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Performance monitoring as fault detection approach on AC power output of monocrystalline grid-connected photovoltaics system

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ABSTRACT

As per the Malaysian Sustainable Energy Development Authority (SEDA), Malaysia has seen a significant growth in renewable energy thanks to the feed-in tariff (FiT) program. However, photovoltaic (PV) systems in tropical countries like Malaysia experience degradation due to technological factors and operating conditions. The effectiveness of PV systems is influenced by geographical location and weather conditions. This research study conducted a comparative analysis between the actual power output P_{AC_actual} and the predicted power output $P_{AC\_expected}$, referred to as the acceptance ratio (AR). The study also assessed the yield and performance ratio (PR) of a PV system situated at the Green Energy Research Center (GERC) in Universiti Teknologi MARA, Malaysia. The actual monocrystalline grid-connected photovoltaic (GCPV) system versus predicted AC power and AR were monitored over a year, with MATLAB software used for simulating output power based on real data. According to the Malaysian Standard MS2692:2020, an AR value of 0.9 or higher is required for approval in testing and commissioning tests. The findings indicate that most AR graphs fall below this threshold, and the PR value for each month is below 0.75, suggesting a need for significant system overhaul.

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1. INTRODUCTION

Renewable energy is produced from energy sources continuously replenished by natural processes. Various available technologies for harnessing renewable energy include photovoltaic (PV) systems, wind turbine generators, geothermal systems, micro hydro systems, wave generators, and more [1]. Among these, solar energy generation stands out as the most efficient means of harvesting energy from all renewable sources [2]. Over the past few decades, the installation of solar systems has experienced substantial growth, primarily attributable to the decreasing costs of solar panels resulting from technological advancements [3].

In Malaysia, the adoption of PV systems has seen a significant surge. The Malaysian Sustainable Energy Development Authority (SEDA) recently reported an increase in PV installations to approximately 269 GW, a notable rise compared to previous years. This growth can be attributed to both the effective tariff schemes implemented by the Malaysian government and a shift in the mindset of Malaysians towards reducing their carbon footprint through PV system installations. Consequently, this has led to an abundance of PV systems in Malaysia that require proper management.

To ensure the dependable and seamless integration of PV systems into the daily energy supply, it becomes imperative to conduct regular performance evaluations. Typically, monitoring the performance of grid-connected PV systems involves the utilization of additional hardware, such as radiation sensors (pyranometers or reference cells), data loggers, or other intelligent monitoring devices. However, this approach can be costly and demands intensive maintenance. To achieve and sustain optimal PV system performance, continuous monitoring is essential. This ongoing monitoring serves the purpose of detecting various types of faults that may arise, thereby preventing any production losses.

As per the research conducted by Firth *et al.* [4] in 2010, their monitoring study indicates that annual power losses in a PV system due to various faults amount to approximately 18.9%. It is important to note that addressing these faults not only has a direct impact on energy production but also plays a crucial role in preventing potential fire disasters that could pose threats to both personal safety and property protection if the faults are severe. Consequently, a significant amount of research and development has been dedicated to the detection of faults, whether they originate from the AC or DC side of the PV system.

There are few researchers have listed fault detection techniques on DC sides including climatic data independent (CDI) technique, electrical current-voltage measurement technique, comparison between measured and modeled PV system outputs (CMM), power loss analysis technique, machine learning (ML) techniques, heat exchange and temperature based models, ground fault detection and interruption fuse, residual current monitoring devices, insulation monitoring devices, frequency spectrum analysis of the voltage or current waveforms, estimating randomness in the voltage signal, spread spectrum time-domain reflectometry, visual inspection and lock-in thermography (LIT) [5]–[7] and to include thermal imaging done by Kaplani and Kaplanis [8].

For failure detection and classification (FDC), CDI approach does not require any measurement of climatic data such as solar irradiance, temperature, humidity, and wind speed. For fault detection, this approach employs external devices such as LCR, inductance (L), capacitance (C), and resistance (R) meters and signal generators. To detect a fault, the reaction of the PV system is analyzed immediately after each signal injection. For example, Takashima *et al.* [9] proposes earth capacitance measurement (ECM) to detect the disconnection of a PV module in a string. Schirone invented the time-domain reflectometry (TDR) technology, which measures the electrical properties of transmission lines to detect failure points, faults, and impedance changes due to degradation without requiring climatic data [10].

For fault detection using electrical current-voltage measurement technique, has just involves the monitoring of electrical signals from the output terminal, such as voltage and current [11]. Benghanem and Maafi [12] created a microcontroller-based real-time expert system to monitor, supervise, and control PV systems, and Mukaro and Tinarwo [13] examined one of its later applications. Automatic fault detection in a grid-connected photovoltaic (GCPV) system was established by Chine *et al*. [14] utilizing voltage and current indicators.

