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Deriving and Validating an Irradiance-Dependent Detection-Limit Floor for a Low-Cost Fixed-Load Photovoltaic Fault Monitor

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Abstract: Although low-cost photovoltaic (PV) monitoring systems are able to indicate underperformance, they can fall short of detecting a fault due to sensor noise and model uncertainty. This paper presents an irradiance-dependent closed-form-like detection limit, and $\Delta P_{\min}(G)$, for reduced fixed load PV fault monitor using power residual thresholding. We derive the limit by cascading the measurement error of module voltage, load current, irradiance and cell temperature through a PV module model using a single PV cell. We validate the noise-propagation model using sixteen days of outdoor measurements on a 10 W crystalline-silicon PV module equipped with an ESP32-based logger. The power-residual scatter in the prediction is in good agreement with the scatter observed under steady irradiance within an order of unity, whereas the residuals are much larger during cloud transition periods. The detection limit rises from an estimated 19 mW under low irradiance to an estimated 100 mW under high irradiance, or from about 14% of operating power to about 1.9% of operating power. The voltage-measurement channel is the main contributor to residual variance, meaning the biggest hardware upgrade to make is an improvement to the voltage signal acquisition. The results give a practical guideline for calculating the minimum power loss that can be detected by the use of a low-cost fixed-load PV monitor. Based on the healthy-module data, this study verifies the sensor-noise floor, and we propose controlled fault-injection experiments as the next step in sensor-noise floor validation.

Keywords: Photovoltaic fault detection; detection limit; sensor noise; uncertainty propagation; single-diode model; low-cost monitoring; ESP32.

I. SCOPE AND LIMITATIONS

This study confirms the sensor-noise model for the detection limit based only on healthy-module baseline data and we deliberately introduced no controlled fault during the measurement campaign. We conducted the experimental validation using one 10 W PV module, one fixed resistive load and one outdoor site for 16 days. The auxiliary PV-cell irradiance channel proved to be unreliable and we thus did not use it quantitatively, instead we used the operating current as the main operating variable regarding the PV-cell irradiance. Furthermore, we found a possible systematic discrepancy, between the measured and the nominal effective load ratio, due to the use of a resistive load, instead of a detector. The degeneracy for fixed loads does not change and the form of the formula for the derived detection limit does not change, but absolute voltage calibration should be independently confirmed in subsequent deployments. The reported detection limit should, therefore, be viewed as the sensor-noise minimum limit, and not as a comprehensive fault-classification evaluation.

II. INTRODUCTION

Photovoltaic (PV) generation is an integral part of the electricity system worldwide. By 2025 the share of solar power reached 8.7 percent, which is the highest value ever recorded¹, and cumulative capacity approached 3 TW, increasing by approximately 700 GW in a year². The majority of discussed technologies are being distributed across residential, commercial and small-scale systems, making centralized monitoring services too expensive². During operation, energy yield decreases due to corrosion, bad solder connections, insulation cuts, or cell-edge leakage causing overheating of the PV modules and increase in fire risks^{3,4,5}.

Understanding different fault classes is important because they require different actions, which involve cleaning out, changing, or reconnecting whichever part is defective. The methods for determining fault classes all have one requirement in common, which is the use of expensive equipment to measure data. The most common method, which is known as I-V curve tracing, allows for the measurement of PV module's voltages and currents and the plotting of the complete I-V curve in order to understand the fault class

according to the I-V curve's deviation from the ideal I-V curve. Commercial devices for I-V curve tracing, such as Fluke Solmetric PVA-1500, cost around \$13,000 to \$22,000 and are not suitable for continuous PV module operation, as the time that is consumed in tracing the I-V curve will lead to downtime of the PV modules. Sometimes, infrared thermography is used, but it requires expensive equipment, as well as trained specialists for interpreting the results. Hence, these two types of devices belong to the category of expensive devices, which cannot be utilized for a small amount of solar energy generation due to the cost involved. On the other hand, cheap devices using microcontroller technology can detect anomalies reliably such as a shortfall in power against expectation but characteristically stop there, reporting that something is wrong without identifying what it is^{6,7,8}.

In addition, the detection limits they discuss are empirical: the minimum deviation that was identified in a specific operation, not the theoretical calculation of the least breakdown a particular gadget is able to detect. How much error information can be theoretically retrieved from the minimal data collection, as well as the limiting factors for detection, have been treated as engineering experiments and tested rather than proved. This paper fills that gap with the most limited reasonable case scenario: a sole PV module with a constant resistive load, inexpensive voltage, current, irradiance, and temperature sensors, and no possibility of changing the load or modifying the operational point — the configuration most likely to be implemented by low-cost system builders. There are three contributions that follow. First, we derive the detection threshold $\delta_{\min}(G)$, the minimum amount of faulty power deviation that can be registered at a particular level of irradiance, in closed form with the help of the sensor-noise budget calculation and the operation of the single-diode model explained (Sec. 2.4). Second, we show mathematically that the usual apparent fault indicator at constant load, the ratio of voltage to current is degenerate, however, the state-dependent residual signatures appear to be non-degenerate residual signatures.

In the third instance, we verify noise propagation against its deployment through comparisons of predictions with actual healthy PV module scatter. We then determine the limit based on the noise information of specific channels, and analyze the violation of Gaussian assumption in interpreting residual operations (refer to section 3). The final outcome is the development of a low-cost PV fault detection technology that provides a closed equation for converting noise budget into minimal detectable fault level, while reflecting on gains and losses related to sensor efficiency.

III. METHODS

This study develops a low-cost method for electrical testing, under which the only necessary measurements for fault determination in a PV module are electrical measurements, and to evaluate the minimum fault that this method could detect in theory. First, we construct a physics-based model of a faultless PV module to predict its voltage, current, and power for given operating conditions (Sec. 2.1). The performance point determined by fixed resistive load is then examined (Sec. 2.2), the influence of the fault under consideration on the operation of the PV module analyzed (Sec. 2.3), and the sensor noise budget applied accordingly to obtain the expression for the minimum fault size as a result of the change in the irradiance value (Sec. 2.4) — the main theoretical contribution of the study. Sections 2.5–2.8 present further details of the instrument under discussion, including its calibration and noise evaluation, the initial operation, and the experiment design steps.

