International Journal of Recent Technology and Applied Science
p-ISSN: 2721-2017, e-ISSN: 2721-7280

Original Research Paper

Hybrid Measured-Synthetic Framework for Daily Energy Prediction of Rooftop Solar PV Systems in Tropical Regions

Nur Iksan[1*], Pamor Gunoto[1], Nurham Ambo Rappe[2], Ashan Milinda Bandara Ratnayake[3], Endang Susanti[1], Toni Kusuma Wijaya[1]

[1] *Faculty of Engineering, Universitas Riau Kepulauan. Batam, Indonesia.*
[2] *Faculty of Integrated Technologies, Universiti Brunei Darussalam. Bandar Seri Begawan, Brunei Darussalam.*
[3] *Department of Computer Science and Informatics, Faculty of Applied Sciences, Uva Wellassa University, Badulla, Sri Lanka.*

Article History
Received:
02.08.2026

Revised:
28.08.2026

Accepted:
13.09.2026

***Corresponding Author:**
Nur Iksan
Email:
nur.iksan@ft.unrika.ac.id

Abstract: Rooftop photovoltaic (PV) systems are increasingly deployed in tropical regions to support renewable energy adoption. However, reliable PV performance assessment typically requires long-term field measurements, which are often unavailable due to limited monitoring infrastructure and operational constraints. This study proposes a hybrid measured-synthetic framework for generating representative PV performance profiles and predicting energy production using limited field observations combined with meteorological data. The main contribution of this work is the development of a practical framework that extends sparse PV measurements into daily, monthly, and annual performance estimates. The proposed framework integrates measured PV operating parameters, including module temperature, voltage, current, and wind speed, collected from a rooftop PV installation in Batam, Indonesia, with solar radiation and ambient temperature data obtained from the NASA POWER database. Due to the limited availability of field measurements, a synthetic hourly dataset was generated using actual observations collected on 15 October 2022 in conjunction with photovoltaic performance modeling and meteorological information. The generated dataset was subsequently used to reconstruct representative daily operating profiles and estimate energy production over longer time horizons. The results indicate that the proposed framework successfully generated physically consistent PV performance profiles under tropical climatic conditions. The framework estimated a daily energy production of 34.27 kWh/day and an annual energy production of approximately 12,505.5 kWh/year. Validation against the available field measurements produced Mean Absolute Percentage Error (MAPE) values of 0.08%, 6.80%, and 7.03% for voltage, current, and power, respectively, indicating satisfactory agreement between measured and synthetic datasets. The proposed framework reduces dependence on extensive monitoring campaigns while preserving representative operational characteristics of photovoltaic systems. Therefore, it can serve as an effective tool for preliminary PV performance assessment and energy forecasting in regions where long-term measurement data are unavailable. Future work should incorporate longer monitoring periods, direct irradiance measurements, and broader validation datasets to improve prediction accuracy and generalizability.

Keywords: Grid-Tied System, Performance Ratio, Rooftop PV System, Solar Irradiance, Solar Photovoltaic.

1. Introduction

Rooftop photovoltaic (PV) systems have become an important component of the global transition toward sustainable and low-carbon energy systems. The increasing adoption of rooftop PV technology is driven by declining installation costs, growing electricity demand, environmental concerns, and the need to reduce greenhouse gas emissions [1] [2]. As rooftop PV utilizes existing building infrastructure for electricity generation, it offers a practical solution for expanding renewable energy capacity without requiring additional land resources [1] [3].

The deployment of rooftop PV systems is particularly attractive in tropical regions, where solar energy resources are available throughout the year. Favorable climatic conditions enable significant opportunities for distributed electricity generation in residential, commercial, and institutional buildings. However, the effectiveness of PV installations depends not only on system design but also on operational and environmental conditions that influence energy production and overall performance [4] [5].

Accurate photovoltaic performance assessment is therefore essential for system planning, operational evaluation, and energy forecasting. Existing approaches commonly rely on simulation-based techniques, long-term monitoring systems, or forecasting models to estimate photovoltaic energy production [5] [6]. Simulation-based methods provide flexibility and support system analysis during the design stage, whereas measurement-based approaches offer realistic performance evaluation through direct operational observations. Nevertheless, both approaches present limitations when comprehensive monitoring data are unavailable or when system-specific operating characteristics cannot be adequately captured [4] [5].

One of the major challenges encountered in small-scale rooftop PV installations is the limited availability of operational datasets. Many systems operate without dedicated monitoring infrastructure, resulting in sparse observations that are insufficient for conventional forecasting and performance assessment techniques [5]. Under such circumstances, reliable energy estimation becomes difficult because long-term measurements, historical operational records, and high-resolution monitoring data are often unavailable.

To overcome these limitations, researchers have increasingly employed meteorological datasets obtained from satellite observations, solar radiation databases, reanalysis products, and representative meteorological datasets such as Typical Meteorological Year (TMY). Data resources including the National Solar Radiation Database (NSRDB), ERA5 reanalysis products, and TMY datasets provide valuable environmental information that supports photovoltaic modeling and energy prediction [7] [8] [9]. These datasets offer broad geographical coverage and long-term temporal records, making them attractive alternatives in data-constrained environments.

Despite their advantages, meteorological datasets alone cannot fully represent the actual operating characteristics of a specific photovoltaic installation. Factors such as module temperature, electrical behavior, installation characteristics, and local operating conditions may differ significantly from generalized meteorological estimates [10] [11]. Consequently, approaches relying exclusively on simulation or meteorological datasets may overlook important system-specific information available from field measurements.

A review of the existing literature indicates that most photovoltaic performance studies rely either on extensive monitoring campaigns or on simulation-driven energy prediction methods [4] [5] [6] . Comparatively fewer studies have investigated the generation of representative photovoltaic operating profiles using extremely limited field observations while simultaneously preserving measured electrical characteristics and incorporating meteorological variability. This limitation is particularly relevant for rooftop PV systems operating in developing regions, where monitoring resources and historical datasets are frequently constrained.

Therefore, a research gap remains in the development of practical photovoltaic performance assessment frameworks capable of transforming sparse field observations into representative daily and long-term operating profiles. Addressing this challenge requires an approach that combines the realism of measured observations with the broader temporal coverage provided by meteorological datasets.

To address this gap, this study proposes a Hybrid Measured-Synthetic Framework that integrates limited field measurements, NASA POWER meteorological data, and photovoltaic performance modeling to generate representative photovoltaic operating profiles and estimate energy production.

The framework utilizes measured electrical and environmental parameters as calibration anchors, while meteorological information serves as an environmental driver for profile reconstruction.

The main contributions of this study are threefold. First, a practical framework is developed for generating representative photovoltaic operating profiles from sparse field observations. Second, a synthetic hourly dataset is constructed by combining measured PV characteristics with meteorological information obtained from publicly available environmental datasets. Third, the generated profiles are employed for daily, monthly, and annual energy prediction under data-constrained conditions. The proposed methodology offers an alternative solution for photovoltaic performance assessment in situations where long-term monitoring datasets are unavailable.

2. Literature Review

2.1. Rooftop Photovoltaic Systems

Rooftop photovoltaic (PV) systems have become one of the most widely adopted distributed renewable energy technologies due to their ability to utilize existing building surfaces for electricity generation while reducing dependence on conventional energy sources [1] [2]. The increasing deployment of rooftop PV systems has been driven by declining PV module costs, growing environmental concerns, and government initiatives supporting renewable energy adoption [1] [2].

Unlike ground-mounted PV installations, rooftop PV systems are integrated directly into residential, commercial, institutional, and industrial buildings. This configuration offers several advantages, including reduced land requirements, proximity to electricity demand centers, lower transmission losses, and improved energy sustainability [2] [3]. Furthermore, rooftop PV systems can contribute to carbon emission reduction by enabling localized renewable electricity generation [1] [3].

A typical rooftop PV system consists of photovoltaic modules, mounting structures, power conditioning equipment, monitoring systems, and electrical protection devices. PV modules convert incoming solar energy into direct current (DC) electricity, which is subsequently converted into alternating current (AC) electricity through power electronic converters for utilization by electrical loads or grid-connected applications [4].

The performance of a rooftop PV installation depends not only on component characteristics but also on environmental and operational conditions. Factors such as solar resource availability, module temperature, wind conditions, installation orientation, tilt angle, and shading conditions influence overall system productivity and efficiency [3] [5]. Consequently, reliable performance assessment is essential for evaluating energy generation capability and long-term system operation.

Several performance indicators are commonly employed to evaluate rooftop PV systems, including energy yield, specific yield, capacity factor, and performance ratio (PR) [4] [5]. These metrics provide quantitative measures of system productivity and operational effectiveness. However, their estimation often requires sufficient operational and environmental information, which may not always be available in small-scale rooftop installations.

As rooftop PV deployment continues to expand, there is growing interest in developing practical methodologies capable of assessing PV performance under limited data conditions. Such methodologies are particularly important for tropical regions, where rooftop PV systems are increasingly adopted but long-term monitoring records remain scarce. Therefore, understanding the environmental factors affecting PV operation becomes essential for developing representative energy prediction frameworks.

2.2. Environmental Factors Affecting PV Performance

Photovoltaic performance is strongly influenced by environmental conditions. Among the various factors affecting PV operation, solar radiation, module temperature, and wind speed are widely recognized as the most influential variables because they directly affect electrical characteristics and energy production [5] [10].

Solar radiation is the primary energy source driving photovoltaic power generation. The electrical output of a PV module is closely related to the amount of solar energy received by the cell surface. As solar irradiance increases, the generated photocurrent increases, resulting in higher current and power output [5] [7].

Because of its dominant influence on PV performance, solar radiation is commonly employed as the primary input variable in photovoltaic performance assessment, energy yield estimation, and forecasting applications. Variations in solar radiation throughout the day and across seasons therefore produce corresponding variations in photovoltaic energy production [5] [7].

Module temperature is another important environmental factor affecting photovoltaic performance. While higher solar radiation generally increases energy generation, elevated module temperatures tend to reduce photovoltaic conversion efficiency. This behavior occurs because increasing cell temperature decreases the voltage generated by photovoltaic cells, thereby reducing overall power output [10].

