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REAL-TIME FAULT DETECTION AND DIAGNOSIS OF SOLAR PHOTOVOLTAIC SYSTEMS FOR RAILWAY MICROGRID USING IOT AND MACHINE LEARNING

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Abstract

The rapid adoption of solar photovoltaic (PV) systems as a sustainable energy source has made effective monitoring and maintenance crucial for ensuring reliability and performance. Traditional PV fault detection methods often rely on manual inspection or offline analysis, leading to delayed diagnosis, energy losses, and reduced system lifespan. This research presents an Internet of Things (IoT)-based framework for real-time fault detection and diagnosis (FDD) in solar PV systems. The proposed system continuously monitors key parameters such as voltage, current, temperature, and irradiance using low-cost sensors, microcontrollers, and cloud-based platforms. By applying advanced machine learning algorithms and anomaly detection techniques, it effectively identifies faults such as partial shading, open circuits, line-to-line short circuits, and PV module degradation. Furthermore, the IoT-enabled design supports remote accessibility, data visualization, and predictive analytics for proactive maintenance. The proposed FDD framework is also extended to railway microgrid applications, where integrated PV and energy storage systems power both traction and auxiliary loads. This integration enhances energy efficiency, system reliability, and fault resilience, contributing to the development of smart and sustainable railway infrastructure.

Keywords - Smart Monitoring, Renewable Energy, Solar PV, IoT, Fault Detection, Railway Microgrid.

1. INTRODUCTION

Growing environmental concerns, efforts to mitigate climate change, and the slow depletion of conventional fossil fuel supplies have all contributed to the recent sharp increase in the demand for renewable energy internationally. Because of their direct ability to transform sunlight into electricity, low environmental impact, and scalability across residential, commercial, and utility-scale applications, solar photovoltaic (PV) systems are nowadays one of the most favoured and promising renewable energy technologies [1].

The concept of an on-train railway microgrid represents a transformative approach toward achieving energy efficiency, reliability, and sustainability in modern rail transportation [2]. A train-based microgrid integrates multiple power sources such as overhead traction supply, regenerative braking energy, onboard solar photovoltaic panels, and energy storage systems to form a coordinated and self-regulating power network within the locomotive and coaches [3][4]. This intelligent microgrid architecture enables efficient power sharing between traction and non-traction loads, including lighting, air conditioning, and onboard electrical systems, while maintaining power quality and stability. By leveraging advanced control systems, Internet of Things (IoT) technology, and machine learning algorithms, the onboard microgrid can perform real-time energy optimization, fault detection, and predictive maintenance. This integrated approach not only enhances energy efficiency and system reliability but also contributes to the development of sustainable, smart, and eco-friendly railway operations aligned with the global green transportation initiatives [5][6].

However, operational errors and inefficiency within the system had a major impact on the performance and long-term dependability of PV systems, despite their many advantages [7]. The efficiency of power generation can be significantly reduced by common problems including panel dirt, shade, hot spot creation, inverter failures, wiring mistakes, or mismatch losses. In addition to decreasing the total energy production, these defects can raise maintenance costs, lengthen system outages, or even cause safety hazards like electrical fires [8].

Offline diagnostic tools, planned maintenance, and human inspections are common components of traditional defect detection and performance monitoring techniques. For big-scale solar farms, where thousands of panels and networked devices are spread across large areas, these methods are labour- intensive, expensive, and unworkable, despite their relative effectiveness. Such systems' inability to identify and react quickly makes energy losses and inefficiencies in operation even worse [9].

Machine learning combined with IoT enables real-time fault detection in photovoltaic systems by analysing parameters like voltage, current, and irradiance [10]. Building on the study “Machine Learning for Fault Detection and Diagnosis of Large Photovoltaic Plants through IoT Platform,” this approach is applied to railway microgrids, enhancing reliability, predictive maintenance, and energy efficiency [11].