A. Single-diode model of a healthy PV module

The single-diode equivalent circuit model effectively describes the electrical characteristics of a crystalline-silicon solar cell, which is represented as a current source powered by the light and is placed in parallel with the diode and a series resistance R_s and a shunt resistance R_{sh} signifying the resistance losses in the contacts and the leakages at the junction; the equivalent circuit is presented in Figure 1. The application of Kirchhoff's law to the model gives rise to the following implicit current-voltage relationship,

$$I = I_{ph} - I_0 \left[\exp \left(\frac{q(V + IR_s)}{n k_B T} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}}, \quad (1)$$

where I is the current at terminals, V is the voltage at terminals, I_{ph} is the current produced due to photo effect, I_0 is the current due to reverse saturation of the diode, q is the charge, n is the ideality factor of the diode, k_B is the Boltzmann's constant and T is the temperature at which the cell operates. The three parameters regarding loss, which are I_0 , R_s , and R_{sh} , are the factors that will be discussed in different categories of faults in Section 2.3.

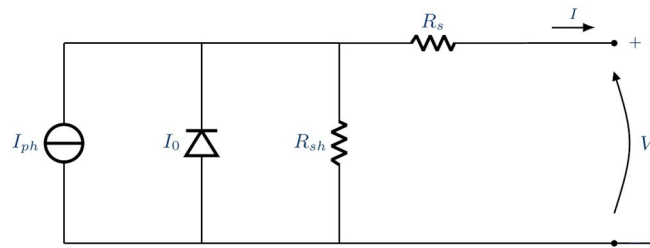


Figure 1: Single-diode equivalent circuit of an illuminated crystalline-silicon photovoltaic cell, corresponding to Eq. (1). The light-generated current source I_{ph} is placed in parallel with the junction diode and the shunt resistance R_{sh} , which represents leakage across the junction; the series resistance R_s represents the resistive losses in the contacts and interconnects. The terminal quantities V and I are those delivered to the external load. Degradation of R_s , R_{sh} and I_{ph} corresponds to the three fault categories analysed in Sec. 2.3.

As seen in Figure 1, the illuminated crystalline-silicon photovoltaic cell is represented with a single diode circuit that connects I_{ph} , which is the source of light-generated current, with the junction diode and shunt resistance R_{sh} , and R_s , which accounts for resistance losses at the contacts. The quantities V and I are the outputs to an external load. The deterioration in R_s , R_{sh} , and I_{ph} corresponds to the different types of fault from Section 2.3. Eq. (1) contains I in it and cannot be inverted directly, but the two operating points at each end of the curve can be derived. Setting $I = 0$ gives the open-circuit voltage V_{oc} ; in contrast, putting $V = 0$ returns I_{sc} which is assumed to equal I_{ph} ; the assumption is valid in working condition, considering negligible diode and shunt elements. In this study, the PV module under consideration was specified by the producer and evaluated under Standard Test Conditions (STC) associated with irradiance equal to 1000 W/m^2 (AM 1.5) and temperature equal to 25°C ; these are

$$P_{\max} = 10 \text{ W}, \quad V_{oc} = 21.07 \text{ V}, \quad I_{sc} = 0.63 \text{ A}, \quad V_{mp} = 17.03 \text{ V}, \quad I_{mp} = 0.59 \text{ A}, \quad (2)$$

for a Waaree WS-10/12V crystalline-silicon module. This model is based mainly on two environmental quantities, namely incident irradiance G and cell temperature T . The relation between photocurrent and the irradiance can be approximated as linear, while the dependence of photocurrent on the temperature of cell is quite weak,

$$I_{ph}(G, T) = \frac{G}{G_{ref}} [I_{sc} + \alpha_I (T - T_{ref})], \quad (3)$$

where STC reference conditions are $G_{ref} = 1000 \text{ W/m}^2$ and $T_{ref} = 25^\circ\text{C}$, while α_I is the temperature coefficient of short-circuit current; open-circuit voltage, unlike photocurrent, decreases with the increase of temperature,

$$V_{oc}(T) = V_{oc}^{ref} + \beta_V (T - T_{ref}), \quad (4)$$

with the temperature coefficient of open-circuit voltage $\beta_V < 0$. According to the manufacturer's information regarding the relative temperature coefficients of this module⁹, $\alpha_I = +0.0681 \text{ }^\circ\text{C}^{-1}$ and $\beta_V = -0.2941 \text{ }^\circ\text{C}^{-1}$, with respect to the equations introduced, it is possible to derive such absolute values: $\alpha_I \approx +4.29 \times 10^{-4} \text{ A/}^\circ\text{C}$ and $\beta_V \approx -6.20 \times 10^{-2} \text{ V/}^\circ\text{C}$. Both equations reflect the interaction of the main environmental dependencies any effective PV module should take into account: it is important to understand that current is dependent predominantly on irradiance and is more sensitive to temperature than voltage (while voltage is controlled mainly by temperature and less sensitive when compared to current).

B. The voltage–current ratio at a fixed resistive load

The power of a functioning PV module at a certain operation point can be described by the $P = VI$ equation, which represents the basic idea of this section. However, the rest of this section will focus on differences between computed and observed power values in terms of the influence of irradiance and temperature. It is reasonable to start from the assumption that the ratio of voltage-to-current

$$\rho \equiv \frac{V}{I} \quad (5)$$

will give insights into its faults, owing to the fact that each failure category influences V and I in a different way - the increase of series resistance will lead to the decrease of V , while I remains unchanged; on the contrary, in the case of shunting, I will decrease, and V will be positively influenced. Yet this idea turned out to be incorrect, which is why we based the rest of this work on residuals.

Consider a PV module with a pure resistance external load of resistance R_L . The operation point (V_{op}, I_{op}) is the single point of intersection between the PV module's current-voltage characteristic and the load line $V = IR_L$. By applying Ohm's law to the load resistor,

$$V_{op} = I_{op} R_L, \quad (6)$$

which holds identically at every operating point. Substituting Eq. (6) into the definition of ρ gives

$$\rho = \frac{V_{op}}{I_{op}} = R_L, \quad (7)$$

independent of V_{op} , I_{op} , the irradiance, the temperature, and the internal state of the PV module. The voltage-current ratio is dependent on the load resistance, but the relationship holds no information about the PV module itself. Instead of moving the operating point, a fault would just change it along the load line direction. This means that the ratio is uninformative as a fault indicator at any fixed load. The case is the same with measurement noise since the average of the sampled ratio $\tilde{V}/\tilde{I}$ will also be pinned to ρ , with its further distribution depending only on measurement error, having no module-related component.

