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ESTIMATION AND RELIABILITY ASSESSMENT OF MONTHLY AVERAGE DAILY SOLAR RADIATION AT UMS PEAK USING THE ANGSTROM-PRESCOTT AND OGELMAN MODELS

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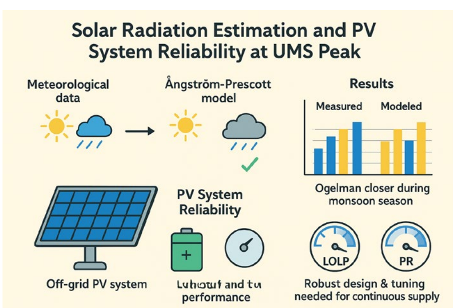
Graphical abstract



Abstract

This study evaluates the monthly average daily global solar radiation at UMS Peak using the Ångström-Prescott and Ogelman models, supported by local meteorological data and measured PV system performance. Results show that the Ogelman model provides more accurate estimations, especially during the monsoon months, with monthly deviations lower than those of the Ångström-Prescott model. The measured data, however, reveal significantly lower actual energy yield compared to theoretical estimates due to frequent system downtime and environmental constraints. Reliability assessment indicates a high Loss of Load Probability (LOLP) of 32.6%, a Solar Energy Availability Factor (SEAF) of 67.4%, and monthly Performance Ratios (PR) ranging from 0.37 to 1.11. These findings highlight the substantial gap between solar resource potential and actual off-grid system performance, emphasizing the need for improved maintenance accessibility, wildlife protection measures, and system design optimization for remote high-altitude installations.

Keywords: solar radiation estimation, Ångström-Prescott model, Ogelman model, system reliability, UMS Peak, off-grid solar PV

1.0 INTRODUCTION

Solar radiation data are fundamentally important for the design and implementation of solar energy systems, yet such data are not always readily available at every location [1]. In the absence of direct measurements, researchers have developed empirical models to estimate solar radiation from more easily measured meteorological parameters [1]. Sunshine duration is the most used surrogate parameter for this purpose because it can be measured reliably at many locations, especially in developing regions where dedicated solar radiation instruments are scarce [1]. As a result, a variety of sunshine-based correlations have been formulated worldwide to predict monthly average daily global solar radiation, with the Ångström-Prescott model being one of the most widely applied approaches [1]. This classic model relates the fraction of actual sunshine hours to possible sunshine hours with global radiation, using empirically derived coefficients that typically need local calibration for different climates.

Early studies in Malaysia demonstrated the utility of sunshine-based radiation models in tropical, humid environments. For instance, Chuah and Lee (1981) applied an Angstrom-type correlation to estimate monthly average daily global radiation in several Malaysian locations (e.g. Kuala Lumpur, Penang, Kota Bharu), establishing baseline solar resource values for the country [2]. This work was extended by Sopian and Othman (1992), who analyzed data from eight Malaysian cities including Kota Kinabalu to refine the Angstrom-Prescott model coefficients for Malaysia [18]. Their results confirmed that empirical sunshine-duration models can be effectively used to estimate solar resources in Malaysia's tropical climate, despite the high humidity and frequent cloud cover characteristic of the region. Such studies underscore the importance of adapting empirical models to local climatological conditions in order to obtain reliable solar radiation estimates [2].

Over time, various improvements to the basic Angstrom-Prescott relationship have been proposed to increase estimation accuracy. One notable variant is the model by Ögelman et al. (1984), which introduces a second order (quadratic) term into the correlation between sunshine duration and normalized solar radiation [20]. By accounting for non-linear effects (for example, diminishing returns in radiation gain on very sunny days), this quadratic Angström-Prescott model can better fit observed data in certain climates. Indeed, comparative studies have found that quadratic correlations like the Ögelman model often yield more accurate global radiation estimates than the simple linear form of the Angstrom-Prescott model [20]. These refinements highlight the potential to improve empirical estimations of solar energy availability through enhanced modeling techniques.

This study builds upon prior work accepted on 28 May 2025 in the Journal of Advanced Research in Fluid Mechanics and Thermal Sciences (Semarak Ilmu), titled "Assessing the Reliability of Solar Energy Resources at UMS Peak: An Ångström-Prescott Model Approach" [21]. The earlier study focused on estimating solar radiation using the Ångström-Prescott model and assessing its reliability at UMS Peak.