Another study by Muhammad *et al.* [15], perform the ratio of voltage and current for fault detection algorithm. This technique calculates the discrepancy in measured and modelled PV system outputs is used to detect faults. This technique is distinguished using the comparison between measured and modeled PV system outputs (CMM). Various prediction models were employed to calculate the predicted output power of the PV system. Typically, these strategies may set theoretical thresholds that the change in system output power does not surpass. If it does, however, surpass the threshold, the system is deemed defective. In certain ways, the expected value of PV outputs was forecasted using parametric models and meteorological factors, as well as configurable parameters [16]. Chao *et al.* [17] developed a technique to detect flaws in PV arrays based on the extended correlation function and the matter element model.

Power analysis techniques is using performance ratio (PR), capture losses, array and grid power loss analysis [18], [19] and numerical method [20]. This method is based on an examination of power losses in the PV system. Power losses in FDC are estimated by comparing measured data to simulated outcomes. Chouder and Silvestre (2010) [21] suggested a supervision and fault detection system based on power loss analysis. Madeti and Singh [2] suggest a technique for detecting defects in both the PV array and the inverter. Silvestre *et al*. (2013) [22] measured PV system losses, current, and voltage.

Machine learning (ML) strategies rely on the learning of certain circumstances matching to a specific type of input. On the basis of past training, each newly presented condition may be detected and exploited for FDC [23]. Due to PV output production vary depending on the weather, determining theoretical limitations for defect identification is a tough problem. This constraint can be circumvented by training a model for certain input-output patterns. In the FDC literature, many machine learning algorithms have been used. Yagi *et al.* [24] employed expert systems to detect defects in a PV array caused by partial shadowing and an inverter. Li *et al.* [25] employed an artificial neural network (ANN) to categorize different type of faults in PV array. Ducange *et al*. [26] and Bonsignore *et al*. [27] describe Takagie Sugeno Kahn Fuzzy Rule

(TSKFRBS), Bayesian belief networks, three-layered ANN, decision tree-based technique, and graph-based semi-supervised for FDC of PV plants. Some other examples for FDC of PV systems can be found in [28]–[33].

The temperature of the PV module fluctuates when a problem occurs in the PV array. This heat exchange and temperature (HET) based models approach uses the heat exchange and module temperature during the faulty situation to find defects. The authors of Hu *et al*. [34] and Vergura *et al*. [35], for example, used the finite element approach to simulate the physical faults of several types of PV cells. It's based on the thermal behavior of PV cells caused by electrical failures.

Another significant approach for identifying faults in PV systems involves the use of infrared/thermal imaging. This technique is founded on the concept of localized heat generation due to the joule heating effect caused by shunted cells, poor connections, short circuits, and similar issues. In a series-connected PV cell setup, certain cells that produce less current than others become reverse-biased and function as resistors, dissipating heat. Consequently, a temperature gradient forms, resulting in a distinct area of brightness when viewed through thermal imaging. Thermal imaging can be conducted in two manners: forward bias imaging (FBI) and reverse bias imaging (RBI). In FBI, the module exposed in the field is connected to a power source, with the module being biased forward [9].

On the AC side, signal processing for fault detection involves both time domain and frequency domain modeling. Hardware-based solutions encompass both analog and digital implementations for fault detection techniques [2], [36]. The primary technical concerns regarding the AC side of PV systems include inadvertent islanding and PV inverter failures. Inverters can fail when passive components or power switches in the converters experience short or open circuits, often due to high thermal and mechanical stress. Previously proposed strategies for detecting inverter failures include power loss analysis [14] and the utilization of machine learning algorithms [24]. Islanding occurs when the PV inverter continues to operate independently from the main grid after a grid disconnection, typically caused by a fault. In such cases, the PV array's electricity can power local loads or charge controllers, which in turn charge batteries for energy storage. Over the past decade, numerous techniques for detecting islanding events have been proposed.

In Malaysia, achieving peak energy output, particularly for PV system installers, underscores the importance of implementing performance monitoring methods endorsed by government authorities. For fault detection, the Malaysian sustainable energy development authority (SEDA) has established a threshold value for acceptable PV system operation. It is deemed necessary for this value to be equal to or greater than 0.9 to classify the system as healthy. Conversely, if the value falls below 0.9, the system is deemed faulty [36].

Therefore, the fault detection approach in this study is mainly focused on the performance monitoring by using acceptance ratio (AR) to detect faults in PV system by comparing and analyse the actual output power P_{AC_actual} and predicted output power $P_{AC\_expected}$ of the PV system. This technique generically is an early technique to monitor the existence of faults and health of the PV systems.