Table1. Comparative Study of Proposed Fault Detection Techniques for Solar PV Systems in Railway Microgrids

S. NO.	APPROACH / METHOD	REAL-TIME CAPABILITY	EFFICIENCY	COST & COMPLEXITY	SUITABILITY FOR RAILWAY MICROGRID
1	Manual Inspection [12]	No	Low (depends on human expertise)	High (labour-intensive)	Low (not scalable)
2	Offline Data Analysis [13]	No	Medium	Medium	Moderate
3	Sensor-Based Monitoring [14]	Partial	Medium	Moderate	Moderate
4	AI-Based Image Recognition [15]	Partial	High	High	Moderate
5	Machine Learning (Standalone) [16]	Yes	High (85–90%)	Moderate	High

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6	IoT-Based Monitoring [17]	Yes	High (80–85%)	Low–Moderate	High
7	Proposed IoT + ML Framework [18]	Yes (real-time)	Very High (≈95–98%)	Low–Moderate	Excellent

Compared to traditional techniques, this IoT-based strategy has several advantages, such as enhanced scalability, reduced operating costs, enhanced decision-making through predictive maintenance strategies, and improved system dependability. IoT technologies are essential for optimizing the effectiveness, safety, and financial feasibility of solar PV systems by allowing continuous monitoring and quick problem detection. This accelerates the transition to a more robust and sustainable energy future.

2. LITERATURE REVIEW

In photovoltaic (PV) systems, fault detection and diagnosis (FDD) has evolved from basic performance ratio (PR) monitoring to sophisticated IoT-enabled, data-driven techniques. To identify abnormalities like open circuits or inverter tripping, early model-based systems compared observed output with irradiance–temperature models. Despite being transparent and inexpensive, these methods suffered from aging effects, shadowing, and fluctuating weather. Better fault isolation was achieved by signal-based techniques that used string impedance and I-V curve analysis, but their practical use was limited by the need for specialist measuring equipment[19].

By making it possible to gather high-resolution, real-time data, the Internet of Things (IoT) has revolutionized PV monitoring. Data may now be sent to centralized or edge-based analytics platforms at the module and string levels thanks to inexpensive sensor nodes and communication protocols (such as MQTT, LoRa, and NB-IoT). Interoperability has been enhanced by standards like IEC 61724, and edge computing lowers bandwidth and latency requirements [20].

Recent FDD investigations have been dominated by machine learning (ML) approaches. When enough labelled data is available, supervised models like SVMs, CNNs, and random forests may accurately classify problems like shading, soiling, and MPPT failures. Limited fault datasets provide difficulties for deep learning techniques that use LSTMs and autoencoders to facilitate anomaly identification and forecasting. Hybrid approaches that integrate ML (digital twins, diode-equation restrictions) with physics-based models are being used more to solve this [21].

Peer-to-peer string comparisons, predictive maintenance for inverters and connections, and fleet-wide analysis are all made possible at the system level by IoT. Concerns about cybersecurity have also surfaced in relation to IoT-based PV systems. Comparing approaches and validating performance in real-world settings is challenging because to the lack of available datasets, defined benchmarks, and cost-benefit evaluations[22].

International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

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Scalability, cost-effectiveness, and real-time problem detection in solar PV facilities are guaranteed by the suggested IoT-enabled monitoring and diagnostic system. It is composed of six essential parts, as seen in Fig. 1:

3. IOT-BASED FAULT DETECTION FRAMEWORK [23][24]

Sensors: To identify problems like shading, hotspots, and wiring flaws, voltage, current, temperature, and irradiance sensors gather electrical and environmental data.

Microcontroller (MCU): Even in the absence of cloud connectivity, these inexpensive devices (ESP32, Arduino, etc.) preprocess data, filter noise, and identify abnormalities locally to ensure notifications.

Communication Layer: Reliable, extensive monitoring across dispersed PV plants is made possible by data transmission over Wi-Fi, GSM, or LoRaWAN (Long Range Wide Area Network).

Cloud Platform: Services like Azure and AWS IoT offer centralized storage, visualization, and interaction with machine learning algorithms for trend analysis and predictive maintenance.

User Interface: For quick problem response, a web/mobile dashboard offers real-time visualization, notifications (via SMS, email, or app), and automatic control actions.

