ENERGY YIELD AND MONTHLY PERFORMANCE ANALYSIS OF A LARGE-SCALE PHOTOVOLTAIC SYSTEM USING ENERGY PERFORMANCE INDEX

Rohana Hasan[1], Ahmad Fateh Mohamad Nor[2]*, Mohamad Zhafran Hussin[3], Rosnani Affandi[4], Khairul Anuar Mohammad[5], Norfaiza Fuad[6]

ABSTRACT

This study aims to evaluate the level of energy generation efficiency and monthly operating performance of large-scale photovoltaic systems using the Energy Performance Index (EPI) approach. This approach is used to overcome the industry's reliance on irradiation data alone, which is insufficient to identify performance degradation caused by internal technical factors of the system. The analysis of this study is based on actual operational data obtained from a large-scale solar plant with a capacity of 31 MWp for the period January to December 2023. The EPI calculation method is developed based on a derating factor model that considers the effects of module temperature, inverter efficiency, power loss in the cable, module surface contamination, and system degradation. Monthly analysis is then used to link EPI values to possible causes of system failure or performance degradation. The results show that recorded EPI values fell below the 0.90 performance threshold throughout the study period, with the largest deviations occurring in February (-18.24%), attributed to inverter failure and October (-16.32%), attributed to system efficiency degradation. By July, in contrast, recorded the best performance with an EPI of 0.893 despite only moderate irradiation input. These findings demonstrate that EPI captures performance deviations more sensitively and completely than irradiation-based assessment alone. The main contribution of this study is therefore a validated EPI-based framework that can serve as a standard metric for monthly performance monitoring, predictive maintenance planning, and long-term operational optimization of PV farms in Malaysia.

[1] Lecturer, Department of Electrical Engineering, Politeknik Ibrahim Sultan, Pasir Gudang, Johor, Malaysia; and PhD Candidate, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), 86400 Parit Raja, Batu Pahat, Johor, Malaysia. Ph. +6012-2503770. Email: rohana@pis.edu.my

[2]Senior Lecturer, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), 86400 Parit Raja, Batu Pahat, Johor, Malaysia, Ph. +607-9508202, Email: afateh@uthm.edu.my

[3]Associate Professor, Faculty of Electrical, Universiti Teknologi MARA (UiTM) Cawangan Johor, Kampus Pasir Gudang, Jalan Purnama, Bandar Seri Alam, 81750 Masai, Johor, Malaysia, Ph. +607-3818187, Email: mzhafran@uitm.edu.my

[4]Senior Lecturer, Department of Electrical Engineering, Politeknik Melaka, No. 2, Jalan PPM 10, Plaza Pandan Malim, 75250 Melaka, Malaysia, Ph. +60-6337600, Email: rosnaniaffandi@gmail.com

[5]Associate Professor, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), 86400 Parit Raja, Batu Pahat, Johor, Malaysia, Ph. +607-9508191, Email: khairulam@uthm.edu.my

[6]Associate Professor, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), 86400 Parit Raja, Batu Pahat, Johor, Malaysia, Ph. +607-9508292, Email: norfaiza@uthm.edu.my

Manuscript received on 11 April 2026, revised on 21 July 2026 and accepted on 22 July 2026 as per publication policies of *NED University Journal of Research*.

https://doi.org/10.35453/NEDJR-Icon3E2025-004-R1

Keywords: Photovoltaic system, energy performance index, monthly performance, large-scale solar farms, predictive maintenance

1. INTRODUCTION

Renewable energy sources have become a central focus of global initiatives in the effort to reduce fossil fuel dependency and control greenhouse gas emissions [1]. The main renewable energy technologies include photovoltaic (PV), hydroelectric power, wind turbines, fuel cells, geothermal systems, and tidal power plants [2]. Each of these renewable energy sources contributes uniquely to sustainable energy. Among them, PV systems are considered one of the cleanest and most sustainable energy technologies. Their ability to generate electricity without producing harmful emissions or pollutants makes them particularly attractive for long-term planning and has high potential to contribute to global energy security [2][3]. As a result of these advantages, PV technology has experienced rapid development and innovation and has been widely applied in various sectors, including industrial, commercial, and large-scale utility sectors.

One of the most notable implementations of PV systems is in large-scale solar farms, where thousands of solar panels are installed across huge areas to harness solar energy on a massive scale [4][5]. Maintaining the optimal performance of a large-scale solar farm remains challenging despite advances in PV technology. For a plant built from thousands of panels spread over a large site, large-scale PV systems introduce numerous potential failure points, including inverter faults, cable failures, module degradation, and shading from nearby obstacles. Furthermore, the likelihood of encountering these faults increases as the installation becomes larger [6]. If left unresolved, any of these failures can significantly reduce energy output, but the physical scale of large solar farms and the complexity of their wiring make manual or visual inspections an unreliable way to detect them early. For this reason, fault detection is a crucial element in ensuring the long-term reliability and efficiency of PV systems and scaling up only makes the problem more difficult. One of the earliest and most obvious indicators of performance problems in photovoltaic systems is the mismatch between recorded irradiance readings and the actual energy generated. For example, if a month receives high levels of sunlight but the resulting energy output is low, this could indicate equipment failure, inverter problems, or technical problems such as short circuits and shading effects. [7]. In addition, if the energy output remains lower than in other months with similar levels of irradiance, it is most likely due to partial system failure or gradual module degradation. [8]. Therefore, such performance patterns are identified through a systematic, data-driven monthly analysis approach, so that any anomalies can be detected early and maintenance actions can be taken proactively, not just after the failure or damage occurs [9]. In this study, it was also possible to develop an approach using the Energy Performance Index (EPI) as a key indicator to assess system efficiency and also to identify months that are likely to experience performance problems. [10]. With this approach, the performance monitoring process can be done more accurately and quickly in detecting early signs of failure. This can also provide an opportunity for plant operators to take corrective action before these performance deviations become more serious, thus helping to maintain the reliability and energy production of the plant in the long term. Previous studies related to the evaluation of the performance of PV systems have used various indices and analysis methods. However, these studies differ in terms of scope, climatic conditions, and the main indices used to evaluate the system performance, as summarized in **Table 1**. Therefore, this study proposes the use of this EPI model based on the derating factor of the actual operating data for twelve months from a large-scale solar plant with a capacity of 31 MWp. Thus, the calculated EPI value is then compared with the actual damage event record and not only depends on irradiation data alone.

In addition, this study also compares EPI with three other performance indices that are often used, namely Reference Yield (Yr), Final Yield (Yf), and Capacity Factor (CF). This comparison aims to clarify the function of each index, including its strengths and limitations in detecting system performance problems. Subsequently, the monthly EPI deviations are linked to a fault classification framework that includes inverter problems, power loss on cables, module degradation, and module surface contamination. With this approach, plant operators have a more practical technical basis for making more effective and efficient predictive maintenance decisions.