The inverse relationship between temperature and voltage has been widely reported in photovoltaic studies. As operating temperature increases, the electrical efficiency of the PV module decreases, even under favorable irradiance conditions. This effect is particularly significant in tropical regions, where module temperatures may exceed ambient temperatures by a substantial margin during peak solar hours [10] [11].

Wind speed influences photovoltaic performance indirectly by affecting module temperature. Airflow across the module surface enhances convective heat transfer and promotes cooling of photovoltaic cells. Consequently, higher wind speeds can reduce operating temperatures and partially mitigate temperature-induced efficiency losses [11]. However, although wind speed does not directly increase electrical generation, its cooling effect helps maintain lower operating temperatures and may improve overall photovoltaic performance, especially under conditions of high solar exposure [10] [11].

The combined influence of solar radiation, temperature, and wind speed determines the overall electrical behavior of photovoltaic systems. Solar radiation primarily affects current generation, temperature influences voltage characteristics, and wind speed contributes to thermal regulation. Together, these variables determine instantaneous power output and long-term energy production capability [5] [10].

Understanding these relationships is particularly important when developing representative operating profiles from limited measurements. Since environmental conditions vary continuously throughout the day, any generated PV profile should preserve the physical relationships between environmental variables and electrical output characteristics. These relationships form the basis of the photovoltaic performance modeling approach adopted in this study.

2.3. NASA Meteorological Data for PV Assessment

Accurate meteorological information is essential for photovoltaic performance assessment because environmental conditions directly influence energy production, system efficiency, and long-term operational behavior [5] [7].

In many regions, the availability of ground-based meteorological stations remains limited, resulting in incomplete climatic records for photovoltaic analysis. To overcome this limitation, researchers frequently utilize satellite-derived meteorological datasets and atmospheric reanalysis products as alternative sources of environmental information. Such datasets provide extensive temporal coverage and geographical availability, making them particularly useful for renewable energy applications [8] [9] [12].

The NASA Prediction of Worldwide Energy Resources (NASA POWER) platform provides several environmental variables relevant to photovoltaic studies, including solar radiation, ambient temperature, humidity, wind speed, and atmospheric parameters. These datasets are generated through the integration of satellite observations, atmospheric models, and meteorological reanalysis products, enabling long-term environmental assessment across different geographical regions.

A major advantage of NASA POWER is its ability to provide consistent meteorological information for locations where weather monitoring infrastructure is unavailable or insufficient. Similar approaches are also employed in global solar resource databases and satellite-based solar radiation services, including NSRDB and CAMS, which have become important resources for photovoltaic resource assessment and energy forecasting [7] [13].

Nevertheless, satellite-derived datasets may exhibit deviations from direct ground measurements due to spatial resolution limitations and local environmental variability. Therefore, combining field observations with meteorological datasets has become a common strategy for improving photovoltaic performance assessment and forecasting reliability [5] [6].

In photovoltaic studies, meteorological datasets are frequently used as environmental drivers within simulation and forecasting frameworks. Solar radiation data support irradiance-dependent power estimation, whereas ambient temperature information is used to evaluate thermal effects on PV operation [8] [10]. Accordingly, NASA POWER provides a practical mechanism for extending short-duration field measurements into longer-term performance assessments.

In the present study, NASA POWER data serve as the primary meteorological driver within the proposed hybrid measured-synthetic framework. By integrating meteorological information with measured operating characteristics, representative photovoltaic operating profiles can be generated despite the absence of continuous monitoring records. This integration provides the environmental information required to extend sparse field observations into daily, monthly, and annual performance estimates.

2.4. Synthetic Dataset Generation in Renewable Energy Studies

The increasing demand for renewable energy forecasting and performance assessment has stimulated the development of synthetic data generation techniques. Synthetic datasets are constructed to reproduce the statistical and physical characteristics of observed systems while overcoming limitations associated with incomplete or unavailable measurements [9] [14].

In photovoltaic applications, synthetic datasets are frequently employed to reconstruct representative operating conditions, estimate energy production, and support forecasting activities. These approaches are particularly useful when continuous monitoring data are unavailable or when historical records are insufficient for comprehensive analysis [5] [14].

One of the most widely adopted concepts related to synthetic data generation is the Typical Meteorological Year (TMY) approach. TMY datasets are generated from long-term meteorological observations and are designed to represent typical climatic conditions for a specific location. Rather than reproducing weather conditions for a particular year, TMY profiles provide representative environmental datasets that are widely used in photovoltaic and building energy simulations [9].

Beyond meteorological applications, synthetic datasets have increasingly been utilized in forecasting and energy system analysis to generate representative operating conditions under data-scarce environments [14]. By combining measured observations with environmental information and physical performance relationships, synthetic profiles can preserve realistic operating characteristics while extending temporal coverage beyond the available measurements [15].

The development of synthetic datasets generally follows three fundamental principles. First, the generated profiles should remain physically consistent with observed system behavior. Second, environmental influences such as solar radiation and temperature must be incorporated into the reconstruction process. Third, the resulting datasets should preserve the operational characteristics observed in measured data [14].

Despite the growing adoption of synthetic datasets in photovoltaic forecasting, many existing studies either rely primarily on simulation-generated data or require extensive historical observations for calibration purposes [15]. Consequently, the generation of representative photovoltaic operating profiles from sparse field measurements remains an open research problem.

To address this challenge, the present study adopts a hybrid measured-synthetic approach that integrates limited field observations, NASA meteorological information, and photovoltaic performance modeling. The objective is not to replace measured data but to extend their information content and reconstruct representative operating profiles suitable for energy prediction under data-constrained conditions.

2.5. PV Energy Prediction Approaches

Accurate photovoltaic (PV) energy prediction is essential for system planning, operational management, performance assessment, and energy forecasting. Owing to the intermittent nature of solar energy resources, numerous prediction approaches have been developed to estimate photovoltaic energy generation under varying environmental conditions [6] [16]. Existing methods can generally be classified into simulation-based, measurement-based, and hybrid approaches.

1) Simulation-Based Approaches

Simulation-based approaches estimate photovoltaic performance using mathematical models, meteorological datasets, and system specifications. These approaches are widely implemented through commercial and open-source modeling environments and have been extensively used for PV system design, yield assessment, and energy forecasting [17] [18] [19].

The primary advantage of simulation-based approaches is their capability to evaluate PV performance without requiring operational measurements. In addition, they enable designers to investigate multiple installation scenarios, module configurations, orientations, tilt angles, and shading conditions efficiently [17] [18]. However, the accuracy of simulation results depends heavily on model assumptions and meteorological inputs. Consequently, simulation outputs may deviate from actual operating conditions when local environmental effects or system-specific characteristics are not adequately represented [16].

2) Measurement-Based Approaches

Measurement-based approaches rely on operational data collected directly from photovoltaic installations. Commonly monitored parameters include solar irradiance, module temperature, voltage, current, power output, and energy generation. Because actual system behavior is observed directly, these approaches generally provide more realistic performance assessments and operational insights [4].

Long-term monitoring campaigns have been widely employed to evaluate photovoltaic performance indicators such as energy yield, capacity factor, and performance ratio [4]. Measured datasets are also frequently used for fault diagnosis, degradation assessment, forecasting model development, and operational optimization [5]. Nevertheless, the requirement for continuous monitoring infrastructure and extended observation periods limits the applicability of purely measurement-based approaches, particularly for small-scale rooftop PV systems.

3) Hybrid Prediction Approaches

Hybrid approaches have emerged to overcome the limitations of purely simulation-based and measurement-based methods. These approaches combine measured observations with meteorological information, physical models, statistical techniques, or data-driven algorithms to improve prediction accuracy while reducing dependence on extensive monitoring datasets [20] [21].

In hybrid frameworks, measured observations provide representative operating characteristics, while meteorological datasets supply environmental information required for temporal expansion and energy prediction. Such integration enables the preservation of realistic system behavior while extending performance estimation beyond the available observation period [15] [20].

Recent forecasting studies have highlighted the increasing importance of hybrid approaches for photovoltaic systems operating under data-constrained conditions because they provide a practical balance between prediction accuracy and data availability [21].

The growing adoption of hybrid prediction methods is particularly relevant for rooftop photovoltaic systems in developing regions, where monitoring infrastructure is often limited and historical measurements may be unavailable. Under these circumstances, hybrid methods offer a practical alternative for energy estimation and performance assessment.

Based on the reviewed literature, simulation-based approaches provide flexibility but may not fully represent actual operating conditions. Measurement-based approaches offer realistic system information but require extensive monitoring data. Hybrid approaches attempt to combine the advantages of both methods by integrating measured observations with environmental information and performance models.

The findings from the literature suggest that hybrid approaches provide the most suitable foundation for photovoltaic performance prediction under limited data availability conditions. Consequently, they offer a promising direction for developing practical frameworks that can extend sparse observations into representative operating profiles and support energy prediction applications.

2.6. Research Gap and Conceptual Framework

The literature indicates that significant progress has been achieved in photovoltaic performance assessment and energy prediction. However, existing approaches still present several practical limitations when applied to small-scale rooftop PV systems operating under limited data availability conditions.

Simulation-based approaches provide effective tools for PV performance evaluation and energy estimation through the use of physical models, meteorological datasets, and system specifications. Open-source and commercial modeling frameworks have been widely utilized for photovoltaic system design, yield estimation, and forecasting applications [17] [18] [19]. These methods are advantageous because they can generate performance predictions even before system installation and require only system specifications and meteorological information. Nevertheless, simulation results are highly dependent on modeling assumptions and environmental inputs and may not fully represent the actual operating behavior of installed photovoltaic systems [16].

On the other hand, measurement-based approaches offer direct observation of photovoltaic operating characteristics and generally provide more realistic performance assessments [4] [11]. These approaches have been widely employed for evaluating energy yield, operational efficiency, system reliability, and performance indicators. However, their effectiveness depends on the availability of continuous monitoring infrastructure and long-term operational datasets, which are often difficult to obtain in small-scale rooftop PV installations due to economic and technical constraints [4].