As for the equipment, the load network is made of a combination of 27 Ω and 39 Ω resistors connected in series (Sec. 2.5), having nominal resistance of 66 Ω , while $\rho = V_{op}/I_{op}$ is actually observed at the logged values of about 49 Ω (for example, $V_{op} = 16.1$ V, $I_{op} = 0.325$ A at strong sunlight) — being constant throughout the entire baseline record, which is a requirement of Eq. (7). However, the nominal 66 Ω value is impossible in line with Eq. (2). The value found for $\rho \approx 49$ Ω conforms to expectations in the sense that it corresponds to the position on the graph at which power equals the product of the load resistance and the voltage at the terminals of the PV module; specifically, it indicates that the value of ρ places the power at 5.2 W for a 10 W PV module thus confirming that the so-called location is in accordance with the theory. It is supposed that the voltage sensor is the most likely source of discrepancy; in this case, it is possible that the voltage divider was formed from the load resistors instead of contacting the terminals of the PV module, and the value recorded is a voltage divider that gave the voltage measurement divided by the known coefficient described in Section 2.6. A systematic error in the current channel might also account for the discrepancy; however, no accurate conclusion can be drawn from the available data, and therefore recalibration against bench instruments should be performed. Firstly, the degeneracy argument requires only that ρ be fixed, not that it take any particular value. Secondly, the sensitivity of Sec. 2.4 is independent from the value of the load resistance; hence, the numerical results of Sec. 3 remain unchanged. It is worth pointing out that the problem concerns the interpretation of the measured voltage as being the voltage at the terminals of the PV module, which remains as a warning throughout the analysis. The information about the problems created by the ratio remains preserved in the location of the operating point on the load line, i.e. in specific values of V_{op} and I_{op} measured under known temperature and irradiance. Different faults lead to the change of the operating point in (V, I) coordinates thus creating different trajectories for their working points in (V, I) space.

C. Fault signatures from the single-diode model

Equation (1) of the single diode model specifies three internal parameters, and each one of them leads to a specific category of an in-field fault in the crystalline-silicon modules^{3,4}: rise of the series resistance R_s caused by corrosion of the interconnects and solder joint delamination; drop of the shunt resistance R_{sh} attributed to cell edge current leakages and insulation damages; and shading that can be represented as a reduction of the photo generated current I_{ph} in the shaded cells and at the same time, closure of the bypass diode in the defective sub-string. The key point discussed around this article is how these three perturbations affect the operations of a fixed-load monitor differently based on the changes in irradiance and temperature throughout a day. The key element of difference among the operations of three cases is the magnitude of deviation and not the actual induced aberrations at any point in time according to Eq. (7).

Series-resistance degradation. An additional resistance ΔR_s in series with the circuit dissipates power according to the square of the current in the circuit. The operating-point voltage and operating current are practically equal to the voltage and current in the healthy PV module and therefore the power deviation is equal to

$$\Delta P_{R_s} \approx -I_{op}^2 \Delta R_s. \quad (8)$$

Since the operating current remains in approximate correlation with the irradiance because of photocurrent from Eq. (3), the deficit grows as $\sim G^{210}$, minimal at low light and maximal at midday.

The shunt-resistance degradation. The reduction of the shunt resistance from R_{sh} to $R_{sh} - \Delta R_{sh}$ allows the leakage current to flow through the cell, according to the terminal voltage and therefore to drain the power,

$$\Delta P_{R_{sh}} \approx -\frac{V_{op}^2}{R_{sh}^2} \Delta R_{sh}. \quad (9)$$

Losses associated with shunting are highest in low light conditions, where a universal loss makes up a large percentage of lower output. McMahon and co-workers experimentally showed this by connecting known shunt resistors to particular cells of a series-connected module and demonstrating a rapid drop in efficiency of maximum power as intensity decreases¹¹. The first group of losses thus shows the contrary behaviour to that of the second group.

The case of partial shading and its consequences. When a cell is partially shaded, its current decreases, thus limiting the output of the entire series-connected chain because of the connection of the cells in series. Commercial design makes use of a separate device, a bypass diode, that is placed in the opposition with each chain so that the cell undergoing shading is not reversed and thus burned out. When the load current is greater than the current induced in a shaded cell, the excess of the current will flow through the bypass diode and will prevent the output chain from being shorted¹². Shading from a stationary object—a chimney, or vent, whatever—has a second, equally distinctive trait: temporal structure. As the sun moves the shadow across the PV module, the residual re-emerges at a given time and has no presence at some other time; the resistance degradation process, on the other hand, is independent of time.

As for the predictions about the shapes. The equations (8) and (9) along with the shading processes mentioned above predict that three types of defects lead to the corresponding residuals with some certain traits: increasing gap (about G^2) for series-resistance degradation, major gap at low irradiance for shunt-resistance degradation and the peculiar gap that appears and disappears during the day for the fixed-geometry shading. (Soiling which is discussed in the protocol from Sec. 2.8 is considered as a combination of the different destructive mechanisms and not as a separate one: a uniform particulate mass leads to the decrease of I_{ph} the same way as uniform shading and results in the gap proportional to the irradiance level.) Thus, the information lost owing to voltage-current ratio at any point in time is determined from the residual. The question whether the signals can be distinguished from noise of the monitor is the subject of Sec. 2.4.

D. The detection limit $\delta_{min}(G)$

The fault signature provided in Section 2.3 is diagnostic up to the degree in which it exceeds the noise caused by the monitoring device: it is impossible to detect a power deviation that is lower than the fluctuation in the PV module in good working conditions. In order to ascertain the minimum level of the fault detectable by the system as a function of the irradiance, we calculate the noise budget of the four sensors with the help of the single-diode model. The monitor measures four variables which are the voltage in the module terminals, load current, the irradiance variable, and the temperature of the solar cell. These four quantities have their own zero-mean noise components with standard deviations σ_V , σ_I , σ_G , and σ_T respectively. We did not take the given values from the manufacturers' data sheets but found them using the baseline record. The main physical sources affecting σ_V are the ADC quantization noise, the ADC non-linearity, and the finite tolerance of the load-correction coefficient. The factors affecting σ_I include the reported precision of the INA219 current sensor ($\pm 0.5\%$) and thermophysical fluctuation; on the other hand, σ_G arises from the ADC noise in irradiance channel. The major contributor of σ_T is the DS18B20 stated accuracy ($\pm 0.5^\circ\text{C}$) alongside conversion noise.

The residual is defined as the difference from the ideal case,

$$R(t) \equiv P_{meas}(t) - P_{pred}(G(t), T(t)), \quad (10)$$

where the measured power $P_{meas}(t) = V(t)I(t)$ is determined by voltage and current measurements and predicted power $P_{pred}(G, T)$ is derived using the single diode model from Eq. (1) employing fixed process operating under a constant load and model parameters acquired from fitting baselined training data to the model. In the case of functioning PV module, $R(t)$ mean value is zero by construction and its variance is assessed by sensor noise; meanwhile if there is defect in the PV module, $R(t)$ mean value becomes non-zero as dictated in Sec. 2.3. Detection in this case is understanding the deviation of new mean value from the departure of residual for the PV module in working order.

