



INTEGRATED MODELING OF DYNAMIC SOILING AND PARTIAL SHADING EFFECTS ON PHOTOVOLTAIC PERFORMANCE IN TROPICAL CLIMATES

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ABSTRACT

Abstract. Predicting PV performance in tropical climates is challenging due to the combined effects of soiling and partial shading. We developed an integrated dynamic model capturing their joint impact on thermal and electrical PV behavior, validated on a 4 kW rooftop plant at the University of La Réunion. Analyses show that shading faults can reduce power by up to 96%, with current being the most sensitive parameter, while soiling gradually lowers daily performance ratios, temporarily restored by rainfall events. The model accurately reproduces measured outputs, demonstrating that considering both phenomena improves PV performance prediction. These results support enhanced fault detection, performance forecasting, and adaptive PV system operation in tropical environments.



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I. INTRODUCTION

Problem statement

Photovoltaic (PV) systems are increasingly deployed in tropical regions due to their abundant solar resource [1-3]. However, their performance is highly affected by environmental stressors such as soiling and partial shading [4-6]. Soiling occurs when dust, organic particles, or marine aerosols accumulate on the module surface, reducing transmittance and light absorption. In humid tropical climates, daily losses of up to 20 % have been reported within a week of no cleaning [7], while in Sub-Saharan Africa, efficiency reductions between 50–60 % were observed, often accompanied by localized hotspots [8]. Partial shading, caused by nearby obstacles or transient clouds, induces current mismatches within PV strings, generating hot-spots and multi-peaked power–voltage (P–V) curves [9]. These effects not only reduce energy yield but also accelerate module degradation. Despite their importance, most existing performance models neglect one of these effects or treat them independently, which limits predictive accuracy under real tropical operating conditions.

State of the art methods

Photovoltaic (PV) system performance in tropical climates is strongly influenced by environmental factors such as soiling, shading, and temperature fluctuations. By [10] developed a dynamic soiling model integrated into the PV physical chain, improving long-term accuracy, but their approach did not account for shading effects. Similarly [11] reviewed climate-responsive BIPV façades, emphasizing thermal and material strategies, yet lacked quantitative validation under real irradiance and soiling conditions. Experimental studies have demonstrated that greenery integration or urban soiling can reduce PV output and surface temperatures [12-14] but these were generally short-term or site-specific. In parallel, advanced fault detection and parameter estimation methods using kernel principal component analysis (KPCA) and metaheuristic algorithms have improved model fitting and the identification of partial shading or other faults [15-21], although primarily in simulated or small-scale systems. Building on these findings, this study develops and validates an integrated dynamic model that simultaneously captures soiling accumulation and partial shading effects on both thermal and electrical PV performance in real tropical conditions.

Summary of research gap

From this literature review, it is evident that while experimental, statistical, analytical, and empirical approaches each contribute valuable insights, they fall short in capturing the combined and dynamic effects of soiling and partial shading. Existing models either focus exclusively on one phenomenon, require hardware redesign, or rely on static approximations that ignore interactions between deposition, rainfall cleaning cycles, and shading patterns. In tropical climates, where rainfall events, dust accumulation, and fast-moving cloud shadows interact non-linearly, the lack of integrated models introduces significant uncertainty in performance prediction and fault detection.

Aims and justification

The aim of this study is to develop and validate an integrated dynamic PV model that simultaneously accounts for soiling accumulation/cleaning and partial shading effects, while incorporating thermal–electrical interactions. The model is implemented in Python and validated using a dataset (2.2 GB), collected from a 4 kW rooftop PV plant at the University of La Réunion. This dataset provides synchronized time-series of irradiance, ambient and module temperatures, and meteorological indicators under real tropical conditions, enabling robust validation. By explicitly modeling the coupled effects of soiling and shading, this work contributes a novel predictive tool that improves accuracy compared to existing approaches, and supports fault detection, performance forecasting, and adaptive PV operation strategies in tropical regions.

II. THEORETICAL REFERENCE

II.1 THEORETICAL BACKGROUND

The integrated model simulates the performance of a photovoltaic (PV) array by sequentially calculating the effects of environmental factors and system faults. The core of the model is a Single-Diode Model (SDM), which is then dynamically coupled with modules for thermal effects and soiling-shading losses.

