

HYBRID SIMULATION AND EXPERIMENTAL FRAMEWORK FOR REAL-TIME FAULT DETECTION IN PV BOOST CONVERTERS USING FUZZY LOGIC AND LoRa CONNECTIVITY

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Abstract. The reliable operation of photovoltaic (PV) energy systems depends heavily on the performance of DC–DC boost converters, which are susceptible to faults in their semiconductor switches and passive components. This paper introduces a hybrid simulation and experimental framework for real-time fault diagnosis in photovoltaic boost converters, integrating fuzzy logic-based diagnostic intelligence with LoRa-enabled remote monitoring. A Python-based time-domain simulation was developed to model converter dynamics under normal and faulty conditions, encompassing scenarios of diode, inductor, and MOSFET degradation. Unlike existing approaches that rely mainly on simulation or limited laboratory validation, the proposed framework combines real-time hardware implementation with IoT-based monitoring, enabling both accurate fault classification and scalable remote supervision. Simulated voltage–current signatures were validated through a hardware prototype based on an Arduino Mega controller, voltage and current sensors, and a LoRa32 module for long-range wireless transmission to a Firebase cloud platform. The fuzzy inference system, implemented in both simulation and hardware environments, successfully classified component-level faults with sub-second response time. The results indicate reliable detection performance, reaching fault diagnosis within 1 s and cloud-based reporting in approximately 1 s, while exhibiting robustness under diverse irradiance and load conditions. The proposed hybrid framework improves diagnostic reliability, facilitates scalable IoT-based monitoring, and creates a replicable basis for the intelligent monitoring of renewable energy converters.

Keywords: photovoltaic systems, DC–DC boost converter, fuzzy logic, fault detection and diagnosis, LoRa communication, IoT-based monitoring

HYBRYDOWA PLATFORMA SYMULACYJNO-EKSPERYMENTALNA DO WYKRYWANIA USTEREK W CZASIE RZECZYWISTYM W PRZETWORNIKACH PODWYŻSZAJĄCYCH NAPIĘCIE W INSTALACJACH FOTOWOLTAICZNYCH Z WYKORZYSTANIEM LOGIKI ROZMYTEJ I ŁĄCZNOŚCI LoRa

Streszczenie. Niezawodne działanie systemów fotowoltaicznych (PV) w dużym stopniu zależy od wydajności przetworników podwyższających napięcie DC–DC, które są podatne na awarie przełączników półprzewodnikowych i elementów pasywnych. W niniejszym artykule przedstawiono hybrydową platformę łączącą symulację z badaniami eksperymentalnymi, służącą do diagnostyki awarii w czasie rzeczywistym w fotowoltaicznych przetwornikach podwyższających napięcie, integrującą inteligentną diagnostykę opartą na logice rozmytej z zdalnym monitorowaniem za pomocą technologii LoRa. Opracowano symulację w dziedzinie czasu opartą na języku Python w celu modelowania dynamiki przetwornicy w warunkach normalnych i awaryjnych, obejmującą scenariusze degradacji diod, cewek indukcyjnych i tranzystorów MOSFET. W odróżnieniu od istniejących podejść, które opierają się głównie na symulacji lub ograniczonej walidacji laboratoryjnej, proponowana platforma łączy implementację sprzętową w czasie rzeczywistym z monitorowaniem opartym na technologii IoT, umożliwiając zarówno dokładną klasyfikację usterek, jak i skalowalny nadzór zdalny. Symulowane sygnatyry napięcia i prądu zostały zweryfikowane za pomocą prototypu sprzętowego opartego na kontrolerze Arduino Mega, czujnikach napięcia i prądu oraz module LoRa32 służącym do bezprzewodowej transmisji dalekiego zasięgu do platformy chmurowej Firebase. System wnioskowania rozmytego, zaimplementowany zarówno w środowisku symulacyjnym, jak i sprzętowym, z powodzeniem klasyfikował usterki na poziomie komponentów z czasem reakcji poniżej jednej sekundy. Wyniki wskazują na niezawodną wydajność wykrywania, pozwalającą na postawienie diagnozy usterki w ciągu 1 s oraz przesłanie raportu do chmury w około 1 s, przy jednoczesnym zachowaniu odporności w zróżnicowanych warunkach natężenia promieniowania słonecznego i obciążenia. Proponowana hybrydowa struktura poprawia niezawodność diagnostyki, ułatwia skalowalne monitorowanie oparte na technologii IoT oraz tworzy podstawę do inteligentnego monitorowania przetworników energii odnawialnej.