2. METHOD

2.1. Site description of monocrystalline PV systems

The experiment was conducted at the Green Energy Research Center (GERC) at Universiti Teknologi MARA (UiTM) Shah Alam Malaysia, with North latitude 3º 04’08.70’’ and East latitude 101º 29’ 49.66”. In this research, a monocrystalline PV module was employed. The data utilized for this study was acquired from the PV system's integrated data logger, collected at 5-minute intervals over a one-year duration spanning from November 2018 to October 2019. The data loggers were linked to both the weather monitoring station and the inverter, enabling the capture of environmental and electrical data, including AC power output, solar irradiance, module temperature, and wind speed. Table 1 provides detailed specifications of the system.

Table 1. The system description

Description	Systems Specification
Type of System	Grid-connected
Nominal Power	9 kWp
Inverter	1 unit × 8000TL-10
Mounting	Retrofitted on metal deck
PV Module	Monocrystalline Yingli Panda 250Wp YL250C-30b
Tilt angle and orientation	10 Deg facing South-East
Array configuration	String 1 = 18 unit modules String 2 = 18 unit modules

2.2. AC power analysis and acceptance ratio

The methodology employed in this study adopts a mathematical approach to assess both the AC power output and the acceptance ratio (AR). Key parameters, including the actual AC power output, irradiance, and module temperature, are extracted from the data logger. Consequently, a mathematical approach is utilized to determine the predicted AC power output, as illustrated in Figure 1. The equations outlined below are essential for computing the predicted AC power output.

$$P_{AC\ predicted} = P_{array_{stc}} \times k_g \times k_{tempt} \times k_{mm} \times n_{inv} \times k_{dirt} \times k_{age} \times n_{cable} \tag{1}$$

$$k_g = \frac{G}{1000} \tag{2}$$

$$k_{tempt} = 1 + [\frac{\delta}{100} \times (T_{cell} - T_{stc}) \tag{3}$$

$P_{array_{stc}}$ is the value of PV array at STC, for this case the value is 9000 Wp, k_g is peak sun factor that can be determine using in (1), k_{tempt} is derating factor due to temperature as stated in (2), k_{mm} is module de-rating factor, n_{inv} is inverter efficiency while k_{dirt} is percentage of soiling factor cause from accumulation of dust and dirt, k_{age} is PV module age derating factor and lastly n_{cable} is cables efficiency. After obtaining the actual and predicted power output, these AC power output can be analyzed and graph can be plotted as demonstrate in Figure 2. Next, the ratio between the actual output power (P_{AC_actual}) and predicted output power ($P_{AC\_predicted}$), acceptance ratio (AR) is calculated. If the value of AR obtained is greater than 0.90, the system is in good condition. However, if the AR of the GCPV system is lower than 0.90, the system is at faulty condition and the performance generated will reduced.

