JREE: Vol. 12, No. 2, (Spring 2025) 186-193

Journal of Renewable Energy and Environment

Journal Homepage: www.jree.ir

Materials and Energy Research Center

MERC

Research Article

Comparison of PV Simulation Tools with Real-World Data: Residential Rooftop Systems in Surabaya, Indonesia

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PAPER INFO

Paper history:
Received: 01 May 2025
Revised: 14 November 2025
Accepted: 20 November 2025

Keywords:
PV System,
Simulation,
Solar Irradiation,
Energy Output

ABSTRACT

Accurate prediction of photovoltaic (PV) energy output is essential for system design, performance assessment, and investment decisions. However, the accuracy of widely used PV simulation tools in tropical residential settings remains insufficiently validated. This study aims to evaluate the predictive performance of three commonly used simulation platforms, PVWatts®, PVGIS, and PVSOL Online, by comparing their monthly and annual energy output estimates with real-world data from a 4.5 kWp residential rooftop PV system in Surabaya, Indonesia. Using standardized input parameters and one year of measured operational data from 2022, the results show that all three tools produce reasonably accurate estimates, with annual deviations below 3%. PVSOL Online yields the closest agreement (+0.56%), followed by PVGIS (+1.52%) and PVWatts® (+2.48%). Although all tools exhibit consistent monthly overestimation, particularly during high-yield dry-season months, they successfully capture the seasonal performance pattern of the system. These findings highlight both the strengths and limitations of current simulation tools in tropical environments and underscore the importance of model calibration and field data validation. The study provides practical guidance for selecting appropriate simulation tools and contributes to improving PV performance modeling for residential applications in humid tropical urban regions.

https://doi.org/10.30501/jree.2026.519083.2368

1. INTRODUCTION

The adoption of solar photovoltaic (PV) systems has gained significant momentum globally as a key solution for reducing greenhouse gas emissions and achieving sustainable energy goals (Gómez-Calvet & Gómez-Calvet, 2025; Government of Indonesia, 2021). Accurate energy output predictions are critical for the successful planning, implementation, and operation of these systems. Simulation software tools play a vital role in estimating the performance of PV systems by modeling energy output based on environmental factors, system configurations, and operational conditions (Subramanian et al., 2018). The accuracy and reliability of software simulation tools can vary due to differences in algorithms, assumptions, and input parameters. Overestimations or underestimations in energy predictions can lead to misinformed decisions regarding system design, financial feasibility, and energy yield expectations. Therefore, a comprehensive comparison of simulation tools with real-world performance data is essential to assess their strengths, limitations, and applicability for specific scenarios.

1.1 Literature Reviews

Numerous simulation studies on photovoltaic (PV) systems have been conducted to predict the energy output and performance of these systems. The following sections review key literature relevant to this field of research: The characterization of PV system performance using a LabVIEW real-time interface, integrating instruments for online measurement and real-time comparison of simulation and monitored data was reported (Chouder et al., 2013). The proposed low-cost method enables secure, reliable analysis and creates a database-ready system for PV performance evaluation. Applied to a grid-connected PV system at Algeria's CDER (Centre de Développement des Energies Renouvelables), the results demonstrate strong alignment between measured and simulated values. This integration approach can be further extended for PV system fault diagnosis.

Modeling and simulation of PV systems are crucial for integrating solar energy into modern grids. Complex nonlinear equations and detailed switching models often lead to slow simulations, especially for long-term analyses. A reported study (Xiao et al., 2013) presents simplified, efficient PV-cell models and parameterization techniques ensuring I-V curves align with manufacturers' data. Power interface models for fast simulation, including two-stage string inverters and single-stage module-level systems, are evaluated. Results from a 2.4-kW grid-tied PV unit show that the proposed method offers advantages over conventional approaches for simulating long-term grid-tied operations. Off-grid hybrid systems offer sustainable energy solutions for rural electrification, addressing

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URL: https://www.jree.ir/article_243201.html

Please cite this article as: Elieser, T. (2025). Comparison of PV Simulation Tools with Real-World Data: Residential Rooftop Systems in Surabaya, Indonesia. *Journal of Renewable Energy and Environment (JREE)*, *12*(2), 186-193. https://doi.org/10.30501/jree.2026.519083.2368.

reliability, sustainability, and environmental concerns. Using HOMER modeling, a reported study (Salau et al., 2024) designed and simulated a hybrid system for Shinshicho Primary Hospital in Ethiopia, combining solar PV, diesel generators, and battery storage. Meeting a daily load of 276 kWh and a peak of 40 kW, the system requires an initial capital of $160,500 and annual O&M costs of $14,824. With a 20-year net present cost of $216,155 and an energy cost of $0.187/kWh, the system is both economically viable and sustainable. Martin et al. (Gutiérrez-Martín et al., 2024) reported a novel model for PV-hydrogen (H2) systems, optimizing design and operation to minimize H2 production costs while meeting target outputs.