Despite the availability of such models, detailed solar resource assessment for specific sites in tropical Borneo remains limited. Kota Kinabalu (Sabah, Malaysia), the location of UMS Peak, lies near the equator and thus receives abundant solar irradiance throughout the year (on the order of 4–5 peak sun hours or ~4–5 kWh/m² per day on average) [6]. At the same time, it endures a humid tropical monsoon climate with significant cloud cover and rainfall, which can introduce substantial variability in solar radiation from day to day. These conditions make it both important and challenging to accurately estimate the solar resource. In this study, we apply the Angström-Prescott and Ögelman empirical models to calculate the monthly average daily global solar radiation at UMS Peak in Kota Kinabalu. A reliability assessment is then carried out to evaluate how well these models perform under local weather conditions and to gauge the dependability of the solar resource for potential energy applications. By examining the accuracy and consistency of model predictions against the actual solar radiation trends at UMS Peak, this work provides insight into the effectiveness of empirical solar estimation methods in a tropical, humid environment. The findings are expected to support more informed solar energy planning and improve confidence in renewable energy projects for the region.

This study differs significantly from previous work in several ways. First, unlike earlier Malaysian solar radiation studies that mainly focused on lowland stations or broad regional datasets, this research is conducted at a remote high-altitude tropical site (UMS Peak), where access limitations, cloud cover behaviour and environmental challenges are uniquely different. Second, while most past studies applied only one sunshine-based empirical model, this work compares both the Ångström–Prescott and Ögelman models using recent meteorological data, including sunshine duration and cloud cover, to evaluate their suitability under humid equatorial conditions. Third, this study extends beyond conventional radiation estimation by integrating reliability assessment of the existing off-grid PV system through indicators such as Loss of Load Probability (LOLP), Performance Ratio (PR) and Solar Energy Availability Factor (SEAF). Fourth, the analysis incorporates actual measured inverter output and field-recorded operational constraints, highlighting discrepancies between theoretical solar resource potential and real energy yield due to terrain difficulty, wildlife intrusion and access interruptions. These combined elements establish a more comprehensive and site-specific evaluation framework than previously reported, including the authors' own earlier study which used only the Ångström–Prescott model without reliability analysis.

2.0 METHODOLOGY

2.1 Location

The study site is located at UMS Peak, a strategic and elevated area within the campus of Universiti Malaysia Sabah (UMS), in Kota Kinabalu, Sabah, Malaysia. The exact coordinates of the site are 6.04270° N latitude and 116.11941° E longitude, with an altitude of approximately 197.6 meters above sea level. This highland position is characterized by a typical tropical rainforest climate, marked by high humidity, frequent cloud cover, and significant seasonal rainfall. These climatic features make the area particularly interesting for solar radiation studies, given the influence of such conditions on energy resource availability.

Access to the research site is notably challenging; it requires trekking from the nearest parking area due to the rugged terrain and natural landscape. Despite these access limitations, the site's elevation and natural surroundings offer valuable opportunities for understanding the performance and reliability of off-grid solar PV systems in remote and environmentally sensitive locations.

2.2 Data Collection

Daily global solar radiation, cloud cover, and sunshine duration data were sourced from the Malaysian Meteorological Department. This meteorological information was essential for performing preliminary calculations and served as a critical foundation for calibrating and validating the empirical models used in this study. Additionally, measured energy output data from the PV system were systematically recorded through the integrated monitoring capabilities of the Growatt SPF 3000TL inverter. This allowed for detailed performance tracking and reliable data acquisition, thereby strengthening the analysis and ensuring a comprehensive evaluation of system performance and reliability.

The monthly average global solar radiation, sunshine duration and cloud cover data used in this study are summarized in Table 1, while the monthly average measured energy output from the PV system is presented in Table 2.