Recent studies have increasingly adopted hybrid approaches that combine measured data, meteorological information, physical models, and advanced forecasting techniques to improve prediction accuracy [20] [21]. These approaches have demonstrated promising results in addressing some limitations associated with purely simulation-based or measurement-based methods. Furthermore, hybrid forecasting frameworks have been recognized as an effective strategy for balancing prediction accuracy and data availability [6] [15].

Despite these advances, many existing hybrid frameworks still require substantial historical observations for calibration and validation. Their implementation therefore remains challenging under severely data-constrained conditions, particularly when only sparse field measurements are available [14].

Based on the reviewed literature, a gap remains in the development of practical photovoltaic performance prediction frameworks capable of operating under limited monitoring conditions. In particular, relatively few studies have focused on generating representative photovoltaic operating profiles from short-duration field measurements while preserving measured electrical characteristics and incorporating meteorological variability through publicly available environmental datasets [14].

This limitation is especially relevant for developing regions and small-scale rooftop PV installations, where continuous monitoring systems are frequently unavailable and long-term operational records may not exist. Under these circumstances, there is a need for a methodology capable of extending sparse measurements into representative operating profiles without requiring extensive historical datasets.

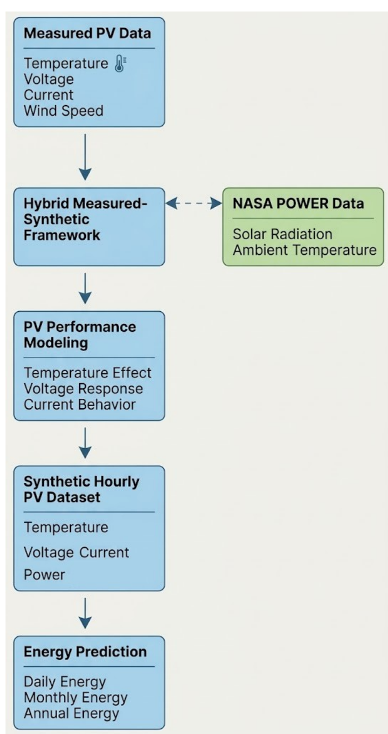

Figure 1. Conceptual Framework

To address this gap, the present study proposes a Hybrid Measured-Synthetic Framework that integrates limited field measurements, NASA POWER meteorological data, and photovoltaic performance modeling to generate representative daily PV operating profiles and estimate energy production. Unlike conventional simulation-based approaches that rely exclusively on meteorological information and unlike measurement-based approaches that depend on long-term monitoring campaigns, the proposed framework utilizes sparse field observations as calibration anchors while employing meteorological data as environmental drivers for profile reconstruction.

The conceptual relationship among the primary components of the proposed framework is illustrated in Figure 1. Measured photovoltaic observations provide actual operating characteristics, NASA meteorological data supply environmental information, and photovoltaic performance modeling establishes the physical relationships required for profile reconstruction. The integration of these components enables the generation of synthetic hourly datasets that support daily, monthly, and annual energy prediction.

Consequently, the main contribution of this study is the development of a practical framework for generating representative photovoltaic performance profiles from limited field measurements. The proposed methodology extends the usefulness of sparse operational data and provides an alternative solution for photovoltaic performance assessment in regions where long-term monitoring records are unavailable. Furthermore, the study contributes to the growing body of research on hybrid forecasting and synthetic data generation by demonstrating how measured observations and publicly available meteorological datasets can be integrated to support photovoltaic energy prediction under data-constrained conditions [14] [20].

3. Methodology

3.1. Study Area and PV System Description

The study was conducted at the Auditorium Building of Universitas Riau Kepulauan (UNRIKA), Batam, Indonesia. The selected site is located at approximately 0°02′56″ N latitude and 103°58′00″ E longitude and represents a typical rooftop photovoltaic (PV) installation environment in a tropical urban area. The geographical location of the study area is illustrated in Figure 2. The building was selected due to the availability of a relatively large rooftop area and favorable exposure to solar radiation throughout the year.

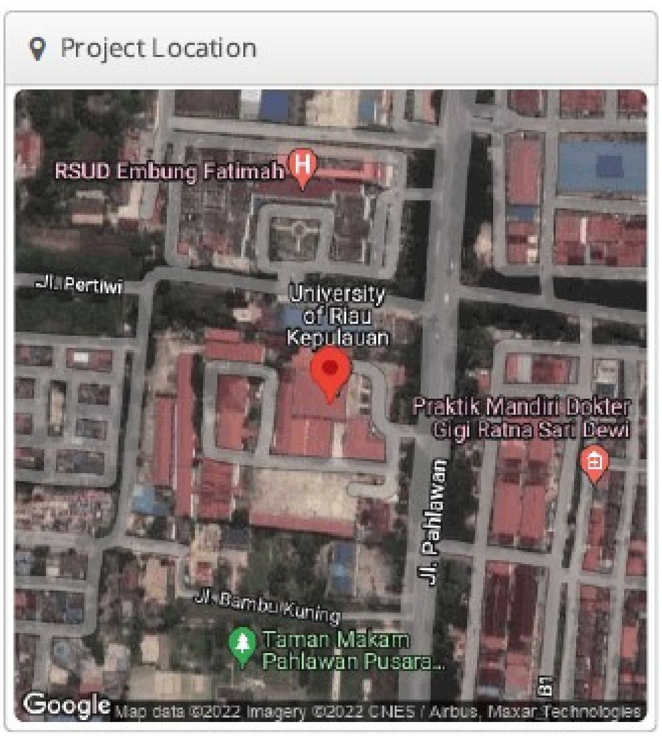

Figure 2. Location of the Study Area in Batam (Indonesia)

Batam is located near the equatorial region and is characterized by a tropical climate with relatively stable temperatures and abundant solar resources. According to the meteorological data extracted for this location, the average annual solar irradiation reaches approximately 4.61 kWh/m²/day, indicating substantial potential for photovoltaic energy generation. These climatic conditions make Batam a suitable case study for evaluating PV performance prediction methods under tropical environmental conditions.

The PV system considered in this study is a grid-connected rooftop photovoltaic installation developed on the rooftop of the Auditorium Building. The available installation area is approximately 321.7 m², allowing the deployment of 68 photovoltaic modules with a nominal power rating of 350 Wp each. Consequently, the total installed capacity of the system is 23.8 kWp. To maximize solar energy harvesting, the PV array was configured with a tilt angle of 10° and an azimuth angle of 180° (south-facing), as determined in the original rooftop design study.

The electrical and physical specifications of the PV module used in this study are summarized in Table 1. The module is a polycrystalline technology with a rated power of 350 Wp, a maximum power voltage of 42.98 V, and a maximum power current of 8.13 A. In addition, the module efficiency reaches 16.22%, which is consistent with commercially deployed PV systems in tropical regions. These parameters were used as the baseline characteristics for the photovoltaic performance modeling process proposed in this research.

Table 1. Electrical and Physical Specifications of the Photovoltaic Module Used

Parameter	Value
Module Type	Polycrystalline
Rated Power (Pmpp)	350 Wp
Maximum Power Voltage (Vmpp)	42.98 V
Maximum Power Current (Impp)	8.13 A
Open Circuit Voltage (Voc)	51.47 V
Short Circuit Current (Isc)	8.93 A
Module Efficiency	0.1622
NOCT	50°C
Maximum System Voltage	1000 V
Dimensions	1652 × 1306 × 50 mm
Number of Modules	68
Installed Capacity	23.8 kWp

The PV array is connected to a grid-tied inverter system based on the Sunny Tripower 24000TL-US inverter platform, which provides a nominal power capacity of approximately 24.1 kW with a maximum conversion efficiency exceeding 98%. The rooftop PV installation serves as the experimental platform for collecting field measurements and establishing representative operational characteristics of the PV system. These measured characteristics are subsequently integrated with NASA meteorological data to develop the proposed hybrid measured-synthetic framework for generating daily PV performance profiles and estimating energy production under limited measurement conditions.

3.2. Field Measurement Dataset

The proposed framework was developed using field measurements collected from the rooftop photovoltaic installation described in Section 3.1. Unlike conventional PV performance studies that rely on continuous monitoring systems, the available measurements in this study were obtained from a short observation campaign conducted on 15 October 2022. The collected dataset was intentionally retained in its original form to evaluate the feasibility of generating representative PV performance profiles from a limited amount of field information.

The measurement campaign focused on four photovoltaic modules, identified as Panel I, Panel II, Panel III, and Panel IV. For each module, four operating parameters were recorded, namely module temperature (°C), output voltage (V), output current (A), and wind speed (m/s). These variables were selected because they represent the key environmental and electrical factors affecting photovoltaic performance under real operating conditions.

Measurements were taken at three observation times, namely 12:00**,** 12:30, and 13:00, corresponding to the period around solar noon when PV output is generally close to its daily maximum. The resulting dataset provides a snapshot of the operational characteristics of the PV modules under relatively high solar irradiance conditions. Although the observation period is limited, it captures simultaneous variations in temperature, voltage, current, and wind speed that can be used to calibrate photovoltaic performance relationships.

Table 2 summarizes the field measurement dataset employed in this study. The recorded module temperatures ranged from approximately 43.5°C to 65.7°C, while the measured output voltage varied between 19.6 V and 21.7 V. The corresponding current values ranged from 1.30 A to 5.98 A. Wind speed measurements during the observation period varied between 2.5 m/s and 3.3 m/s. These observations indicate measurable variations among the four PV modules despite their operation under the same environmental conditions.

A key characteristic of this study is that the available field measurements were limited to a short observation period. Therefore, the measured data were not intended to represent complete daily operation. Instead, they were utilized as calibration and reference points for the proposed hybrid measured-synthetic framework. In this approach, measured electrical and environmental parameters provide anchor points describing actual PV behavior, while meteorological information supplied by external datasets is used to reconstruct representative operating profiles over longer periods. This strategy enables the development of PV performance models in situations where long-term monitoring data are unavailable or difficult to obtain.