Propagation of noise through the residual. Using the law of propagation of uncertainty¹³, we start from the general formulation in Eq. (10),

$$\sigma_R^2(G) = \left(\frac{\partial P}{\partial V}\right)^2 \sigma_V^2 + \left(\frac{\partial P}{\partial I}\right)^2 \sigma_I^2 + \left(\frac{\partial P}{\partial G}\right)^2 \sigma_G^2 + \left(\frac{\partial P}{\partial T}\right)^2 \sigma_T^2. \quad (11)$$

The four noise components in Eq. (11) are assumed to act independently in the sense that the channels for voltage and current and temperature use their own converters or channels, and the only possible case of violation of the independence assumption is the voltage and irradiance channels. However, we have checked the influence of the possible dependence by means of measuring the Pearson correlation among noise signals (Sec. 2.6), and the correlation turned out to be weak enough to make the diagonal form results applicable (Sec. 3.2). The partial derivatives of Eq. (11) are taken at the regular operating point (V_{op}, I_{op}) defined by the load and the corresponding (G, T) . After substituting $P = VI$, the two electrical partials being obvious,

$$\frac{\partial P}{\partial V} = I_{op}, \quad \frac{\partial P}{\partial I} = V_{op}, \quad (12)$$

the two factors of the environment are obtained from the chain rule applied to the equivalent diode characteristics of Eqs. (3) and (4),

$$\frac{\partial P}{\partial T} = I_{op} \beta_V + V_{op} \alpha_I, \quad \frac{\partial P}{\partial G} = I_{op} \frac{\partial V_{op}}{\partial G} + V_{op} \frac{\partial I_{op}}{\partial G}. \quad (13)$$

There is an important caveat about Eq. (13), and it is important to note that this equation describes an approximation and not the identity. (The same goes for the irradiance partials, which in this case remain irrelevant since the irradiance channel delivered $\sigma_G \approx 0$ (Sec. 3.2).) There is a rationale behind the approximation used here: the temperature term contributes less than 1% to the overall variance of residuals at every point of the operating record (Sec. 3.5) meaning that errors of tens of percent in temperature partials change the value of δ_{min} only marginally since the variations introduced by the approximated temperature do not exceed a small fraction of a percent against the factor of two variations of the validation itself (Sec. 3.3). Only an apparatus with noise budget legitimately limited by temperature would require the rigorous treatment.

The detection threshold. A fault is considered detected once the magnitude of the measured residual exceeds some multiple of the noise-induced standard deviation,

$$|R(t)| > k \sigma_R(G(t)), \quad (14)$$

in which case the detection coefficient k is determined based on allowable false alarm rate of the healthy PV module. Given the convention with respect to the Gaussian assumption, $k = 3$ leads to nominal false alarm probability of approximately 0.27% for every sample; the empirical false alarm rate based on the held-out part of the baseline record is provided in the next chapter and may differ from the nominal value to the extent that the noise distribution departs from Gaussian.

The limit of detection. Through the use of equations (11) and (14), it can be deduced that the fault should cause a minimal degree of power deviation that would allow its detection at the irradiance level G ,

$$\delta_{min}(G) = k \sigma_R(G) = k \sqrt{I_{op}^2 \sigma_V^2 + V_{op}^2 \sigma_I^2 + \left(\frac{\partial P}{\partial G}\right)^2 \sigma_G^2 + \left(\frac{\partial P}{\partial T}\right)^2 \sigma_T^2}. \quad (15)$$

The equation (15) represents the most important theoretical result of this study, which is a general equation of the minimum power deviation detectable by an established load measurement method subject to a noise level. The calculation in (15) implies the official measurement values instead of estimated ones, which are the voltage and current at the healthy operating point of the sensor and the sensor noise variance. The equation (15) has an interesting physical significance, which presumes that one electrical component is weighted by operating current and another one by the voltage; i.e., $I_{op}^2 \sigma_V^2$ and $V_{op}^2 \sigma_I^2$. The ratio of the two prefactors for a routine case of high irradiance conditions $(V_{op}, I_{op}) \approx (16.1 \text{ V}, 0.325 \text{ A})$ is $V_{op}/I_{op} \approx 50$, but in order for this limit to be current-limited, the expressions should fulfill the condition when σ_V/σ_I is less than V_{op}/I_{op} . From the datasheet on noise figures, it can be assumed the system would be limited due to current; however, as presented in section 3.5, that is not the case because the present figures show that there is a restriction due to voltage channel noise.

2.5 Hardware



1629

There are two sensors DS18B20 (one of them is mounted on the back of the PV module and another – is freely exposed to the surrounding air) connected to a one-wire bus measuring unit temperatures (temperature of the cell and that of the environment). A small auxiliary solar cell (in an independent circuit with a fixed resistive load of $510\ \Omega$) works as a surrogate for the incoming irradiance, and its voltage is recorded at pin D35. The aforementioned surrogate is an absolute value expressed in volts, and it is linearly linked with incoming irradiance. The data is recorded on a microSD card with a fixed duration of 60 s, each data entry containing the sample number, timespan, and four measured values retrieved, together with the calculated power value. The total costs for the hardware amounted to about \$30. Figure 2 illustrates the configuration of the fixed-load photovoltaic fault monitor. The module current is transmitted from the PV module's positive terminal, through the INA219 high side current sensor, and then through the power resistances in series ($27\ \Omega$ then $39\ \Omega$), before arriving at the module negative terminal. Resistors $100\ \text{k}\Omega / 10\ \text{k}\Omega$ formed a voltage divider. Through it, the voltage at node A comprising a circuit of both resistors connected in series is sensed and forwarded to GPIO34. This voltage at GPIO34 node A is the probable source of inconsistency between the expected load of $66\ \Omega$ and the measured load of $49\ \Omega$ as discussed in Section 2.2. The current measurements are communicated via I²C bus, while measurements from the DS18B20 temperature sensors follow one wire protocol on GPIO15 and the auxiliary irradiance-proxy sensor reading takes place via GPIO35. The readings are obtained at intervals of 60 s to the microSD card.