Table 1. Summary of Related Studies on PV Performance-Assessment Indices

Study (Ref.)	Plant / Location	Indices Used	Methodology	Key Finding	Limitation
Saleheen et al. [3]	Commercial GCPV, Malaysia	Energy yield, PR	Target-oriented model development	Model matched measured yield within acceptable error	Single building-scale system, one climate year
Rahman et al. [11]	25 MWac PV, Pasir Gudang, Malaysia	Power output forecasting	LSTM univariate/multivariate forecasting	LSTM improved short-term forecast accuracy	Focused on forecasting, not fault attribution
Cubukcu & Gumus [18]	GCPV plant, eastern Turkey	Energy yield, PR	Field performance analysis	Identified seasonal PR variation	Temperate climate, not directly comparable to tropics
Gulkowski [20]	9 rooftop PV systems, Poland	Final/specific yield	Field measurement and financial assessment	Annual specific yield 868.8-1102.9 kWh/kWp	Small rooftop systems, temperate climate
Haibaoui et al. [21]	GCPV, Casablanca, Morocco	Yr, Yf, PR, CF	Field performance indicators case study	Reported full set of standard performance indices	Single system, no fault-cause analysis
Muhammad et al. [22]	GCPV, UiTM, Malaysia	System performance modelling	Simulation-based performance modelling	Model supported predictive monitoring	Simulation-based, limited field validation
This study	31 MWp PV, LSS	EPI, Yr, Yf, PR, CF	Derating-factor model + multi-index comparison + fault classification	EPI more sensitive to anomalous loss than Yr/Yf/PR/CF alone	Single plant; validated across two years (2023-2024) rather than a second independent plant

2. MATERIALS AND METHODS

2.1 Study Site

This study uses actual performance data from a large-scale photovoltaic system [11]. This study site is also one of the large-scale solar plants or Large-Scale Solar Plant (LSS) in Malaysia with an installed capacity of 31 MWp. Therefore, this system consists of 92,500 solar modules and 160 inverter units, and covers an area of 112 acres. [12]. Based on the capacity and configuration of the system, this plant is expected to be able to generate approximately 40,000 MWh of clean electricity per year. In addition to contributing to the supply of renewable energy, the operation of this plant also has the potential to reduce carbon emissions by up to 28,000 metric tons per year [13].

2.2 PV Module Specification

For the photovoltaic module used in this study, the JA Solar JAP72S09-335/SC model is a polycrystalline type [14]. The selection of this module is important because its technical characteristics, such as maximum power, voltage, current, module efficiency and temperature coefficient, affect the overall energy generation performance of the PV system. These technical specifications for this module are also summarized in **Table 2**.

2.3 Inverter Specification

The inverter is one of the main components in a photovoltaic system because it functions to convert direct current (DC) generated by solar modules into alternating current (AC) suitable for distribution to the electrical grid system. In this study, the inverter model used in this solar farm is the Huawei SUN2000-185KTL-H1 type [15]. Where the technical specifications of this inverter are power capacity, input voltage range, conversion efficiency and the main operating characteristics, summarized as in **Table 3**.

Table 2. Datasheet of PV Module

Parameter	Value
Peak Power (Pmax)	335 W
Open Circuit Voltage (Voc)	46.10 V
Max Power Voltage (Vmp)	37.45 V
Short Circuit Current (Isc)	9.42 A
Max Power Current (Imp)	8.95 A
Power Tolerance	0 to +5W
Temperature Coefficient of Pmax (γ_Pmp)	-0.400%/°C
Operating Temperature	-40°C to +85°C

Table 3. Datasheet of Solar Inverter

Parameter	Value
Max. DC Input Voltage	1500 VDC
Max. Input Current	9 × 26 A
MPPT Voltage Range	500–1500 VDC
Output Rated Power	175 kW
Max Power Current (Imp)	8.95 A
Output Apparent Power	185 kVA
Output Apparent Power	185 kVA
Max. Output Current	134.9 A
Operating Temperature Range	-25 °C to +60 °C
Efficiency	>98% (not stated but typical for this model)

The inverter used in this system achieves a maximum efficiency of 99.03% and is equipped with nine Maximum Power Point Trackers (MPPTs) [16] [10]. It supports up to 18 PV string inputs, which gives flexibility for different system configurations. The solar farm operates at a system voltage of 1,500 V, with a nominal input voltage of 1123.5 V, supplying a 175-kW grid-connected inverter [17]. Approximately 160 such inverters are deployed on-site, and together they provide a total installed capacity of approximately 28 MWac.

2.4 Energy Yield Calculation

For the main parameter in evaluating the effectiveness of this large-scale photovoltaic system is the energy yield. This parameter is essential because it allows the performance of this PV system to be compared more fairly even though the systems have different installed capacities. [18]. This is because the calculation of this energy yield considers the actual amount of electricity generated compared to the installed capacity of the system. Based on the guidance from the Sustainable Energy Development Authority (SEDA) Malaysia where in the book Design and Sizing of Grid-Connected Photovoltaic Power System [19], the value of energy yield is usually expressed in kilowatt-hours per kilowatt-peak (kWh/kWp). In this study, this energy yield is calculated using **Eq. (1)** as follows [20].

$$Energy\ Yield\ (kWh/kWp) = \frac{Total\ Energy\ Output\ (kWh)}{Installed\ Capacity\ (kWp)} \tag{1}$$

In **Eq. (1)**, E_{output} refers to the actual amount of energy generated by the PV system in kilowatt-hours (kWh), while Pinstalled refers to the installed capacity of the system in kilowatt-peak (kWp). This **Eq. (1)** can be widely used in industry and also in academic studies to evaluate the actual performance of the PV system based on the installed operating capacity [19]. In this study, the equation for the standard referred to from the Design and Sizing of Grid-Connected Photovoltaic Power System by SEDA Malaysia (2022), is used to calculate the monthly energy yield. This calculation is done based on the ratio between the total electricity generated and the installed capacity of the system. This approach ensures that the performance analysis carried out is in line with international performance assessment practices, where this energy yield is used as the main indicator of system efficiency because it allows performance comparisons to be made between PV systems of different sizes and also in actual operating conditions [19][21]. These same conclusions are reported elsewhere [9], [22], showing that these parameters make PV performance monitoring and prediction more responsive and proactive.