Recent urban-scale assessments further highlight the importance of understanding solar potential under varying spatial and climatic conditions. For example, a recent work (Kaleshwarwar & Bahadure, 2024) used a grid divisional method to analyze PV generation dynamics across heterogeneous urban environments, while a work by (Kaleshwarwar & Bahadure, 2023a) evaluated solar potential across diverse built forms in Nagpur, India, demonstrating how morphology and shading influence energy yield. These studies reinforce the need for location-specific validation of PV performance models, particularly in regions with complex urban and climatic characteristics such as tropical cities.

Nallamothu et al. (2024) explored the feasibility and design of a 500 kWp grid-connected rooftop solar PV system at Bapatla Engineering College, Andhra Pradesh, India, leveraging its ideal solar potential (16.77° N, 80.63° E). Utilizing PVsyst software, the system's performance was forecasted, designed, and simulated. Rooftop installations are advantageous for educational institutions, avoiding land acquisition issues. Simulation results highlight the system's viability for promoting green initiatives in educational settings. Anang et al. (2021) evaluated the real performance of a 7.8 kWp grid-connected rooftop PV system at a residential house under a feed-in-tariff scheme. Based on 2018–2019 data, PVsyst identified optimal tilt (5°) and orientation, enhancing energy production by 4.8%. HOMER Pro simulated the system using a calculated derating factor, achieving a 1.7% annual error. Performance ratios peaked at 75.72%, with capacity factors of 13%–16%. Economic analysis revealed a 5–7 year payback and annual net profit of RM 3,000, reducing CO_2 emissions by 7.45 tons/year.

Milosavljević et al. (2022) tested 13 tools, including PVGIS, PVWatts, PVsyst, and HOMER, using experimental data from a 2 kWp on-grid PV system in Niš, Serbia (2019). SolarPro showed the lowest deviation for solar irradiation, while PVGIS performed best for electricity production, yielding 2,455.6 kWh annually. The findings aim to enhance PV system modeling accuracy and support tool selection for PV design.

1.2 Objectives

While several comprehensive validation studies have compared multiple PV simulation tools with measured datasets, such as the work of Milosavljević et al. (2022), which assessed four system-based and three online platforms, and Kaleshwarwar & Bahadure (2023b), which tested over a dozen tools under real-world conditions, most of these investigations were conducted in temperate or semi-arid regions, with limited focus on tropical urban environments. Moreover, previous studies primarily evaluated large-scale or institutional PV systems, whereas residential-scale systems operating under high humidity and intermittent cloud cover remain underrepresented in the literature.

The primary objective of this paper is to compare the energy output predictions of three widely used simulation software tools: PVWatts® (pvwatts.nrel.gov, 2024), PVGIS (re.jrc.ec.europa.eu, 2024), and PV*SOL Online (pvsol-online.valentin-software.com, 2024), referred to as Software 1, Software 2, and Software 3, respectively, with actual measurements from a residential solar photovoltaic (PV) system. This study aims to analyze monthly and annual trends to identify biases, deviations, and variations in the predictions, thereby offering a comprehensive understanding of the performance and limitations of these tools. Furthermore, the paper seeks to evaluate how closely each software's predictions align with real-world energy output patterns, thereby assessing their reliability and practical applicability. The findings from this research are used to propose recommendations for improving the accuracy of energy output predictions, focusing on bias correction, algorithm enhancement, and validation with field data. Ultimately, the study aspires to provide valuable insights for selecting and utilizing simulation tools effectively, contributing to better planning, implementation, and optimization of solar PV systems for enhanced performance and sustainability, thereby addressing the research gap in PV performance modeling in tropical residential environments.

This study contributes a novel perspective by focusing on a residential 4.5 kWp rooftop PV system in Surabaya, Indonesia, located in a humid tropical climate with significant diurnal variability. It uniquely compares the predictive accuracy of three widely accessible simulation platforms against real operational data from 2022, using standardized parameters across all models. By quantifying deviations at both monthly and annual scales, this research provides practical insights for tool selection and calibration for small-scale systems in Southeast Asian urban contexts, where such validation remains scarce.

2. METHODOLOGY

2.1 Software and Simulation

Simulations of the PV system were conducted using three different software tools: PVWatts® (pvwatts.nrel.gov, 2024), PVGIS (re.jrc.ec.europa.eu, 2024), and PV*SOL Online (pvsol-online.valentin-software.com, 2024). These tools were selected due to their global recognition, reliability, and ability to provide detailed estimations of PV system performance. The simulations aimed to estimate the energy production of the 4.5 kWp residential PV system under conditions that closely matched the actual installation setup.