E. Calibration and sensor-noise characterisation

The accuracy of the four channels and a faithful characterisation of their noise are the bases for fidelity in the detection limit derived in Sec. 2.4. We calibrated each channel against one independent reference, while we computed the residual noise straight from the baseline record rather than relying on values from the datasheet. We tested the voltage channel using a laboratory multimeter placed right on the module terminals in the load conditions across the entire voltage range of the PV module. Since the divider taps downstream of the series load, it was possible to establish the firmware scale constant field empirically so that the recorded voltage precisely matched the reading of the multimeter at the several irradiance levels, with a small two-percent range. We validated the current channel using the series circuit element with a known resistance and the two thermometers in comparison with an independent laboratory thermometer under both room and warm temperatures. The irradiance proxy is a special case; it is a relative measure because its noise enters the limit of the detection, but its absolute values are used only in interpretation and not in calculations. We used a clear-sky day within the baseline period to build the clear-sky model of irradiance with a peak of local solar noon denoting the clear-sky maximum and providing the conversion from proxy volts to W/m^2 for plotting; the associated calibration uncertainty is propagated wherever the absolute irradiance scale is used.



Figure 3: The deployed monitor. (a) The 10 W PV module is shown in its outdoor setting, with the irradiance proxy cell next to it and the enclosure behind it. (b) The enclosure is shown in opened condition, showing the ESP32, the INA219, the microSD module and the load resistors. (c) There is detail of the load network and the sensing connections.

We determined the σ_V , σ_I , σ_G , and σ_T which enter Eq. (15) using a reliable successive difference estimator¹⁴ applied to each contiguous daytime period of the training period. We used the lag-one difference of each channel in each segment to remove the slow environmental variation occurring over 60 seconds and to find out the measurement noise as the median absolute deviation of the differences which were then converted to standard deviation and divided by $\sqrt{2}$ to account for the variance-doubling effect of differencing. The application of this technique requires mentioning two details. Firstly, the significance of division assumes that the noise is white at the sampling time, while the correlation at lag-one makes this assumption valid only as a first approximation.

In the second place, the estimator can be applied to all segments of the training, quiet and transient as well: the pooled estimate gets a contribution from cloud-transition periods and is therefore conservative for lots of steady bright sun; the difference steady - transition regimes is taken into account only at the validation phase, where the bins are developed. To estimate confidence intervals we used block bootstrap with a block length of one day (2000 resamples), taking into consideration strong serial correlation within a day while treating different days as independent. The results of the noise in standard deviation and in confidence intervals are shown in Sec. 3 and used in the formula for calculating noise (Eq. 15). Finally, we performed some tests of the independence assumption in Eq. (11): we obtained the Pearson's correlation coefficient for the high-frequency residuals of voltage and irradiance channels using a daily block bootstrap. A correlation close to zero confirms the diagonal nature of (11); a significant non-zero value would indicate the cross-term should be included.

F. Baseline acquisition and the train-test split

We obtained the reference data from the equipment which has been in proper function for almost sixteen days without any faults. With the further exclusion of testing the commissioning time and the sensors malfunction periods, we used only daytime data with no faults to form the basis. Hence, the selected time frames of the record have to be freely split; no random distribution is allowed, to preserve the reliability of the data used for evaluation. The first part defines the training set, the training of the baseline system on the data which belongs to the particular type of the photovoltaic module. In addition to that, we will determine the sensor noise standard deviations. The second part serves as the testing set where the last six days of operation of the system have to be considered. The splitting of the data must be chronological. The operational data of photovoltaic module possess a very high degree of auto-correlation which means that the randomly selected dataset could be of similar nature and be used as an overestimate of the baseline efficiency. We report the false-alarm rate with a one-day block bootstrap interval, because an interval computed naively from the held-out set would be too narrow to be useful.

G. Planned experimental validation

Two aspects of the design are yet to be implemented, and they form the future tasks of this research. The first involves controlled fault induction. The three types of faults discussed in Section 2.3 should be intentionally induced, that is, introducing additional series resistance, establishing a controlled ratio of shaded area, and providing uniform particulate coating to represent soiling. The fault levels should be selected so that they fluctuate around the detection limit judged in Section 3.4 at any particular value of irradiance and repeated over the days so that measurement is taken throughout a range of different conditions. The importance of this task is in the choice of fault levels to be set: the implementation of only large faults will render all of the tests way above the predicted detection limit, providing no useful information; on the contrary, the manipulations at different levels of faults will directly test the prediction above $\delta_{\min}(G)$ and the failure below it. The second task consists of comparing detectors according to those tested trials. This threshold indicates a fault when power loss goes beyond $k\sigma_R(G)$. This threshold will be compared to a simple fixed threshold that corresponds to the same false-positive rate on the test dataset and a low-capacity regression model: a second-degree polynomial ridge regression using only the three environmental factors with the parameters estimated using five-fold block cross-validation. A more complex model would depend on too little data, as the baseline includes around 10-16 independent day-length blocks and not tens of thousands records, as was initially assumed.

IV. RESULTS

This section reports the results obtainable from the fault-free baseline deployment alone. The controlled fault-injection programme described in Sec. 2.8 is identified as the principal direction for future work (Sec. 4); the present results characterise and validate the detection limit against which those future trials are to be assessed.

A. Deployment overview

The baseline log is a continuously recorded sixteen days of log with a resolution of 60 seconds. For the first seven days, daily cycles were undisturbed by any interference with midday values; power values during the first week were about 5 W–6 W. After the seventh day, daily peaks significantly decreased due to the start of the local monsoon and increased cloudiness, with several days' power readings falling below 1 W. We use this natural decline in irradiance, as well as the transient effects brought by clouds themselves, as a source of actual deviations from the clean behavior of the PV module in Section 3.7. The following residual analysis relies on two properties of the proper baseline. First of all, detection limits rely on the assumption that the residuals are zero on average; otherwise, it could be misestimated due to the nonzero mean of the healthy residuals. We designed the local baseline

used here to obtain a zero median value, and during the training period, its mean value has been only several mW close to zero, which tells that the model misalignment contribution is negligible in comparison with the sensor noise floor yielding several mW. Secondly, we exclude power readings below 50 mW throughout. Instead of being a parameter that can be tuned, it is a threshold from which any current exceeding this threshold will lead to reliable operation. The exact value for this threshold is not of great importance since results remain the same within a factor of two.