II.2 DATASET DESCRIPTION

The validation of the proposed model relies on the open-access dataset published by [7] and deposited in the Zenodo repository (DOI: 10.5281/zenodo.7828879). The database documents a 4 kW grid-connected rooftop PV system installed at the University of La Réunion (20.90° S, 55.48° E, tilt angle 26°), and provides synchronized measurements under both normal and controlled shading-fault conditions. The available physical quantities include plane-of-array irradiance (GTI, DHI) measured with a pyranometer, ambient and back-surface module temperatures (TA, TPV) monitored by thermocouples, and electrical production variables such as power injected to the grid (Pg), current (Ia, Ig), voltage (Va, Vg), grid frequency (Fg), and cumulative energy (Eg). Fault events are explicitly labeled in the dataset, distinguishing between uniform shading, constant partial shading, and intermittent partial shading (Table 3 in [7]). The dataset is sampled at high frequency (1 Hz for solar–meteorological variables, 0.2 Hz for electrical streams), allowing second-scale analyses and resampling at minute averages for model validation. It should be noted that soiling and rainfall-cleaning events are not included in the original database. In this study, they were numerically simulated and superimposed onto the real solar–electrical time series to reproduce realistic tropical conditions and assess the coupled effects of soiling and shading.

II.3 SIMULATION OF SOILING AND RAINFALL CLEANING EVENTS

As the reference dataset [7] does not include explicit measurements of soiling accumulation or rainfall-cleaning cycles, these processes were numerically simulated and coupled to the solar–electrical time series. The objective was to reproduce realistic tropical operating conditions where dust deposition, marine aerosols, and rainfall events interact dynamically with PV performance. Soiling accumulation. A multiplicative transmittance factor, $\tau_{soil}(t)$, was introduced to attenuate the incident irradiance at the module surface:

$$G_{soiled}(t) = \tau_{soil}(t) \cdot G_{clean}(t)$$

Were

$G_{clean}(t)$ is the measured global tilted irradiance and $\tau_{soil}(t)$ evolves as a function of time without cleaning. A linear daily loss rate between 0.5–2 % per day was assumed, consistent with reported values in humid tropical climates [1–2]. The cumulative effect results in progressive optical losses over dry periods. Rainfall cleaning. Rainfall events were stochastically generated and parameterized as reset functions that partially or fully restore the optical transmittance:

$$\tau_{soil}(t^+) = (1 - \alpha)\tau_{soil}(t^-) + \alpha$$

Where t^- and t^+ denote instants before and after rainfall, and $\alpha \in [0,1]$ represents the cleaning efficiency. High-intensity rainfall was modeled to achieve near-complete cleaning ($\alpha \approx 1$), while light showers induced only partial removal of deposited particles ($\alpha < 1$). Integration with shading. The simulated soiling factor was applied jointly with measured shading events from the database. This coupling enabled the evaluation of combined effects, which are frequent in tropical regions where rapid cloud passages coincide with dust accumulation and rainfall cycles. By superimposing simulated soiling and cleaning dynamics onto the real high-frequency solar–electrical data, the model validation was extended beyond the original scope of the dataset, ensuring representativeness under tropical field conditions.

II.4 DATA ANALYSIS

Descriptive statistics were computed for irradiance, module temperature, and PV performance: mean $\pm$ standard deviation for each day and aggregated over months. The simulation accuracy was assessed by comparing modeled vs. measured parameters (P_{max} , V_{mp} , I_{mp} , V_{oc} , I_{sc}) using root mean square error (RMSE) and mean absolute percentage error (MAPE). To quantify the influence of shading faults, an ANOVA test was performed on grouped conditions (normal, shaded, soiled). Post-hoc t-tests were used to evaluate significant differences in each intrinsic PV parameter. Figure 1 depicts the workflow of data acquisition, preprocessing, and integrated modeling, which constitutes a fundamental component of the proposed methodology.