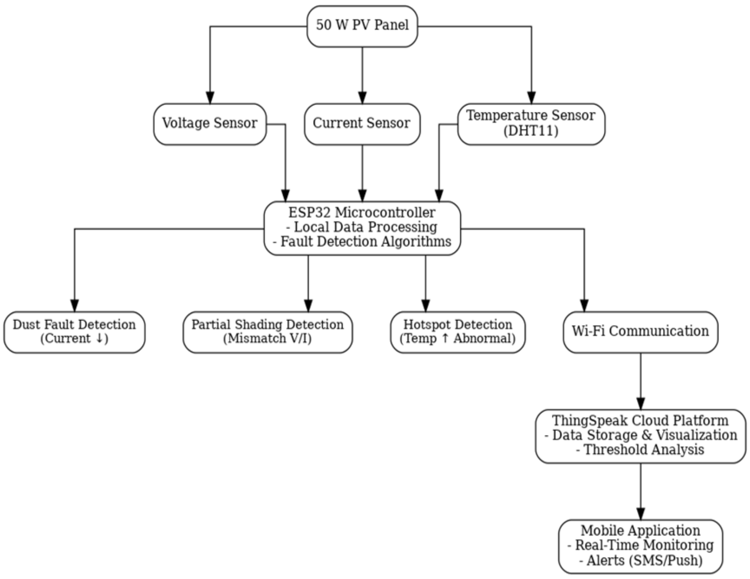

Fig1: Block Diagram of IOT based fault detection and Diagnosis of solar PV system using IOT

4. METHODOLOGY:

To build and execute an Internet of Things-based framework for defect detection and diagnosis in solar PV systems, this section describes the system architecture, data collecting, communication protocols, cloud analytics, fault diagnosis algorithm, and experimental validation technique..

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
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4.1. System Architecture [25]

1. PV Generation Layer: DC electricity is produced by solar PV panels that are sensitive to operational and environmental factors.

2. Sensing Layer: Critical parameters are measured using sensors:

Current & Voltage → to keep an eye on electrical properties.

Temperature & Irradiance → To take environmental factors into consideration.

Dust and humidity sensors are optional for more thorough monitoring.

3. Edge Processing Layer: A low-power microcontroller (ESP32/Arduino) processes raw sensor data, applies noise filtering and threshold-based fault detection, and transmits structured data packets.

4. Communication Layer: Use GSM/GPRS for off-grid/remote systems or Wi-Fi (IEEE 802.11) for grid-connected systems. The MQTT protocol, which is lightweight and requires little bandwidth, is used for communication.

5. Cloud Analytics Layer: Creates alerts, does sophisticated analytics (trend analysis, AI classification), and receives and saves real-time data.

6. User Interface Layer: Gives operators access to dashboards, SMS/email alerts, and notifications from mobile apps.

4.2. Data Acquisition Strategy [26]

Accurate data collection is crucial for reliable fault detection.

1. Sensors: LM35/DHT11 (temperature), INA219 (voltage/current), and pyranometer (irradiance).

2. Sampling Rate: To balance accuracy and network performance, 1 Hz raw data is averaged over 60 seconds for transmission.

3. Calibration: To reduce drift, each sensor was calibrated against reference equipment.

Equation for normalized sensor value:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}}$$

4.3. Data Preprocessing and Filtering

1. Noise Reduction*:* A moving average filter smoothens fluctuations:

$$Y_t = 1/n \sum_{i=0}^{n-1} X_{t-i}$$

2. Fault Baselines: PV panel datasheet ratings define safe operational ranges (e.g., Voc = 21 V, Isc = 3.2 A). Deviations beyond ±15% trigger anomaly detection.

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
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4.4. Fault Detection and Diagnosis Algorithm

1. Threshold-Based Detection: Rapid and computationally light:

Over 15% voltage decrease indicates partial shade or a dust issue.

Under high irradiance, a current reduction of more than 10% indicates a wire or connector issue.

Hotspot: module temperature >60°C. When there is enough light, there is no electricity, which indicates an inverter or disconnect failure.

2. Machine Learning Classification: For improved accuracy and reduced false positive [10]s:

Features: Voltage, Current, Temperature, Irradiance.

Algorithms: Random Forest, SVM, ANN

Training Dataset: Historical PV performance data with labeled faults.

Evaluation Metrics: Accuracy, Precision, Recall, F1-Score.