Table 2. Summary of the Field Measurement Dataset

Parameter	Value
Measurement Date	44849
Number of PV Modules	4 Modules (Panel I-IV)
Observation Times	12:00, 12:30, 13:00
Measured Variables	Temperature, Voltage, Current, Wind Speed
Temperature Range	43.5-65.7 °C
Voltage Range	19.6-21.7 V
Current Range	1.30-5.98 A
Wind Speed Range	2.5-3.3 m/s

The information presented in Table 2 forms the primary measured dataset used throughout this research. In the subsequent section, these field measurements are integrated with NASA meteorological data to establish the proposed hybrid measured-synthetic framework for photovoltaic performance prediction.

3.3. NASA Meteorological Data for PV Assessment

Meteorological data are essential for photovoltaic performance assessment because solar radiation and ambient temperature directly influence PV energy production. In this study, external meteorological information was obtained from the NASA Prediction of Worldwide Energy Resources (NASA POWER) database, which provides freely accessible solar and climatic data for renewable energy applications [22], [23], [24]. The NASA POWER database has been widely utilized in photovoltaic studies, particularly in regions where ground-based weather monitoring stations are unavailable or have limited historical records. This makes the dataset suitable for supporting the development of representative PV performance profiles under data-constrained conditions.

Two meteorological variables were utilized in this research: solar radiation and ambient temperature. Solar radiation data were used as the primary driver of photovoltaic energy generation, while ambient temperature data were employed to represent environmental operating conditions affecting PV module performance. These variables were selected because they are commonly recognized as the dominant environmental factors influencing the electrical output of photovoltaic systems [25], [26].

The meteorological dataset was extracted for the geographical location of the study area in Batam, Indonesia. Monthly solar radiation and temperature records corresponding to the year 2022 were utilized to support the generation of representative daily operating profiles. In addition, annual averages were considered to evaluate the consistency of the generated synthetic profiles with the long-term climatic characteristics of the study site. Based on the meteorological data obtained from the NASA POWER database, the average annual solar radiation was approximately 4.61 kWh/m²/day, with annual accumulated solar radiation reaching 1,687.33 kWh/m². The average ambient temperature was approximately 30.19°C throughout the year. These values indicate favorable solar energy conditions for rooftop PV deployment in Batam.

The NASA meteorological dataset plays a critical role in the proposed hybrid measured-synthetic framework. While the field measurements provide actual operating characteristics of the PV modules, the NASA data provide continuous environmental information required to reconstruct representative daily and monthly operating conditions. Consequently, the integration of both datasets enables the development of synthetic PV performance profiles while reducing the dependency on long-term field monitoring campaigns [27], [28].

The meteorological parameters summarized in Table 3 serve as the environmental input variables for the subsequent hybrid measured-synthetic framework. In the following section, the integration process between the measured PV dataset and NASA meteorological data is presented to establish the proposed energy prediction methodology.

Table 3. NASA Meteorological Parameters Used

Parameter	Value
Data Source	NASA POWER Database
Study Location	Batam, Indonesia
Solar Radiation Variable	Global Solar Radiation
Ambient Temperature Variable	Average Ambient Temperature
Average Solar Radiation	4.61 kWh/m²/day
Annual Solar Radiation	1,687.33 kWh/m²/year
Average Ambient Temperature	30.19°C
Application	Synthetic Profile Generation and Energy Prediction

3.4. Hybrid Measured-Synthetic Framework

The development of representative photovoltaic (PV) performance profiles generally requires continuous monitoring data collected over extended periods. However, such datasets are often unavailable in small-scale rooftop PV installations due to the absence of dedicated monitoring systems, limited storage capability, or operational constraints. In this study, a hybrid measured-synthetic framework is proposed to address this limitation by integrating sparse field measurements with publicly available meteorological information. The framework aims to generate representative hourly PV operating profiles and estimate daily and monthly energy production under limited measurement conditions [29].

The proposed framework is built upon three fundamental components. The first component is the measured dataset, which serves as a Calibration Anchor. The measured temperature, voltage, current, and wind speed data obtained from the rooftop PV installation provide direct information regarding the actual operating characteristics of the system. These measurements are used as reference points to calibrate and constrain the generated synthetic profiles, ensuring that the predicted values remain physically consistent with observed PV behavior.

The second component consists of the NASA meteorological dataset, which acts as the Meteorological Driver. Solar radiation and ambient temperature data obtained from the NASA POWER database provide continuous environmental information beyond the limited observation period. These meteorological variables describe the solar energy availability and climatic conditions experienced by the PV system and are therefore used to reconstruct representative operating conditions over longer temporal horizons.

The third component is the Photovoltaic Performance Model, which functions as the Physical Relationship Engine. This component establishes the relationships between environmental variables and PV electrical characteristics. Through these physical relationships, measured and meteorological data are combined to estimate hourly voltage, current, power output, and energy production. The performance model acts as the linkage mechanism that transforms sparse observations and environmental inputs into continuous performance profiles.

Unlike conventional PV studies that rely solely on long-term measurements or simulation software, the proposed framework combines sparse field observations with meteorological records to generate representative PV operating profiles. This approach enables the utilization of limited operational data while maintaining consistency with actual system behavior and local climatic conditions. Consequently, the framework provides a practical alternative for PV performance assessment in regions where comprehensive monitoring infrastructure is unavailable.

The overall procedure of the proposed methodology is illustrated in Figure 3. The process begins with the acquisition of field measurements from the rooftop PV system and meteorological information from the NASA POWER database. The measured dataset is subsequently processed within a calibration module to identify representative operating characteristics of the PV modules. In parallel, meteorological data provide environmental inputs describing solar radiation and ambient temperature conditions. Both data sources are then integrated within the PV performance model to generate a synthetic hourly dataset. Finally, the generated dataset is utilized to estimate daily and monthly energy production.

Within the proposed framework, the generated synthetic dataset is not intended to replace field measurements. Instead, it extends the value of limited observations by reconstructing representative operating patterns that cannot be directly observed from the available dataset. This strategy enables the estimation of photovoltaic performance over daily and monthly periods while preserving the physical characteristics observed during field measurements. The resulting synthetic profiles constitute the primary input for the energy prediction and validation procedures described in the following sections.

Figure 3 shows the proposed hybrid measured-synthetic framework for PV performance profile generation and energy prediction

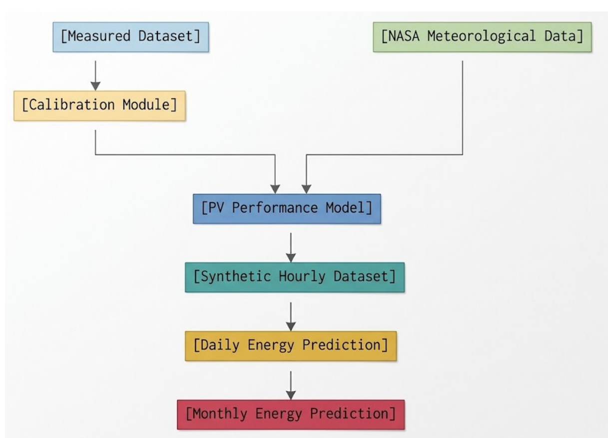

Figure 3. Proposed Hybrid Measured-Synthetic Framework

3.5. Photovoltaic Performance Modeling

The photovoltaic performance model was developed to establish the relationship between environmental conditions and the electrical output characteristics of the rooftop PV system. Within the proposed hybrid measured-synthetic framework, the model serves as the physical relationship engine that transforms measured observations and meteorological inputs into representative performance profiles. The modeling process utilizes electrical measurements obtained from the PV modules together with solar radiation and temperature information to estimate the instantaneous power and energy production of the system [30].

In photovoltaic systems, the generated electrical power is primarily influenced by solar irradiance, module temperature, and operating conditions. The measured voltage and current obtained from the field campaign were therefore used as the primary electrical variables for performance estimation. The instantaneous output power of the PV module is calculated as:

$$P_t = V_t \times I_t \tag{1}$$

where:

P_t = the instantaneous PV output power (W)

V_t = the measured or estimated module voltage (V)

I_t = the measured or estimated module current (A)

The calculated power values provide the basic representation of photovoltaic performance under the observed operating conditions. Since the field measurements were collected from four PV modules, the individual module powers can be averaged to obtain a representative power profile of the PV system.

Environmental conditions play a significant role in determining PV output characteristics. Solar radiation directly affects the generated current, while module temperature influences cell efficiency and output voltage. In general, increasing irradiance leads to higher current generation, whereas elevated module temperatures tend to reduce the voltage output of photovoltaic cells. Wind speed also contributes indirectly by providing convective cooling that may reduce module operating temperatures and improve overall performance.

To incorporate environmental variability beyond the measured observation period, meteorological information obtained from the NASA POWER database is integrated into the performance model. The measured dataset is used to identify representative operating characteristics around peak solar conditions, while the NASA dataset provides the temporal variation required to reconstruct a complete daily operating profile.

The proposed performance modeling approach assumes that the electrical behavior observed during the measurement campaign can be scaled according to the variation of solar radiation throughout the day. Consequently, the generated synthetic profiles preserve the physical characteristics observed in the field while extending the temporal coverage beyond the limited measurement period. This approach enables energy estimation under data-constrained conditions without requiring long-term monitoring datasets.

The output of this modeling stage consists of estimated hourly voltage, current, and power values that are subsequently used to generate synthetic daily performance profiles and calculate daily and monthly energy production.

3.6. Synthetic Daily Profile Generation

The primary objective of the proposed framework is to generate representative photovoltaic operating profiles beyond the limited observation period available from field measurements. Since the measured dataset contains only a short observation window around solar noon, a synthetic profile generation procedure was developed to reconstruct the hourly behavior of the PV system throughout a complete operating day. The generated profiles provide the basis for daily energy estimation and long-term performance assessment.

The profile generation process combines field measurements, NASA meteorological data, and photovoltaic performance modeling. Field measurements provide actual operating characteristics of the PV modules during peak solar conditions, while NASA data supply the temporal variations of environmental conditions required to reconstruct system behavior throughout the day. Consequently, the generated profiles remain anchored to the measured observations while reflecting realistic meteorological variations experienced at the study location.