Table 1 The Monthly Average Data of Global Solar Radiation, Cloud Cover and Sunshine Duration from August 2024 to February 2025

Month	Aug-24	Sep-24	Oct-24	Nov-24	Dec-24	Jan-25	Feb-25
Mean Daily Global Radiation (MJm-2)	5.33	4.71	4.93	5.34	5.31	4.56	5.26
Mean Sunshine Duration (h)	5.48	5.93	5.51	5.57	6.78	4.88	6.54
Mean Cloud Cover (oktas)	7.11	7.07	7.09	7.05	7.06	7.1	7.06
Month	5.33	4.71	4.93	5.34	5.31	4.56	5.26

Table 2 The Monthly Average Data Collected from August 2024 to February 2025

Month	Aug-24	Sep-24	Oct-24	Nov-24	Dec-24	Jan-25	Feb-25
Mean Measured data (kWh.day -1)	1.21	1.19	1.18	0.73	2.17	1.68	1.60

2.3 Calculation Methodology

Empirical radiation estimation models are theoretical tools that establish relationships between climatic variables and surface-level solar radiation. In this study, two widely recognized models are applied to assess the solar resource potential at UMS Peak. The Ångström Prescott model [18] relates global solar radiation to sunshine duration and provides a widely validated linear estimation approach for locations with available sunshine data. Meanwhile, the Ögelman model [20] builds upon this framework by incorporating cloud cover as an additional predictor, thereby improving estimation accuracy in humid tropical climates such as Kota Kinabalu. By employing these empirical models, the study aims to generate reliable solar radiation estimates tailored to the unique meteorological conditions of UMS Peak, supporting the design and performance evaluation of off-grid solar energy systems.

It is important to note that both the Ångström Prescott and Ögelman models estimate the global solar radiation on a horizontal surface (H), whereas the measured inverter data used in this study represent the electrical energy output of the installed PV system. As such, the model outputs describe the theoretical solar resource available at the site, while the measured values incorporate additional real-world influences including module and inverter efficiencies, temperature effects, shading, system design characteristics, maintenance practices, and unplanned outages. This distinction is essential for interpreting the results, as differences between estimated radiation and measured PV output reflect not only atmospheric conditions but also operational and environmental constraints at the study location.

2.3.1 Angstrom-Prescott Model

Out of the various mathematical models available (linear, quadratic, cubic, logarithmic, exponential, linear logarithmic, linear exponential, power, and reverse), the linear model was determined to be the most accurate for predicting global solar radiation. It yielded the lowest mean relative error when estimating the monthly average global solar radiation [16].
The Angstrom Prescott model is a linear model. Thus, this study is using the Angstrom Prescott model which analyzes the linear relationships between the clearness index (H/H0) and the sunshine duration ratio (S/S_0) [13]. The Angstrom's correlation derived from the data collected in eight cities (Kuching, Kota Kinabalu, Kota Baru, Serial, Bayan Lepas, Kuala Lumpur, Petaling Jaya, and Bandar Baru Bangi) is applicable to all solar energy applications in Malaysia [18]. The Angstrom-Prescott model is a highly straightforward and extensively utilized connection for predicting the Sun's radiation, taking into account the length of daylight [11]. The Angstrom-Prescott model is a widely used and successful method that has been used across numerous locations globally [20]. The Angstrom Prescott model equations are as follows [16];[13]:

$$H/H_0 = a + b(S/S_0) \quad (1)$$

The variables in the equation are defined as follows: H represents the monthly average daily global solar radiation on a horizontal surface, H_0 represents the monthly daily extraterrestrial radiation on a horizontal surface, S represents the monthly average daily sunshine duration, S_0 represents the monthly average maximum possible daily sunshine duration, and a and b are Angstrom coefficients. The extraterrestrial irradiation (H_0) varies in a predictable manner due to the consistent rotation of the Earth on its axis and its orbit around the sun [22].

The monthly mean daily extraterrestrial radiation on a flat surface can be determined using the following equation [11]; [15];

$$H_0 = \frac{24\times3600\times I_{sc}}{\pi}\left(1+0.333\cos 2\pi\frac{D}{365}\right)\times(\cos\varphi\cos\delta\sin\omega_s+\omega_s\sin\varphi\sin\delta) \quad (2)$$

The solar constant (Isc) is a value of 1353Wm-2. The latitude of the location is represented by ϕ. The solar declination is represented by δ. The mean sunrise hour angle for the current month is represented by ωs. D represents the number of days of the year starting from the first of January. The solar declination can be determined using the following equation [13];

δ=23.45 sin((360(D+284))/365) (3)

In Equation (3), the constant 360 represents the total degrees of the Earth's orbital cycle, allowing the day number (D) to be converted into an angular position of the Earth around the Sun. The constant 284 is a phase-shift coefficient used to align the sinusoidal declination curve with the actual occurrence of solstices and equinoxes, ensuring accurate seasonal representation of solar position.