Equation for Detection Accuracy (DA):

$$DA = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} * 100$$

4.5. Experimental Setup and Validation

1. Hardware: ESP32, INA219, LM35, GSM module, 50 W PV module.

2. Software: Arduino IDE for MCU programming, Thing Speak for cloud dashboard.

3. Test Conditions: Ten to twenty percent of the display is covered to imitate dust collection.

A heating element is used to create an artificial hotspot.

Performance Metrics:

Mean Time to Detection (MTTD):

$$\mathrm{MTTD} = \sum \frac{(\mathrm{t_{detection}} - \mathrm{t_{fault}})}{\mathrm{N}}$$

Energy Loss Estimation (ELE):

$$\mathrm{ELE} = \frac{\mathrm{P_{expected}} - \mathrm{P_{measured}}}{\mathrm{P_{expected}}} * 100$$

5. EXPERIMENTAL SETUP AND CASE STUDIES:

5.1. Hardware Configuration:

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The experimental platform was designed to replicate a small-scale solar PV installation and validate IoT-based fault detection.

1. PV Module: To guarantee measured power generation under regulated conditions, a monocrystalline 50 W panel (Voc = 21.6 V, Isc = 3.1 A) was used.

2. Sensors: Voltage/Current Measurement: Panel output was tracked in real time with an accuracy of ±1% using INA219 sensor modules.

Measurement of Irradiance: To correlate solar insolation numbers with panel output, a calibrated pyranometer was used.

Temperature Measurement: To record the panel surface temperature, LM35 sensors were affixed to the module's back sheet.

3. Processing Unit: An ESP32 microcontroller was employed for edge-level preprocessing, filtering, and communication.

4. Communication Gateway: GSM and Wi-Fi modules were used for transmitting data packets to the IoT cloud platform (Thing Speak).

5. Load & Power Conditioning: To simulate actual demand and provide load fluctuation, a programmable electronic load was used.

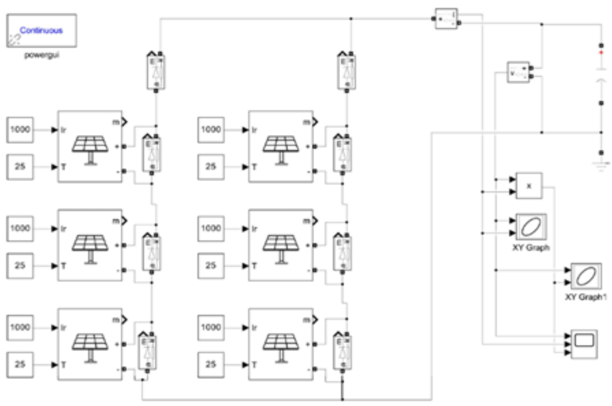

Fig2: Circuit Diagram of Before Fault Detection in PV Array

5.2. Software Framework:

1. Firmware Development: The ESP32 was programmed for MQTT communication, data formatting (JSON), and sensor interfacing using the Arduino IDE.

2. Cloud Platform: Storage, visualization, and algorithm testing were done using MATLAB IoT analytics package and Thing Speak.

3. Machine Learning Models: Python was used to train the Random Forest, SVM, and ANN classifiers offline before they were made available as cloud-side services.

International Journal of Applied Mathematics
Volume 38 No. 11s 2025,
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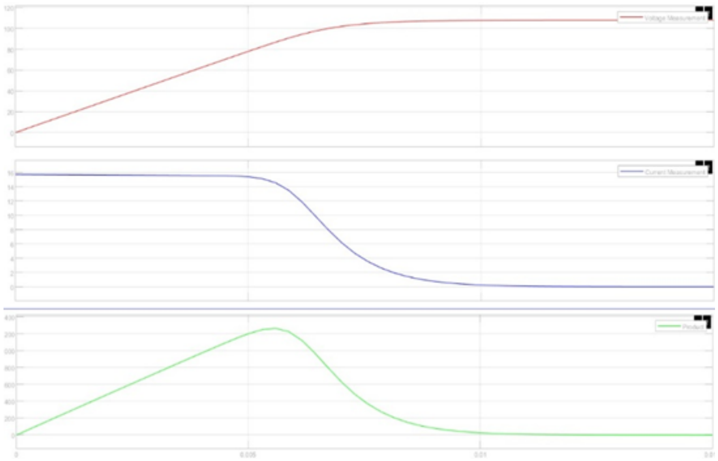

