Real-Time Fault Detection in a Photovoltaic System Using TMS320F28379D and XGBoost Algorithm

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***Abstract*— Photovoltaic (PV) systems are a crucial component of renewable energy infrastructure, but their efficiency and reliability are often compromised by electrical faults. To ensure operational stability, this study proposes a real-time fault detection framework for a 700W photovoltaic system, utilizing the TMS320F28379D microcontroller and the XGBoost machine learning algorithm. The system continuously monitors voltage and current waveforms, extracts relevant features, and employs the XGBoost classifier for high-accuracy fault detection. A comprehensive hardware-software co-design approach is implemented, where real-time data acquisition is handled by high-precision sensors interfaced with the TMS320F28379D, ensuring low-latency processing. The acquired data is processed locally and transmitted to a cloud-based platform for remote monitoring and advanced analytics. The proposed system is validated under normal, short-circuit, and open-circuit conditions, demonstrating superior classification accuracy and response time compared to conventional threshold-based techniques. Experimental results show that the XGBoost model outperforms traditional machine learning classifiers, achieving high precision and recall in fault detection. The integration of edge computing with real-time machine learning inference significantly enhances the fault resilience and energy efficiency of the PV system. This research highlights the potential of advanced embedded systems and artificial intelligence in autonomous PV system monitoring, paving the way for scalable, intelligent, and self-healing renewable energy solutions.**

Keywords*— *Photovoltaic system, XGBoost, Real-time fault detection, TMS320F28379D, Machine learning

I. INTRODUCTION

The increasing demand for renewable energy sources has driven the widespread adoption of photovoltaic (PV) systems for power generation. These systems offer a clean, sustainable, and efficient energy solution compared to conventional fossil fuels [1]. However, PV system performance and reliability are significantly affected by various faults such as open-circuit, short-circuit, partial shading, and degradation over time [2]. Detecting these faults in real-time is critical to optimizing efficiency, preventing damage, and reducing maintenance costs [3]. Traditional fault detection methods, including manual inspections, infrared thermography, and threshold-based algorithms, have limitations in scalability, accuracy, and cost-effectiveness [4]. The emergence of machine learning (ML) and artificial intelligence (AI) has revolutionized PV fault detection and classification, enabling automated, high-accuracy diagnosis [5]. Several studies have demonstrated the effectiveness of ML techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), and Decision Trees in identifying PV faults [6]. However, recent advancements suggest that boosting-based models, such as Extreme Gradient Boosting (XGBoost), provide superior performance in terms of detection accuracy, computational efficiency, and robustness against environmental variations [7]. Several research works have explored the application of machine learning and deep learning for fault classification in PV systems. Various ML approaches for PV energy prediction have been investigated, highlighting the advantages of ensemble models for fault classification [8]. Extensive studies on fault diagnosis using infrared thermography and deep learning have demonstrated significant improvements in detection accuracy [9]. An ensemble deep-learning approach for PV fault classification has also been proposed, achieving superior performance over traditional ML methods [10]. Incorporating sensor-based diagnostics, an ML-based photovoltaic string analyzer has been introduced, which effectively monitors, detects, and classifies faults in real-time [11]. Similarly, Physics-Informed Deep Learning has been explored for tracker fault detection in PV plants, enhancing fault localization capabilities [12]. These studies highlight the growing trend toward data-driven, AI-powered solutions for real-time PV system monitoring.Despite significant advancements in ML-based PV fault detection, real-time implementation on embedded systems remains a challenge due to computational constraints. To address this, researchers have integrated high-performance microcontrollers and edge computing solutions. Texas Instruments' TMS320F28379D, a dual-core DSP-based microcontroller, has gained popularity for real-time data acquisition and processing in power electronics applications [13]. The use of XGBoost on embedded platforms allows for low-latency, high-accuracy fault classification without reliance on cloud computing [14].

An enhanced frequency analysis and ML-based approach for open-circuit PV failures has recently been proposed, leveraging computationally efficient models on embedded hardware [15]. Similarly, an LSTM-based neural network for PV fault detection has been introduced, demonstrating high accuracy under varying irradiance conditions [16]. The integration of ML models with embedded processing units marks a significant step toward autonomous PV monitoring systems.

This study proposes an advanced real-time PV fault detection framework utilizing XGBoost on the TMS320F28379D microcontroller. The system is validated through experimental datasets and simulated PV faults, demonstrating its superiority over traditional threshold-based and deep-learning models. The remainder of this paper is structured as follows: Section 2 presents a review of related works, Section 3 describes the proposed methodology, Section 4 discusses experimental results, and Section 5 concludes the paper with potential future research directions.