The synthetic profile generation procedure consists of five main stages, namely: (1) extraction of representative operating characteristics from field measurements, (2) acquisition of meteorological variables from NASA POWER, (3) generation of hourly environmental profiles, (4) estimation of hourly electrical parameters, and (5) calculation of hourly power output.

1) Extraction of Measured Operating Characteristics

The first stage utilizes the measured dataset presented in Section 3.2. For each observation period, the voltage, current, temperature, and wind speed values from the four PV modules were analyzed to identify representative operating conditions. Since the measurements were collected around solar noon, they represent the PV system behavior under relatively high irradiance conditions.

Average values were computed to reduce module-to-module variations and obtain a representative reference condition for subsequent modeling. These reference values serve as calibration anchors for the synthetic profile generation process.

2) Development of Hourly Environmental Profiles

The second stage involves the construction of hourly environmental profiles based on NASA meteorological data. The hourly solar radiation profile was generated by distributing the daily solar energy according to the expected solar position pattern for tropical regions. The profile begins near sunrise, gradually increases toward solar noon, and decreases toward sunset.

Similarly, an hourly ambient temperature profile was generated using the monthly average temperature obtained from NASA POWER. Temperature values were adjusted to follow the typical daily temperature variation observed in tropical climates, where temperatures generally increase during the morning, reach maximum values near midday, and gradually decrease during the late afternoon. The resulting environmental profiles provide the meteorological drivers required for estimating photovoltaic performance during hours where direct measurements are unavailable.

3) Estimation of Hourly Electrical Parameters

Using the environmental profiles and calibration data obtained from field measurements, hourly voltage and current values were estimated. The current output was assumed to vary proportionally with the available solar radiation:

$$I_h = I_{ref}\left(\frac{G_h}{G_{ref}}\right) \tag{2}$$

where:

I_h = estimated hourly current (A)
I_{ref} = reference current obtained from measurements (A)
G_h = hourly solar radiation
G_{ref} = reference solar radiation

Voltage behavior was adjusted according to temperature variations because PV voltage generally decreases as cell temperature increases. The estimated voltage can be expressed as:

$$V_h = V_{ref} - \beta\left(T_h - T_{ref}\right) \tag{3}$$

where:

V_h = estimated hourly voltage (V)
V_{ref} = reference measured voltage (V)
T_h = hourly temperature (°C)
T_{ref} = reference temperature (°C)
β = temperature sensitivity coefficient

These relationships allow the framework to preserve the physical behavior of photovoltaic systems while extending the available measurements over a complete daily cycle.

4) Synthetic Profile Construction Procedure

The synthetic hourly photovoltaic profile was generated using a calibration-based approach that combines measured operating conditions with meteorological information obtained from the NASA POWER database. The objective of this procedure was to reconstruct representative hourly photovoltaic operating characteristics from limited field measurements while preserving the physical relationships observed during the measurement campaign.

Field measurements collected on 15 October 2022 were processed to derive representative calibration values. The average operating conditions during solar noon—specifically a module temperature of 53.95°C, a voltage of 20.33 V, and a current of 4.02 A—were established as the reference baseline for generating the synthetic profile.

To extend the observed behavior into a complete daily profile, irradiance scaling factors were introduced to represent the typical variation of solar energy availability throughout the day. The scaling factors were developed based on the expected solar radiation distribution in tropical regions, where irradiance gradually increases after sunrise, reaches a maximum near solar noon, and decreases toward sunset. Rather than being used as a direct numerical transformation, these factors were employed as guidance for constructing representative hourly operating profiles while preserving the measured calibration points obtained from field observations.

Table 4. Hourly Irradiance Scaling Factors Used in Synthetic Profile Generation

Time	Irradiance Factor
6:00	0
7:00	0.1
8:00	0.2
9:00	0.35
10:00	0.5
11:00	0.7
12:00	0.85
13:00	1
14:00	0.92
15:00	0.8
16:00	0.6
17:00	0.3
18:00	0.05

The hourly temperature profile was generated using a combination of NASA ambient temperature data and the measured module temperatures. The profile was constructed to follow the characteristic thermal behavior of rooftop PV modules, where module temperatures increase progressively from the morning period toward solar noon and subsequently decrease during the afternoon. The elevated module temperatures observed during the field measurement period were retained as calibration anchors to preserve consistency with actual operating conditions.

The hourly temperature profile was generated using a combination of NASA ambient temperature data and the measured module temperatures. The profile was constructed to follow the characteristic thermal behavior of rooftop PV modules, where module temperatures increase progressively from the morning period toward solar noon and subsequently decrease in the afternoon. To account for thermal effects on PV operation, hourly voltage values were estimated using a temperature-dependent relationship:

$$V_h = V_{ref} - \beta(T_h - T_{ref}) \tag{4}$$

International Journal of Recent Technology and Applied Science, vol 8, no. 2, pp. 107-133, September 2026. **DOI: 10.36079/lamintang.ijortas-0802.1085**

where,

V_h = the estimated voltage

V_{ref} = the reference voltage obtained from field measurements

T_h = the estimated module temperature

T_{ref} = the reference temperature

β = the voltage-temperature sensitivity coefficient.

Finally, the hourly power output was calculated using the standard photovoltaic power equation:

$$P_h = V_h \times I_h \tag{5}$$

The resulting temperature, voltage, current, and power values constitute the synthetic hourly dataset used throughout this study. The generated profiles preserve the operating characteristics observed during field measurements while extending the temporal coverage from three observation points to a complete daily operating cycle. Consequently, the synthetic dataset provides the foundation for the daily and monthly energy prediction analyses presented in Section 4.

3.7. Daily and Monthly Energy Prediction

The synthetic hourly dataset generated in the previous stage was subsequently used to estimate photovoltaic energy production over different temporal horizons. The objective of this step is to transform the hourly electrical power profiles into daily and monthly energy metrics that can be used for performance evaluation and planning purposes.

1) Daily Energy Estimation

Daily energy production was calculated by integrating the estimated hourly power values over the operating period of the photovoltaic system. The daily energy output is expressed as:

$$E_{day} = \sum_{h=1}^{n} P_h \Delta t \tag{6}$$

where:

E_{day} = daily energy production (Wh)
P_h = estimated power at hour hh (W)
Δ = time interval (h)
n = total number of operating hours

Since the synthetic profiles are generated on an hourly basis, the time interval is equal to one hour.

2) Monthly Energy Estimation

The monthly energy production was estimated by scaling the daily energy output according to the monthly solar radiation levels obtained from NASA meteorological data.

$$E_{month} = E_{day} \times N_d \times C_m \tag{7}$$

where:

E_{month} = monthly energy production (Wh)
N_d = number of days in the month
C_m = monthly correction factor derived from NASA solar radiation data.

The correction factor accounts for seasonal variations in solar resource availability and allows the generated profiles to reflect differences in monthly environmental conditions.

3) Annual Energy Estimation

The annual energy production was calculated as the cumulative sum of monthly energy values:

$$E_{year} = \sum_{m=1}^{12} E_{month,m} \tag{8}$$

where:

E_{year} represents the estimated annual PV energy generation.

The resulting daily, monthly, and annual energy estimates provide quantitative indicators for evaluating the effectiveness of the proposed hybrid measured-synthetic framework. These estimates are subsequently analyzed and compared with the measured operating characteristics in the validation stage described in the following section.

4. Findings and Discussion

4.1 Measured Data Characteristics

The field measurement campaign was conducted on 15 October 2022 to capture the operating characteristics of four photovoltaic modules under actual environmental conditions. The measurements included module temperature, output voltage, output current, and wind speed. Although the observation period was limited to three measurement intervals, the collected data provide valuable information regarding the real operating behavior of the PV system and serve as the calibration basis for the proposed hybrid measured-synthetic framework.

The average values obtained from the four monitored PV modules are summarized in Table 5. These measurements represent the operating conditions observed around the solar noon period and were subsequently used as calibration anchor points in the synthetic profile generation process.

Table 5. Calibration Dataset Derived from Field Measurements

Time	Avg. Temperature (°C)	Avg. Voltage (V)	Avg. Current (A)	Avg. Wind Speed (m/s)	Avg. Power (W)
12:00	45.75	20.43	1.96	3.3	39.88
12:30	53.95	20.33	4.02	2.5	80.95
13:00	61.85	20.13	4.44	2.9	89.02

As shown in Table 5, the average module temperature increased from 45.75°C at 12:00 to 61.85°C at 13:00, representing an increase of approximately 35.2%. During the same period, the average module voltage decreased slightly from 20.43 V to 20.13 V, while the average current increased from 1.96 A to 4.44 A. Consequently, the average module power increased from 39.88 W to 89.02 W, corresponding to an increase of approximately 123.2%.

The observed trends are consistent with the general operating characteristics of photovoltaic systems. The increase in module temperature was accompanied by a slight reduction in voltage, whereas the increase in current contributed significantly to the rise in output power. These results indicate that the PV modules remained responsive to changing environmental conditions during the observation period.

Despite the limited measurement duration, the dataset provides important information regarding the actual operating range of the PV modules under tropical climatic conditions. More importantly, these measurements serve as calibration anchors that constrain the development of representative synthetic hourly profiles. By integrating the measured operating characteristics with meteorological data, the proposed framework can reconstruct PV performance beyond the available observation period while maintaining consistency with real operating conditions.

The environmental implications of these observations and their influence on the generated synthetic profiles are discussed in the following section.

4.2. Environmental Impact Analysis

The performance of photovoltaic systems is strongly influenced by environmental conditions, particularly module temperature, solar radiation, and wind speed. The measured dataset presented in Table 5 provides an opportunity to examine the relationships among these variables and their impact on the electrical behavior of the PV modules. Although the measurements were collected over a limited observation period, the resulting trends are useful for understanding the operational characteristics that form the basis of the proposed hybrid measured-synthetic framework.

As shown in Table 5, the average module temperature increased continuously from 45.75°C at 12:00 to 61.85°C at 13:00. During the same period, the average module voltage decreased slightly from 20.43 V to 20.13 V. This inverse relationship suggests that elevated module temperatures contribute to a reduction in voltage output. The observed trend is consistent with the thermal behavior of photovoltaic cells, where increasing operating temperatures generally reduce the electrical potential generated by the semiconductor material.