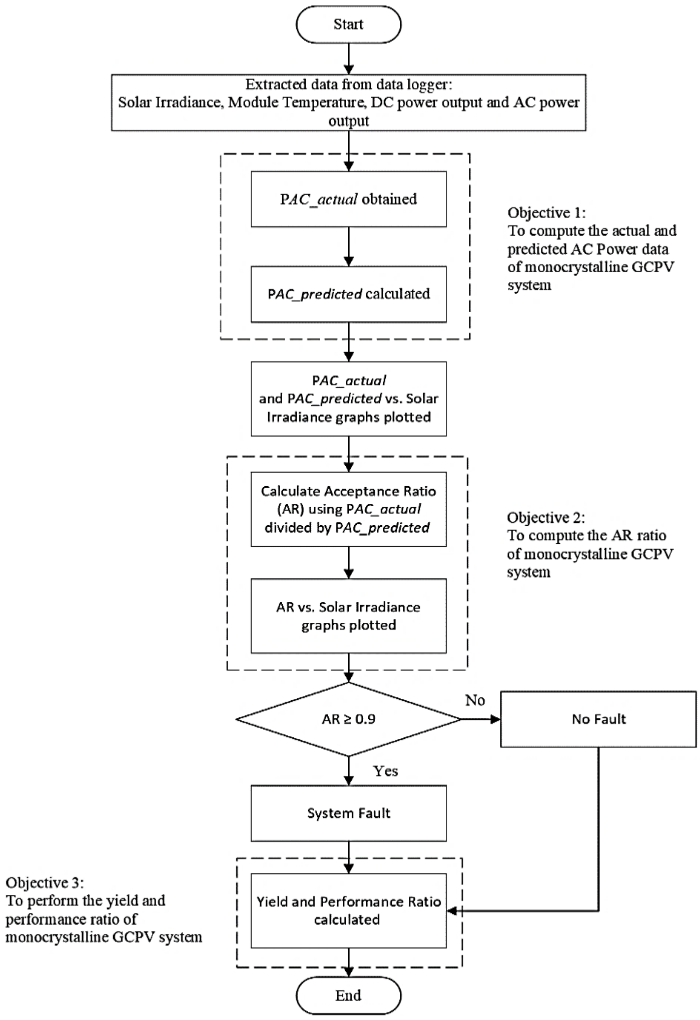

Figure 1. The flowchart of research work

2.3. Yield of monocrystalline PV systems

According to SEDA, yield refers to the energy produced by the system. Y_{actual} represents the actual yield and is determined by multiplying the actual AC power output by peak sun hours (PSH) for the tilt angle in hours (h), then dividing by 1 kWh, as outlined in (4). To delve further into the details, the actual yield Y_{actual} essentially represents the real-world energy output of the system, accounting for factors such as the tilt angle and the duration of peak sun exposure. The PSH value serves as a multiplier, considering the intensity and duration of sunlight that the solar panel system receives. On the other hand, $Y_{predicted}$, indicating the predicted yield, can be computed using the formula presented in (5).

$$\mathrm{Y_{actual}} = \frac{\mathrm{P_{AC_{actual}}} \times \mathrm{PSH}}{1\ \mathrm{kwh}} \tag{4}$$

$$\mathrm{Y_{predicted}} = \frac{\mathrm{P_{AC_{actual}}} \times (\frac{5}{60})}{1\ \mathrm{kWh}} \tag{5}$$

2.4. Performance ratio of monocrystalline PV systems

The performance ratio (PR) stands as a unitless measure that encapsulates the comprehensive quality and efficiency of a given system. In the specific climate conditions of Malaysia, the Sustainable Energy Development Authority (SEDA) has established a benchmark for an acceptable PR, setting the standard at a value exceeding 70%. This criterion reflects the desired level of effectiveness for solar energy systems operating in the Malaysian climate. To break down the computation of the performance ratio, reference is made to (6). This formula takes into account two key variables: Y_{actual} and $Y_{predicted}$, both of which are obtainable from (4) and (5). Y_{actual} represents the actual yield, quantifying the real-world energy output of the system, while $Y_{predicted}$ is the anticipated yield, calculated based on predictive parameters.

$$\mathrm{PR} = \frac{\mathrm{Y_{actual}}}{\mathrm{Y_{predicted}}} \tag{6}$$

3. RESULTS AND DISCUSSION

The research process encompassed a thorough analysis, yielding valuable results and insightful graphical representations concerning AC power and the acceptance ratio. The Figure 2 offer a comprehensive view of the relationship between actual and predicted AC power output in relation to solar irradiance. These comparisons were conducted on a monthly basis over the course of a full year, allowing for a detailed examination of performance variations across different seasons and weather conditions.

In the graphical presentation, the actual AC power data is denoted in a striking red color, while the predicted AC power data is depicted in a vivid blue. Additionally, linear lines are introduced in yellow, representing the trends in actual values, and in green, depicting the linearly predicted values. Notably, the fact that these two lines do not closely align with each other indicates potential discrepancies between the actual and predicted AC power performance. This observation aligns with the findings discussed by Muhammad *et al*. (2019), who suggested that when such misalignment occurs, and the percentage difference between the two sets of data is significant, it may signal a fault within the system [37].

To further quantify and analyze the performance variation, the slope of the graph for both actual and predicted values was extracted through their respective linear equations, as detailed in Table 2. Percentage discrepancies were then calculated to gauge the extent of difference between the actual and predicted AC power values. This process is facilitated through the use of (7), which enables researchers to assess the degree of deviation in the slope between the actual and predicted values, providing valuable insights into system health and performance.

$$\text{Percentage Difference} = \frac{|Actual - Predicted|}{|Actual + Predicted|} \times 100\% \tag{7}$$

In Figure 3, which provides a year-long overview of the acceptance ratio in relation to solar irradiance, several key observations come to light. The graph presents a comprehensive range of solar irradiance values, spanning from 0 to 1,400 $\mathrm{Wm^{-2}}$, with a prominent red straight line signifying an acceptance ratio (AR) of 0.90. This reference line serves as a benchmark for evaluating the system's performance.

Interestingly, the most notable fluctuations in the acceptance ratio occur within the solar irradiance range of 200 to 600 $\mathrm{Wm^{-2.}}$ This range seems to be particularly sensitive to variations in system performance, highlighting the importance of monitoring and addressing issues within this critical irradiance window.