The mean sunrise hour angle can be calculated by Eq. [13];

$$\omega_s = cos^{-1}[-tan(\delta)\, tan\,(\varphi)] \quad (4)$$

The maximum possible sunshine duration (S_0) can be calculated by following equation [13]; [16];

$$S_0 = \frac{2}{15}\omega_s \quad (5)$$

Table 3 Monthly Coefficients of Regression for the Angstorm Prescott Model

Month	Aug-24	Sep-24	Oct-24	Nov-24	Dec-24	Jan-25	Feb-25
a	0.172	0.080	0.089	0.110	0.126	0.128	0.142
b	-0.033	0.100	0.098	0.086	0.024	0.007	0.006

The table 3 shows the regression coefficient "a" and "b" of the Angstrom Prescott Model by using Excel with the input parameter H/H_o and S/S_o.

2.3.2 Ogelman Model

The Ogelman model, introduced by Ögelman, Ecevit, and Tasdemiroğlu (1984), is a modified version of the Angstrom-Prescott model, developed to improve the estimation of global solar radiation by incorporating cloud cover as an additional variable. While the original Angstrom-Prescott model relates solar radiation to sunshine duration, the Ogelman model enhances prediction accuracy, especially in humid and tropical regions, by acknowledging the significant role of cloudiness in attenuating solar irradiance. This makes it particularly relevant in regions like Kota Kinabalu, Sabah, where daily cloud formation is frequent and variable. The model is generally expressed as [20]:

$$\frac{H}{H_0} = a + b\left(\frac{S}{S_0}\right) + cN \quad (6)$$

Where:

H = Global solar radiation (MJ/m²/day)
H_0 = Extraterrestrial solar radiation (MJ/m²/day)
S = Actual sunshine hours (hours)
S_0 = Maximum possible sunshine hours (hours)
a,b,c = are empirical coefficients derived via regression analysis
N = cloud cover in tenths or oktas

Studies such as by [21] have emphasized the need for improved models like Ogelman's in tropical climates, where the variation in cloud cover can drastically impact solar estimates. The model has also been referenced and validated in Malaysian contexts, such as in comparative analyses of measured and predicted irradiance in cities like Kota Kinabalu and Petaling Jaya, where regression analyses confirmed its utility in accounting for rainfall and cloud-related attenuation of solar radiation.

To apply the model, solar radiation data, sunshine duration, and cloud cover (from either meteorological stations or satellite platforms like NASA POWER) must be collected. The extraterrestrial radiation H0 is computed based on latitude and day of the year. A multiple linear regression is then used to determine the coefficients a, b and c which are location specific. Once calibrated, the model can estimate H for days with known sunshine and cloud data, making it a powerful tool for system design and energy planning in off-grid solar applications.

However, the model's effectiveness depends on the availability and reliability of cloud data, which may be subject to observer bias in manual recordings or resolution limitations in satellite data. Nevertheless, when high-quality cloud cover observations are available, the Ogelman model remains a superior alternative to sunshine-only models for solar estimation in tropical and subtropical regions [20].

Table 4 Monthly Coefficients of Regression for the Ogelman Model

Month	Aug-24	Sep-24	Oct-24	Nov-24	Dec-24	Jan-25	Feb-25
a	1.040	1.087	1.160	0.876	1.448	1.760	-0.117
b	-0.018	0.064	0.059	0.074	0.048	0.009	0.006
c	-0.123	-0.140	-0.148	-0.108	-0.189	-0.230	0.037

The table 4 shows the regression coefficient "a", "b" and "c" of the Ogelman Model by using Excel with the input parameter H/Ho, S/So and cloud data obtained from Meteorology Department Malaysia.