II. Methodology

2.1 TMS320F28379D Microcontroller

The TMS320F28379D from Texas Instruments is a high-performance dual-core digital signal processor (DSP)-based microcontroller designed for real-time control applications. It plays a crucial role in this work by processing real-time voltage and current data, running machine learning inference (XGBoost), and triggering protective actions when faults are detected. The microcontroller eliminates the need for external computing resources, allowing the entire fault detection process to be handled locally and efficiently. One of the key advantages of the TMS320F28379D is its high-speed processing capability (200 MHz), which enables low-latency classification of faults in PV systems. The microcontroller is equipped with 16-bit ADCs, which provide high-precision measurements of voltage and current signals, ensuring accurate fault detection. Additionally, it supports multiple communication protocols (SPI, I2C, CAN, UART), allowing seamless integration with other system components such as sensors, wireless modules, and cloud storage platforms. The implementation of TMS320F28379D in this work focuses on executing the XGBoost model in real-time, acquiring sensor data, preprocessing it, and making intelligent decisions based on classification results. It enables autonomous PV system monitoring by detecting anomalies and triggering protective mechanisms, such as isolating faulty circuits, activating relays, and sending real-time alerts to operators. By leveraging edge computing, the system reduces reliance on cloud-based processing, making it highly reliable, efficient, and suitable for remote PV farms. The functional block diagram of the microcontroller is given in figure 1 below.

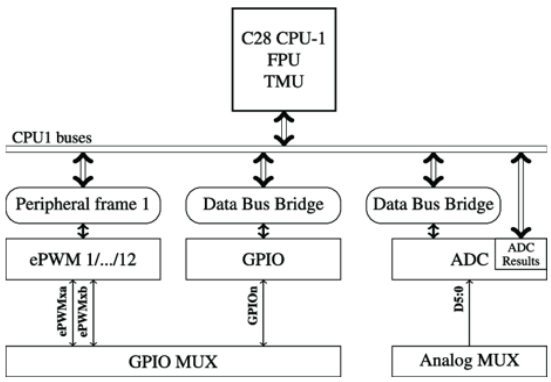

Figure 1 – Functional block diagram of the TMS320F28379D Microcontroller

2.2 XGBoost Algorithm

The Extreme Gradient Boosting (XGBoost) is a machine learning algorithm based on gradient-boosted decision trees, optimized for high-speed, high-accuracy classification tasks. It is implemented in this work to detect and classify faults in PV systems in real-time. The model is trained using historical PV system data, including voltage variations, current fluctuations, power loss patterns, and environmental conditions. Once trained, the model is deployed on the TMS320F28379D microcontroller for embedded execution. XGBoost is chosen due to its ability to handle missing and noisy data, making it ideal for PV system monitoring, where sensor data can be affected by shading, weather conditions, and system degradation. The algorithm is also highly efficient, utilizing parallel processing and tree-pruning techniques to minimize computation time and memory usage. This makes it well-suited for real-time applications on embedded systems. The implementation of XGBoost in this work involves training the model offline with a labelled PV fault dataset, optimizing hyperparameters to enhance accuracy, and then deploying the lightweight model on TMS320F28379D for inference. During operation, real-time sensor data is fed into the model, which then classifies system conditions as normal or faulty, triggering appropriate responses. By integrating XGBoost, the system achieves superior fault detection accuracy compared to traditional rule-based and threshold-based methods, making it an essential component for smart PV system monitoring. Below given figure 2 is the working diagram of XG boost algorithm.