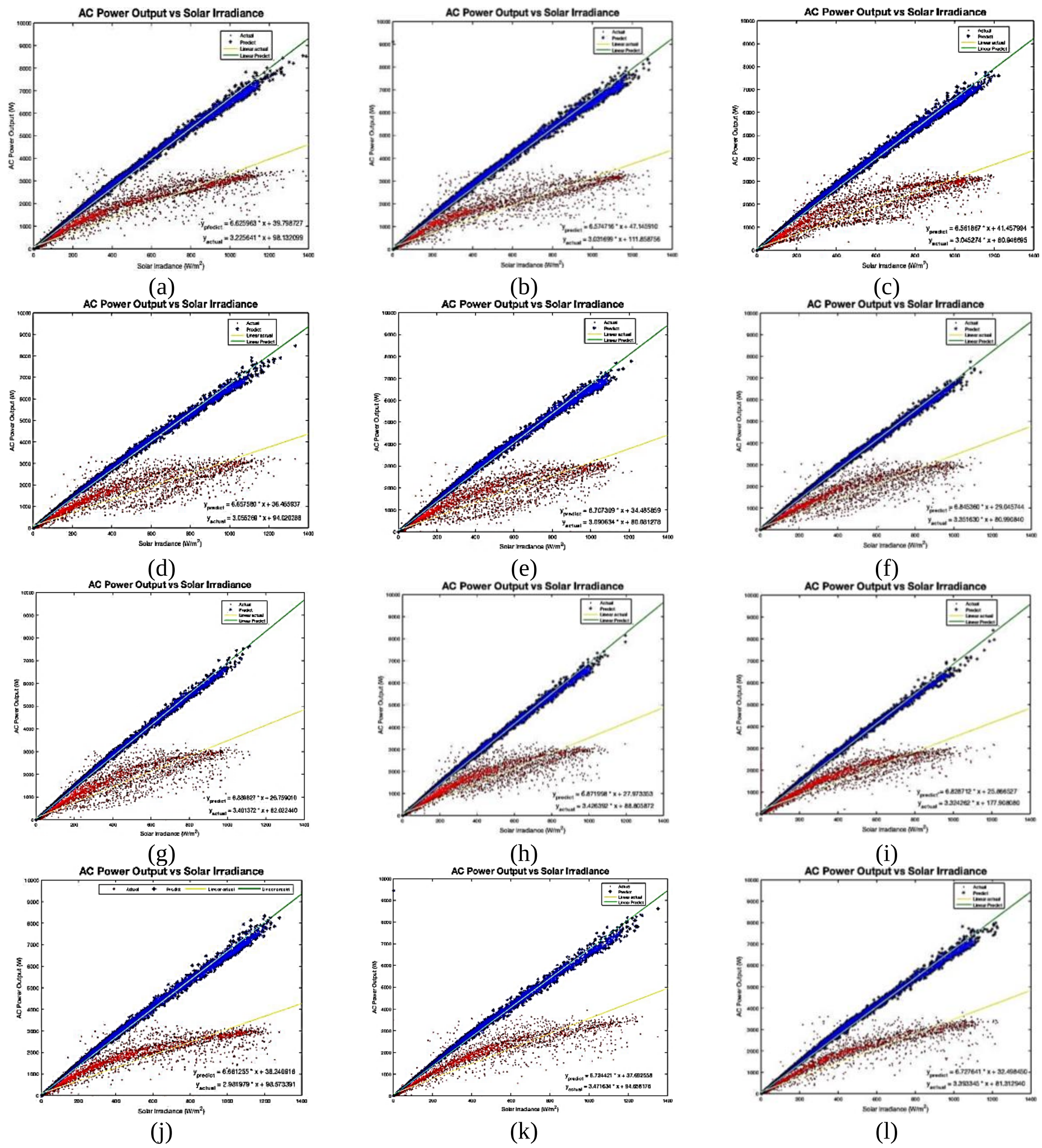

Figure 2. Graph of actual and predicted AC power output versus solar irradiance in one year: (a) November 2018, (b) December 2018, (c) January 2019, (d) February 2019, (e) March 2019, (f) April 2019, (g) May 2019, (h) June 2019, (i) July 2019, (j) August 2019, (k) September 2019, and (l) October 2019

Table 2. Gradient value of actual and predicted AC power and percentage difference of gradient

Month	Gradient value of Actual AC Power	Gradient Value of Predicted AC Power	Percentage Difference (%)
November 2018	3.47	6.72	31.90
December 2018	3.39	6.73	32.94
January 2019	3.22	6.63	34.52
February 2019	3.03	6.57	36.88
March 2019	3.05	6.56	36.60
April 2019	3.06	6.66	37.09
May 2019	3.09	6.71	36.91
June 2019	3.35	6.85	34.26
July 2019	3.40	6.89	33.90
August 2019	3.43	6.87	33.46
September 2019	3.32	6.83	34.52
October 2019	2.98	6.66	38.15