2.5 AC Output Energy Calculation

Estimating the expected monthly AC output energy ($E_{out\ expected}$) accurately, this study relies on a performance model that accounts for the various factors that degrade output (derating factors), drawn from the technical specifications of the JA Solar JAP72S09-335/SC module and the Huawei SUN2000-185KTL-H1 inverter, consistent with SEDA Malaysia's (2022) guidelines and standard international practice. So this calculation is according to **Eq. (2)** [19]:

$$E_{out\ expected} = P_{A\ stc} \times PSH_i \times f_{mm} \times f_{temp\ ave} \times f_{clean} \times f_{degrad} \times f_{unshade} \times \eta_{cable} \times \eta_{inv} \quad (2)$$

Therefore, when considering the value, the long-term degradation factor *(f_{degrad})* as in **Eq. (2)** is taken directly from the linear power warranty published by the module manufacturer. Where JA Solar's warranty for JAP72S09-335/SC polycrystalline modules used in plants such as the W-class 345 series, 5-busbar cell design also guarantees at least 97.5% of the rated P_{max} in Year 1 where the maximum first year degradation is 2.5%, followed by a linear decline of no more than 0.7% per year until Year 25, and ending at no less than 80.7% of the rated output. Since this solar plant has also been in continuous commercial operation for several years prior to the 2023 study period, the degradation factor values. The average temperature factor $f_{temp\ ave}$ is determined based on **Eq. (3)** [19], which takes into account the difference in the module operating temperature compared to the Standard Test Condition (STC) temperature:

$$f_{temp,ave} = 1 + \frac{\gamma Pmax}{100}\ x\ (T_{mod,avg} - T_{STC}) \quad (3)$$

The average temperature of the photovoltaic module ($T_{mod.avg}$) is calculated using **Eq. (4)** [19], which integrates both irradiance-weighted temperature averaging and an empirical temperature model specific to the Malaysian climate. The first part of the **Eq. (4)** estimates the irradiance-weighted average temperature over time, while the second part incorporates the empirical influence of ambient temperature (T_{amb}) and global irradiance (G_i) based on the model by Zainuddin (2014) [23]. **Eq. (4)** which is based on the weight of irradiance against the module temperature throughout the year:

$$T_{mod,avg} = \frac{\Sigma_k (G_{i,k}\ x\ T_{mod,k})}{\Sigma_k G_{i,k}}\ ,\ T_x = -15.76 + 0.02 G_i + 1.64 T_{amb} \quad (4)$$

Note: Irradiance (W/m²) refers to solar power per second, while Irradiation (kWh/m²) refers to the amount of solar energy integrated with time per unit area. The energy generated by the PV system ($E_{out\ measured}$) is then compared with the expected value to evaluate the system's performance based on natural resources and design capacity. For this factor is defined mathematically as shown in **Eq. (5)** [19]:

$$E_{\{measured\}} = \{Actual\ amount\ of\ energy\ generated\ by\ the\ PV\ system\ (kWh)\} \quad (5)$$

By comparing ($E_{out\,measured}$) and with ($E_{out\,expected}$) this provides a quantitative reading of the system performance, when the actual value is far below the expectation, the gap indicates a technical problem, inverter damage, faulty cable connection or module degradation.

2.6 Energy Performance Index (EPI)

Energy Performance Index (EPI) is a measure used to assess the extent to which a photovoltaic system produces actual energy compared to expected energy [10], [24]. This value is important because it provides an overview of the level of efficiency of the system's operation and helps identify any performance deviations at an early stage. Through EPI, the performance of this PV system can be assessed more comprehensively because the comparison is made not only based on the amount of energy generated but also takes into account the expected energy that should be produced based on operating conditions and system loss factors. The EPI value is calculated using the ratio between the actual energy recorded and the expected energy calculated based on the irradiance profile and system performance factors. From **Eq. (6)** [19] is used in this study to calculate the EPI value:

$$EPI = \frac{E_{out,measured}}{E_{out,expected}}\; x\, 100\% \tag{6}$$

Where the value $E_{out\,measured}$ is the actual energy (in kWh) recorded through the AC energy meter reading. Meanwhile, the value $E_{out\,expected}$ is the expected energy calculated based on monthly irradiance data, installed system capacity, and performance factors such as inverter efficiency, cable losses, module temperature, and energy harvesting factor based on **Eq. (2)**. A high EPI value (near 100%) indicates that the PV system is operating at its optimum level, whereas a significant decrease in EPI reflects the possibility of inverter damage, module degradation, loose cable connections, or external disturbances such as dirt and shade. In the context of smart system monitoring, EPI thus becomes a performance indicator that supports predictive maintenance actions and data-driven operations management [25].

2.7 Data Acquisition and Instrumentation

The parameters used in **Eq. (2)** to **Eq. (6)** are obtained from the plant's on-site monitoring instrumentation. Global irradiance ($G_{i,k}$) is measured using an in-plane pyranometer installed at the solar farm's weather station, and ambient temperature (T_{amb}) is recorded by the same station. Module temperature ($T_{mod,k}$) is obtained from module-mounted temperature sensors, cross-checked against the empirical model of Zainuddin (2014) [23] used in **Eq. (4)**. Measured AC energy ($E_{out\,measured}$) is read directly from the revenue-grade AC energy meter installed at the plant's point of interconnection. Inverter efficiency and cable efficiency figures are taken from the manufacturer datasheets for the Huawei SUN2000-185KTL-H1 inverter [15] and the site cabling specification, cross-checked against Supervisory Control and Data Acquisition (SCADA) records. All parameters are logged by the plant's SCADA system and aggregated from sub hourly readings into the monthly values reported in **Table 4**.

2.8 Uncertainty Analysis and Validation

Uncertainty analysis was conducted to estimate the error in EPI calculations arising from measurement tolerances of the input parameters. The uncertainty ranges adopted, ±2% for irradiance, ±1°C for module temperature, and ±0.5% for inverter efficiency, are consistent with Class B monitoring accuracy as defined by IEC 61724-1:2021, Photovoltaic system performance – Part 1: Monitoring [26] and were used to determine the likely actual EPI range for each month. The validation of this model is done by comparing the calculated monthly EPI values with the historical performance records of the solar plant and actual maintenance reports. This method is also used to assess the accuracy of calculations and also to ensure that the decrease in the EPI value detected has a consistent relationship with damage records, operational disruptions or maintenance activities occurring on site.

Table 4. Monthly Energy Output, Fault Detection Indicators, and Possible Causes

Month	Solar Irradiation (kWh/m²)	$E_{out\ measured}$ (kWh)	$E_{out\ expected}$ (kWh)	Error (kWh)	EPI	Fault Type	Possible Cause
Feb	38.4750	831511.160	1017036.608	-185525.448	0.818	Inverter Fault	48-hour downtime, reduced conversion efficiency.
Mar	141.552	3118327.210	3741743.102	-623415.892	0.833	Cable Power Loss	Loose or corroded cable connections cause higher resistance and power loss.
April	128.245	2869369.200	3389989.857	-520620.657	0.846	Module Degradation	Aging modules, microcracks, or cell degradation.
May	140.928	3191702.380	3725248.474	-533546.094	0.857	Cable Power Loss	Damaged or oxidized connectors reduce current flow.
Jun	112.512	2631340.240	2974108.454	-342768.214	0.885	Module Soiling	Dust accumulation on panel surfaces.
Jul	120.017	2833390.140	3172493.373	-339103.233	0.893	Stable / Minor Fault	Minor inverter fluctuation, negligible energy loss.
Aug	118.254	2761568.670	3125890.760	-364322.090	0.883	High Module Temperature	Elevated module temperature reduces efficiency.
Sep	128.580	2928819.150	3398845.146	-470025.996	0.862	Cable Power Loss	Partial shading or cable resistance losses.
Oct	153.418	3393589.560	4055405.387	-661815.827	0.837	Inverter Fault	Internal component failure reduces conversion.
Nov	112.556	2504129.950	2975271.537	-471141.587	0.842	Module Degradation	Reduced module output due to aging cells.
Dec	112.280	2470072.410	2967975.836	-497903.426	0.832	Inverter Fault	DC-AC conversion efficiency drops.