Software 1- PVWatts®

PVWatts® is a web-based application developed by the National Renewable Energy Laboratory (NREL) to estimate the electricity production of grid-connected PV systems. It provides preliminary assessments of roof- or ground-mounted systems using crystalline silicon or thin-film photovoltaic cells. Key features of PVWatts® include:

- Ease of use: Users input basic design and location details, such as module tilt, orientation, and geographic position, to generate estimates.
- Output: Annual and monthly electricity production estimates, along with system performance parameters such as capacity factor and energy losses.

- Accessibility: As a free online tool, PVWatts® is widely utilized by homeowners, small-scale PV installers, and researchers.

Despite its limitations, such as less detailed modeling of environmental losses like shading and soiling, PVWatts® is well-cited (Abdallah et al., 2022; Pathirana et al., 2024; Pedraza-Centeno et al., 2023) for its simplicity and effectiveness in preliminary PV performance evaluations.

Software 2 - Photovoltaic Geographical Information System (PVGIS)

PVGIS, developed by the European Commission Joint Research Centre (JRC), is an advanced tool for solar energy analysis. It provides solar radiation data and PV performance estimates for most global locations. Key features of PVGIS include:

- Comprehensive database: Solar radiation and climate data are sourced from global satellite and ground-based measurements, enhancing accuracy.
- Simulation options: Users can simulate performance for various PV system configurations, including fixed-tilt and tracking systems.
- Output details: Results include monthly and annual energy production, peak sun hours, and performance ratios.

PVGIS has evolved through multiple versions, with the latest, PVGIS 5, offering enhanced capabilities. It has been extensively used in research and solar resource assessments (Costa et al., 2024; Khazieva, 2024; Ukoima et al., 2024), making it a valuable tool for this study.

Software 3 - PV*SOL Online

PVSOL Online is a streamlined version of the full-featured PVSOL software, designed for quick and accurate PV system simulations. Key features of PV*SOL Online include:

- User-friendly interface: Allows input of system parameters such as module specifications, inverter details, location, and load profile.
- Automatic configuration: Optimizes the connection between PV modules and the inverter for maximum efficiency.
- Detailed results: Provides outputs such as annual energy production, performance ratio, self-consumption, and solar fraction.

As an online tool, PV*SOL Online is accessible and efficient, supporting informed decision-making in PV system design and planning (Gaur et al., 2024; Bylykbashi & Filkoski, 2024).

Each simulation platform, PVWatts®, PVGIS, and PVSOL Online, operates using its own proprietary database and internal data-processing workflow, which are not publicly accessible. As these processes are controlled by the software developers rather than by the authors, detailed flowcharts describing data collection and internal computations cannot be provided. This study focuses on the comparative evaluation of the simulation outputs rather than on the internal mechanisms of each tool. In all simulations, the input parameters were standardized to closely match the actual system configuration.

These parameters included the system's geographical position, latitude -7.34° S and longitude 112.80° E, azimuth, east-facing, tilt angle, 15°, module specifications, Longi 0.45 kWp monocrystalline modules, inverter details, Sungrow SG4K-D, and estimated energy losses of approximately 14% due to shading, soiling, and other environmental factors.

This uniform approach ensured consistency across the three tools and alignment with real-world operating conditions.

The simulation results were compared with the actual performance data recorded over one year. Key metrics for analysis included annual and monthly energy production, performance ratios, and estimated energy losses. The comparative analysis highlighted discrepancies between simulated and measured data, providing insights into the tools' accuracy and identifying factors influencing system performance.

This integrated methodology facilitated a comprehensive evaluation of the PV system, bridging theoretical predictions and actual operational outcomes.

2.2 Actual PV System Installation

The PV modules, with specifications showed in Table 1, were mounted on the roof following its natural tilt and orientation. The roof has an approximate tilt angle of 15° and is oriented eastward. This configuration was selected to reflect typical residential installations in which roof orientation and tilt are determined by existing architectural structures rather than optimized for maximum solar energy capture.