One noteworthy recommendation from the Malaysian Sustainable Energy Development Authority (SEDA) suggests that utilizing data collected when solar irradiance exceeds 350 Wm^{-2} tends to yield more accurate and dependable results. This guideline underscores the significance of focusing on higher irradiance levels for reliable system assessment. Upon closer examination of the data presented in Figure 3, it becomes evident that the acceptance ratio consistently falls below the critical threshold of 0.90. This pattern raises concerns about the system's overall performance and efficiency. These findings align with the insights shared by Muhammad *et al*. [37], who assert that if a substantial portion, more than half, of the data points fall below the acceptance ratio threshold of 0.90, it strongly suggests underlying issues within the systems. In summary, Figure 3 serves as a compelling indicator of a fault within the system, as the majority of data points consistently fall below the specified acceptance ratio threshold, warranting further investigation and corrective measures to ensure optimal system performance.

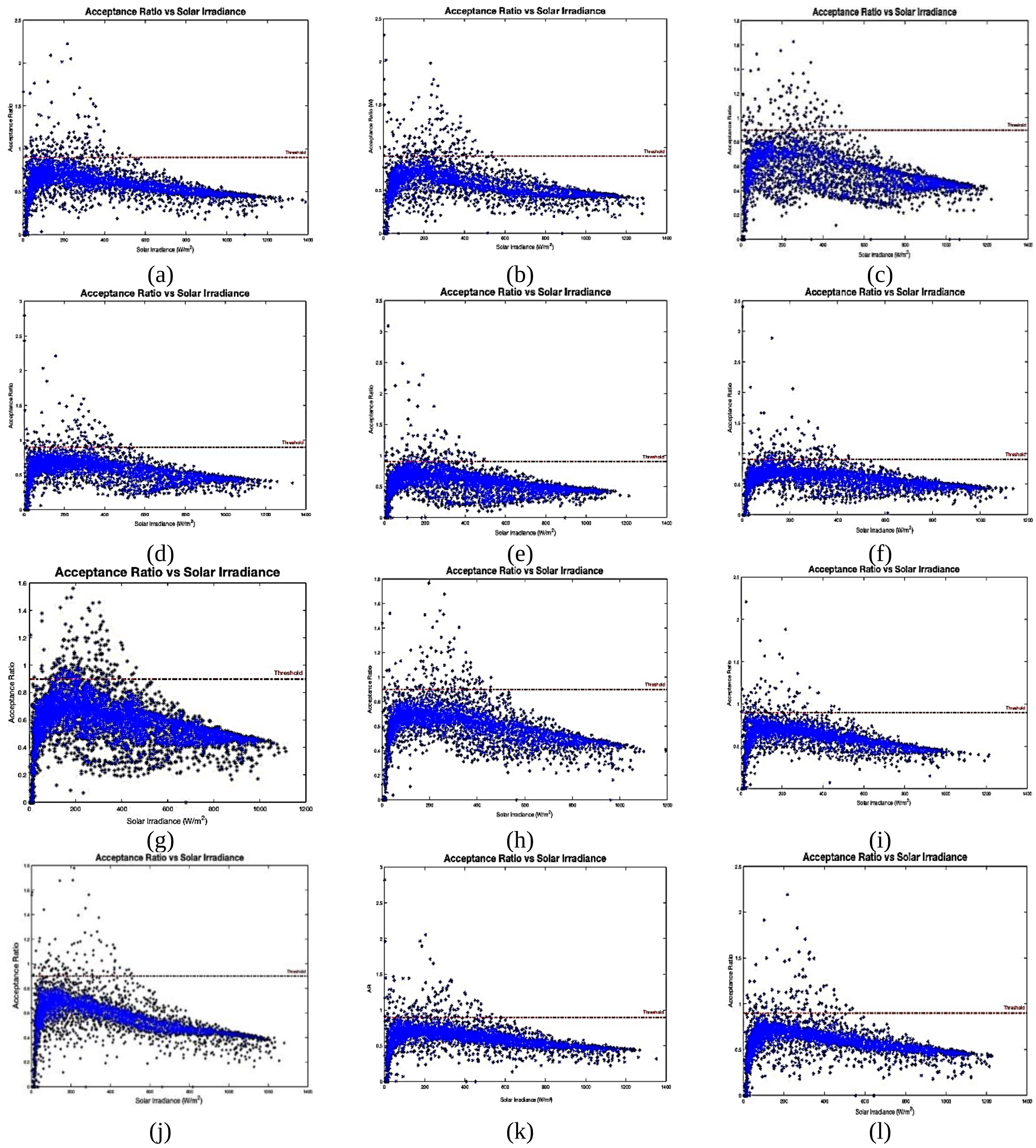

Figure 3. Acceptance ratio versus solar irradiance in a one year period: (a) November 2018, (b) December 2018, (c) January 2019, (d) February 2019, (e) March 2019, (f) April 2019, (g) May 2019, (h) June 2019, (i) July 2019, (j) August 2019, (k) September 2019, and (l) October 2019