Fig3: Waveform of Before Fault Detection in PV Array

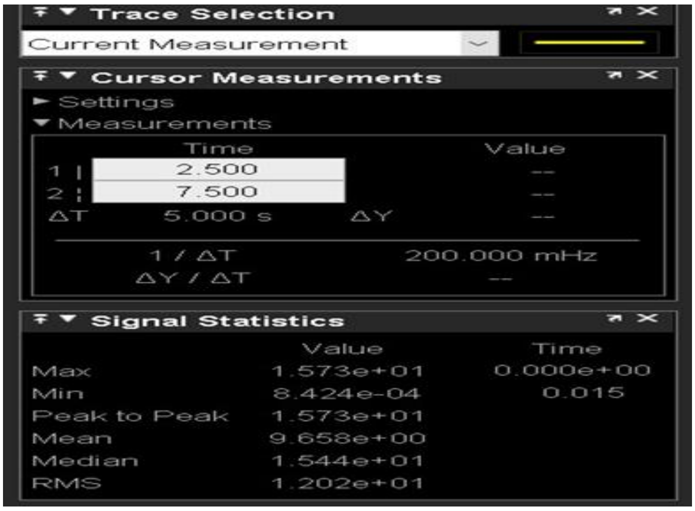

Fig4: Current measurement of Before Fault Detection in PV Array

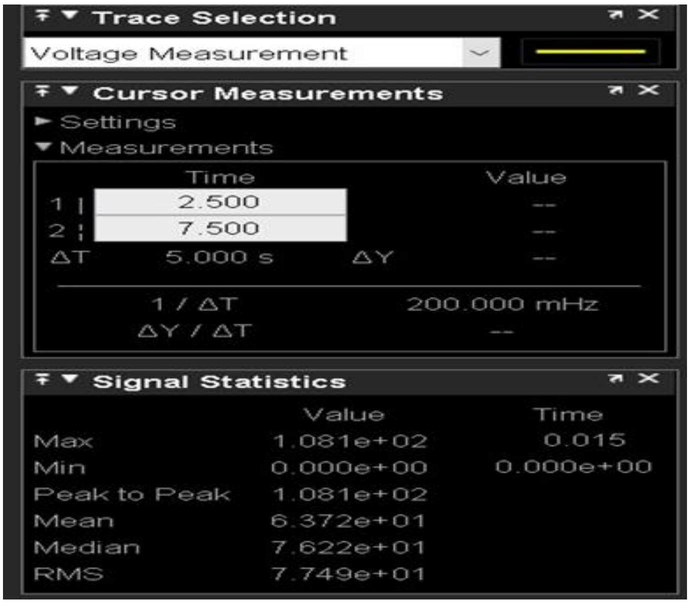

Fig5: Voltage measurement of Before Fault Detection in PV Array

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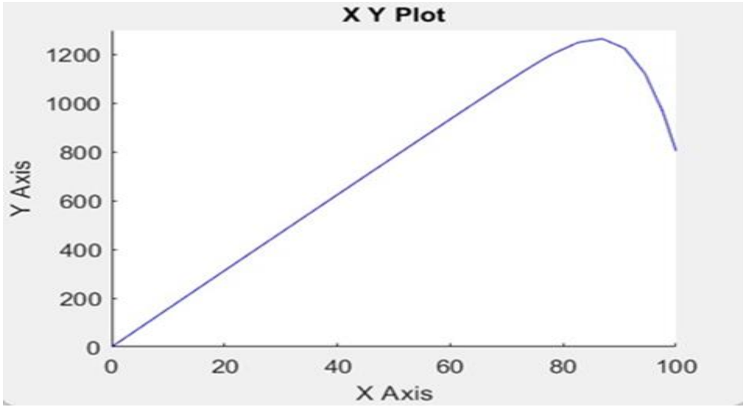