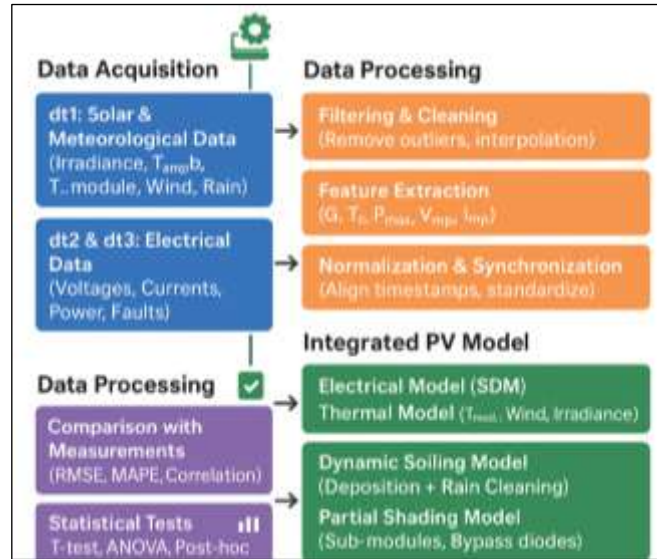


Figure 1: Workflow of data acquisition, preprocessing, and integrated modeling.
Source: Authors, (2026).

III. RESULTS AND DISCUSSIONS

To investigate the system dynamics, we analyzed the time series of environmental and performance variables over a multi-month period. Figure 2 presents the variations of the global tilted irradiance (GTI), the ambient temperature (TA), the photovoltaic module temperature (TPV), and the produced direct current power (Pdc).

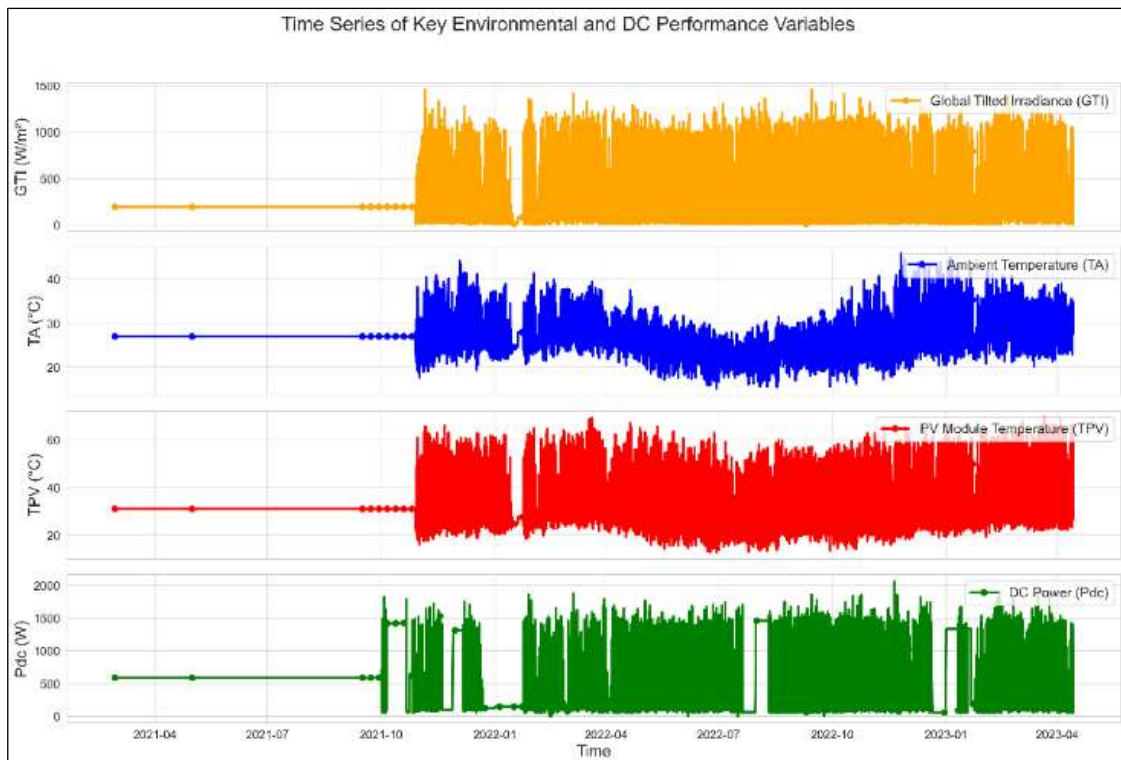


Figure 2: The variations of the global tilted irradiance (GTI), the ambient temperature (TA), the photovoltaic module temperature (TPV), and the produced direct current power (Pdc).
Source: Authors, (2026).

