured data, with the UKF consistently achieving slightly better accuracy than the EKF. This superiority is reflected in the MSE and RMSE values obtained by the UKF across both parameter settings. Overall, Table III provides empirical evidence that both filtering methods are reliable for nonlinear PV power forecasting, while highlighting the advantage of UKF in minimizing prediction errors and improving the short-term forecasting accuracy.

TABLE III. FORECASTING FOR 100 DAYS FORWARD

Trial	**Power generated**	**Forecasted by EKF with R-value of 0.03**	**Forecasted by UKF with R-value of 0.03**	**Forecasted by EKF with R-value of 0.01**	**Forecasted by UKF with R-value of 0.01**
1601	5.80	15.40	14.77	15.40	14.77
1602	0.0079	6.09	5.65	6.09	5.65
1603	13.57	10.72	10.54	10.72	10.54
1604	39.42	28.38	28.39	28.38	28.39
1605	53.75	44.14	44.06	44.14	44.06
1606	55.66	51.54	51.23	51.54	51.23
1607	61.74	58.19	57.72	58.19	57.72
1608	47.28	51.96	51.27	51.96	51.27
1609	49.22	50.68	50.00	50.68	50.00
1610	44.30	47.16	46.48	47.16	46.48
1611	26.69	34.99	34.24	34.99	34.24
1612	14.57	22.75	22.08	22.75	22.08
1613	2.72	10.66	10.12	10.66	10.12
1614	0.0079	4.21	3.87	4.21	3.87
...	...	...	...	...	...
1700	53.28	52.74	52.25	52.74	52.25

IV. CONCLUSIONS

This study presents a comprehensive comparison of the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) for short-term photovoltaic (PV) power forecasting using real field data measured under tropical conditions in Indonesia. Both methods effectively handled the nonlinear and stochastic behaviors inherent in solar power generation. The results revealed that the UKF achieved superior accuracy with a lower Root Mean Squared Error (RMSE) of 0.09041 compared to EKF that exhibited 0.09381, while maintaining a computational efficiency between 0.1 and 0.3 s, indicating their potential for real-time PV monitoring and control applications. The novelty of this work lies in the empirical validation of the EKF and UKF on real tropical PV datasets rather than simulated data, providing new insights into their comparative performance in dynamic and high-variability environments.

Compared with previous studies, the findings corroborate the superior accuracy and stability of the UKF while demonstrating that the EKF remains a computationally efficient alternative for practical implementations. Overall, this study contributes both methodological and practical advancements to renewable energy forecasting by establishing the suitability of Kalman-based filters for nonlinear PV power prediction in tropical climates. Future studies should integrate these algorithms with adaptive or data-driven approaches, such as neural networks or ensemble learning, to further enhance the prediction accuracy, resilience, and scalability of intelligent renewable energy systems.

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REFERENCES

[1] E. Alagoz and Y. Alghawi, "The Future of Fossil Fuels: Challenges and Opportunities in a Low-Carbon," *International Journal of Earth Sciences Knowledge and Applications*, vol. 5, no. 3, pp. 381–388, Dec. 2024.

[2] M. Calvia, "Fossil energy use and carbon emissions: An easy-to-implement technical policy experiment," *Green Finance*, vol. 6, no. 3, pp. 407–429, 2024, https://doi.org/10.3934/GF.2024016.

[3] M. Farghali *et al.*, "Social, environmental, and economic consequences of integrating renewable energies in the electricity sector: a review," *Environmental Chemistry Letters*, vol. 21, no. 3, pp. 1381–1418, June 2023, https://doi.org/10.1007/s10311-023-01587-1.

[4] M. J. B. Kabeyi and O. A. Olanrewaju, "Sustainable Energy Transition for Renewable and Low Carbon Grid Electricity Generation and Supply," *Frontiers in Energy Research*, vol. 9, Mar. 2022, Art. no. 743114, https://doi.org/10.3389/fenrg.2021.743114.

[5] R. Yasmeen, X. Yao, I. Ul Haq Padda, W. U. H. Shah, and W. Jie, "Exploring the role of solar energy and foreign direct investment for clean environment: Evidence from top 10 solar energy consuming countries," *Renewable Energy*, vol. 185, pp. 147–158, Feb. 2022, https://doi.org/10.1016/j.renene.2021.12.048.

[6] V. Prema, M. S. Bhaskar, D. Almakhles, N. Gowtham, and K. U. Rao, "Critical Review of Data, Models and Performance Metrics for Wind and Solar Power Forecast," *IEEE Access*, vol. 10, pp. 667–688, 2022, https://doi.org/10.1109/ACCESS.2021.3137419.