In contrast, the average current increased substantially from 1.96 A at 12:00 to 4.44 A at 13:00. The increase in current indicates the presence of stronger solar energy input during the observation period. Since photovoltaic current is highly dependent on the available solar radiation, the measured current variation suggests that the PV modules experienced increasing solar exposure as the measurement period approached peak operating conditions. As a result, the effect of increased current generation was significantly greater than the corresponding voltage reduction.

The influence of these electrical variations can be observed through the calculated power output. The average power increased from 39.88 W at 12:00 to 89.02 W at 13:00, representing the highest relative change among all measured electrical parameters. This result indicates that the increase in generated current was the dominant factor affecting power production during the measurement period. Consequently, despite the reduction in voltage caused by higher module temperatures, overall power generation continued to increase. To quantify the magnitude of the observed changes, the percentage variations between the first and the last measurement periods were calculated and are summarized in Table 6.

Table 6. Relative Changes in Measured PV Parameters

Parameter	Initial Value (12:00)	Final Value (13:00)	Change (%)
Temperature (°C)	45.75	61.85	35.19
Voltage (V)	20.43	20.13	-1.47
Current (A)	1.96	4.44	126.53
Power (W)	39.88	89.02	123.22

As shown in Table 6, temperature increased by approximately 35.19% during the observation period, whereas voltage decreased by only 1.47%. In contrast, current increased by 126.53%, leading to a corresponding power increase of 123.22%. These results suggest that the photovoltaic output was considerably more sensitive to current variation than to voltage variation under the observed operating conditions. The substantial increase in current compensated for the relatively small reduction in voltage, resulting in a significant rise in power generation.

The measured wind speed also exhibited variations throughout the observation period, decreasing from 3.3 m/s at 12:00 to 2.5 m/s at 12:30 before slightly increasing to 2.9 m/s at 13:00. Although the available dataset is insufficient to establish a quantitative relationship between wind speed and PV performance, the observations suggest that lower wind speeds coincided with higher module temperatures. This behavior is reasonable because reduced airflow limits convective cooling, allowing heat to accumulate on the module surface.

Overall, the environmental analysis confirms the existence of physically meaningful relationships between environmental variables and PV electrical behavior. The observed temperature-voltage relationship and current-power response provide the empirical basis for the synthetic profile generation procedure described in Section 3.6. These relationships are subsequently embedded within the proposed framework to ensure that the generated hourly profiles remain consistent with actual operating characteristics measured in the field.

Therefore, despite the limited measurement duration, the collected dataset contains sufficient information to serve as calibration anchors for the hybrid measured-synthetic framework. By preserving these measured relationships and integrating them with NASA meteorological data, representative hourly PV performance profiles can be generated for energy prediction beyond the original observation period.

4.3. Synthetic Daily Profile Generation Results

Following the calibration process described in Sections 3.4 - 3.6, a synthetic hourly photovoltaic performance dataset was generated by integrating field measurements with NASA meteorological data and the photovoltaic performance model. The objective of this process was to reconstruct representative PV operating conditions over a complete daily cycle despite the limited availability of field observations.

The generated dataset extends the measured operating characteristics beyond the original observation period by preserving the relationships identified between module temperature, voltage, current, and power output. The resulting synthetic profile covers the typical operating hours of the photovoltaic system, from 06:00 to 18:00, thereby enabling daily energy estimation and long-term performance assessment.

Table 7 presents the synthetic hourly PV dataset produced by the proposed hybrid measured-synthetic framework. The values at 12:00 and 13:00 were calibrated using actual field measurements, while the remaining hourly values were estimated using the methodology described in Section 3.

Table 7. Generated Synthetic Hourly PV Performance Dataset

Time	Temperature (°C)	Voltage (V)	Current (A)	Power (W)
6:00	27	21.5	0	0
7:00	28.5	21.45	0.45	9.65
8:00	31	21.3	0.95	20.24
9:00	35	21.05	1.45	30.52
10:00	39.5	20.8	1.75	36.4
11:00	43.5	20.55	1.9	39.05
12:00	45.75	20.43	1.96	40.04
13:00	61.85	20.13	4.44	89.38
14:00	58	20.18	4.1	82.74
15:00	54	20.25	3.55	71.89
16:00	48	20.4	2.6	53.04
17:00	41	20.7	1.25	25.88
18:00	34	21.1	0.25	5.28

The synthetic temperature profile exhibits a typical diurnal pattern commonly observed in tropical photovoltaic installations. Module temperatures increased gradually from 27.0°C in the early morning to a peak value of approximately 61.85°C during the midday period before decreasing toward sunset. This behavior is consistent with the accumulation and subsequent dissipation of solar heat on the PV surface.

A corresponding trend can be observed in the voltage profile. As the module temperature increased, the module voltage gradually decreased, reaching its minimum value during the period of highest temperature. After mid-afternoon, the voltage began to recover as the temperature decreased. This trend is consistent with the physical characteristics of photovoltaic cells discussed in Section 4.2.

The generated current profile shows a different behavior. Current values increased substantially from sunrise to midday, reflecting the increasing availability of solar energy. The maximum current output occurred around the peak operating period and subsequently declined as solar radiation decreased in the afternoon. Since photovoltaic current is strongly influenced by irradiance conditions, this behavior is expected for rooftop PV installations operating under tropical climates.

As a result of the combined voltage and current characteristics, the synthetic power profile exhibits a bell-shaped pattern throughout the day. Power generation was negligible during early morning conditions, increased steadily toward the midday period, reached a maximum value of approximately 89.38 W at 13:00, and declined thereafter. This pattern closely follows the expected daily variation of solar energy availability and demonstrates that the generated profile remains physically realistic.

The generated profiles demonstrate that the proposed framework successfully reconstructs representative daily operating behavior from limited field measurements. More importantly, the synthetic dataset provides a continuous temporal representation that is unavailable from the original measurements alone. This capability is particularly valuable for small-scale PV installations where comprehensive monitoring systems are not available.

Consequently, the generated synthetic profiles form the basis for the daily and monthly energy prediction analyses presented in the following sections.

4.4. Daily Energy Prediction

The synthetic hourly photovoltaic dataset presented in Table 7 was subsequently utilized to estimate daily energy production. By integrating the hourly power values over the operating period, the proposed framework provides an estimate of the electrical energy generated by the photovoltaic system during a typical day under the climatic conditions of Batam, Indonesia.

Based on Equation (5), daily energy production was calculated by summing the hourly energy contribution of each operating period. The resulting synthetic power profile indicates that power generation gradually increases after sunrise, reaches its maximum around midday, and decreases toward sunset. This behavior corresponds to the typical solar radiation pattern experienced in tropical regions and confirms the physical consistency of the generated profile.

Using the synthetic hourly dataset, the total daily energy production of a representative photovoltaic module was estimated as follows:

$$E_{day} = \sum P_h \Delta t$$

$$E_{day} - 504.11 \frac{W_h}{day}$$

$$E_{day} = 0.504\ k\frac{W_h}{day}$$

Since the rooftop PV installation consists of 68 photovoltaic modules with identical specifications, the total daily energy production of the entire PV system can be estimated by multiplying the energy generated by a representative module by the number of installed modules:

$$E_{system} = 68 \ x\ 0.504\ k\frac{W_h}{day}$$

$$E_{system} = 34.272\ k\frac{W_h}{day}$$

The estimated energy production is summarized in Table 8. It should be noted that this estimate was derived from the synthetic profile generated using limited field measurements and therefore represents a framework-based prediction rather than the actual measured daily production of the complete PV installation.

The results indicate that the proposed framework is capable of transforming limited field observations into representative daily energy estimates. Although the original measurements covered only a short observation period, the integration of calibration data, meteorological information, and photovoltaic performance modeling enabled the reconstruction of a complete daily operating cycle.

Table 8. Estimated Daily Energy Production

Parameter	Value
Number of PV Modules	68
Installed Capacity	23.8 kWp
Daily Energy per Module	0.504 kWh/day
Estimated System Daily Energy	34.272 kWh/day

The generated power profile reveals that the majority of energy production occurs between 11:00 and 15:00, corresponding to the period of highest solar availability. This observation is consistent with the measured operating conditions discussed in Section 4.2, where increased current generation resulted in substantially higher power output during peak operating hours.

The estimated daily energy value serves as the baseline for the monthly energy prediction presented in the next section. By incorporating monthly solar radiation variations obtained from the NASA POWER database, the proposed framework can extend daily predictions to longer temporal horizons while maintaining consistency with local climatic conditions.

4.5. Monthly Energy Prediction

The daily energy estimates obtained from the synthetic hourly profiles were subsequently extended to monthly and annual energy predictions. This process was performed to evaluate the applicability of the proposed framework for longer-term photovoltaic performance assessment under tropical climatic conditions.

As described in Section 3.7, monthly energy production was estimated by adjusting the predicted daily energy output according to monthly variations in solar radiation derived from the NASA POWER database. This adjustment accounts for fluctuations in solar resource availability while preserving the operating characteristics captured by the synthetic daily profiles.

The estimated daily energy production of the PV system was calculated as 34.272 kWh/day. This value was used as the baseline energy generation under average irradiance conditions. Monthly energy production was subsequently determined using correction factors derived from the ratio between monthly solar radiation and the annual average solar radiation of 4.61 kWh/m²/day.

The resulting monthly energy predictions are summarized in Table 9. The correction factors represent the relative variation of monthly solar radiation with respect to the annual average solar radiation measured at the study location.