Table 1. Electrical and Operational Specifications of the PV Module

Parameters	Value
Maximum Power (Pmax/W)	450
Open Circuit Voltage (Voc/V)	49.3
Short Circuit Current (Isc/A)	11.60
Voltage at Maximum Power (Vmp/V)	41.5
Current at Maximum Power (Imp/A)	10.85
Module Efficiency (%)	20.6
Operational Temperature	-40°C ~ +85°C
Power Output Tolerance	0 ~ +5 W
Voc and Isc Tolerance	±3%
Maximum System Voltage	DC1500V (IEC/UL)
Maximum Series Fuse Rating	20A
Nominal Operating Cell Temperature	45 ± 2° C
Temperature Coefficient of Isc	+0.049%/°C
Temperature Coefficient of Voc	0.270%/°C
Temperature Coefficient of Pmax	-0.350%/°C

The PV system generates direct current (DC) electricity when exposed to solar radiation. This DC power is converted into alternating current (AC) using a Sungrow SG4K-D inverter with a rated capacity of 4000 VA and an efficiency of 98.4%. The AC electricity is delivered to the utility grid through an export-import kWh meter, enabling the system to feed surplus energy into the grid and draw power as needed.

The schematic diagram of the grid-connected PV system is shown in Figure 1, and a photograph of the installed system is presented in Figure 2. The system components include the PV modules, the inverter, and the export-import kWh meter.

To enable continuous monitoring and data acquisition, an EyeM4 Wi-Fi communication device was integrated into the system. This device connects to the inverter via a standard RS485 interface and facilitates wireless data transmission. It collects operating data from the inverter and transmits it to a remote server via Wi-Fi.

The transmitted data include real-time and historical performance metrics. The performance of the PV system is monitored using the iSolarCloud mobile application, which provides a comprehensive suite of tools for operational analysis, remote parameter configuration, and maintenance. Key features of the iSolarCloud application include:

- WLAN configuration for seamless connectivity.
- Remote monitoring of device performance and fault management.
- Alarm notifications for system anomalies.
- Access to a knowledge repository for troubleshooting and optimization.

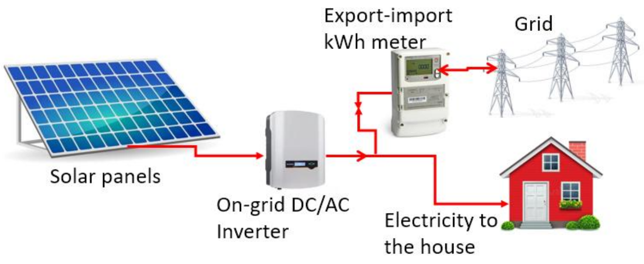


Figure 1. Schematic Diagram of the Grid-Connected PV System

Figure 2. Photograph of installed PV System Components

For the purpose of this research, the output data from the PV system were recorded over a full calendar year. The data were collected to analyze system performance, including daily and monthly energy generation and seasonal variations in energy output. This year-long data collection enabled a comprehensive evaluation of the system's operational performance and provided insights into its reliability and contribution to residential energy needs in a tropical urban environment.

In addition to the comparative evaluation of monthly and annual energy outputs, a statistical error analysis was conducted using two widely adopted performance indicators, Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE). These metrics were used to quantify the deviation between simulated results and actual measured data. MAPE expresses the average absolute error as a percentage of the actual value, calculated using the formula:

$$\text{MAPE} = \frac{1}{n}\sum\left|\frac{A_t-F_t}{A_t}\right| \times 100\% \quad (1)$$

where A_t is the actual value, F_t is the predicted value, and n is the number of observations. RMSE represents the square root of the mean of the squared differences between predicted and actual outputs, given by:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum(A_t - F_t)^2} \quad (2)$$

These indicators provide a quantitative basis for assessing the accuracy of each simulation tool and strengthening the robustness of the comparison.

3. RESULTS AND DISCUSSIONS

3.1 Simulation Results

Figure 3 shows the summary of the monthly and annual solar irradiation values simulated by three different software tools, Software 1, Software 2, and Software 3, for the same location. A detailed analysis reveals significant variations in monthly and annual results, both in terms of absolute values and percentage differences, which provide insights into the accuracy and characteristics of each software tool.

The description has been condensed to emphasize only the major deviations among the three simulation tools. Rather than restating monthly values already visible in the figure, the revised text highlights the most significant discrepancies, such as the pronounced difference in April and the convergence of estimates during mid-year months. This approach ensures that the figure serves as the primary reference, while the narrative provides additional analytical context rather than repetition.

From January to March, the monthly solar irradiation values are relatively low, with Software 1 consistently reporting the smallest values compared to the other tools. In January, Software 1 predicts the lowest monthly irradiation at 145.08 kWh/m², while Software 2 and Software 3 estimate higher values at 155 kWh/m² and 149.2 kWh/m², respectively. February shows a slight increase across all tools, with Software 2 again providing the highest estimate at 153 kWh/m². March results indicate closer alignment between Software 2 and Software 3, with both tools reporting approximately 157 kWh/m², whereas Software 1 remains lower at 139.5 kWh/m². A significant decline in solar irradiation occurs in April, marking the lowest monthly values of the year. Software 1 predicts 128.1 kWh/m², which is 27.3% lower than the 163 kWh/m² estimated by Software 2, highlighting a considerable discrepancy. By May and June, the irradiation values recover, with Software 2 consistently reporting higher results than the other tools. For instance, in June, Software 2 predicts 157 kWh/m², while Software 1 and Software 3 report slightly lower values of 143.1 kWh/m² and 146.55 kWh/m², respectively.