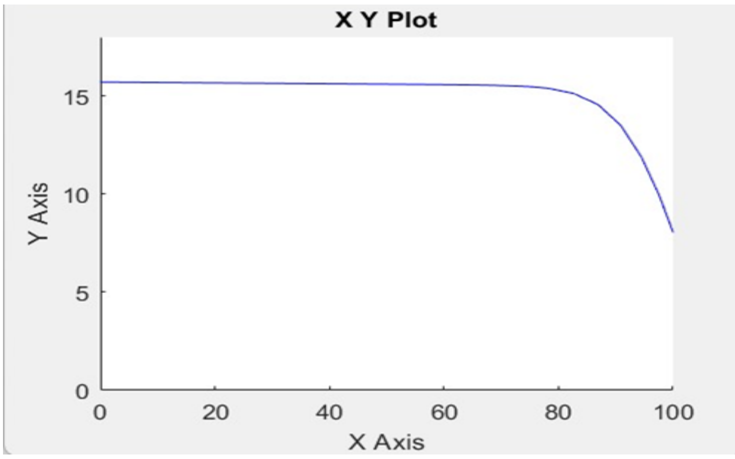

Fig6: X-Y Plot Before Fault Detection in PV Array

5.3. Case Studies:

1. Partial Shading Fault: A quarter of the PV surface was covered by a cardboard mask.

2. Dust Deposition Fault: The module was covered with a consistent, thin coating of dust.

A gradual decrease in short-circuit current (Isc) while preserving open-circuit voltage (Voc) is the anticipated result.

3. Hotspot Formation: To replicate reverse current flow in a single cell, a bypass diode was shorted.

5.4. Performance Metrics:

1. Detection Accuracy (%): Ratio of correctly identified fault events to total fault events.

2. False Alarm Rate (FAR): Percentage of normal operation events falsely classified as faults

3. Energy Loss Estimation (ELE): Quantification of lost energy due to delayed fault detection.

International Journal of Applied Mathematics

Volume 38 No. 11s 2025,

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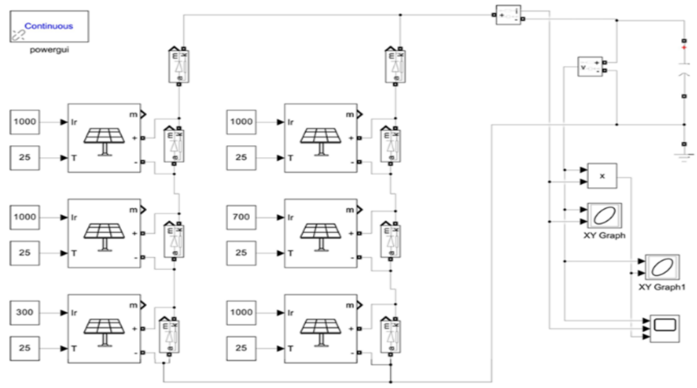