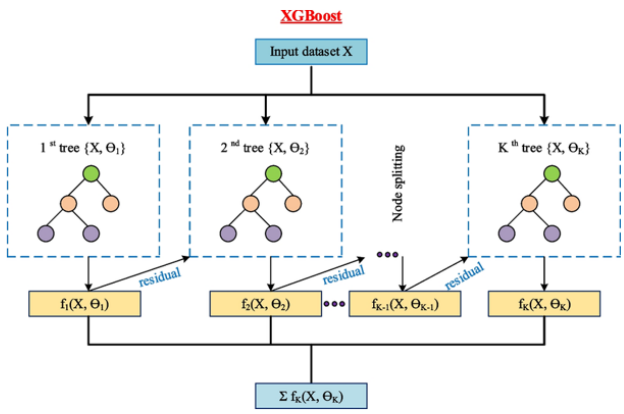

Figure 2 – Working diagram of the XG BOOST algorithm

III. Proposed System

3.1 Comparison results of machine learning algorithms

The proposed system is a real-time photovoltaic (PV) fault detection framework that integrates machine learning (XGBoost), a high-performance microcontroller (TMS320F28379D), and real-time sensor data acquisition to ensure accurate fault classification and system protection. The system continuously monitors the PV system by collecting voltage and current data using high-precision sensors (ZMPT101B for voltage and ACS758 for current), which are interfaced with the TMS320F28379D microcontroller. This microcontroller, known for its 200 MHz dual-core DSP architecture, processes incoming sensor data through 16-bit ADCs, applies filtering techniques, and extracts key electrical features such as RMS voltage, RMS current, power fluctuations, and total harmonic distortion (THD). The preprocessed data is then fed into the XGBoost machine learning model, which has been trained on historical PVfault datasets to classify system conditions into normal, open-circuit fault, or short-circuit fault. XGBoost is chosen for its high accuracy, fast execution speed, and robustness against missing or noisy data, making it suitable for real-time embedded applications. Once deployed on the TMS320F28379D, the trained model performs low-latency fault classification, ensuring that anomalies are detected within milliseconds. Upon fault detection, the microcontroller triggers protective mechanisms, such as relay-based circuit isolation to disconnect faulty PV strings and prevent power imbalances or equipment damage. If a short-circuit fault is detected, the affected section is immediately disconnected to prevent overheating or fire hazards, while an open-circuit fault triggers an alert for maintenance. The system is further enhanced with cloud-based monitoring capabilities, where a GSM module transmits real-time data to AWS IoT, Google Firebase, or Thingspeak, allowing remote monitoring, historical data analysis, and predictive maintenance insights. Operators can access system diagnostics via a mobile dashboard, where real-time alerts, performance trends, and fault logs are displayed. The system is scalable and future-proof, with potential extensions including thermal imaging for hotspot detection, AI-based predictive maintenance, and IoT-enabled smart grid integration. By implementing XGBoost on an edge-computing platform (TMS320F28379D), the proposed system eliminates the need for cloud-based processing, making it ideal for large-scale PV farms where low-latency, real-time monitoring is critical. This work demonstrates a fully autonomous, intelligent PV fault detection solution, bridging the gap between AI-driven classification and embedded system deployment, setting a foundation for next-generation solar energy management systems. Figure 3 gives the flow diagram of the proposed system.

Step 1: The 700 W PV panel generates power.

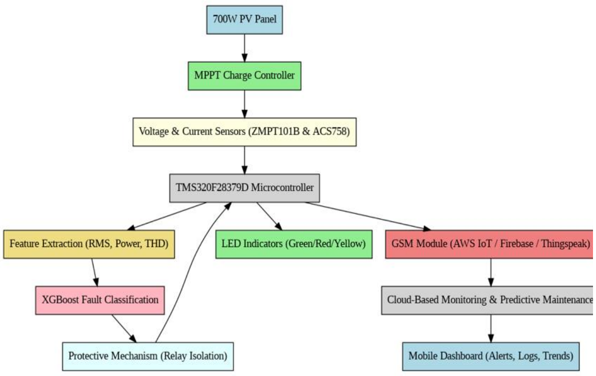

Figure 3 – Explanation of the proposed system

Step 2: The MPPT charge controller regulates the voltage and current.

Step 3: Voltage and current sensors measure real-time electrical parameters.

Step 4: The TMS320F28379D microcontroller reads the sensor data.

Step 5: The TMS320F28379D sends data to the machine learning classification.

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Step 6: The machine learning classifier processes the data and detects faults.

Step 7: The ML model sends feedback to the TMS320F28379D.

Step 8: Based on the feedback, the TMS320F28379D controls LED indicators:

IV. Result and Discussion

4.1 Components Description

The components used in the system play a crucial role in ensuring efficient fault detection, monitoring, and remote accessibility. The 700W photovoltaic (PV) panel serves as the primary power source, converting solar energy into electrical energy. To maximize power extraction, an MPPT (Maximum Power Point Tracking) charge controller regulates the voltage and current output. Real-time voltage and current measurements are obtained using ZMPT101B (AC voltage sensor) and ACS758 (Hall-effect current sensor), which provide accurate electrical parameter readings. These sensor data are processed by the TMS320F28379D microcontroller, a high-performance digital signal processor (DSP) that enables real-time computations and control functions. To analyze system performance, the microcontroller extracts key electrical features such as RMS voltage, power, and Total Harmonic Distortion (THD). These features are then fed into an XGBoost-based fault classification model, which