[7] M. V. Dambhare, B. Butey, and S. V. Moharil, "Solar photovoltaic technology: A review of different types of solar cells and its future trends," *Journal of Physics: Conference Series*, vol. 1913, May 2021, Art. no. 012053, https://doi.org/10.1088/1742-6596/1913/1/012053.

[8] K. Ukoba, K. O. Yoro, O. Eterigho-Ikelegbe, C. Ibegbulam, and T.-C. Jen, "Adaptation of solar energy in the Global South: Prospects, challenges and opportunities," *Heliyon*, vol. 10, no. 7, Apr. 2024, Art. no. e28009, https://doi.org/10.1016/j.heliyon.2024.e28009.

[9] A. M. Soomar, A. Hakeem, M. Messaoudi, P. Musznicki, A. Iqbal, and S. Czapp, "Solar Photovoltaic Energy Optimization and Challenges," *Frontiers in Energy Research*, vol. 10, May 2022, Art. no. 879985, https://doi.org/10.3389/fenrg.2022.879985.

[10] J. Gaboitaolelwe, A. M. Zungeru, A. Yahya, C. K. Lebekwe, D. N. Vinod, and A. O. Salau, "Machine Learning Based Solar Photovoltaic Power Forecasting: A Review and Comparison," *IEEE Access*, vol. 11, pp. 40820–40845, 2023, https://doi.org/10.1109/ACCESS.2023.3270041.

[11] T. A. Nguyen *et al.*, "A Study on Novel Solar Power Forecasting using an XGB-LiGBM-RF Hybrid Model and the L-BFGS-B Optimization Algorithm," *Engineering, Technology & Applied Science Research*, vol. 15, no. 4, pp. 24516–24522, Aug. 2025, https://doi.org/10.48084/etasr.11308.

[12] S. Li and Z. Yin, "Power Forecast of Renewable Energy Power Plant Based on Kalman Filter Method," *Renewable Energy and Power Quality Journal*, vol. 22, no. 6, pp. 42–51, Aug. 2024, https://doi.org/10.52152/4051.

[13] A. Muhith, T. Herlambang, D. Rahmalia, Irhamah, and M. Y. Anshori, "Estimation of fresh frozen plasma blood in PMI Gresik using ensemble and extended Kalman filter," *AIP Conference Proceedings*, vol. 2679, no. 1, Jan. 2023, Art. no. 020021, https://doi.org/10.1063/5.0112684.

[14] M. A. González-Cagigal, J. A. Rosendo-Macías, and A. Gómez-Expósito, "Estimation of Equivalent Model of Photovoltaic Array Using Unscented Kalman Filters," *Journal of Modern Power Systems and Clean Energy*, vol. 12, no. 3, pp. 819–827, May 2024, https://doi.org/10.35833/MPCE.2023.000510.

[15] N. Rahimi *et al.*, "A Comprehensive Review on Ensemble Solar Power Forecasting Algorithms," *Journal of Electrical Engineering & Technology*, vol. 18, no. 2, pp. 719–733, Mar. 2023, https://doi.org/10.1007/s42835-023-01378-2.

[16] T. Herlambang, H. Nurhadi, F. A. Susanto, and B. P. Tomasouw, "Comparison of H-Infinity and Ensemble Kalman Filter for Estimating Motion of Middle Finger," *BAREKENG: Jurnal Ilmu Matematika dan Terapan*, vol. 17, no. 4, pp. 2433–2442, Dec. 2023, https://doi.org/10.30598/barekengvol17iss4pp2433-2442.

[17] S. Feng, X. Li, S. Zhang, Z. Jian, H. Duan, and Z. Wang, "A review: state estimation based on hybrid models of Kalman filter and neural network," *Systems Science & Control Engineering*, vol. 11, no. 1, Dec. 2023, Art. no. 2173682, https://doi.org/10.1080/21642583.2023.2173682.

[18] E. Jamalinia, Z. Zhang, J. Khazaei, and R. S. Blum, "Data-Driven Dynamic State Estimation of Photovoltaic Systems via Sparse Regression Unscented Kalman Filter," *IEEE Transactions on Industrial Informatics*, vol. 21, no. 3, pp. 2550–2559, Mar. 2025, https://doi.org/10.1109/TII.2024.3507953.

[19] 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, https://doi.org/10.1109/ACCESS.2023.3315591.

[20] N. HajiHeydari Varnoosfaderani and A. Khorsandi, "State estimation in an islanded hybrid solar-wind DC microgrid using Unscented Kalman Filter," *Heliyon*, vol. 11, no. 3, Feb. 2025, Art. no. e42073, https://doi.org/10.1016/j.heliyon.2025.e42073.