3. RESULTS AND DISCUSSION

This section presents an evaluation of the operational performance of a 31 MWp large-scale photovoltaic (PV) system, using one of Malaysia's large-scale solar (LSS) power plants as a case study. The analysis is based on actual operational data from 2023 and follows the technical methodology and six-step evaluation procedure outlined in the Sustainable Energy Development Authority (SEDA) Malaysia guidelines (2022). The expected energy value ($E_{out\ expected}$), is calculated using a performance model that accounts for several key loss factors, including module mismatch, temperature effects, module surface contamination (soiling), long-term degradation, shading, cable losses, and inverter efficiency. The use of this derating factor allows for a more realistic estimate of expected energy because it also considers the actual energy loss that commonly occurs during PV system operation in the field. According to **Table 4**, this details the monthly energy performance of the PV system based on a comparison between the actual energy generated ($E_{out\ measured}$) and the expected energy ($E_{out\ expected}$). In addition, monthly irradiation data, error values (Error), and Energy Performance Index (EPI) are also displayed as quantitative indicators to identify the level of system efficiency and the possibility of technical failures. Therefore, each month was associated with the type of fault (Fault Type) and the possible cause of the fault (Possible Cause) which is formulated based on Supervisory Control and Data Acquisition (SCADA) data records and the pattern of system performance degradation. Based on the results obtained, all months from February to December also recorded EPI values below 0.90, which is the optimal threshold value for PV system performance. However, July showed the best performance with the highest EPI value, which is 0.893, despite only receiving moderate irradiation of 120.017 kWh/m². On the other hand, October showed the most significant performance deviation, with an energy loss of -661,815.827 kWh and an EPI value of only 0.837, even though that month recorded the highest irradiation in the study year, which was 153.418 kWh/m². These findings indicate that high irradiation levels do not necessarily produce high energy but if there are internal technical issues such as inverter damage, cable power loss, module surface contamination, or system degradation. This pattern also shows that the amount of solar energy received is not the only factor that determines the efficiency of energy generation. On the contrary, it is an internal stability of the system that also plays a very important role in ensuring that the plant's operational performance remains optimal. Among the critical factors detected are inverter failure, module degradation, power loss on the cable, high module temperature, as well as contamination or dirt on the module surface. The use of this Energy Performance Index (EPI) as the main performance monitoring metric shows its ability to detect actual operational deviations more sensitively than methods that only rely on irradiation data alone. With this approach, it supports a more comprehensive and sustainable energy optimization process for large-scale solar farm operations in Malaysia. To ensure that the determination of the type of fault (Fault Type) and also the possible cause of the fault (Possible Cause) as shown in **Table 4** is based on verifiable monitoring records, the plant's SCADA alarm logs for the year 2023 were cross-referenced with the monthly EPI results. Based on the log, a total of 13,175 separate alarm events were recorded involving 171 inverter devices and combiner boxes. Of these, 7,050 alarms were categorized as Major, 1,432 as Minor, and 4,693 as Warning. A summary of these by alarm category is shown in **Table 5**.

Table 5. SCADA Alarm Categories Recorded in 2023 and Corresponding Fault Category in Table 4

Alarm Name (SCADA)	Severity	Events (2023)	Typical Duration	Linked Category in Table 4
External fan exception	Major	4,734	~2 h, self-clearing	High Module Temperature / Inverter Fault
String current back feed	Warning	3,973	<1 h	Cable Power Loss
Communication Fault	Minor	1,429	Minutes (comms only)	Monitoring gap, not generation loss
Abnormal Residual Current	Major	1,235	<15 min, transient	Cable Power Loss (wet season related)
PV String Loss	Warning	582	Days to several months	Module Degradation / Cable Power Loss
Low Insulation Resistance	Major	206	Short-moderate	Cable Power Loss (moisture ingress)
Grid Loss	Major	200	Short	Inverter Fault (grid-side trip)

The External Fan Exception alarm is the most frequently recorded Major category alarm. This condition also indicates the occurrence of repeated thermal cycling in the inverter's forced air-cooling system, especially when the inverter is operating in continuously high ambient and module temperatures. From this finding, it is in line with the High Module Temperature and Inverter Fault categories identified for August and December. In addition, string level alarms such as String Current Back Feed, Abnormal Residual Current, and Low Insulation Resistance indicate the possibility of recurring issues with the PV system's cables and connectors. This pattern is more consistent with the Cable Power Loss category identified for March, May, and September. Abnormal Residual Current alarms are more concentrated in the wetter period, namely between November and March, which indicates the possibility of stress on the insulation due to moisture in the cables or electrical connections. This most serious individual event also involves the PV String Loss alarm, which is a warning condition at the Warning level that in some cases persists on the same string for several weeks to several months before cleaning or corrective action is taken manually. This is consistent with the Module Degradation category identified for April and November. However, not all of these EPI degradations directly correspond to specific SCADA alarms. For example, the Module Soiling in June did not have a specific SCADA fault code because it is a build-up of dust or dirt on the panel surface that does not typically trigger a system protection alarm. Therefore, the effect of this soiling is identified indirectly through the remaining gap between the actual energy generated $E_{out\ measured}$ and the expected $E_{out\ expected}$ after other derating factors have been considered.

Figure 1 shows a comparison between the actual energy generated by the photovoltaic system $E_{out\ measured}$ and the expected energy $E_{out\ expected}$ based on the system performance model for the period from February to December 2023. The expected energy value is calculated using monthly irradiation data and the system derating factor, while the actual energy is obtained from field operation readings. Based on the results shown, there is a consistent energy deviation almost every month, where the actual energy generated is always lower than the expected energy. The most significant deviation occurs in February, when the actual energy of 831,511.160 kWh is compared to the expected energy of 1,017,036.608 kWh, resulting in an energy deficit of more than 185,000 kWh. For the month of October, the second largest deviation is recorded, although that month also has the highest irradiation value and the highest actual energy, which is 3,393,589.560 kWh. On the other hand, July and August show a smaller difference between actual and expected energy, reflecting a more stable system condition during that period. This pattern confirms that irradiation alone is not sufficient to explain the actual performance of a PV system. In fact, internal technical factors such as inverter efficiency, power loss in cables, module degradation, and component operational stability also play an important role in determining the overall system performance The comparison in **Figure 1** therefore provides a critical picture of the performance gap in PV systems and confirms the need for monitoring based on real-world data through the EPI approach.