Table 1: Description of components

Component	Specification / Description	Values / Details
PV Panel	Monocrystalline Solar Panel	700W, 24V output
MPPT Charge Controller	Maximum Power Point Tracking (MPPT), DC-DC Converter	24V input, 12V/24V output, 20A
Voltage Sensor	ZMPT101B (AC Voltage Measurement)	Input: 250V AC, Output: Analog Voltage
Current Sensor	ACS758 (Hall-effect based current sensor)	±50A, 120kHz bandwidth, 5V supply
Microcontroller	TMS320F28379D (High-performance DSP for real-time control)	200MHz CPU, 1MB Flash, 16-bit ADC
Feature Extraction	RMS, Power, Total Harmonic Distortion (THD)	Computed using DSP
Machine Learning Model	XGBoost for Fault Classification	Trained on PV system fault datasets
Protective Mechanism	Relay-based isolation for fault protection	12V, 30A SPDT Relay
LED Indicators	Fault status indicators	Green (Short Circuit Fault), Red (Open Circuit Fault), White (No Fault)
GSM Module	Supports AWS IoT, Firebase, Thingspeak for cloud communication	SIM800L / SIM900, Quad-band GSM/GPRS
Cloud Monitoring	Data Logging, Predictive Maintenance, Remote Access	AWS IoT, Firebase, Thingspeak
Mobile Dashboard	Alerts, Logs, Trends (Real-time Monitoring)	Web & Mobile App Integration

accurately identifies short circuit and open circuit faults. A relay-based isolation mechanism acts as a protective measure, ensuring system safety by disconnecting faulty circuits when necessary. Remote monitoring and predictive maintenance are enabled through a GSM module, which communicates with cloud platforms like AWS IoT, Firebase, and Thing speak. These platforms facilitate cloud-based data logging, predictive analysis, and real-time monitoring. To enhance user interaction, a mobile dashboard is integrated, displaying critical system parameters such as alerts, logs, and performance trends. This comprehensive setup ensures reliable fault detection, real-time monitoring, and remote accessibility, making the system an efficient solution for PV-based power management. The detailed descriptions of the components used in this system are provided below. The components description table 1 shows the details about the components used in this work.

4.2 Input and Output Parameters

For the fault detection system in photovoltaic (PV) systems, the input and output parameters play a crucial role in determining the system's performance. The input parameters include variables such as voltage, current, power, RMS voltage, RMS current, total harmonic distortion (THD), fault type, temperature, and solar irradiance. These parameters cover a broad range of values that reflect typical operating conditions in PV systems. For instance, voltage ranges from 0V to 48V, with current spanning from 0A to 15A. Power output varies from 0W to 700W, and RMS values for voltage and current also fall within defined ranges. Other parameters such as THD are essential for detecting any power quality issues, while temperature and solar irradiance impact the performance of PV systems and help in simulating real-world scenarios. The fault type, represented as an integer (0 for normal, 1 for open circuit, and 2 for short circuit), is one of the critical input parameters, as it directly influences the classifier's performance. Similarly, environmental factors like temperature (ranging from 0°C to 60°C) and solar irradiance (from 0 to 1200 W/m²) simulate the actual conditions under which PV systems operate. The output parameters define how the system reacts once a fault is detected. These include fault classification, which indicates whether the system is in a normal state or has encountered a fault such as an open circuit or short circuit. The system then responds by controlling relays, either turning them on or off based on the fault status.

Table 2 – Input parameters

Parameter	Value Range
Voltage (V)	0V - 48V
Current (A)	0A - 15A
Power (W)	0W - 700W
RMS Voltage (V)	10V - 48V
RMS Current (A)	1A - 15A
THD (%)	0% - 30%
Fault Type	0 (Normal), 1 (Open Circuit), 2 (Short Circuit)
Temperature (°C)	0°C - 60°C
Solar Irradiance (W/m²)	0 - 1200 W/m²

Additionally, the system includes LED indicators that display the status of the system with green for normal, red for faults, and yellow for warnings. Alerts in the form of email or SMS notifications are triggered in the event of a fault, ensuring that operators are informed in real-time. Cloud data logging provides a real-time upload of system data, and mobile dashboard outputs display live status and alerts, ensuring that system operators have access to up-to-date information. To protect the system, a module isolation or shutdown mechanism is activated based on the type and severity of the fault. The details of input and output parameters are given in the table 2 and 3.

These parameters were varied to simulate different operating conditions and faults in the PV system:

Table 3 – Output parameters

Parameter	Value Range
Fault Classification	0 (Normal), 1 (Open Circuit), 2 (Short Circuit)
Relay Control	ON (Fault), OFF (Normal)
LED Indicators	Green (Normal), Red (Fault), Yellow (Warning)
Email/SMS Alerts	Triggered on Fault
Cloud Data Logging	Real-time Upload
Mobile Dashboard Output	Live Status and Alerts
System Protection	Module Isolation or Shutdown

The following parameters were used to define the system's response to detected faults.