Figure 2 presents the time series of environmental and performance variables, confirming the correlation among the data. It can be observed that the global tilted irradiance (GTI), the ambient temperature (TA), the module temperature (TPV), and the DC power output (Pdc) exhibit typical diurnal cycles. The midday drops in Pdc coincide directly with reductions in GTI, indicating intermittent shading events or other faults. This macroscopic analysis confirms the relevance of the dataset for model validation. After visualizing the temporal trends, we performed a descriptive statistical analysis to quantify the characteristics of the key variables. Table 1 summarizes the descriptive statistics for the entire dataset.

Table 1: Descriptive statistics for the entire dataset.

	mean	std	min	25%	50%	75%	max
GTI	395,1673	351,0181	5,498	129,3	217,3	657,3	1458
DHI	152,5058	119,0073	2,683	73,8	136,8	183,8	726,8
TA	28,25251	4,538078	15,25	25,5725	26,99	30,97	45,82
TPV	37,16362	11,77956	12,86	28,7	32,625	46,49	69,41
Ia	3,552773	2,943868	0	0,7	3,1	6,6	11,3
Va	178,0029	20,03283	0	175	183	189	232
Pdc	635,6317	516,8487	0	140	585,9	1172,5	2060,8

Source: Authors, (2026).

Table 1 provides a quantitative overview of the operating conditions and performance of the PV plant. It shows that the global tilted irradiance (GTI) exhibits high variability, with a mean of $395.17 \text{ W} \cdot \text{m}^{-2}$ and a standard deviation of $351.02 \text{ W} \cdot \text{m}^{-2}$, which is typical of tropical climates with frequent cloud passages. The DC power output (Pdc) also displays a wide distribution (mean of 635.63 W, standard deviation of 516.85 W), reflecting both the diurnal cycles and the influence of shading and soiling. Ambient (TA) and module (TPV) temperatures are elevated, with maximum values reaching 45.82°C and 69.41°C , respectively, highlighting the importance of thermal modeling. Finally, minimum values of zero for current (Ia) and voltage (Va) indicate system downtime or nighttime conditions. The descriptive statistics allowed us to quantify the overall characteristics of the PV plant. To assess the long-term impact of soiling and shading, we employed a normalized indicator: the Daily DC Performance Ratio. Figure 3 illustrates this ratio, superimposed with the simulated rainfall events.