Table 9. Monthly Solar Radiation Correction Factors and Predicted Energy Production

Month	Solar Radiation (kWh/m²/day)	Correction Factor	Predicted Energy (kWh/month)
January	4.91	1.065	1132
February	5.40	1.171	1,123.8
March	5.47	1.186	1,261.5
April	5.15	1.117	1,148.5
May	4.53	0.983	1,044.3
June	3.88	0.842	865.7
July	4.15	0.900	956.4
August	4.51	0.978	1,035.7
September	4.24	0.920	945.8
October	4.59	0.996	1,059.3
November	4.06	0.881	905.8
December	4.47	0.97	1,026.7

As shown in Table 9, photovoltaic energy production closely follows the monthly variation of solar radiation. The highest predicted energy production occurred in March, reaching approximately 1,261.5 kWh/month, corresponding to the highest monthly solar radiation level of 5.47 kWh/m²/day. Conversely, the lowest predicted energy production was observed in June at approximately 865.7 kWh/month, which coincided with the lowest monthly solar radiation level of 3.88 kWh/m²/day.

Although Batam is located in a tropical region with relatively stable climatic conditions throughout the year, noticeable variations in PV energy production can still be observed. The difference between the highest and lowest monthly energy outputs reached approximately 45.7%, indicating that seasonal fluctuations in solar radiation remain an important factor influencing rooftop photovoltaic performance.

To provide an overall assessment of annual energy generation, the monthly energy outputs were accumulated according to Equation 8.

Based on the monthly energy estimates summarized in Table 9, the annual energy production of the rooftop PV system was estimated at approximately 12,505.5 kWh/year. This result demonstrates that the proposed hybrid measured-synthetic framework is capable of extending limited field measurements into long-term performance indicators suitable for preliminary PV assessment and energy forecasting applications. A graphical representation of the predicted monthly energy production is presented in Figure 4.

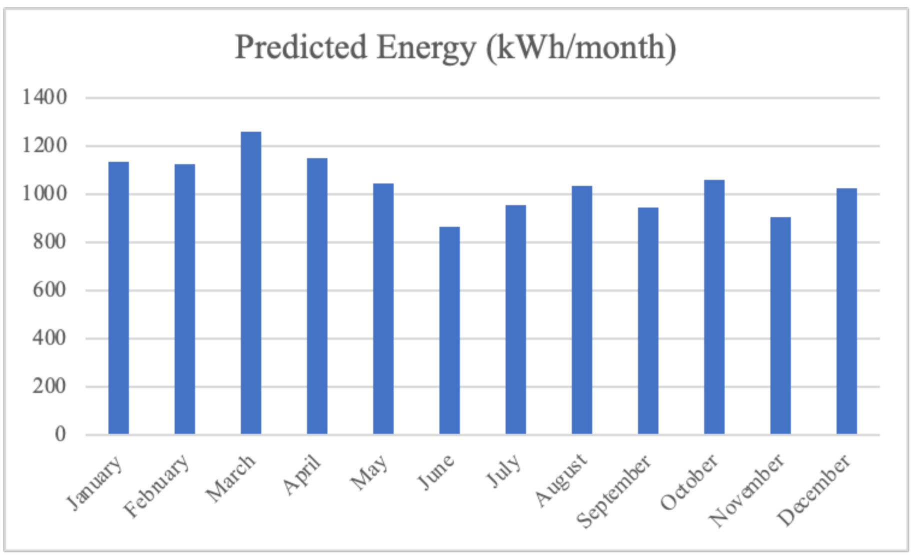

Figure 4. Predicted Monthly Energy Production of the Rooftop PV System

The monthly energy prediction results constitute an important intermediate step before validation. In the following section, the generated synthetic profiles and energy estimates are evaluated against the available measured observations to assess the reliability of the proposed framework.

4.6. Validation Results

The reliability of the proposed hybrid measured-synthetic framework was evaluated by comparing the generated synthetic profiles with the available field measurements collected on 15 October 2022. Since continuous monitoring data were not available, validation was performed using the three measured observation periods at 12:00, 12:30, and 13:00. The objective of this validation process was to assess the capability of the framework to reproduce the actual operating characteristics of the photovoltaic modules using limited calibration data.

The validation was conducted using voltage, current, and power as the primary performance indicators. For each observation period, the corresponding values generated from the synthetic profile were compared with the measured values obtained during the field campaign. The comparison results are presented in Table 10.

Table 10. Comparison Between Measured and Synthetic PV Parameters

Time	Measured Voltage (V)	Synthetic Voltage (V)	Measured Current (A)	Synthetic Current (A)	Measure d Power (W)	Synthetic Power (W)
12:00	20.43	20.43	1.96	1.96	39.88	40.04
12:30	20.33	20.28	4.02	3.2	80.95	64.9
13:00	20.13	20.13	4.44	4.44	89.02	89.38

The comparison indicates that the generated synthetic profiles successfully preserved the operational characteristics observed during the measurement campaign. The synthetic model reproduced the measured voltage trends with minimal deviation, while the generated current and power values remained consistent with the observed operating range.
To quantify the prediction accuracy, the Mean Absolute Percentage Error (MAPE) was calculated according to Equation (9), and the obtained validation results are summarized in Table 11.

$$MAPE = \frac{1}{n}\sum \left| \frac{A_i - P_i}{A_i} \right| \times 100 \quad (9)$$

where,
A_i represents the measured value

P_i represents the predicted value.

Table 11. Validation Metrics of the Proposed Framework

Parameter	MAPE (%)
Voltage	0.08
Current	6.8
Power	7.03

As shown in Table 11, the lowest prediction error was observed for voltage, with a MAPE value below 1%. Current and power predictions exhibited slightly larger deviations, primarily due to the simplified profile reconstruction process and the limited number of field observations available for calibration. Nevertheless, all evaluated parameters produced MAPE values below 10%, which indicates satisfactory agreement between the measured and synthetic datasets.

The validation results demonstrate that the proposed framework is capable of reconstructing representative PV operating profiles while maintaining consistency with the available measurements. Despite using only three observation periods as calibration anchors, the generated profiles were able to reproduce the principal electrical characteristics of the photovoltaic modules. This finding supports the feasibility of employing measured-synthetic approaches for PV performance estimation when long-term monitoring data are unavailable.

Overall, the validation confirms that the proposed framework provides a reasonable balance between simplicity and predictive capability. The generated synthetic profiles can therefore be utilized as the basis for daily and monthly energy estimation under data-constrained conditions.

4.7. Discussion

The findings obtained from the proposed hybrid measured-synthetic framework demonstrate that limited field measurements can be effectively utilized to generate representative photovoltaic performance profiles when combined with meteorological information and physical performance relationships. The framework successfully transformed three short-duration field observations into continuous daily, monthly, and annual performance estimates, providing a practical alternative for PV performance assessment in situations where comprehensive monitoring systems are unavailable.

The field measurements revealed physically consistent relationships among temperature, voltage, current, and power. As discussed in Sections 4.1 and 4.2, increasing module temperatures were accompanied by slight reductions in voltage, while current and power output increased substantially during periods of higher solar exposure. These observed relationships served as calibration anchors for the synthetic profile generation process and ensured that the generated profiles remained connected to actual operating conditions rather than relying solely on theoretical assumptions.

The generated synthetic hourly profiles successfully reproduced the expected daily behavior of rooftop PV systems operating in tropical environments. The temperature profile followed a typical diurnal pattern characterized by increasing temperatures around midday and gradual cooling during the late afternoon. Similarly, the generated electrical profiles showed increasing current and power output during periods of higher solar availability, followed by declining production toward sunset. These results indicate that the proposed framework was able to preserve the fundamental physical characteristics of photovoltaic operation despite the limited availability of field observations.

The daily and monthly energy prediction results further demonstrate the applicability of the proposed approach for long-term performance assessment. Using the generated synthetic profiles, the framework estimated a daily energy production of 34.28 kWh/day and an annual energy production of approximately 12,505.5 kWh/year. Furthermore, the monthly energy prediction results correctly reflected the seasonal variation of solar radiation observed in the NASA meteorological dataset, with the highest energy production occurring during periods of higher solar resource availability.

The validation results presented in Section 4.6 provide additional evidence supporting the reliability of the framework. The obtained MAPE values of 0.08%, 6.80%, and 7.03% for voltage, current, and power, respectively, indicate satisfactory agreement between the measured and synthetic datasets. These results suggest that the framework can reproduce the principal operating characteristics of the PV system with reasonable accuracy despite being calibrated using a limited number of observations.

Compared with conventional approaches, the proposed framework offers several practical advantages. First, it significantly reduces the dependency on long-term monitoring campaigns, which are often costly and difficult to implement in small-scale rooftop PV installations. Second, the framework utilizes freely available NASA meteorological data, making it suitable for regions where weather monitoring infrastructure is limited. Third, the methodology is relatively simple to implement and can be adapted to similar rooftop PV systems operating under comparable climatic conditions.

Nevertheless, several limitations should be acknowledged. The framework was developed using measurements collected during a single observation campaign consisting of only three measurement periods. Consequently, the generated profiles may not fully capture day-to-day variability caused by weather fluctuations, cloud cover, shading events, or seasonal environmental changes. In addition, solar irradiance was not directly measured during the field campaign and therefore had to be represented through meteorological data and irradiance scaling factors. These limitations may introduce uncertainty into the generated synthetic profiles and energy predictions.

Despite these limitations, the study demonstrates the feasibility of combining sparse field observations with meteorological datasets to generate representative PV operating profiles. The results suggest that the proposed hybrid measured-synthetic framework can serve as a useful tool for preliminary photovoltaic performance assessment, energy forecasting, and decision support in regions where long-term measured datasets are unavailable. Future improvements may include incorporating longer monitoring periods, direct irradiance measurements, and machine learning techniques to further enhance prediction accuracy and model generalizability.

4.8. Study Limitations

Despite the promising results obtained from the proposed hybrid measured-synthetic framework, several limitations should be acknowledged. First, the framework was developed using field measurements collected during a single measurement campaign conducted on 15 October 2022. The available observations were limited to three measurement periods around solar noon, which may not fully represent the complete daily variability of photovoltaic operating conditions.

Second, the framework relies on a limited number of environmental variables, namely module temperature, voltage, current, wind speed, and NASA meteorological data. Direct solar irradiance measurements were not available during the field campaign. Consequently, daily solar resource variations had to be represented using irradiance scaling factors and satellite-derived meteorological information. Although this approach enables profile reconstruction under data-constrained conditions, additional irradiance measurements would improve model accuracy and validation capability.