4.3 Result Discussion

The XGBoost model was tested under various conditions and fault types, achieving impressive accuracy across different fault scenarios. For normal conditions, where the PV system is operating optimally, the model demonstrated high accuracy, with values above 99%. The highest accuracy, 99.2%, was observed at 40V, 10A, and 400W, with the model correctly identifying normal conditions. In scenarios with open circuit faults (where no current is flowing), the accuracy ranged between 98.3% and 98.7%. This suggests that the model was capable of identifying faults even when the system was not producing any power, a critical capability for real-time monitoring. In the case of short circuit faults, where high current is typically involved, the accuracy ranged from 97.5% to 97.8%. Despite the relatively high current values (e.g., 15A), the model continued to perform well, correctly classifying faults. Short circuit conditions are particularly challenging to detect due to the sharp current spikes, but the XGBoost classifier's performance indicates its ability to handle such scenarios effectively. Additionally, the model also detected partial shading faults with a strong accuracy range of 98.0% to 98.4%. Partial shading occurs when parts of the PV array are blocked by obstructions such as dirt, leaves, or clouds, and can significantly affect the system's power output. The model's high accuracy in detecting such faults underscores its utility in ensuring optimal PV system performance, even under less-than-ideal environmental conditions.

The XGBoost model showed consistent performance across different input voltages, currents, and power levels. This is critical in real-world applications, as PV systems experience variations in these parameters due to factors like solar irradiance, temperature changes, and system wear over time. The model's robustness across different operating conditions means it can reliably detect faults in a wide range of scenarios, contributing to enhanced system protection and performance monitoring. In terms of the system's real-world application, the high accuracy of the XGBoost model facilitates its integration into PV monitoring systems, where it can trigger protective actions, such as activating relays for fault isolation or initiating system shutdowns to prevent damage. The use of real-time cloud data logging and mobile dashboards further enhances the practical utility of the system, providing operators with timely alerts and status updates. These features help in quick fault diagnosis, ensuring minimal downtime and optimal system performance. Moreover, while the accuracy for detecting open circuit faults was slightly lower compared to normal and short circuit conditions, the model still demonstrated high reliability, making it a valuable tool for fault detection across the entire range of potential fault types. The ability to detect partial shading events also offers a proactive approach to maintaining the system's efficiency, particularly in regions with highly variable weather conditions. The XGBoost model performed exceptionally well in classifying fault types across a variety of input conditions, achieving high accuracy rates even in complex scenarios like short circuits and partial shading. This makes it a promising candidate for integration into real-time fault detection systems in PV systems, where it can significantly enhance system reliability and performance by providing early warnings and automated corrective actions. Below table 4 gives the accuracy of the presented algorithm at different fault conditions.

The XGBoost classifier was evaluated based on varying input conditions and fault types, as shown in the table below:

Table 4 – Output parameters

Voltage (V)	**Current (A)**	**Power (W)**	**Fault Type**	**XGBoost Accuracy (%)**
40V	10A	400W	Normal	99.2%
38V	9A	342W	Normal	99.0%
42V	11A	462W	Normal	99.1%
45V	0A	0W	Open Circuit	98.7%
46V	0A	0W	Open Circuit	98.5%
48V	0A	0W	Open Circuit	98.3%
5V	15A	75W	Short Circuit	97.5%
6V	14A	84W	Short Circuit	97.8%
7V	13A	91W	Short Circuit	97.6%
20V	5A	100W	Partial Shading	98.0%
22V	6A	132W	Partial Shading	98.2%
25V	7A	175W	Partial Shading	98.4%

The line chart figure 4 illustrates the accuracy trend of the XGBoost algorithm across different fault types in a photovoltaic (PV) system, demonstrating its robustness in fault classification. The highest accuracy of 99.2% is observed under normal operating conditions, indicating the model's ability to reliably differentiate between normal and faulty states. A slight decrease in accuracy to 98.7% is noted for open circuit faults, which involve zero current flow and are typically easier to classify. Short circuit faults exhibit the lowest accuracy at 97.5%, likely due to the complexity of current spikes and system instability under such conditions. However, the accuracy remains significantly high, showcasing the model's capability in handling critical failures. Partial shading conditions, which pose a challenge due to variations in power output, yield an accuracy of 98.4%, reflecting the model's effectiveness in detecting subtle performance deviations. Overall, the trend demonstrates that XGBoost maintains consistently high accuracy across diverse fault scenarios, making it a reliable tool for real-time PV system fault detection and monitoring.