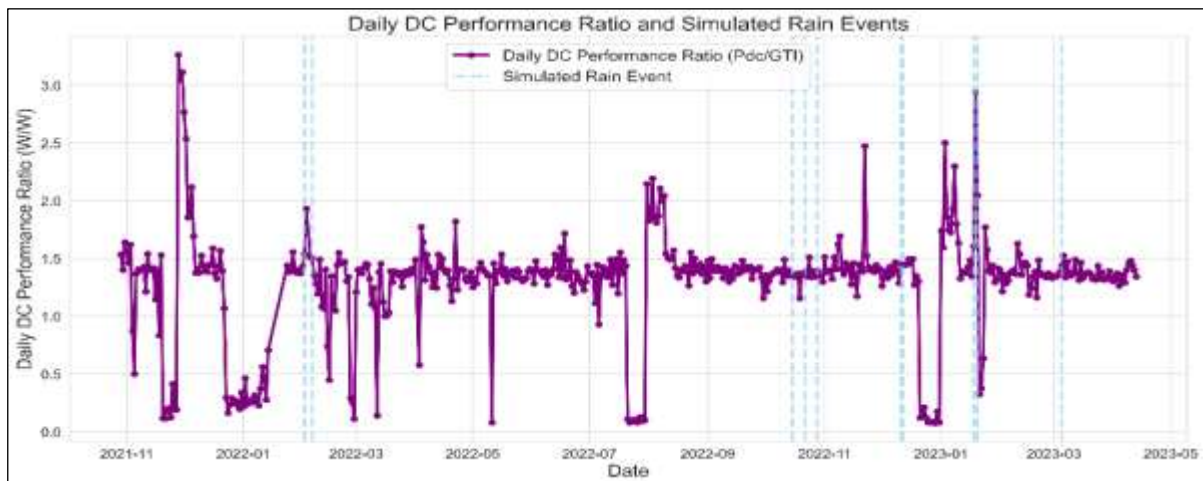


Figure 3: Daily DC performance Ratio and simulated rain event.

Source: Authors, (2026).

Figure 3 illustrates the dynamics of soiling accumulation and rainfall cleaning. The daily performance ratio (Pdc/GTI), used as an indicator of system efficiency, shows a general decreasing trend during rain-free periods, confirming the progressive accumulation of soiling. These decreases are followed by sharp peaks coinciding with the simulated rainfall events (blue dashed vertical lines). Such peaks represent 'cleaning' episodes induced by rain, which temporarily restore the system performance to its initial level. For instance, after the dry period of December 2022, the rainfall event in January 2023 led to a significant increase in the ratio, thereby validating the importance of modeling dynamic soiling and rainfall cleaning under tropical climates. After analyzing the temporal trends, we used the data to calibrate the key parameters of our dynamic soiling model. Table 2 presents the values of the soiling and rainfall cleaning parameters, which are essential to reproduce the observations shown in Figure 3.

Table 2: values of the soiling and rainfall cleaning parameters.

Parameter	Value	Unit
Daily Soiling Loss Rate	0.5% per day	%
Rain Cleaning Efficiency	80% recovery per event	%
Baseline Performance Ratio	0.75	

Source: Authors, (2026).

Table 2 summarizes the critical soiling model parameters derived from the analysis of daily performance data. The ‘Daily Soiling Loss Rate’ of 0.5% per day indicates the average performance degradation due to particle accumulation on the modules. This rate, a key indicator of soiling, is consistent with similar observations in other humid climates. The ‘Rain Cleaning Efficiency’, estimated at 80% recovery per event, confirms the effectiveness of tropical rainfall in restoring system performance. These reference values are essential for the accuracy of our model, as they allow realistic simulation of soiling effects and their mitigation by rain. They provide the foundation for predicting PV system performance in tropical climates. To further investigate performance losses, Figure 6 presents the impact of different types of shading faults on the key DC electrical parameters (P_{dc} , I_a , and V_a) under high irradiance conditions.