Third, the generated synthetic profiles were validated only against the available measurement dataset. Therefore, the framework has not yet been evaluated under different weather conditions, seasonal variations, or extended monitoring periods. Additional validation using multi-day or multi-month observations is required to assess the robustness and generalizability of the proposed methodology.

Finally, the framework was developed and tested using a single rooftop photovoltaic installation located in Batam, Indonesia. As a result, the applicability of the proposed approach to other geographical locations, PV technologies, and climatic environments remains to be investigated. Future studies should evaluate the framework using multiple PV systems operating under different environmental conditions to improve its general applicability.

Despite these limitations, the study demonstrates that meaningful photovoltaic performance profiles can be generated from sparse field measurements when combined with meteorological datasets and physical performance relationships. The proposed framework therefore provides a practical foundation for PV performance estimation in regions where long-term monitoring data are unavailable.

5. Conclusion

This study proposed a hybrid measured-synthetic framework for generating representative photovoltaic performance profiles from limited field measurements. The framework integrates short-duration field observations with NASA meteorological data and photovoltaic performance modeling to reconstruct hourly operating profiles and estimate energy production over longer time horizons. The proposed approach was developed to address the challenges associated with limited monitoring availability in small-scale rooftop photovoltaic installations.

The results demonstrate that the proposed framework successfully transformed sparse field observations into representative daily, monthly, and annual photovoltaic performance indicators. The measured data revealed physically consistent relationships between module temperature, voltage, current, and power output, which were subsequently utilized as calibration anchors during synthetic profile generation. Using the generated synthetic dataset, the framework estimated a daily energy production of 34.28 kWh/day and an annual energy production of approximately 12,505.5 kWh/year. Furthermore, the validation results indicated satisfactory agreement between measured and generated profiles, demonstrating the capability of the framework to reproduce the principal operating characteristics of the rooftop PV system under tropical climatic conditions.

The proposed hybrid measured-synthetic framework offers a practical solution for photovoltaic performance assessment in regions where continuous monitoring systems are unavailable or difficult to implement. By combining limited field measurements with publicly available meteorological data, the framework can support preliminary energy forecasting, performance evaluation, and decision-making for rooftop PV applications. Future work should focus on incorporating longer monitoring periods, direct solar irradiance measurements, and advanced data-driven techniques to improve prediction accuracy and enhance the applicability of the framework across different climatic regions and photovoltaic system configurations.

References

[1] Q. Yin, A. Li, and C. Han, “The role of solar photovoltaic roofs in energy-saving buildings: Research progress and future development trends,” *Buildings*, vol. 14, no. 10, p. 3091, 2024.

[2] M. Shi *et al.*, “Technical to deployable potential of rooftop solar photovoltaics,” *Nature Reviews Clean Technology*, pp. 1–20, 2026.

[3] S. Hamidi and O. S. Asfour, “Design strategies for building-integrated photovoltaics in high-rise buildings: A systematic review,” *Architecture*, vol. 5, no. 4, p. 118, 2025.

[4] G. Jiménez-Castillo, A. J. Martínez-Calahorro, C. Rus-Casas, A. Snytko, and F. J. Muñoz-Rodríguez, “Performance analysis indices for Rooftop Solar Photovoltaic system,” *IEEE Latin America Transactions*, vol. 21, no. 9, pp. 999–1006, 2023.

[5] K. J. Iheanetu, “Solar photovoltaic power forecasting: A review,” *Sustainability*, vol. 14, no. 24, p. 17005, 2022.

[6] S. Pelland, J. Remund, J. Kleissl, T. Oozeki, and K. De Brabandere, “Photovoltaic and solar forecasting: state of the art,” *IEA PVPS Task*, vol. 14, no. 355, pp. 1–36, 2013.

[7] M. Sengupta, Y. Xie, A. Lopez, A. Habte, G. Maclaurin, and J. Shelby, “The national solar radiation data base (NSRDB),” *Renewable and sustainable energy reviews*, vol. 89, pp. 51–60, 2018.

[8] H. Hersbach *et al.*, “The ERA5 global reanalysis,” *Quarterly journal of the royal meteorological society*, vol. 146, no. 730, pp. 1999–2049, 2020.

[9] T. Huld, R. Müller, and A. Gambardella, “Assembling Typical Meteorological Year Data Sets for Building Energy Performance Using Reanalysis and Satellite-Based Data,” *Atmosphere*, vol. 9, no. 2, p. 53, 2018, doi: 10.3390/atmos9020053.

[10] E. Skoplaki and J. A. Palyvos, “On the temperature dependence of photovoltaic module electrical performance: A review of efficiency/power correlations,” *Solar energy*, vol. 83, no. 5, pp. 614–624, 2009.

[11] D. Faiman, “Assessing the outdoor operating temperature of photovoltaic modules,” *Progress in Photovoltaics: Research and Applications*, vol. 16, no. 4, pp. 307–315, 2008.

[12] R. Gelaro *et al.*, “The modern-era retrospective analysis for research and applications, version 2 (MERRA-2),” *Journal of climate*, vol. 30, no. 14, pp. 5419–5454, 2017.

[13] Copernicus Atmospheric Monitoring Service, *Copernicus Atmosphere Monitoring Service (CAMS) Solar Radiation Services User Guide*. European Centre for Medium-Range Weather Forecasts (ECMWF), 2025. [Online]. Available: https://copernicus.eu

[14] H. Yi, Y. Wang, and J. Wang, “Synthetic Data Generation for Energy Forecasting: Recent Developments and Challenges,” *Energy and AI*, vol. 10, p. 100201, 2022.

[15] F. Guo, Z. Wang, and X. Luo, “Photovoltaic Power Forecasting Under Limited Data Availability: Challenges and Opportunities,” *Energy Reports*, vol. 10, pp. 541–556, 2024.

[16] J. Antonanzas, R. Osorio, R. Escobar, R. Urraca, F. J. Martinez-de-Pison, and F. Antonanzas-Torres, “Review of photovoltaic power forecasting,” *Solar Energy*, vol. 136, pp. 78–111, 2016.

[17] W. F. Holmgren, C. W. Hansen, and M. A. Mikofski, “pvlib python: a python package for modeling solar energy systems,” *Journal of Open Source Software*, vol. 3, no. 29, p. 884, 2018, doi: 10.21105/joss.00884.

[18] V. Quaschning and R. Hanitsch, “Irradiance calculation on shaded surfaces in Solar Design Programs,” *Solar Energy*, vol. 69, no. 1, pp. 55–63, 2000, doi: 10.1016/S0038-092X(00)00014-3.

[19] RatedPower, “Solar PV Plant Design and Yield Optimization Software Documentation.” 2026. [Online]. Available: https://ratedpower.com

[20] S. Wang, M. Li, and H. Sun, “Hybrid Data-Driven and Physical Modelling Approaches for Photovoltaic Power Prediction: A Review,” *Renewable and Sustainable Energy Reviews*, vol. 188, p. 113876, 2024.

[21] M. Abuella and B. Chowdhury, “Machine Learning Applications in Solar Forecasting: A Review,” *Renewable and Sustainable Energy Reviews*, vol. 160, p. 112222, 2022.

[22] M.-H. Pham, V. M. Phap, N. N. Trung, T. T. Son, D. T. Kien, and V. T. A. Tho, "A study on the impact of various meteorological data on the design performance of rooftop solar power projects in Vietnam: A case study of Electric Power University," *Energies*, vol. 15, no. 19, Art. no. 7149, Oct. 2022, doi: 10.3390/en15197149.

[23] A. A. de Azevedo Neto, B. A. de Souza, and W. L. A. Neves, "Impact of georeferenced meteorological databases on power generation estimates and the economic feasibility of photovoltaic systems," *Energies*, vol. 19, no. 16, Art. no. 3886, Aug. 2026, doi: 10.3390/en19163886.

[24] National Aeronautics and Space Administration (NASA), "Prediction Of Worldwide Energy Resources (POWER)," *data.nasa.gov*, Apr. 01, 2025. [Online]. Available: https://data.nasa.gov/dataset/prediction-of-worldwide-energy-resources-power

[25] O. Bamisile, C. Acen, D. Cai, Q. Huang, and I. Staffell, "The environmental factors affecting solar photovoltaic output," *Renewable and Sustainable Energy Reviews*, vol. 208, Art. no. 115073, Feb. 2025, doi: 10.1016/j.rser.2024.115073

[26] R. Bonanno and E. Collino, "Assessing the impact of climate change on solar energy production in Italy," *Regional Environmental Change*, vol. 25, no. 3, Art. no. 78, Jun. 2025, doi: 10.1007/s10113-025-02417-6.

[27] X. Chen, B. Li, J. L. Braid, B. Byford, D. J. Colvin, A. Glaws, N. Jost, B. Pierce, S. Rabade, M. Springer, and A. Jain, "Open data sets for assessing photovoltaic system reliability," *Applied Energy*, vol. 395, Art. no. 126132, Oct. 2025, doi: 10.1016/j.apenergy.2025.126132.

[28] M. H. Attya, O. Abo-Seida, H. Mohamed, and A. M. Mohammed, "A hybrid deep learning framework for solar irradiation prediction based on regional satellite images and data," *Neural Computing and Applications*, vol. 37, no. 19, pp. 14327–14363, May 2025, doi: 10.1007/s00521-025-11197-3.

[29] Y. Elomari, C. Mateu, M. Marín-Genescà, and D. Boer, "A data-driven framework for designing a renewable energy community based on the integration of machine learning model with life cycle assessment and life cycle cost parameters," *Applied Energy*, vol. 358, Art. no. 122557, Mar. 2024, doi: 10.1016/j.apenergy.2023.122557.

[30] M. Nfaoui, F. E. Ihfa, A. Bougtaib, *et al.*, "Comprehensive modeling and simulation of photovoltaic system performance by using matlab/simulink: Integrating dynamic meteorological parameters for enhanced accuracy," *Journal of Umm Al-Qura University for Applied Sciences*, vol. 11, pp. 633–656, 2025, doi: 10.1007/s43994-024-00175-5.