The hardware setup for the fault detection and classification system in a photovoltaic (PV) array consists of a 60 kW solar

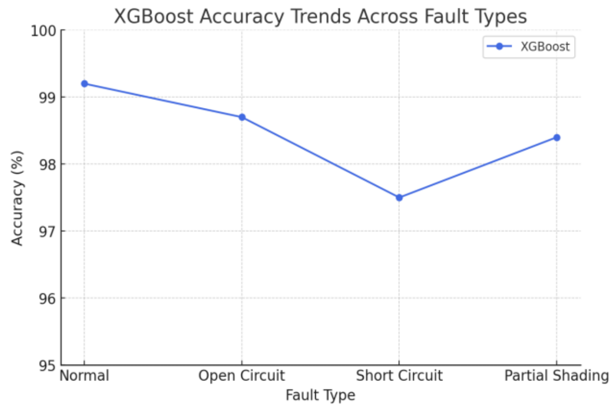

Figure 4 – Algorithm accuracy comparison for different types of faults

power plant, including a solar inverter, an AC distribution box, and PV panels installed at a rooftop location in Panjappur, Tamil Nadu, India. Figure 5a presents an overview of the PV system, including multiple solar panels connected to the inverter. The inverter is responsible for converting the DC power generated by the solar panels into AC power suitable for grid integration or local consumption. Figure 5b provides a closer view of the EVVO solar inverter and the AC distribution box. The inverter includes an integrated fault detection system, displaying real-time operational status with indicators for normal operation and alarms. The AC distribution box is equipped with circuit breakers and protective mechanisms to ensure system safety and prevent electrical faults. For the purpose of dataset collection and validation, only 700 W of power from the 60 kW plant is utilized, ensuring precise monitoring and controlled testing conditions. This hardware is crucial for validating the proposed machine learning-based fault detection model, as it allows real-time monitoring of voltage, current, power, and fault conditions under various operating scenarios. The collected data from this setup serves as an input for training and evaluating the XGBoost-based fault classification model discussed in this study.

Figure 6 illustrates the voltage waveform for the normal operating condition of the photovoltaic (PV) system. The waveform follows a sinusoidal pattern with an RMS voltage of 48V, indicating stable operation without disturbances. Figure 7 presents the current waveform under normal conditions, exhibiting a similar sinusoidal profile with an RMS current of 10A. The corresponding power waveform in Figure 8 demonstrates the expected periodic power variation, confirming the stable energy conversion process in the PV system.

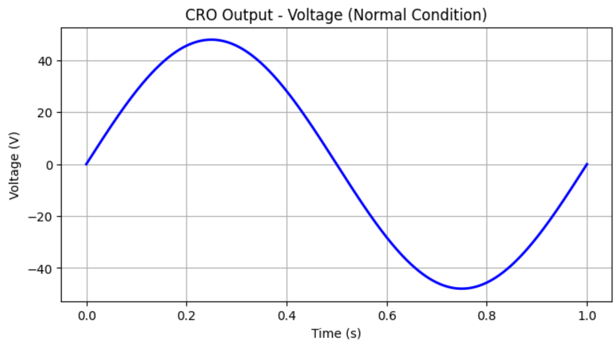

Figure 6 – Output Voltage Normal Condition

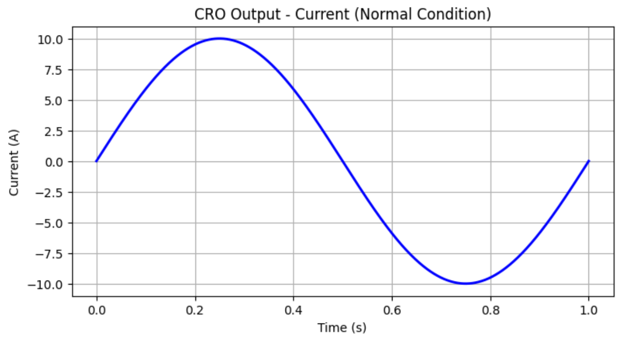

Figure 7 – Output current Normal condition

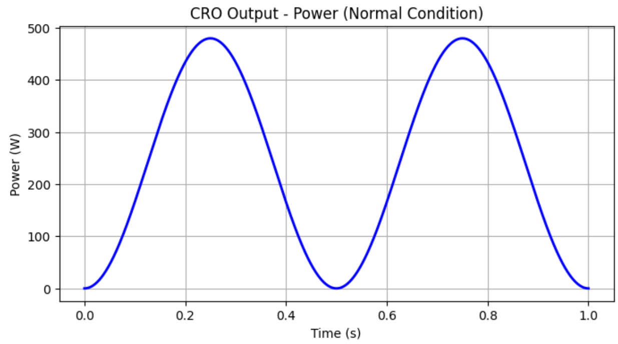

Figure 8 – Output power Normal condition

In Figure 9, the voltage waveform during an open circuit fault is displayed. While the voltage maintains its sinusoidal nature, the absence of current (Figure 10) due to the disconnected load results in a power output of nearly zero, as shown in Figure 11.