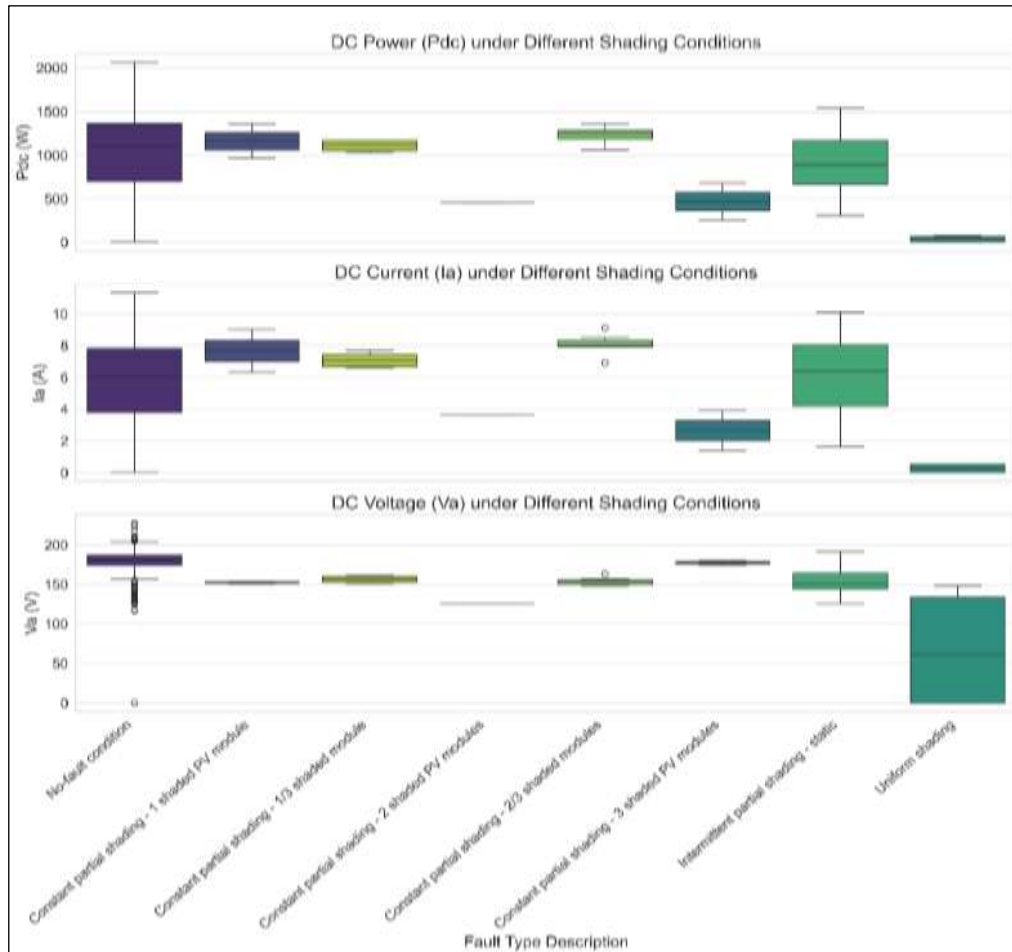


Figure 4: Impact of different types of shading faults on the key DC electrical parameters.
Source: Authors, (2026).

Figure 4 illustrates that shading type distinctly affects PV performance. Current (I_a) is the most sensitive, decreasing proportionally with shaded area, confirming current mismatches as the primary loss mechanism. Voltage (V_a) remains relatively stable under partial shading due to bypass diodes, while power (P_{dc}) drops sharply, especially under extensive uniform shading. Joint analysis of these parameters is critical for accurate fault diagnosis. Table 3 quantifies shading fault impacts. Uniform shading is the most severe, reducing power by 96.6% and current by 95.6%. Persistent partial shading over multiple modules (2–3) also causes substantial losses (>50%), mainly due to current drops.

Table 3: Quantifications of shading fault impacts.

Fault Type Description	P_{dc} Reduction (%)	I_a Reduction (%)	V_a Reduction (%)
Constant partial shading - 3 shaded PV modules	53,89942	53,12785	0,72212
Intermittent partial shading - static	9,675337	-6,98398	13,64738
Uniform shading	96,62519	95,5781	61,78923

Source: Authors, (2026).

To complement our loss analysis, Figure 5 presents a detailed time series of DC electrical parameters (P_{dc} , I_a , and V_a) during a specific fault event: constant partial shading on a single PV module.