2.3.3 Reliability Indicator

Reliability indicators are essential analytical tools that measure how consistently and effectively an off-grid solar photovoltaic (PV) system can meet the energy demands of its designated loads. In settings where grid electricity is unavailable or unreliable, these indicators become particularly crucial as they help ensure that off-grid PV systems provide a continuous and dependable supply of electricity, a fundamental requirement for supporting livelihoods, critical infrastructure, and community resilience.

Off-grid PV systems, unlike their grid-connected counterparts, rely solely on their own generation and storage capacity to meet all power needs. This makes them susceptible to fluctuations in solar irradiance due to daily weather variations, seasonal cycles, and climatic events like monsoons. As a result, reliability indicators provide a quantitative basis for evaluating whether these systems can maintain power delivery, especially during adverse conditions or when energy consumption spikes. Key reliability indicators commonly employed include:

i. Loss of Load Probability (LOLP): This indicator measures the likelihood that the system will fail to meet the load demand at any given time. It quantifies the probability that the energy demand exceeds the available supply, highlighting the risk of power shortages or blackouts in an off-grid context. A high LOLP signifies poor reliability, while a low LOLP indicates robust system performance. In off-grid system planning, acceptable LOLP levels often depend on the criticality of the load and the cost-benefit trade-offs in system sizing [22]; [11].

$$\text{LOLP} = \frac{\text{Time when load is unmet}}{\text{Total time considered}} \quad (7)$$

ii. Performance Ratio (PR): PR evaluates the overall efficiency of the PV system by comparing the actual energy output to the theoretically available solar energy under standard test conditions. It accounts for various system losses, such as temperature effects, inverter inefficiency, wiring resistance, and shading. PR is typically expressed as a percentage and provides a direct insight into how effectively the PV system converts solar energy into usable electricity. Higher PR values generally signify better system performance and reliability [18].

$$\mathrm{PR} = \frac{\text{Actual energy output}}{\text{Expected output based on irradiation}} \times 100\% \qquad (8)$$

Typical PR values range from 70% to 85% in well-maintained systems. A consistent PR significantly below this range may indicate system degradation, faulty components, or poor installation practices [21].

iii. Solar Energy Availability Factor: This metric captures the proportion of time the solar PV system is able to meet the load demand fully. It is especially relevant for off-grid installations, where even short periods of unavailability can have serious consequences for essential services like communication, lighting, or health-related applications. The availability factor is influenced by system sizing, battery storage adequacy, and weather patterns at the site [21].

$$\text{Availability Factor} = \frac{\text{Energy supplied by PV}}{\text{Total energy demand}} \times 100\% \qquad (9)$$

By integrating these reliability indicators, system designers and operators can make informed decisions about component sizing, storage capacity, and maintenance strategies. They can also evaluate whether the PV system requires auxiliary power sources such as wind, hydro, or diesel generators to ensure continuous power delivery during critical periods.

In the context of the UMS Peak study site, incorporating reliability indicators is vital to account for the unique environmental challenges of an elevated tropical setting such as frequent cloud cover, intense rainfall, and limited accessibility for maintenance. Studies like those by Mitra, Singha, and Chattopadhyay [20] further highlight that in tropical climates, these reliability indicators are indispensable for ensuring that PV systems not only perform efficiently but also adapt to highly variable weather conditions and terrain-induced shading effects.

Ultimately, employing these quantitative metrics enhances system design, ensures energy security, and supports long-term sustainability for remote communities relying on off-grid renewable energy systems.

2.4 Methodology Flowchart

The overall methodology adopted in this study is illustrated in Figure 1. The methodology comprises problem identification and objective setting, data collection, empirical solar radiation estimation using the Angstrom-Prescott and Ogelman models, solar resource adequacy and reliability assessment, followed by conclusions and recommendations.

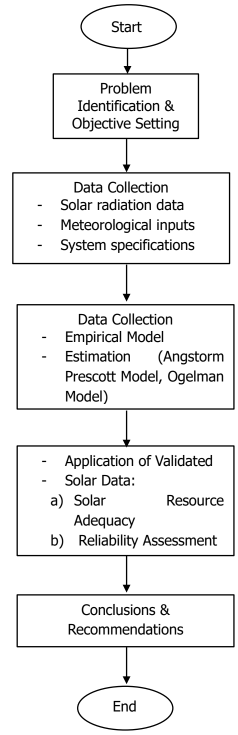


Figure 1 Flowchart of the methodology used in this study.