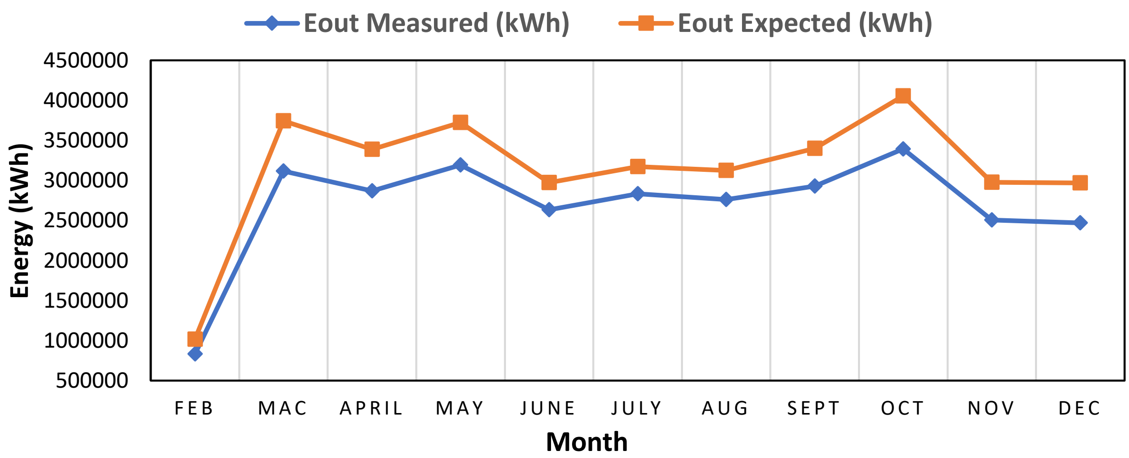

Figure 1. Comparison of Measured vs Expected Monthly Energy Output

Figure 2 also shows the monthly trend of EPI values throughout 2023. The EPI value is the ratio between actual and expected energy output, and it indicates PV system operational efficiency; the red dotted line at 0.90 marks the industry's minimum threshold for optimal performance. July recorded the highest EPI, at 0.893, almost reaching the optimal level, while February recorded the lowest, at 0.818, marking the most significant efficiency decline of the study period. No month exceeded the 0.90 threshold, indicating that this system experienced inconsistent performance with the potential for large energy losses. For the EPI decline after August, it also indicates internal system damage such as reduced inverter efficiency, unstable cable connections, high module temperatures, or impurities on the panel surface. Furthermore, this pattern once again emphasizes that the performance of a PV system is highly dependent on the technical integrity of the system's internals, and not simply on the amount of irradiation received. Factors such as inverter efficiency, cable condition, module degradation, operating temperature, and even the cleanliness of the panel surface also affect the system's ability to optimally convert solar energy into electrical energy.

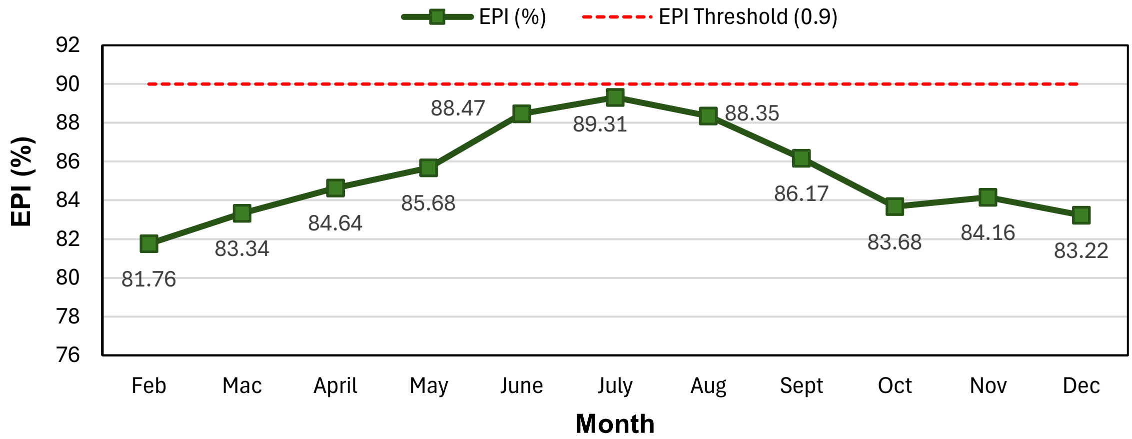

Figure 2. Monthly Trend of Energy Performance Index (EPI)

Figure 3 shows the percentage of monthly performance deviation between the actual energy generated and the expected energy of the PV system. All the values of the deviations recorded are negative, indicating that the system did not achieve the energy generation level as targeted based on the developed performance model. February recorded the highest deviation, which was -18.24%, followed by March at -16.66% and December at -16.78%. However, July showed the lowest deviation, which was -10.69%, at this value it still shows that the system is not operating at an optimal level. From these findings it is shown that even if the received irradiation is sufficient, the system performance can still deteriorate due to hidden technical issues such as inverter damage, power loss in the cable, PV module degradation, or uncontrolled increase in operating temperature. The consistent negative deviation pattern throughout the year also emphasizes the need for continuous technical monitoring to detect problems early and support the implementation of predictive maintenance.

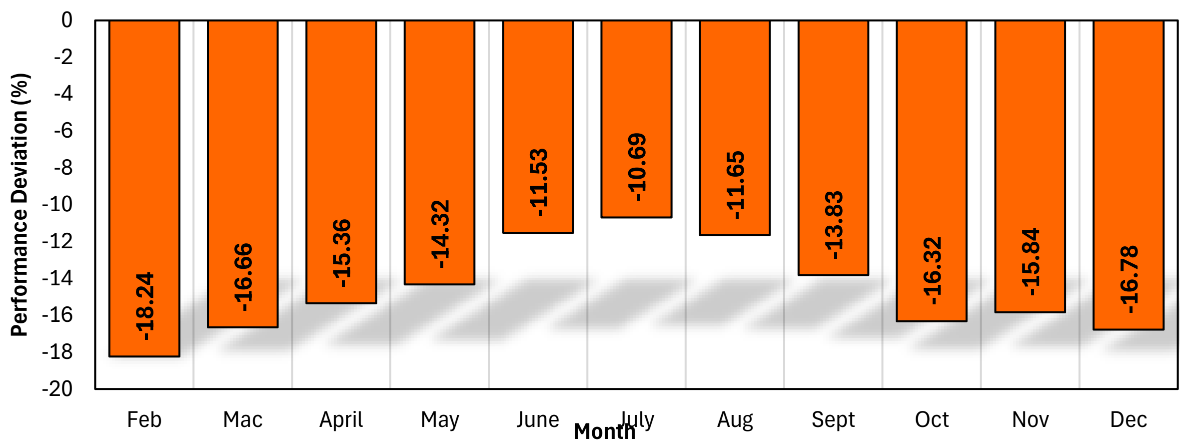

Figure 3. Monthly Performance Deviation Between Measured and Expected Output

Finally, **Figure 4** illustrates the relationship between monthly irradiation values and EPI values throughout 2023. This analysis also shows that changes in irradiation are not directly proportional to the energy performance of the system. In other words, a high amount of sunlight does not necessarily produce a high EPI value if there is energy loss or technical disruption in the PV system.