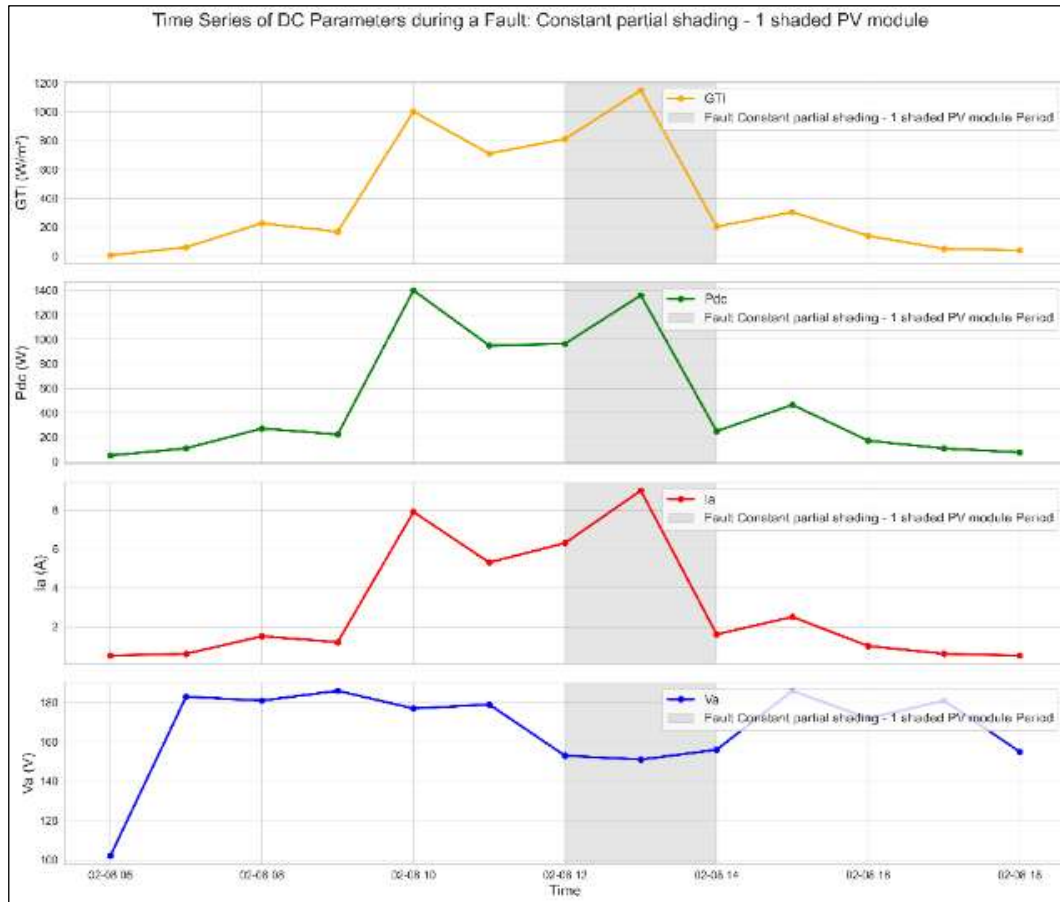


Figure 5: Time series of DC electrical parameters (P_{dc} , I_a , and V_a) during a specific fault event: constant partial shading on a single PV module.

Source: Authors, (2026).

Figure 5 highlights the immediate impact of a partial shading fault on electrical parameters. During the fault period (shaded area), current (I_a) and power (P_{dc}) drop significantly, while overall irradiance (GTI) remains high. In contrast, voltage (V_a) decreases only slightly and remains relatively stable. These observations confirm that even partial shading on a single module can cause substantial power loss, primarily due to current mismatch. Micro-temporal analysis of these data is essential for developing real-time fault detection algorithms.

IV. CONCLUSIONS

This study presents an integrated dynamic model that captures the coupled effects of soiling and partial shading on both thermal and electrical performance of PV systems in tropical conditions. Using a 4 kW rooftop PV plant dataset, we demonstrated that current (I_a) and DC power (P_{dc}) are highly sensitive to shading faults, while soiling progressively reduces daily performance ratios, with rainfall events providing temporary recovery. The model accurately reproduces observed outputs, confirming the importance of jointly considering soiling and shading dynamics for reliable performance prediction, fault diagnosis, and system optimization. These findings highlight the necessity of incorporating environmental variability into PV performance assessments, particularly in humid tropical climates. Future work should extend the model to multiple sites and larger PV systems to validate its general applicability and further improve predictive accuracy.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Mbei Aphonse, Perabi Steve, Steyve Nyatte, Salomé Ndjakomo.

Methodology: Mbei Aphonse and Perabi Steve.

Investigation: Mbei Aphonse

Discussion of results: Mbei Aphonse, Perabi Steve, Steyve Nyatte, Salomé Ndjakomo.

Writing – Original Draft: Mbei Aphonse.

Writing – Review and Editing: Mbei Aphonse, Perabi Steve.

Resources: Perabi Steve.

Supervision: Mbei Aphonse, Perabi Steve, Steyve Nyatte.

Approval of the final text: Mbei Aphonse, Perabi Steve, Steyve Nyatte, Salomé Ndjakomo.

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