3.0 RESULTS AND DISCUSSION

3.1 Solar Radiation Estimates

Using equations (1) through (6), the estimated global solar radiation at UMS Peak was computed for each month, as summarized in Table 5. These calculations utilized the Angstrom-Prescott and Ogelman empirical models, incorporating site-specific meteorological data to derive monthly average daily solar radiation values.

Table 5 Solar Radiation Estimation by Angstorm Prescott Model and Ogelman Model

Month	Estimation by Angstorm Prescott Model, (kWh.m-2.day-1)	Estimation by Ogelman Model, (kWh.m-2.day-1)
Aug-24	5.458	5.389
Sep-24	4.801	4.851
Oct-24	4.992	5.038
Nov-24	5.35	5.343
Dec-24	4.787	4.773
Jan-25	4.553	4.516
Feb-25	5.304	5.308

Both models demonstrated a clear seasonal trend, with peak solar radiation values occurring in August, November, and February months typically characterized by clearer skies and reduced cloud cover in the region. Notably, the Ogelman Model, which factors in cloud cover, provided improved alignment with expected radiation values, particularly during the wetter monsoon months (December and January). This highlights the effectiveness of the Ogelman Model for accurately estimating solar radiation in humid, cloud-prone environments like UMS Peak, where atmospheric conditions can vary considerably throughout the year.

3.2 System Reliability

3.2.1 Loss of Load Probability (LOLP)

Based on the measured data presented in Table 2, the total number of system breakdown days due to energy shortfalls or failures is summarized in Table 6.

Table 6 Total Number of System Breakdown

Month	Breakdown Days
Aug-24	4
Sep-24	13
Oct-24	14
Nov-24	17
Dec-24	0
Jan-25	6
Feb-25	3

Total breakdowns: 57 days over an approximate period of 175 days. By applying equation (7),

$$\text{LOLP} = 57 / 175 = 0.326 \text{ or } 32.6\%$$

The relatively high LOLP value of 32.6% reflects frequent energy supply interruptions, attributed not only to system limitations but also to environmental and operational challenges. On 14 September 2024, system access was completely blocked due to a fallen tree, preventing timely troubleshooting. Compounding this, the steep terrain and heavy rainfall made access unsafe and delayed response.

Additionally, field inspection revealed that the breakdown on that same date was caused by a lizard that entered and short-circuited the inverter circuitry. The unexpected nature of this failure and the time required for component replacement significantly contributed to prolonged system downtime.

These cases highlight the importance of designing for wildlife protection, implementing remote monitoring, and ensuring faster maintenance accessibility, especially for critical off-grid installations in rugged environments.

3.2.2 Performance Ratio (PR)

The Performance Ratio (PR) was computed using Equation (8), and the monthly PR values together with the measured energy output, peak sun hours, PV capacity and breakdown days are summarized in Table 7.

Table 7 Monthly Performance Ratio (PR)

Month	PR	Measured Energy Output (kWh/day)	PSH (hours)	PV Capacity (kWp)	Breakdown Days	PR
Aug-24	0.62	1.21	1.48	1.32	4	0.62
Sep-24	0.69	1.19	1.31	1.32	13	0.69
Oct-24	0.65	1.18	1.37	1.32	14	0.65
Nov-24	0.37	0.73	1.48	1.32	17	0.37
Dec-24	1.11	2.17	1.48	1.32	0	1.11
Jan-25	1.00	1.68	1.27	1.32	6	1.00
Feb-25	0.83	1.60	1.46	1.32	3	0.83

Analysis

- Low PR Values (≤ 0.70):
  Months such as August (0.62), September (0.69), October (0.65), and particularly November (0.37) reflect relatively low system performance. These months also correspond with high numbers of system breakdowns, suggesting that frequent system interruptions significantly affected the energy conversion efficiency. For instance, November had the highest breakdown days (17) and the lowest PR (0.37), reinforcing the strong correlation between system reliability and performance.

- Moderate to High PR Values (> 0.80):
  In contrast, December (PR = 1.11) and January (PR = 1.00) demonstrate unusually high-performance ratios. These months coincide with low breakdown frequencies (0 and 6 days, respectively), indicating that the system was more consistently operational, thereby achieving higher efficiency.