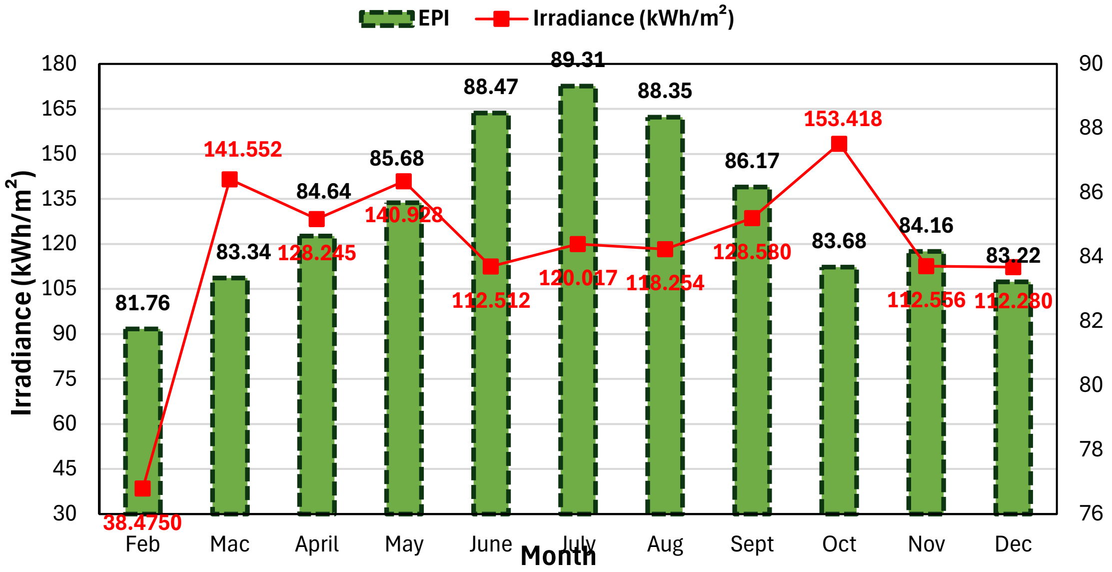

Figure 4. Monthly Irradiance and EPI

For example, March recorded the second highest irradiation, which was 141.552 kWh/m², but the EPI value recorded was only 83.34%. This value is also much lower than in July which recorded an EPI of 89.31%, although the irradiation in July was lower, which was 120.017 kWh/m². This finding also shows that the performance of this PV system is not only influenced by the level of irradiation but also depends on the stability of internal components such as inverters, cables, PV modules, as well as the overall operating conditions of the system. This confirms that internal factors, such as high module temperature, dirt on the panel surface, inverter degradation, and unstable cable connections, are more influential than total irradiation alone. This result agrees with the recommendation of SEDA Malaysia (2022), which supports the use of EPI as a broader monthly performance indicator, and it confirms that low EPI values can still occur despite high irradiation, pointing to internal technical problems that need to be identified proactively. EPI, as a monthly technical performance indicator, is therefore more comprehensive and effective at detecting hidden faults, supporting predictive maintenance and the long-term operational effectiveness of large-scale PV systems.

3.1 Comparative Performance Indices: Reference Yield, Final Yield, Performance Ratio, and Capacity Factor

To address performance beyond the EPI-irradiation comparison alone, **Table 6** reports three additional standard indices computed from the same monthly data in **Table 4:** Reference Yield (Yr = monthly irradiation divided by the 1 kW/m² reference irradiance), Final/Specific Yield (Yf = $E_{out\ measured}$ divided by the 31,000 kWp installed DC capacity), Performance Ratio (PR = Yf divided by Yr), and Capacity Factor (CF = $E_{out\ measured}$ divided by the product of the 28,000 kW rated AC capacity and the number of hours in the month).

PR and CF both fall sharply in February, consistent with the confirmed 48-hour inverter outage identified through EPI and **Table 4**. For the remaining months, PR (0.70-0.76) and CF (12-16%) stay comparatively stable, in the range typically reported for tropical utility-scale PV plants, while EPI shows a more pronounced mid-year peak and a later decline. This difference arises because PR and CF benchmark output against the ideal STC-irradiance-only reference, so they capture the total system loss including expected temperature, soiling, and cable derating, whereas EPI benchmarks output against an already-derated expected value, so its remaining variation isolates anomalous, fault-driven losses beyond what is normally expected. This comparison shows that Yr, Yf, PR, and CF describe the plant's overall energy-conversion efficiency, while EPI is the more sensitive indicator for early fault detection, and the two sets of indices are therefore complementary rather than interchangeable.

Table 6. Monthly Reference Yield, Final Yield, Performance Ratio, and Capacity Factor (2023)

Month	Yr (h)	Yf (kWh/kWp)	PR (Yf/Yr)	CF (%, AC basis)	EPI
Feb	38.48	26.82	0.697	4.42	0.818
Mar	141.55	100.59	0.711	14.97	0.833
Apr	128.25	92.56	0.722	14.23	0.846
May	140.93	102.96	0.730	15.32	0.857
Jun	112.51	84.88	0.754	13.05	0.885
Jul	120.02	91.40	0.762	13.60	0.893
Aug	118.25	89.08	0.753	13.26	0.883
Sep	128.58	94.48	0.735	14.53	0.862
Oct	153.42	109.47	0.714	16.29	0.837
Nov	112.56	80.78	0.718	12.42	0.842
Dec	112.28	79.68	0.710	11.86	0.832

3.2 Practical Application of EPI Monitoring

The EPI thresholds identified in this study can be translated into an operational decision rule for plant operators: an EPI at or above 0.90 indicates normal operation; an EPI between 0.85 and 0.90 warrants a scheduled inspection; and an EPI below 0.85 should trigger an immediate maintenance dispatch. When this decision rule is applied to the study data, the February EPI value of 0.818, along with the 48-hour record of inverter outages as shown in **Table 4**, should have triggered an alert and immediate action to the maintenance team. This early action could also potentially help recover some of the 185,525-kWh energy deficit recorded that month. This decision rule provides a clearer, data-driven basis for plant operators to prioritize maintenance work at large-scale PV sites. This approach is practical because it does not require overly complex predictive models but can still help identify months or components that require more immediate technical attention.

3.3 Validation Using a Second Year of Operational Data (2024)

To validate the effectiveness of this EPI method beyond a single year analysis, **Table 7** shows the same monthly indicators for 2024 at the same solar plant. This calculation is also carried out using the same derating factor model as described in **Section 2.5**.