3.1 Yield of monocrystalline PV systems

In Figure 4, we gain valuable insights into the actual and predicted yields across each month throughout an entire year. These insights are crucial for understanding the system's performance and its ability to generate energy effectively. Figure 5 complements this by illustrating the percentage variation between the actual and predicted output values, providing a quantitative measure of the system's accuracy in yield predictions.

According to the standards set forth by the Malaysian Sustainable Energy Development Authority (SEDA), “yield” denotes the total energy output generated by the system. Figure 4 offers a detailed breakdown of the highest and lowest yield values observed during this monitoring period. Notably, the peak actual yield was recorded in March 2019 at 375.42 kWh, while the highest predicted yield for the same month was notably higher at 570.04 kWh. Conversely, the lowest actual yield was documented in September 2019, amounting to 231.70 kWh, with the lowest predicted yield occurring in December 2018, totaling 429.50 kWh.

Figure 5 serves as an essential analytical tool for evaluating the precision of yield predictions. It quantifies the percentage difference between the actual and predicted yield values for each month. The largest percentage difference, reaching 37.30%, was observed in September 2019, suggesting a substantial deviation between the actual and predicted yields during that period. In contrast, the smallest percentage difference of 20.58% was noted in March, indicating a relatively closer alignment between the actual and predicted yield values for that specific month.

These findings underscore the importance of accurate yield predictions, as discrepancies between actual and predicted values can impact the system's overall performance and efficiency. The data presented in Figures 4 and 5 offer valuable insights into the system's strengths and areas that may require optimization, contributing to more informed decision-making and system improvement efforts.

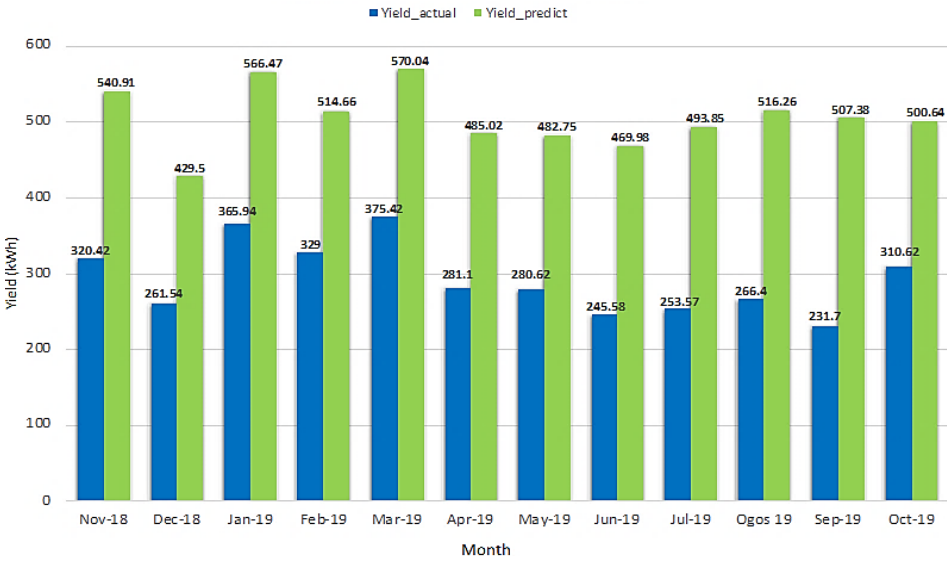

Figure 4. Actual and predicted yield versus month

3.2. Performance ratio of monocrystalline PV systems

Figure 6 serves as a succinct visual representation, offering a comprehensive overview of the performance ratio (PR) across each month over the span of one year. The PR, in the context of photovoltaic (PV) systems, holds significant importance as it serves as a key indicator of the system's overall quality and efficiency. It's essentially a metric that quantifies how effectively a PV system converts available sunlight into electrical energy, and it is often referred to as a quality factor.

The calculation of PR is based on a specific formula, as outlined in (6). To assess a system's performance, guidelines provided by the Malaysian Sustainable Energy Development Authority (SEDA) suggest that a PR value exceeding 75% is indicative of a well-performing system, especially within the climatic conditions of Malaysia. To conduct a thorough evaluation, the recommended analysis period typically spans around one year, although a minimum evaluation period of one month is considered acceptable.