The dry season, typically spanning July to September, exhibits the highest irradiation levels. During this period, Software 1 reports a steady increase, from 155.93 kWh/m² in July to 191.7 kWh/m² in September.

Software 2 and Software 3 follow a similar trend but consistently predict higher values. In September, Software 3 records a peak monthly irradiation of 194.14 kWh/m², slightly exceeding the 182 kWh/m² reported by Software 2 and the 191.7 kWh/m² reported by Software 1.

This trend continues into October, when Software 3 reports the highest single-month value among all tools at 198.79 kWh/m², reflecting favorable solar conditions. A sharp decline in solar irradiation is observed in November and December, signaling the return of the rainy season. Software 1 reports the lowest value in December at 127.1 kWh/m², while Software 2 and Software 3 estimate higher values of 162 kWh/m² and 149.2 kWh/m², respectively. This seasonal decline is consistent with increased cloud cover and reduced solar availability typical of the local climate.

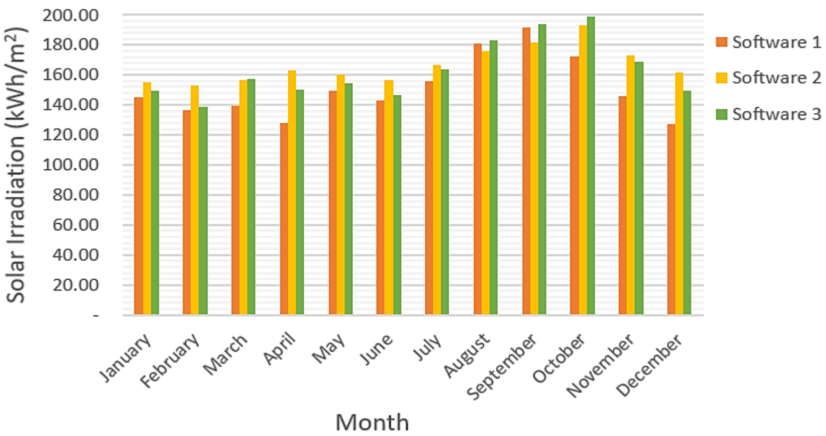


Figure 3. Monthly solar irradiation from three different software

On an annual scale, the total solar irradiation simulated by each tool shows notable differences. Software 2 predicts the highest annual irradiation at 1,998 kWh/m², followed by Software 3 with 1,953.06 kWh/m², and Software 1 with the lowest total at 1,815.77 kWh/m². The annual difference between Software 2 and Software 1 is substantial, amounting to 182.23 kWh/m², or 10.04%. Similarly, Software 3 exceeds Software 1 by 137.29 kWh/m², or 7.56%. These differences highlight variability in the modeling approaches and assumptions employed by each software tool.

Monthly variations among the tools are also considerable. The largest monthly discrepancy occurs in April, when Software 2 predicts a value 27.3% higher than that of Software 1. Conversely, the smallest variation is observed in February, when Software 1 and Software 3 differ by only 1.36%, indicating closer alignment during this period. Overall, the greatest discrepancies occur in transitional months, such as April and October, which may reflect differences in how the tools model seasonal weather changes.

These results emphasize the importance of software selection in solar energy system design and planning. Software 2, with its consistently higher predictions, may be more suitable for applications that prioritize maximizing potential energy yield. In contrast, the more conservative estimates provided by Software 1 may better align with real-world performance, particularly in regions characterized by variable weather patterns. Software 3 represents an intermediate option, providing results that are generally closer to those of Software 2 in most months. Future work could involve validating these simulated results against measured solar irradiation data at the site to assess the accuracy and reliability of each tool. Additionally, analyzing the impact of local weather factors, such as cloud cover and humidity, on seasonal trends could further refine the understanding of performance variations. Addressing these aspects would contribute to more precise solar energy system design and optimization for the studied location.

3.2 Actual PV System Performance

The performance of PV systems can be monitored in real time, with options to record and display data on a monthly, daily, or yearly basis. As mentioned earlier, this monitoring is conducted using the iSolarCloud application for Android smartphones. Although the application offers various features, the primary method for assessing PV system performance is through energy yield. Online monitoring is beneficial for quantifying energy yield and detecting potential issues or faults in the system that could affect performance. The data analyzed in this study encompass a full year of monitoring, specifically from January to December 2022.