Table 7. Monthly Energy Output and Energy Performance Index (2024)

Month	Solar Irradiation (kWh/m²)	$E_{out\ measured}$ (kWh)	$E_{out\ expected}$ (kWh)	Error (kWh)	EPI
Jan	115.948	2,543,788.670	2,965,370.100	-421,581.430	0.858
Feb	155.123	3,293,093.740	3,967,270.725	-674,176.985	0.830
Mar	169.683	3,759,865.850	4,339,642.725	-579,776.875	0.866
Apr	132.176	3,172,482.610	3,380,401.200	-207,918.590	0.938
May	111.598	2,726,636.180	2,854,118.850	-127,482.670	0.955
Jun	111.006	2,735,741.190	2,838,978.450	-103,237.260	0.964
Jul	126.999	3,036,790.200	3,247,999.425	-211,209.225	0.935
Aug	120.748	2,953,516.920	3,088,130.100	-134,613.180	0.956
Sep	132.161	3,173,435.710	3,380,017.575	-206,581.865	0.939
Oct	126.189	2,997,686.910	3,227,283.675	-229,596.765	0.929
Nov	107.913	2,537,910.070	2,759,874.975	-221,964.905	0.920
Dec	125.724	2,604,619.090	3,215,391.300	-610,772.210	0.810

The findings for 2024 show the same basic pattern as 2023, namely that the EPI value does not move directly with the change in irradiation. For example, March 2024 also recorded the highest irradiation for the year, which is 169.683 kWh/m², but the EPI value obtained is only at a moderate level, which is 0.866. On the other hand, June recorded a much lower irradiation, which is 111.006 kWh/m², but recorded the highest EPI value for 2024, which is 0.964. Overall, the average EPI increased from 0.853 in 2023 for the period from February to December to 0.908 in 2024. In addition, six months in 2024, namely from April to September, also managed to exceed the performance threshold of 0.90, compared to no months exceeding the threshold in 2023. This improvement demonstrates that the EPI method can be used consistently to assess changes in system performance from year to year, as well as helping to identify whether operational and maintenance actions have had a positive impact on plant efficiency. This is consistent with the plant addressing the inverter and cable faults identified in 2023 (**Table 4**). At the same time, the lowest EPI values in both years fall in the November-to-February window, at 0.818 in February 2023 and 0.810 in December 2024, which lines up with Malaysia's northeast monsoon season and its higher cloud cover and rainfall. Because this recurring seasonal dip shows up in both years even though the year-round average improved, it is unlikely to be a one-off measurement artefact. This second-year comparison was carried out at the same 31 MWp plant rather than a second, independent site, so it addresses year-to-year validation but does not yet establish how the EPI thresholds used in Section 3.7 would transfer to a differently sized or differently located PV system; cross-plant validation is identified as a direction for future work.

4. CONCLUSION

This study shows that the Energy Performance Index (EPI) approach evaluates large-scale photovoltaic (PV) system performance better than approaches that rely on solar radiation data alone, because it also picks up faults that irradiation-only methods miss. Analysis of actual operating data throughout 2023 shows that eleven of the twelve months recorded EPI values below the minimum threshold of 0.90, indicating a significant decline in system performance. This trend points to internal factors, PV module wear, loose cable connections, deteriorating inverter efficiency, high module operating temperature, and surface impurities, as the main causes of energy loss, even when solar radiation input is sufficient and stable. Low EPI values also serve as early indicators of hidden faults that cannot be detected through irradiation monitoring alone.

Therefore, monthly performance monitoring based on EPI can be used as the basis for a more structured and effective periodic maintenance strategy, without the need for the use of overly complex predictive models. By adopting EPI-based monitoring, solar farm operators can target technical interventions more accurately, optimize energy generation, and extend system life. These findings show that EPI is a useful metric for monitoring large-scale PV systems: the method supports more systematic preventive maintenance and can inform renewable energy planning for PV systems in Malaysia and other tropical regions.

5. ACKNOWLEDGEMENT

The authors would like to acknowledge the financial support provided through a Tier 1 Research Grant (Q878). Appreciation is also extended to the personnel involved in the data collection process at the large-scale solar farm, as well as to all individuals who contributed technical support, guidance, and assistance throughout the completion of this study.

6. REFERENCES

[1] Hamid AK, Mbungu NT, Elnady A, Bansal RC, Ismail AA, AlShabi MA. A systematic review of grid-connected photovoltaic and photovoltaic/thermal systems: benefits, challenges and mitigation. Energy Environ. 2023;34(7):2775-2814. doi:10.1177/0958305X221117617

[2] International Renewable Energy Agency (IRENA). World energy transitions outlook 2023 [Internet]. Abu Dhabi: IRENA; 2023 [cited 2026 Jul 31]. Available from: https://www.irena.org/Digital-Report/World-Energy-Transitions-Outlook-2023