Figure 6, as previously mentioned, presents the PR values plotted against each month over a one-year analysis period. Notably, the highest PR value recorded during this period was only 0.66 in March 2019, while the lowest PR value was documented at 0.46 in September 2019. These variations in PR values provide insights into the system's performance fluctuations over the course of the year.

What is particularly noteworthy is that the overall average monthly PR values depicted in Figure 6 consistently fall below the optimal threshold of 0.75, as recommended by SEDA. This recurring pattern of PR values below the acceptable threshold raises concerns about the system's efficiency and overall health. In conclusion, this section underscores the system's performance challenges, as the PR values consistently remain below the recommended threshold of 0.75. These findings collectively suggest that the system is experiencing faults or suboptimal performance, warranting further investigation and remediation efforts to ensure its optimal functionality and energy generation.

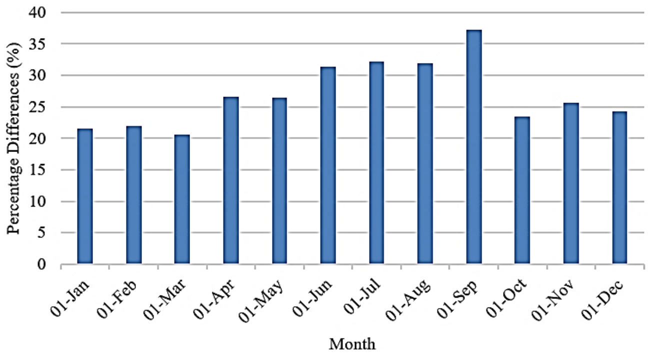

Figure 5. Percentage difference of yield for each month

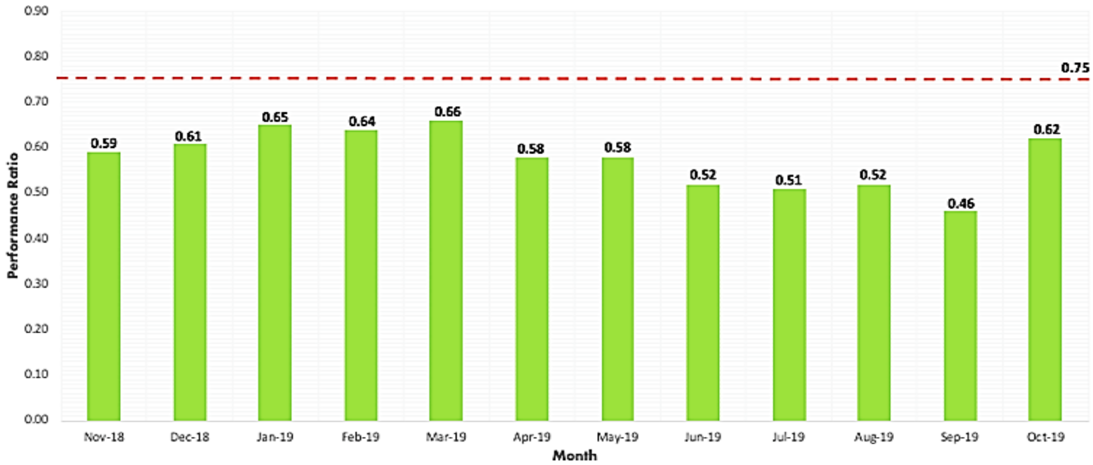

Figure 6. Performance ratio versus month

4. CONCLUSION

The graphical representations of AC power output (actual and predicted) over the course of a full year display a notable and significant difference between the actual power output and the values predicted by the system. This discrepancy suggests that the system is not performing as expected, and there may be underlying issues affecting its energy generation capabilities. Furthermore, when examining the graphs that plot actual and predicted AC power output against solar irradiance, a consistent pattern emerges. The percentage difference between the actual and predicted values ranges from 31% to 38%. Such a substantial variation indicates that the system's predictive capabilities are not aligning with the actual performance, pointing to potential faults or inefficiencies within the system. The data gathered from this study serves as a compelling verification of the system's problematic state. This is particularly evident when analyzing the acceptance ratio (AR) and performance ratio (PR) graphs. The majority of AR graphs consistently fall below the AR threshold value of 0.9, indicating that the system is not meeting the expected performance standards. Additionally, the PR values for each month remain consistently below the recommended threshold of 0.75, further emphasizing the suboptimal performance of the system. In summary, the comprehensive data and graphical representations presented in this study provide strong evidence that the system is experiencing faults or inefficiencies. The discrepancies observed in AC power output, as well as the significant percentage differences in the actual and predicted values, underscore the need for further investigation and corrective measures to ensure the system's optimal functionality and energy generation.

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