The PV system exhibited notable anomalies in its monthly performance. The lowest energy output in January coincides with Surabaya's peak rainy season, during which dense cloud cover and high atmospheric moisture substantially reduce solar irradiation. Conversely, the unusually high production in August corresponds to clearer dry-season conditions and minimal cloud presence. Daily data further reveal abrupt drops during isolated cloudy events, illustrating the sensitivity of residential PV output to short-term weather fluctuations. These extreme cases underscore the importance of validating simulation tools under tropical climatic variability.

Figure 4 illustrates the monthly energy production in kilowatt-hours (kWh). The minimum monthly output occurs in January at approximately 236.2 kWh, while the maximum output reaches around 639 kWh in August. Daily energy production varied between 8.0 kWh and 24 kWh, with an average of 19.5 kWh. The total annual energy production is approximately 6,122 kWh. Based on these data, the annual specific energy output for the system is calculated to be 1,360 kWh per kilowatt-peak (kWp).

Figure 5 illustrates the performance of the photovoltaic (PV) system observed in August 2022. Monthly performance is represented by the daily energy yield and the total energy output for the month. The data indicate that the PV system's daily energy yield varied between 10.4 and 23.3 kWh, resulting in a total of 639.6 kWh for the month. This performance is closely linked to weather conditions, which influence solar irradiation.

The lowest energy output occurred in January, coinciding with the peak rainy season. This reduced energy yield is likely attributable to cloud cover over the solar panels. Conversely, it is recommended that further research be conducted to examine the impact of dust on energy generation from the PV system during the dry season. In Surabaya, the peak rainy season occurs between January and February, which may explain the decreased energy production observed in January.

The daily performance of the PV system in terms of power output can be tracked by selecting a specific day from the overview menu. Figure 6 (top) illustrates the average daily power output and total energy yield for August 21, 2022, which amounted to 22.5 kWh on a notably clear day. In contrast, Figure 6 (bottom) depicts typical power output under rainy or cloudy conditions on December 21, 2022, when the total energy output was 11 kWh.

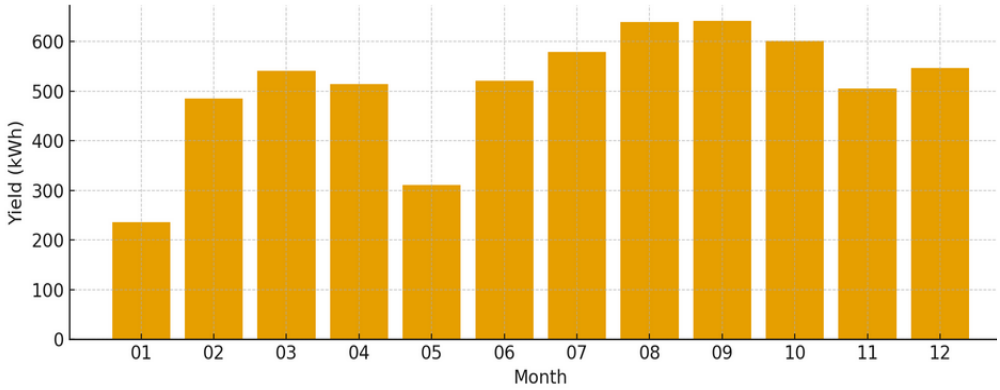


Figure 4. Monthly energy production of the PV system

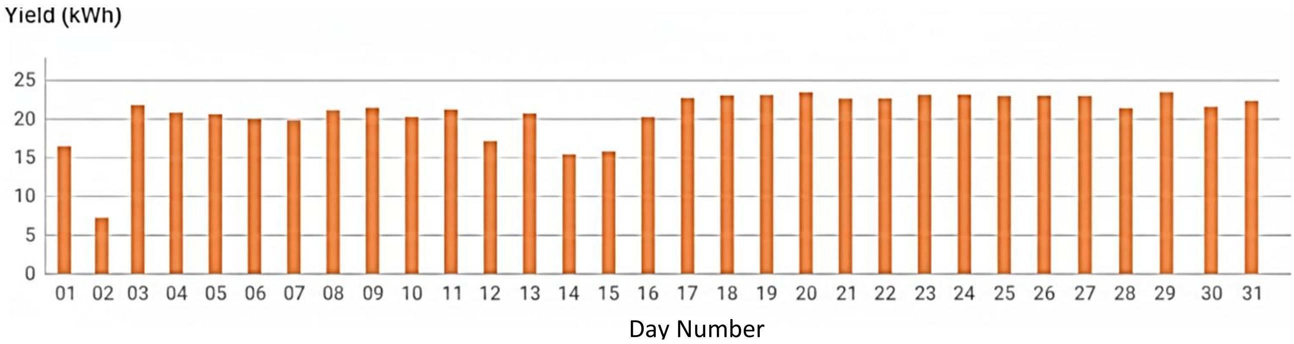
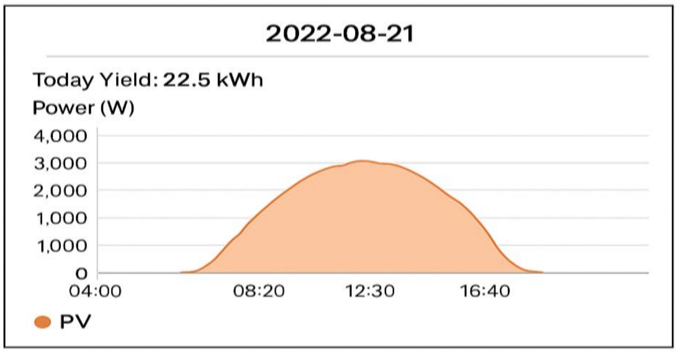