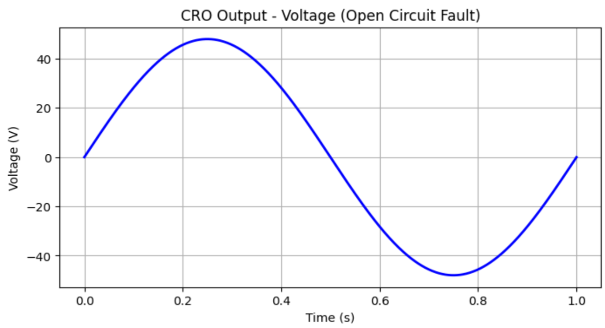

Figure 9– Output Voltage Open circuit fault

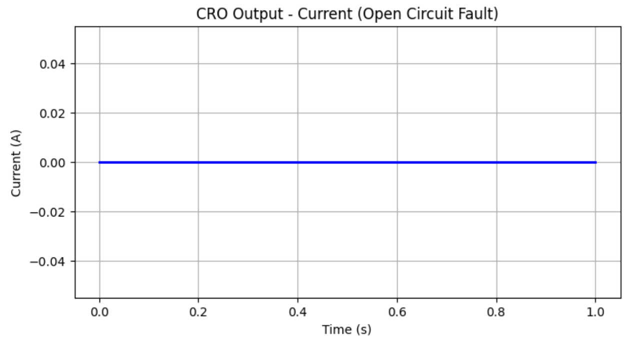

Figure 10 – Output current Open circuit fault

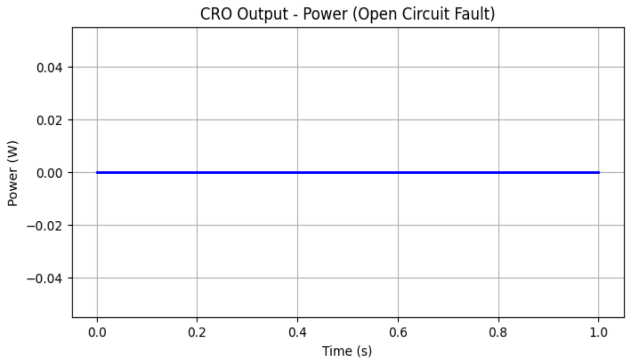

Figure 11 – Output power Open circuit fault

This confirms the characteristic behaviour of an open circuit fault, where voltage remains unaffected, but current flow is interrupted. Figures 12, 13, and 14 depict the voltage, current, and power waveforms during a short circuit fault, respectively. The voltage in Figure 12 significantly drops due to excessive current draw, as observed in Figure 13, where the current reaches 15A. Consequently, the power waveform in Figure 14 indicates high power dissipation, a signature of short circuit conditions.