[3] Saleheen MZ, Salema AA, Islam SMM, Sarimuthu CR, Hasan MZ. A target-oriented performance assessment and model development of a grid-connected solar PV (GCPV) system for a commercial building in Malaysia. Renew Energy. 2021;171:371-382. doi:10.1016/j.renene.2021.02.108
[4] Mohd Chachuli FS, Mat S, Ludin NA, Sopian K. Performance evaluation of renewable energy R&D activities in Malaysia. Renew Energy. 2021;163:544-560. doi:10.1016/j.renene.2020.08.160
[5] Lim CH, Lim S, How BS, Ng WP, Ngan SL, Leong WD, Lam HL. A review of industry 4.0 revolution potential in a sustainable and renewable palm oil industry: HAZOP approach. Renew Sustain Energy Rev. 2021;135:110223. doi:10.1016/j.rser.2020.110223
[6] Haruna T, Ndem Ikot A, Big-Alabo A. A review of factors affecting the efficiency and output of PV systems applied in the tropical climate of South-South Nigeria. Afr J Adv Sci Technol Res. 2024;16(1):1-17. doi:10.62154/ajastr.2024.016.010328
[7] Aboshady FM, Taha IBM. Fault detection and classification scheme for PV system using array power and cross-strings differential currents. IEEE Access. 2021;9:112655-112669. doi:10.1109/ACCESS.2021.3104007
[8] Limpaporn P, Khomfoi S. Fault detection and predictive maintenance paradigm for solar PV systems. In: 2024 International Conference on Materials and Energy: Energy in Electrical Engineering (ICOME-EE). IEEE; 2024. p. 1-4. doi:10.1109/ICOME-EE64119.2024.10845651
[9] Syamsuddin A, Adhi AC, Kusumawardhani A, Prahasto T, Widodo A. Predictive maintenance based on anomaly detection in photovoltaic system using SCADA data and machine learning. Results Eng. 2024;24:103589. doi:10.1016/j.rineng.2024.103589
[10] Gradwohl C, Dimitrievska V, Pittino F, Muehleisen W, Montvay A, Langmayr F, Kienberger T. A combined approach for model-based PV power plant failure detection and diagnostic. Energies. 2021;14(5):1261. doi:10.3390/en14051261
[11] Rahman NHA, Hussin MZ, Sulaiman SI, Hairuddin MA, Saat EHM. Univariate and multivariate short-term solar power forecasting of 25 MWac Pasir Gudang utility-scale photovoltaic system using LSTM approach. Energy Rep. 2023;9:387-393. doi:10.1016/j.egyr.2023.09.018
[12] Bernama. UiTM first public varsity to own and operate two LSSPV plants [Internet]. [cited 2026 Jul 31]. Available from: https://www.bernama.com/en/news.php?id=1919804
[13] Sebestyen V. Environmental impact networks of renewable energy power plants. Renew Sustain Energy Rev. 2021;151:111626. doi:10.1016/j.rser.2021.111626
[14] JA Solar Technology Co., Ltd. JAP72S09 325-345/SC series datasheet [Internet]. 2019 [cited 2026 Jul 31]. Available from: https://www.jasolar.com/uploadfile/2019/0603/20190603114747608.pdf
[15] Huawei Technologies Co., Ltd. SUN2000-185KTL-H1 smart string inverter datasheet [Internet]. [cited 2026 Jul 31]. Available from: https://solar.huawei.com/-/media/Solar/attachment/pdf/apac/datasheet/SUN2000-185KTL-H1.pdf
[16] Dhimish M, Holmes V, Dales M. Parallel fault detection algorithm for grid-connected photovoltaic plants. Renew Energy. 2017;113:94-111. doi:10.1016/j.renene.2017.05.084
[17] Rahman RA, Sulaiman SI, Omar AM, Shaari S, Zain ZM. Performance analysis of a grid-connected PV system at a Malaysian energy centre. In: 2010 4th International Power Engineering and Optimization Conference (PEOCO). IEEE; 2010. p. 480-483. doi:10.1109/PEOCO.2010.5559155
[18] Cubukcu M, Gumus H. Performance analysis of a grid-connected photovoltaic plant in eastern Turkey. Sustain Energy Technol Assess. 2020;39:100724. doi:10.1016/j.seta.2020.100724
[19] Sustainable Energy Development Authority (SEDA) Malaysia. Design and sizing of grid-connected photovoltaic power system. 1st ed. Putrajaya: SEDA Malaysia; 2022.
[20] Gulkowski S. Specific yield analysis of the rooftop PV systems located in south-eastern Poland. Energies. 2022;15(10):3666. doi:10.3390/en15103666
[21] Haibaoui A, Hartiti B, Elamim A, Karami M, Ridah A. Performance indicators for grid-connected PV systems: a case study in Casablanca, Morocco. IOSR J Electr Electron Eng. 2017;12(2):55-65. doi:10.9790/1676-1202015565
[22] Muhammad N, Zakaria NZ, Shaari S, Omar AM. System performance modelling of a grid-connected photovoltaic system in UiTM, Malaysia. Int J Adv Sci Eng Inf Technol. 2017;7(4):1275. doi:10.18517/ijaseit.7.4.2290
[23] Zainuddin H. Module temperature: equatorial climate [technical report]. Shah Alam: Universiti Teknologi MARA, Faculty of Applied Sciences; 2014.

[24] Panicker K, Anand P, George A. Assessment of building energy performance integrated with solar PV: towards a net zero energy residential campus in India. Energy Build. 2023;281:112736. doi:10.1016/j.enbuild.2022.112736

[25] Kathirgamanathan A, De Rosa M, Mangina E, Finn DP. Data-driven predictive control for unlocking building energy flexibility: a review. Renew Sustain Energy Rev. 2021;135:110120. doi:10.1016/j.rser.2020.110120

[26] International Electrotechnical Commission (IEC). Photovoltaic system performance - Part 1: monitoring. IEC 61724-1:2021. Geneva: IEC; 2021.

AUTHORS' PROFILE

Rohana Hasan *is a Lecturer in the Department of Electrical Engineering at Politeknik Ibrahim Sultan, Malaysia. She received her bachelor's degree and master's degree from Universiti Tun Hussein Onn Malaysia (UTHM) in 2010 and 2016, respectively, with an academic background in communication engineering. She is currently pursuing her PhD at Universiti Tun Hussein Onn Malaysia (UTHM). Her research interests include photovoltaic systems, grid-connected renewable energy systems, energy performance analysis, fault detection, predictive maintenance, and data-driven monitoring for sustainable energy applications.*

Ahmad Fateh *Mohamad Nor is a Senior Lecturer in the Department of Electrical Engineering, Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM), Johor, Malaysia. He received his B.Eng., M.Eng., and Ph.D. degrees in Electrical Power Engineering from Universiti Teknikal Malaysia Melaka (UTeM) in 2011, 2013, and 2017, respectively. His research interests include power systems, photovoltaic (PV) systems, renewable energy integration, artificial intelligence (AI)-based power system analysis, voltage stability assessment, and optimisation techniques for sustainable energy systems.*

Mohamad Zhafran Hussin *is an Associate Professor at Universiti Teknologi MARA (UiTM) Cawangan Johor, Kampus Pasir Gudang. He received his PhD in Electrical Engineering by research in 2014 and holds professional technologist qualifications. His research activities cover solar photovoltaic progress, performance indices of grid-connected photovoltaic systems in tropical regions, module temperature modelling, solar power forecasting, and renewable energy system assessment. He has contributed to indexed publications, grants, consultations, and supervision activities related to photovoltaic systems and sustainable energy technologies.*

Rosnani Affandi *is a Senior Lecturer in the Department of Electrical Engineering at Politeknik Melaka, Malaysia. She received her PhD in Electrical Engineering with a specialization in Renewable Energy from Universiti Teknikal Malaysia Melaka (UTeM), a Master of Education in Technical and Education, and a Bachelor of Science in Electrical Engineering with a specialization in Instrumentation and Control from Universiti Teknologi Malaysia. Her research interests include renewable energy systems, solar power, concentrating solar power, instrumentation, programmable logic control, automation, and engineering education. She has also been actively involved in research, innovation, commercialization, academic supervision, and technical project development.*

Khairul Anuar Mohamad *is an Associate Professor at the Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM). He received his PhD in Engineering for Composite Function from Muroran Institute of Technology. His research focuses on device fabrication, process technology and characterisation. His current innovation interests include wireless power transfer, energy harvesting, and sensor systems and their applications. More recently, his work has expanded into data-driven technologies, particularly in the development of intelligent engineering solutions.*

Norfaiza Fuad *is an Associate Professor at the Faculty of Electrical and Electronic Engineering, Universiti Tun Hussein Onn Malaysia (UTHM). She received her PhD in Electrical Engineering from Universiti Teknologi MARA (UiTM) Shah Alam. Her field of expertise is electrical and electronic engineering, with research interests in EEG and brainwave signal analysis, human potential, image processing, mobile learning, microcontrollers and microprocessors, data encryption, IC design, and multi-network analysis. She has led and participated in projects involving intelligent systems, signal processing, neural networks, and Internet of Things applications.*