Figure 5. Daily performance of the PV system in August 2022.



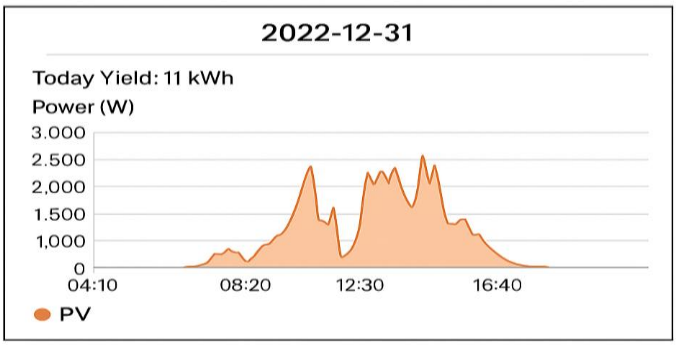


Figure 6. The daily power output and overall energy production under two distinct weather conditions: a clear day (top) and a cloudy day (bottom).

3.3 Comparison of Energy Output with Actual PV System

The monthly trends for energy output predictions from all three software tools, along with the actual energy output, reveal distinct patterns throughout the year (Figure 7). Software 1 consistently overestimates energy output compared to the measured values, with notable overestimations in September (+3.1%) and October (+3.1%). It records its highest energy output in October (670 kWh) and the lowest in April (440 kWh), exhibiting larger deviations during late September and early October.

Software 2 demonstrates closer alignment with the actual outputs but still slightly overestimates, particularly in September (+2.3%) and October (+2.3%). Its highest monthly output occurs in October (665 kWh), and the lowest in April (435 kWh).

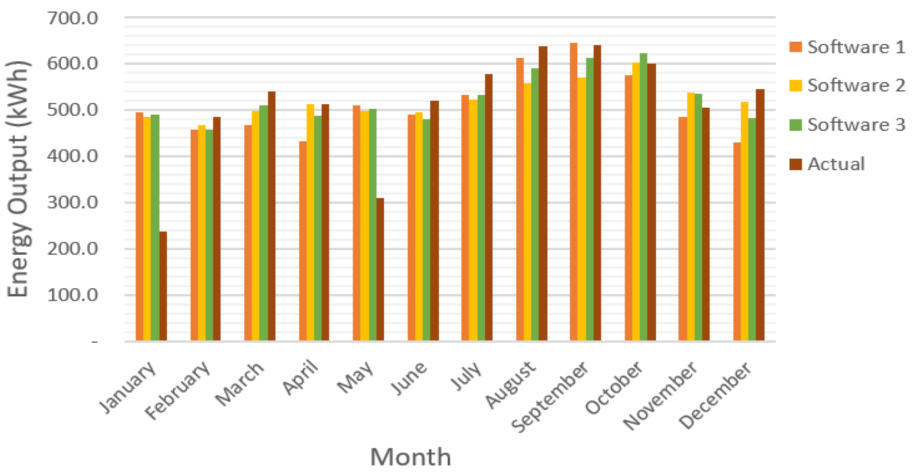


Figure 7. Comparison of Energy Output between the simulation and the actual PV system

Meanwhile, Software 3 provides the most accurate predictions, with minimal deviations from the actual values throughout the year. It slightly overestimates in September (+1.6%) and October (+1.5%), with a peak in October (660 kWh) and a trough in April (430 kWh).