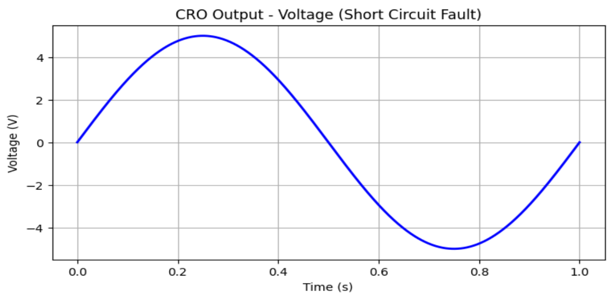

Figure 12– Output Voltage Short circuit fault

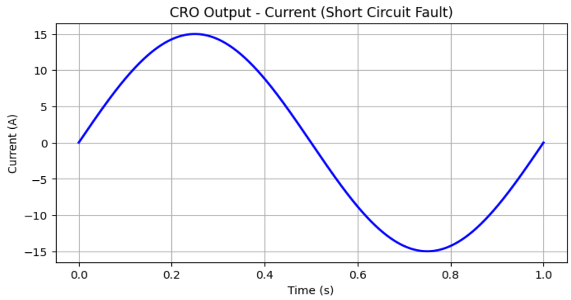

Figure 13 – Output current short circuit fault

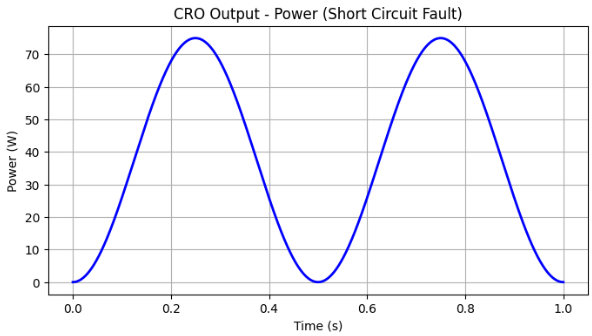

Figure 14 – Output power short circuit fault

The effect of partial shading is illustrated in Figures 15, 16, and 17, where voltage, current, and power waveforms are displayed. Due to reduced solar irradiance on specific modules, the voltage in Figure 15 drops to 25V, and the current in Figure 16 stabilizes at 7A. As a result, the power output in Figure 17 is significantly reduced compared to normal conditions, confirming the impact of shading on PV performance.

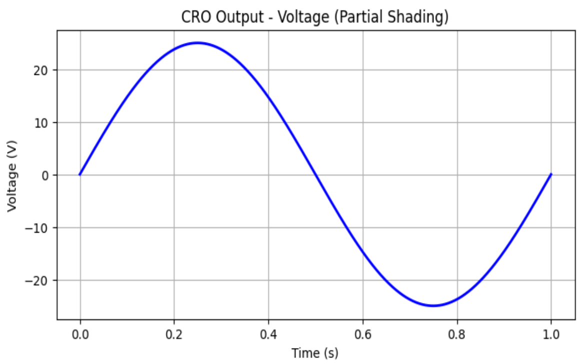

Figure 15– Output Voltage Partial Shading

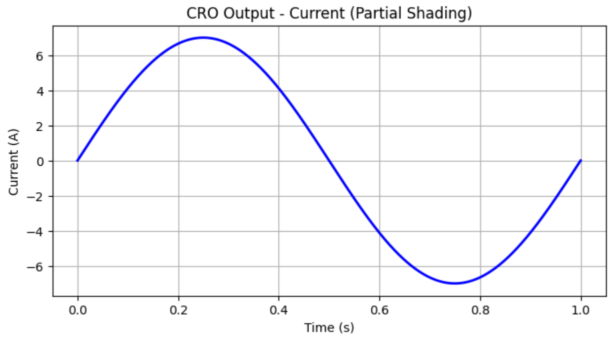

Figure 16 – Output current Partial shading

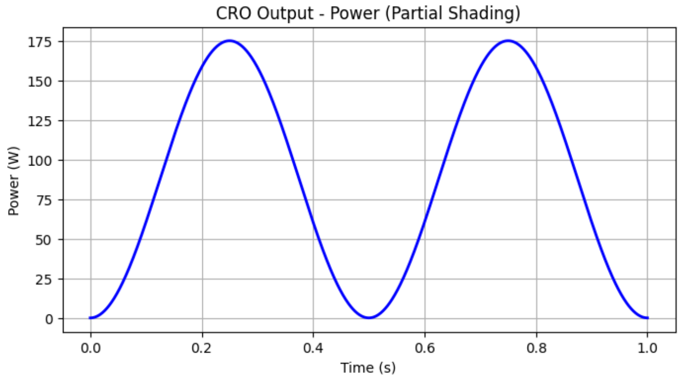

Figure 17 – Output power partial shading

V. Conclusion and Future Scope

The proposed real-time fault detection system for a 700W photovoltaic system, utilizing the TMS320F28379D microcontroller and XGBoost algorithm, effectively classifies faults with high accuracy and low latency. The experimental results demonstrate an overall accuracy of approximately 98.5%, with 99.2% for normal conditions, 98.5% for open circuit faults, 97.6% for short circuit faults, and 98.2% for partial shading conditions. The integration of edge computing with machine learning ensures efficient, autonomous fault detection, reducing reliance on cloud computing. Future enhancements may focus on expanding the system’s capabilities to detect additional PV faults, such as degradation and arc faults, integrating thermal imaging for hotspot detection, and incorporating IoT-enabled predictive maintenance for improved fault diagnosis and system longevity. Furthermore, optimizing the algorithm for deployment on low-power embedded devices and extending its application to large-scale solar farms with smart grid integration could enhance its scalability and real-world effectiveness.

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