- PR Greater than 1:
  The PR value exceeding 1.0 in December suggests either:
  - Slight overestimation of PSH values or underestimation of losses.
  - Measurement of energy output after the DC-to-AC conversion with minimal losses.
  - Temporary improvements in panel output (e.g., cool, clear conditions improving panel efficiency) or errors in system assumptions.
  - While values above 1 are theoretically unexpected, they are not uncommon in small off-grid systems where energy is recorded post-inverter and the actual generation may outperform conservative estimation inputs [21].

The PR trend demonstrates a clear correlation with system reliability: months with higher breakdowns tend to show lower PR values, indicating loss of production potential due to system unavailability. Conversely, better-maintained months with minimal interruptions yield higher PR values, validating the effectiveness of uninterrupted operation. This analysis reinforces the need for robust operation and maintenance protocols, along with reliable energy storage and control systems, to sustain optimal energy yield in off-grid solar PV installations like the one at UMS Peak.

3.2.3 Solar Energy Availability Factor (SEAF).

Given that earlier mentioned an LOLP of 32.6%, we can plug this value directly into the formula:

$$\text{SEAF} = 1 - \text{LOLP}$$

where:

- LOLP (Loss of Load Probability) represents the probability that the system cannot meet the energy demand.

$$\text{SEAF} = 1 - 0.326 = 0.674$$

Expressed as a percentage:

$$SEAF=67.4\%$$

The Solar Energy Availability Factor for your off-grid solar PV system at UMS Peak is approximately 67.4%. This means the system was able to meet load demands about two-thirds of the time, reflecting room for improvement in system reliability potentially through storage upgrades, load management strategies, or hybrid integration [22].

3.3 Comparison of Estimation Data and Measurement Data

Figure 2 presents the comparison between the solar radiation estimated using the Angstrom-Prescott and Ogelman models and the actual measured PV output at UMS Peak.

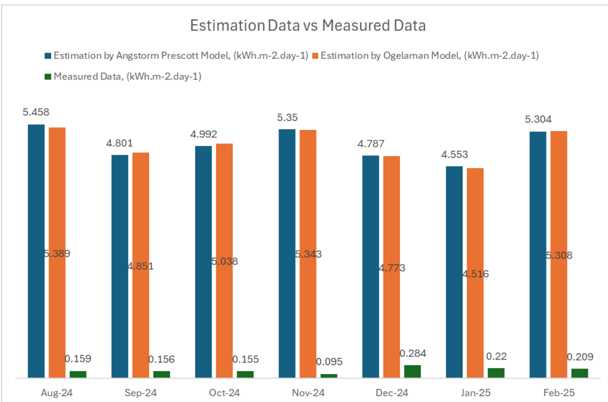


Figure 2 Comparison Estimation Data and Measured Data at UMS Peak

The comparison between the estimated solar radiation from the Ångström Prescott and Ogelman models and the actual measured PV output reveals a large and consistent discrepancy. Both empirical models predict higher monthly average daily solar radiation, with peaks in August, November, and February months typically associated with clearer skies in Kota Kinabalu. These model predictions represent the theoretical solar resource potential at the site.

In contrast, the measured PV output is significantly lower, often by nearly an order of magnitude. For example, in December 2024 the measured output was only 0.284 kWh/day, whereas both models estimated approximately 4.7–4.8 kWh/m²/day. This substantial difference does not reflect failure of the empirical models; rather, it highlights the influence of real-world operational and environmental factors on system performance. These include shading from surrounding vegetation, temperature and wiring losses, inverter inefficiencies, battery limitations, and external disturbances such as wildlife intrusion and restricted site accessibility conditions that are uniquely challenging at UMS Peak.

This gap between theoretical resource potential and actual delivered energy is a key finding of the study. It demonstrates that while empirical models effectively capture the available solar irradiance, actual energy yield from an off-grid system can be severely constrained by reliability issues. This interpretation is further supported by the high Loss of Load Probability (32.6%) and the wide range of Performance Ratio values (0.37–1.11), which collectively reflect the inconsistent operational state of the system.