The actual energy output exhibits a natural seasonal variation, increasing from May to August, peaking in September (640 kWh) and October (650 kWh), and declining toward December. This pattern is typical for solar energy systems, reflecting the influence of seasonal solar irradiation. All three software tools capture this seasonal trend; however, Software 1 consistently overestimates output, particularly during the peak months. In contrast, Software 3 remains the most reliable, with predictions closely matching the actual energy output throughout the year.

These monthly trends highlight the importance of understanding both seasonal variations and software-specific biases in energy predictions. The consistent overestimations by the software tools, especially during peak months, underscore the need to account for such deviations in solar energy project planning and performance evaluations. This analysis enables stakeholders to make more informed and realistic decisions based on predicted energy outputs.

A statistical evaluation was conducted using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) to quantify deviations between simulated and actual monthly outputs. Software 2 achieved the lowest MAPE at 19.01%, followed by Software 3 at 19.54%, while Software 1 showed the highest error at 21.34%. In terms of RMSE, Software 3 produced the smallest deviation (98.34 kWh), closely followed by Software 2 (98.70 kWh), indicating that these two tools provide more reliable estimates in absolute terms. Software 1 exhibited the highest RMSE (107.06 kWh), confirming its tendency to overestimate monthly energy production. These statistical indicators reinforce the earlier conclusion that Software 3 aligns most closely with measured performance, whereas Software 1 consistently diverges from actual field data. Table 2 presents the MAPE and RMSE metrics for the three PV simulation tools.

Table 2. MAPE and RMSE error metrics for the three PV simulation tools.

Software	MAPE (%)	RMSE (kWh)
Software 1	21.34%	107.06
Software 2	19.01%	98.70
Software 3	19.54%	98.34

The analysis of annual differences highlights important implications for the accuracy and reliability of the simulation software in predicting energy output. Software 1 exhibited the highest annual difference at +2.48%, indicating a tendency to slightly overestimate energy output. While this overestimation makes it less conservative, it may introduce an optimistic bias in project projections. Software 2 showed a lower annual difference of +1.52%, suggesting closer alignment with actual results and making it a more balanced option for energy modeling. Software 3 demonstrated the smallest annual difference at +0.56%, indicating the highest accuracy among the three tools and making it the most reliable choice for precise energy output predictions. The mean of the three software results also showed an annual difference of +1.52%, aligning closely with Software 2 and providing a balanced estimate.

The consistent overestimation across all three software tools indicates an inherent optimistic bias, possibly arising from assumptions about ideal system performance or weather conditions that may not fully reflect real-world losses. Although this overestimation remains within an acceptable range (less than 3%), it could influence decision-making, particularly in financial modeling and ROI calculations, by slightly inflating expectations of energy generation. Software 3, with its minimal deviation, is particularly suitable for scenarios requiring conservative and realistic estimates, whereas Software 1 may be preferred in cases where a more optimistic outlook is acceptable.

These findings underscore the importance of careful consideration of simulation tool outputs in project planning and highlight the potential benefits of refining software parameters to better reflect site-specific conditions. Overall, the analysis confirms the reasonable accuracy of the tools while emphasizing the need for calibration and adjustment to achieve more precise operational predictions. This approach ensures that project stakeholders can make informed decisions while accounting for potential deviations from actual system performance.

4. CONCLUSSIONS

This study compared the monthly and annual energy output predictions of three simulation tools, PVWatts®, PVGIS, and PVSOL Online, against real operational data from a residential 4.5 kWp PV system. All tools demonstrated reasonably good accuracy, with annual deviations below 3%, and PVSOL Online showing the closest agreement (+0.56%), followed by PVGIS (+1.52%) and PVWatts® (+2.48%). Although all three models consistently overestimated energy output, particularly during high-irradiance months, they effectively captured the seasonal performance trends of the system. These findings indicate that PVSOL Online is most suitable for applications requiring precise predictions, whereas PVGIS and PVWatts® may be appropriate for preliminary assessments or moderately conservative evaluations. Regular validation with field data and the application of correction factors are recommended to reduce optimistic bias and improve reliability. Future work should extend the dataset to multi-year observations, evaluate additional simulation platforms, and explore a broader range of system configurations. Further studies are also needed to quantify the influence of tropical environmental factors, such as dust accumulation during the dry season, microclimatic variations, and temperature-related losses, which are not fully captured in current models. Expanding the analysis to other regions and system types will support the generalization of these findings and enhance the applicability of PV simulation tools for planning and optimizing solar PV installations in diverse tropical environments..

5. ACKNOWLEDGMENT

The authors gratefully acknowledge the financial support provided by the Center for Environment and Renewable Energy Studies (PuSLET), University of Surabaya. This support has been instrumental in the successful completion of this work. We sincerely appreciate PuSLET's continued commitment to advancing research in sustainable and renewable energy.

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