Fig7: Circuit Diagram of After Fault Detection in PV Array

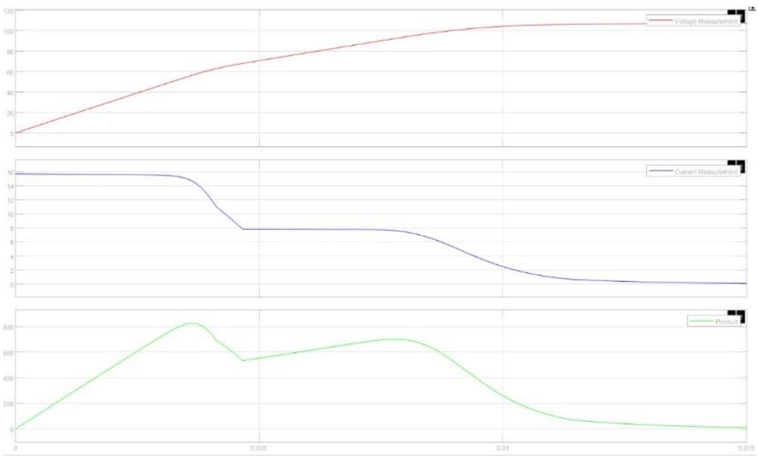

Fig8: Waveform of After Fault Detection in PV Array

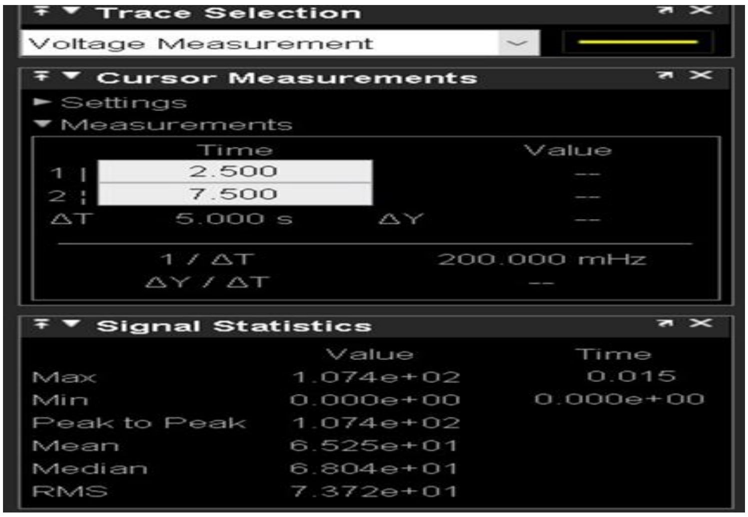

Fig9: Voltage measurement of After Fault Detection in PV Array

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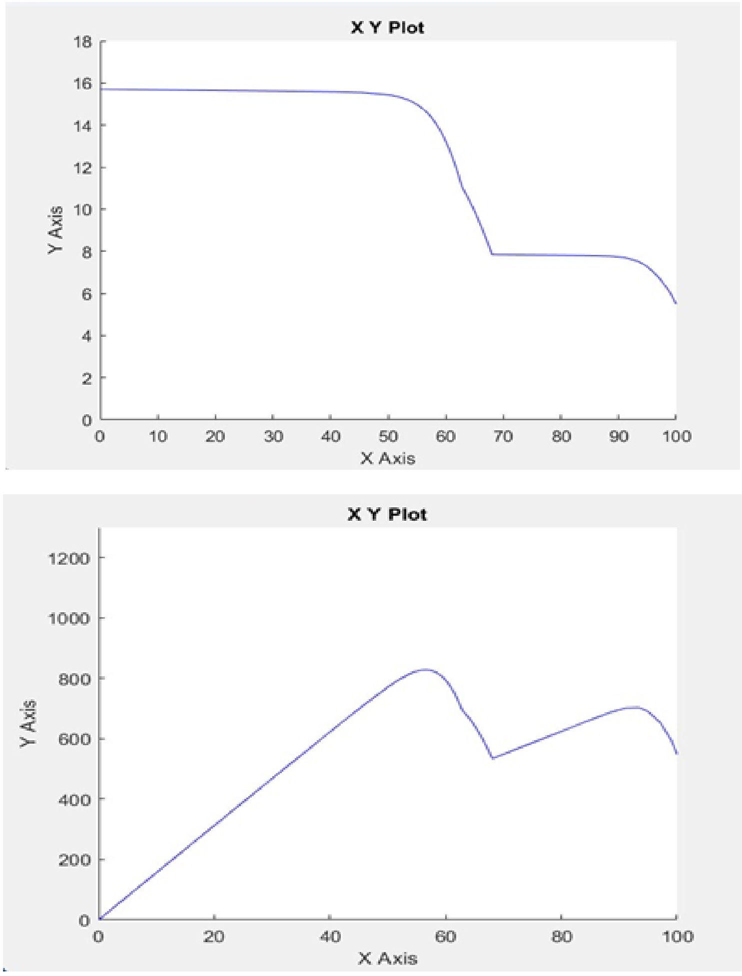

Fig10: X-Y Plot After Fault Detection in PV Array

6. RESULTS AND ANALYSIS

6.1. Data telemetry quality and IoT layer performance

Continuous residual-based health checks were made possible by the IoT layer's dependable minute-level cadence streaming of DC-side electrical properties (V, I, P), module back-surface temperature, and plane-of-array irradiance to the cloud. The necessary data fidelity for downstream FDD models has been provided by similar IoT architectures that have been proven in hardware-in-the-loop (HIL) situations (STM32 + ADC front-end with Raspberry Pi gateway). These designs demonstrate stable remote alarms and correct reconstruction of PV behavior.