B. Measured noise budget

The noise measurements for each channel are $\sigma_v = 0.082$ V for voltage and $\sigma_i = 1.26$ mA for current as measured using the reliable successive difference method described in Sec. 2.6. For the irradiance proxy channel, the value is very close to zero as shown by the measurements taken with this channel at a time interval of 60 seconds and reported in Sec. 3.7 about its malfunctioning. The treatment of the temperature channel is hybrid since the value of temperature noise for the time intervals when the channel is working is taken before converting it into the power term using the formula $\partial P / \partial T$. The effect of these aspects is limited: at the high irradiance point, the temperature channel contributes about 3.5 mW to σ_R , and thus the error of $\pm 50\%$ in the supposed temperature coefficients will change it by less than ± 2 mW, which is insignificant compared to the 33 mW electrical contribution to σ_R and the 100 mW detection limit that it entails. We assume the contribution due to the off-diagonal term in (11) to be equal to zero, while we found the voltage–irradiance correlation to be equal to $\rho_{VG} = 0.156$ with the bootstrap 95% confidence interval [0.055, 0.264]. Thus, the correlation is small but statistically significant, and consequently, the multiplicative correction due to this correlation is also small compared to the diagonal terms at the operating levels of interest, hence we have disregarded it.

C. Validation of the noise-propagation model

This research’s primary internal consistency test focuses on whether the expected scatter of short-timescale power residuals from the propagation of measured channel noise through $P = VI$ matches with the scatter directly observed on the healthy baseline. Table 1 provides the comparison for the experiment’s training and validation phases with different quantiles of the operating current forming the basis of the bins used.

TABLE 1: A comparison between observed and expected power-residual standard deviation, grouped by operational current, providing information about periods of training as well as held-out test. Expected values show the propagation of training-period channel noise via $P = VI$ for the median operating point per bin; observed values show the robust residual deviations of power.

Period	I_{op} (mA)	n	Observed (mW)	Predicted (mW)	Ratio
Train	84	948	8.1	7.6	1.07
Train	155	946	52.1	15.3	3.41
Train	306	953	80.2	31.3	2.57
Train	321	947	17.5	33.0	0.53
Train	326	940	19.1	33.4	0.57
Test	58	74	5.0	4.9	1.02
Test	66	74	9.6	5.8	1.67
Test	76	74	19.9	6.8	2.93
Test	90	74	39.4	8.3	4.75
Test	136	74	235.8	13.4	17.66

The observed-to-expected ratio median of 1.07 is reached only during the training interval and is highly dependent on the regime. The ratio equals 1.07 when reading the lowest current bin (in persistent cloudy conditions). As for the two highest current bins (in steady sunny conditions), the ratio in these bins equals 0.53 and 0.57, the predictions being conservative since both bins include transition disturbances that are included in channel noise estimation. In the intermediate bins, the observed values exceed the estimated ones by 2.6 to 3.4 times since these bins include transitions from cloud edges that are absent in the predictions of sunny bins. For the tested monsoon onset time period, the excess systematically increases with the current reading, reaching approximately 18 times value in the upper bin since the short-term variability includes rapid fluctuations due to the clouds. The small number of observations in the test period (n approximately equals 74 against n being 950 during the training period) should not be attributed to

filtering since the held-out period coincides with the onset of the monsoon period when only 370 daytime samples exceeding the 50 mW generation threshold were made. Hence, the upper test bin compared to which the ratio of 17.7 is calculated contains only about two hours of generation and should be read as indicative rather than exact.

The results of this comparison need to be clearly defined. They do not serve as independent proof that σ_V and σ_I values are accurate, as it tests three separate assumptions at a time: whether the first-order linearisation $\delta P \approx I \delta V + V \delta I$ is valid, whether voltage and current noises can be considered independent, and whether there is any other significant source of short-timescale power noise. The first two assumptions turn out to be justified and the third one localised. In a case of steady irradiance, the total sensor noise explains the calculated noise with a factor around 1 (ratios 0.5-1.1); in a case of changing irradiance, the fluctuation of the source leads to unpredictable power noise which cannot be even partially explained by the obtained model. This distinction governs the interpretation of the detection limit below.

D. The detection limit

The operational point is defined by the operational current I_{op} because the auxiliary channel to measure the irradiance turned out to be a poor replacement for irradiance (the voltage taken from it was only weakly and not necessarily correlated with the amount of generated energy). During constant load, the photocurrent is directly proportional to the irradiance and therefore to I_{op} , which is strongly and directly correlated with power ($r = 0.99$). However, the use of this method has a methodological disadvantage because the noise σ_I in δ_{min} comes from the same circuit as the I_{op} signal, which means that dividing depending on the operational current makes us dependent on the variable we want to analyze. Basically speaking, by using the method of segment averaging, we make the sensors less sensitive to the noise, which will surely allow minimizing the dependence of this method on the noise evaluation. The measurement limit grows with the irradiance starting from ≈ 19 mW with the lowest I_{op} value and ending with ≈ 100 mW at the highest value, taking into account that both terms grow almost continuously with the irradiance level: $I_{op}\sigma_V$ contributes to the current measurement while $V_{op}\sigma_I$ contributes to the operating voltage. The limit improves in relation to irradiance, decreasing from roughly 14% at low irradiance to about 1.9% at high irradiance, indicating that power increases more rapidly than noise level. Thus, the two observations are complimentary: the lowest fault that can be detected has the highest absolute power in case of high irradiance but has the smallest fractional loss. The dependency on irradiance is consistent with earlier findings, which suggest that the use of irradiance-dependent threshold is more efficient than the use of a fixed threshold^{4,15}. All values are based on precise estimations for σ_V and σ_I . When their 95% bootstrap confidence intervals ($\sigma_V \in [39,116]$ mV, $\sigma_I \in [0.73,1.89]$ mA) are taken into account, the uncertainty for δ_{min} is about $\pm 45\%$, which means that high irradiance limits of 100 mW become 52 mW to 146 mW if a 95% precision interval is calculated.

Thus, while making use of these numbers, it is possible to compare them to those provided by other studies, as shown in Table 2. To begin with, the loss value obtained from this study, which is approximately 1.9% of the operating power at high irradiance, is in accordance with the losses originating from faults that are reported in those studies, meaning that the faults occurring in practice can be detected by this kind of monitors. Second, and in closer proximity to this work, all values cited have an empirical basis and/or differ from each other in each installation, unlike it has been done here for the values of δ_{min} .

TABLE 2: Comparisons of detected and reported fault magnitudes with the one obtained in this study. The systems differ in terms of their size, instrumentations and the type of reporting, so the comparison has to be based on it, rather than on numerical similarities.