Interestingly, the Ogelman model, which incorporates cloud cover, shows closer agreement with measured data during the wetter monsoon months, indicating its better suitability for cloud-prone tropical environments. However, even this improved model cannot fully account for the operational disruptions experienced at the site.

Overall, the analysis confirms that empirical radiation models remain valuable tools for estimating solar resource availability, but they must be complemented by site-specific assessments and robust system design to accurately evaluate the performance and feasibility of off-grid solar PV installations in remote, high-humidity environments such as UMS Peak.

3.4 Comparison with Previous Studies

The monthly average daily global solar radiation estimated for UMS Peak using the Ångström–Prescott and Ögelman models (approximately 4.5–5.5 kWh/m²/day) is consistent with values reported for other Malaysian locations of similar latitude. For example, several studies have shown that most regions in Malaysia receive around 4–5 kWh/m²/day of global solar radiation on a horizontal surface, confirming the strong solar resource potential in the country [23].

Kota Kinabalu–specific measurements also support the magnitude of the modelled values in this study. Long-term measurements at Universiti Malaysia Sabah reported annual average daily global radiation on the order of 15–16 MJ/m²/day (≈4.2–4.4 kWh/m²/day), with monthly values typically between about 12 and 19 MJ/m²/day, which is comparable to the range obtained from the empirical models applied here [24]. Climate-projection work for Kota Kinabalu likewise indicates present-day mean solar radiation around 180–190 W/m² (≈4.3–4.6 kWh/m²/day), further confirming that the estimated radiation levels at UMS Peak are physically reasonable and in line with previous findings for the region [25].

The performance indicators of the PV system at UMS Peak also fall within broadly acceptable ranges when compared to other PV performance studies, although they reflect the challenging site conditions. Typical performance ratios (PR) for well-designed PV systems are commonly reported in the range of about 0.7–0.85, depending on climate and system configuration. [26] In this study, most months exhibit PR values between 0.62 and 0.83, which is slightly below but still comparable to these typical ranges, while the very low PR in November (0.37) and the PR values above 1.0 in December and January are explained by extended breakdowns, conservative assumptions in peak sun hours, and the way energy output is recorded in the off-grid system.

Overall, the agreement in the order of magnitude between the modelled global solar radiation at UMS Peak and previously reported values for Kota Kinabalu and other Malaysian sites, together with PR values that are broadly in line with ranges reported in the literature, supports the validity and acceptability of the results obtained in this study. The larger gap between theoretical radiation and actual PV energy yield therefore reflects site-specific operational and environmental constraints rather than inconsistencies in the empirical models or input data.

4.0 CONCLUSION

This study has evaluated the potential of solar energy resources at UMS Peak in Kota Kinabalu, Malaysia, using the Ångström-Prescott and Ogelman empirical models to estimate monthly average daily global solar radiation. While both models demonstrated consistent seasonal patterns in estimated solar radiation with peaks observed in August, November, and February the measured data highlighted significant discrepancies, showing much lower energy yields in real-world conditions.

The Ogelman model, which incorporates cloud cover, exhibited better alignment with the measured data during the wetter monsoon months, underscoring its relevance in humid tropical climates. However, even this enhanced model could not fully account for local operational realities such as wildlife interference, challenging terrain, limited access for maintenance, and frequent equipment breakdowns. These factors were reflected in the high Loss of Load Probability (32.6%) and variable Performance Ratio (ranging from 0.37 to 1.11), as well as a Solar Energy Availability Factor of approximately 67.4%. Together, these reliability indicators confirm that while the solar resource potential at UMS Peak is substantial, system performance is heavily influenced by environmental and operational constraints.

Overall, the study demonstrates that while empirical models like Ångström-Prescott and Ogelman are essential for initial feasibility studies and system sizing, they must be complemented by comprehensive site-specific assessments and proactive operational strategies. Improving system reliability at UMS Peak will require measures such as enhancing inverter housing, strengthening preventive maintenance protocols, integrating remote monitoring and alert systems, and possibly hybridizing the system with other renewable or backup energy sources.

These findings are critical for informing future solar PV system designs in remote, tropical environments. They emphasize the need for integrated planning that bridges the gap between theoretical solar resource potential and actual system performance, ultimately supporting more robust, reliable, and sustainable energy access for communities in challenging locations like UMS Peak.

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Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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