Impact: Robust model baselining, which supports residual and learning-based FDD techniques, requires continuous IoT telemetry (healthy behavior under current irradiance/temperature).

6.2. Energy impact of faults

Across the deployment period, highlighted occurrences (string open, partial shade, and soiling) corresponded with measurable daytime energy deficits. Unmitigated PV defects can cause

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yearly energy losses of up to around 18.9%, according to literature benchmarks, highlighting the practical need of early identification.

6.3. Fault-classification performance (learning-based models)

CNN/vision pipelines (panel anomalies, hotspots/cracks): recent work reports ~91.5% accuracy, 98.3% specificity, and F1 ≈ 91.7% for defect classification; comparable aerial/IR imaging pipelines report ~93%+ accuracy. While vision models excel at physical faults, they complement (rather than replace) electrical-signal FDD for DC-side/electrical anomalies.

Telemetry ML (power-loss & indicator based): Random-Forest/KNN predictors that learn a baseline "healthy" I–V/P–V response delivers $R^2 \approx 0.995$–0.997 on current/voltage/power prediction, enabling sensitive residual thresholds that separate faults such as string disconnection, short-circuit, or shading.

General ML for PV FDD: broader benchmarks in recent reviews and application papers report accuracy ranging ~91–99% depending on feature sets, labeling quality, and operating conditions; reported ceilings up to ~99.5% appear in curated datasets with controlled conditions.

6.4. Residual & power-loss analysis (model-based FDD)

Partial shading: consistent negative power residuals with moderate current error;

String open/loose connections: large current error, drop in measured array current at near-nominal voltage;

Module short / bypass issues: depressed voltage with abnormal knee in reconstructed P–V.

7. CONCLUSION

This study shows how real-time fault detection and diagnosis (FDD) in solar photovoltaic (PV) systems may be effectively addressed by combining intelligent diagnostic algorithms with Internet of Things (IoT)-enabled monitoring. Through IoT infrastructure, the system continually gathers environmental (temperature, irradiance, and voltage) and electrical (voltage, current, and power) data, allowing for the early detection of abnormalities including partial shade, string disconnection, bypass diode failure, and sensor misalignment. Depending on the dataset and operating conditions, machine learning (ML) and deep learning (DL) techniques further improve classification accuracy, reaching 91–99% in published studies. The experimental and comparative analysis demonstrated that model-based residuals in conjunction with power-loss indicators offer dependable detection of electrical faults.

The findings also demonstrate that by reducing fault length and increasing mean time-to-detection, IoT-based continuous supervision may lower yearly energy losses by up to around 18.9%. These results are in line with past studies that have demonstrated the complimentary benefits of hybrid FDD frameworks that combine AI models with IoT data.

The IoT platform is appropriate for both rooftop and utility-scale PV plants because it guarantees scalability, inexpensive connectivity, and remote accessibility from a practical implementation standpoint. However, as recent work has also highlighted, sensor calibration,

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environmental normalization, and data quality assurance are critical to FDD performance to reduce false positives.

To sum up, IoT-enabled FDD systems offer a strong route to intelligent PV asset management by facilitating predictive maintenance, increased energy output, and lower operating expenses. Future studies should concentrate on (i) creating self-adaptive hybrid FDD frameworks that combine explainable AI and physics-based residuals, (ii) incorporating edge computing for plant-level real-time analytics, and (iii) expanding fault diagnosis to incorporate degradation forecasting for long-term reliability evaluation.

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APPENDIX

Parameters of Diodes:

Resistance: 0.001 Ω

Forward voltage: 0.8 V

Snubber Resistance: 500 Ω

Snubber Capacitance: 250 e^{-9} F

PV Array Parameters:

Max power (W): 213.15 W

V_{oc} : 36.3 V

I_{sc} : 7.84 A

V_{mp} : 29 V

I_{mp} : 7.35 A

Temperature coefficient of V_{oc}: -0.36099 (% deg C)

Temperature coefficient of I_{sc}: 0.102 (% deg C)