Study	System	Basis of threshold	Reported value
Firth et al. ¹⁶	Domestic grid-connected	Model-predicted versus measured efficiency	Annual energy loss from faults 3.6% to 18.9%
Chouder and Silvestre ¹⁷	Grid-connected, kilowatt scale	Power-loss indicators, thresholds evaluated empirically on a fault-free reference	Thresholds set per installation, not derived
Leloux et al. ¹⁸	BIPV fleet, daily indicator	Three standard deviations below the mean of the healthy distribution	Nominal type-I error 0.3%
This work	Single 10 W PV module, fixed load	Propagated sensor-noise budget, derived in closed form	$\delta_{min} = 100$ mW, 1.9% of operating power; empirical false-alarm rate 13%

E. Channel-limiting decomposition

According to the measurements at high-irradiance operating point ($V_{op} = 16.1$ V, $I_{op} = 325$ mA), the voltage channel's contribution to the variance was approximately 63% while the current channel's contribution was about 37%. This result does not correspond to the originally formulated expectation that the system would be limited by current shown in section 2.4 and proves that channel-limiting regime can only be defined using direct measurements. The measured noise in the voltage channel ($\sigma_v = 82$ mV, taken from the training-period data presented in Sec. 3.2) is in line with the combined impact of the ADC quantization of the ESP32 device and the divider source impedance. The apparatus with the 100 k Ω /10 k Ω divider behaves as a Thévenin source with the equivalent impedance of ~ 9 k Ω throughout the ADC sampling period; therefore, high source impedance gives rise to the known offset and noise of the converter due to lack of adequate settling during the sampling period. Therefore, the design implications of this finding are: installation of a unity-gain buffer between the divider and the ADC or using an alternative low-impedance (10 k Ω /1 k Ω) divider will produce a significant improvement in the voltage channel noise without requiring external converters. The measured noise in the current channel ($\sigma_i = 1.26$ mA) exceeds the best case resolution of the INA219; therefore, it can be concluded that the sensor was used in a very wide range of currents, where the noise due to quantization and the noise introduced by the I²C bus prevail. The range configuration was not documented during deployment; documenting and narrowing it is a zero-cost improvement for future builds. For the present apparatus, this means detector performance is most easily enhanced by reducing voltage-channel noise or increasing the resolution of the voltage measurement.

F. Healthy-state false-alarm behaviour

The two impacts should be differentiated when applying the three-sigma limit to the residual normalized by the predicted σ_R . The false-alarm frequency during the training phase, being probably the closest approximation to normal stationary conditions, was found to be around 13%. The false-alarm rate is much higher than the 0.27% threshold expected for the Gaussian residual. This is because the power residual is truly heavy-tailed, even in favorable weather conditions, with the tails being produced by the glitches of the A/D converter. The fault rate rises to almost 40% in the held-out test period of monsoon onset. This is not due to the noise of the sensors but rather due to genuine effects of the environment and the train-to-test shift into cloudy weather (Sec. 3.7). Both contributions are separate; applying the threshold does not provide a clear indication of the noise and does not qualify as such. The practical aspect is straightforward. At the observed rate of clear sky at about 13% and the number of samples equal to ~ 600 per day, one day of clear sky will be able to provide approximately 80 threshold crossings (about ~ 250 for a monsoon day). Therefore, a pure three-sigma test cannot be used. Increasing k does not provide any benefit, as the clear sky surplus kurtosis is about 277, meaning that the tail does not fall as it should according to the Gaussian principles, and 1 false alarm per clear sky day would necessitate $k \approx 130$, which leads to the operational threshold at high irradiance increasing from the 100 mW to several watts, which exceeds the total output of the PV module. What really works is the use of the temporal structure of false alarms. The heavy tail is formed by isolated single-sample glitches, while real problems last longer. Making it necessary for the threshold to be passed several times decreases the clear sky frequency. For instance, it goes down from about 80 times per day to about 10 when three consecutive samples are taken, to about 3 times when there are 5 samples taken, at a very small price in terms of the possibility of detecting any faults lasting a couple of minutes. Hence, this paper suggests not an increase in the threshold of the device, but rather the same threshold δ_{min} combined with a short persistence requirement or an explicit single-sample glitch filter.

G. Response to natural deviations

We intentionally added no errors, but actual cloud-related deviations from typical behaviour can be seen in the monsoon-onset dataset, and those deviations were flagged by the detector as non-standard conditions, demonstrating the functioning of all pipeline components in detecting real deviations. This, in turn, is more a demonstration of the performance of the whole pipeline than a true validation: one does not know in advance the magnitude of natural cloud-related deviations, and those deviations do not correspond to the expected values as an injected fault would. An auxiliary irradiance indicator (small PV cell connected to its load) proved to be an unreliable irradiance indicator; the voltage recorded by the indicator is only weakly and non-monotonically related to the power being delivered ($r = -0.36$ with the maximum power samples being associated with the lowest voltage), and its binned voltage produced an unphysical relationship with the power related to real irradiance. Besides, the channel's reading was practically frozen at the time scale of 60 seconds ($\sigma_G \approx 0$) which does not mean that the sensor had been quiet — an efficient irradiance sensor would have shown much more variability.

In the absence of a post-mortem analysis of the bench results, it is not possible to distinguish between the possible causes (such as the presence of proxy sensor out of plane) resulting in a malfunction, and therefore, the channel is recorded as failed rather than diagnosed. It is worth noting that the operating current I_{op} , which is simply proportional to photocurrent and thus to irradiance, is significantly connected with power ($r = 0.99$). The operating current I_{op} is the measure of power and is used in the results, taking into consideration the technical limitations mentioned in Sec. 3.4.

V. DISCUSSION

The above results present a quantifiable understanding of the detection capability of a basic passive-load PV monitor using only clean data. There are three practical implications as a result of these findings. First, we validate the noise-propagation methodology in the region where it can be correctly tested (Sec. 3.3), where we show that the sensor noise propagation accounts for the residual scatter under constant irradiance within a factor of order unity, while for changing irradiance the scatter is mostly due to real environmental changes. Given the defined area of applicability — specifically the sensor-noise floor but not the operational residual in the presence of clouds — it is thus possible to use δ_{min} as an accepted lower bound and thus a measure in the design process. Next, the noise floor is very strongly dependent on the irradiance, and in the case of the present system, on the voltage channel. The procedure of establishing this dependence — propagating the measurement noise budget and calculating the variance — can be generalized and applied to absolutely any fixed load monitor thus obtaining both detection level and the channel that most improves its value; however, the choice of the type of load is left behind: in this work, δ_{min} depends on V_{op} and I_{op} so that a different load will set another operating point and change both the noise floor and the sensitivity of the system with regard to series and shunt resistance faults, thus allowing to calculate the trade-off with Eq. (15). Then, it should also be noted that the detection limit and the false alarm behavior are of a different nature, but both should be taken into consideration in designing the monitor.

The budget is being dominated by the voltage channel and the quantization along with the nonlinearity of the internal converter of the ESP32 is also making the existence of budget inevitable. If an external sixteen-bit converter is employed, it can reduce the error term significantly but the budget remains dependent on the voltage. The aspects of the current channel have been addressed properly and the statements made above could be backed with enough clarity as compared to thresholds defined earlier. Noise values in Table 3 refer to the prediction made during the training time referred to in Sec. 3.2 above; the contributions are presented in the form stated in the above section.

TABLE 3: Design choices and their consequences for δ_{min} . Noise values are the training-period estimates of Sec. 3.2; contributions refer to the share of σ_R^2 at the high-irradiance operating point.

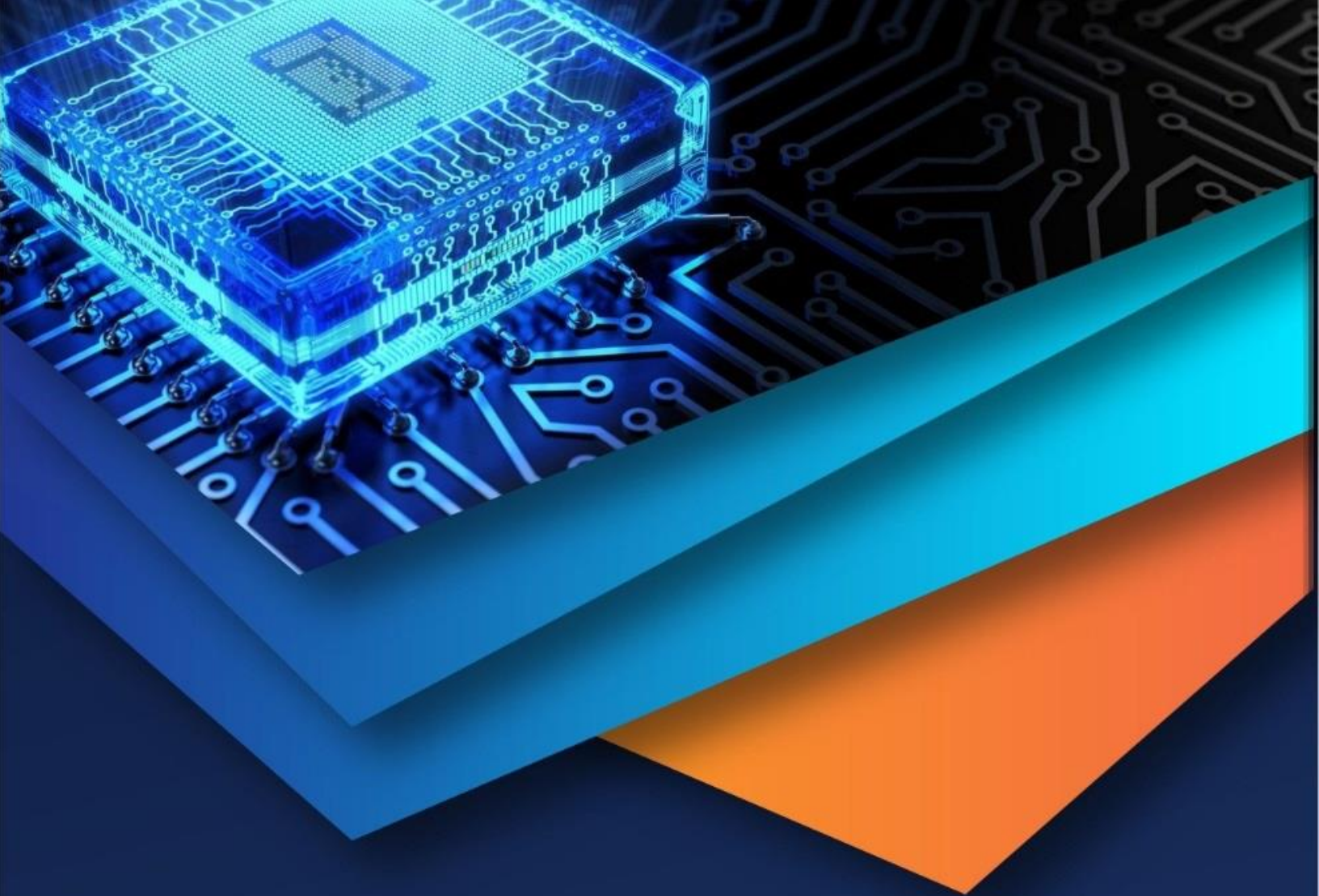
Design choice	Consequence for δ_{min}	Implication
ESP32 internal ADC for voltage	$\sigma_V = 82$ mV; 63% of residual variance; the limiting channel	An external high-resolution converter is the single highest-value upgrade
INA219 current sensor	$\sigma_I = 1.26$ mA; 37% of variance	Adequate; improving it yields little while the voltage channel dominates
Fixed resistive load	Renders V/I uninformative (Sec. 2.2)	Residual-based detection is obligatory, not merely preferable
DS18B20 temperature sensors	$\sigma_T = 0.26$ °C; under 1% of variance; intermittent in service	Contribution negligible; reliability, not precision, is the concern
Auxiliary PV cell as irradiance proxy	Failed: non-monotonic against power, $\sigma_G \approx 0$ (Sec. 3.7)	Replace with a calibrated co-planar reference, or use I_{op}

There are many limitations in our findings as indicated above. One of the basic limitations that emphasizes the findings above is that detection limit has successfully been “validated as a noise floor” but it has not been validated against any controlled failures taking place in between the detection limits. The second limitation is that the detection limit applies to power-residual thresholding at a fixed operating point; a detector using the full voltage and current time series could in principle resolve smaller deviations. Third, the results come from one PV module, one load, and one climate over 16 days across monsoon initiation; moreover, we show that the irradiance-proxy channel is unusable, with the current used instead as a substitute; as for the contribution of the temperature channel, it is based on the datasheet coefficients, which is perfectly valid considering the fact that the electrical channels contribute predominantly; the small value of the correlation between voltage and irradiance (0.156) could be ignored. This limits the generalisability as far as the numerical values are concerned, but not the method itself.

As for the future work, there are four aspects that are of importance. The first is the controlled fault-injection programme of Sec. 2.8, which alone tests the central prediction that faults above $\delta_{\min}$ are detected and those below are missed. The second step is an independent calibration of both voltage and current channels using a reference that can be traced back to the origin of the measurements, and this is necessary to resolve the problem of discrepancy with the load ratio as indicated in Sec. 2.2. The third step, which is needed to create a fully functioning system and not just to define its characteristics, includes a comparison to the data-fitted comparator using a robust method for detection of glitch, thereby leading to the generalisation that allows applying results to the data in the PV module, including variations related to the load and environment as well as to the possibility of replacing the broken cell with a properly calibrated coplanar reference.

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