Słowa kluczowe: systemy fotowoltaiczne, przetwornica DC–DC podwyższająca napięcie, logika rozmyta, wykrywanie i diagnostyka usterek, komunikacja LoRa, monitorowanie oparte na technologii IoT

Introduction

The global transition toward renewable energy has accelerated the adoption of photovoltaic (PV) systems due to their sustainability, low environmental impact, and decreasing cost per watt [13]. The efficiency and long-term reliability of these systems strongly depend on the performance of DC–DC boost converters, which elevate the output voltage of PV modules to levels suitable for load or battery charging [26]. However, these converters are prone to faults in key components – particularly the MOSFET, diode, and inductor – which can degrade power quality, reduce conversion efficiency, and potentially damage connected loads [25].

Traditional fault detection methods, usually reliant on static threshold monitoring of voltage or current, often face limitations in dynamic solar conditions characterized by varying irradiance or fluctuating loads [15]. These limitations often result in delayed or inaccurate fault detection. Researchers have investigated advanced Fault Detection and Diagnosis (FDD) methodologies employing fuzzy logic, neural networks, and machine learning to address these challenges [14]. Fuzzy logic has demonstrated particular effectiveness in managing the nonlinearity and uncertainty inherent in photovoltaic systems [1]. However, the majority of published studies validate their methodologies

solely through simulations or in limited laboratory conditions, resulting in a gap between theoretical reliability and practical applicability [20].

The rapid development of the Internet of Things (IoT) and low-power wireless protocols like LoRa (Long Range) has improved the monitoring of distributed renewable systems [7]. LoRa technology facilitates long-range, low-power communication suitable for remote photovoltaic installations, making it appropriate for real-time fault reporting and system monitoring [12]. Many current IoT-based photovoltaic monitoring systems typically emphasize environmental factors, while neglecting converter-level faults and allowing component degradation to remain unnoticed until significant malfunctions arise [30].

This paper introduces a hybrid simulation and experimental framework for real-time fault diagnosis in photovoltaic boost converters to tackle these problems. The proposed system integrates a Python-based numerical simulation with hardware-level validation to guarantee both theoretical precision and practical dependability. The fuzzy logic controller constitutes the diagnostic core, categorizing converter states according to input-output voltage and current behaviour, while a LoRa-based IoT interface relays fault alerts and operating data to a cloud platform for display. This dual validation approach establishes a reproducible benchmark that strengthens confidence

in the system's fault classification under diverse operational conditions [10].

Unlike existing studies that primarily rely on simulation-based validation or focus solely on IoT-based monitoring, the proposed approach introduces a fully integrated hybrid framework that combines real-time fuzzy logic-based fault diagnosis, hardware-level experimental validation, and LoRa-enabled cloud communication. This unified architecture enables accurate component-level fault identification while ensuring scalable and reliable remote monitoring, thereby bridging the gap between theoretical models and practical deployment in photovoltaic systems [18, 24, 28, 29].

The main contributions of this work are summarized as follows:

1. Development of a hybrid simulation–experimental framework for real-time fault diagnosis in PV boost converters under normal and faulty conditions.
2. Development of a fuzzy logic-based diagnostic layer capable of differentiating among normal, degraded, and critical fault conditions.
3. Integration of LoRa-enabled remote monitoring with Firebase cloud visualization, facilitating long-range, low-power data transmission and real-time fault reporting.
4. Experimental validation using both simulation and hardware testing, demonstrating fault detection within 1 s and remote notification in approximately 1 s.

This hybrid methodology bridges computational modelling with real-world implementation, creating a solid basis for intelligent, scalable, and IoT-integrated photovoltaic energy systems.

1. Literature review

Fault detection and monitoring in photovoltaic systems have been extensively studied in recent years, employing methodologies ranging from basic threshold-based techniques to advanced intelligent and IoT-enabled approaches. This section examines current advancements in boost converter fault detection, fuzzy logic diagnostic techniques, and IoT/LoRa monitoring systems [10].

1.1. Fault identification in photovoltaic boost converters

DC–DC boost converters are essential in photovoltaic systems but are susceptible to component-level failures, especially in power switches, diodes, and inductors. Conventional methods depend on monitoring voltage and current thresholds, which are simple but often inaccurate under varying irradiance

and load conditions. Recent studies have proposed current-based fault detection [25] and switch open-circuit fault analysis [15], improving detection accuracy but still facing limitations in scalability and response time [17]. In addition, recent hybrid modelling approaches highlight the importance of combining computational models with practical validation frameworks in applied technical systems [16]. However, these approaches remain limited in real-time implementation and often lack integration with scalable monitoring systems, which restricts their applicability in distributed photovoltaic installations.

1.2. Intelligent fault diagnosis using fuzzy logic and AI

To address the limitations of traditional monitoring, advanced methodologies, including fuzzy logic controllers, neural networks, and hybrid data-driven algorithms, have been utilized. Fuzzy logic is recognized for its ability to handle uncertainty and nonlinear behaviour in photovoltaic systems. Studies such as [18] and [27] have demonstrated effective diagnosis of partial shading and converter faults using fuzzy-based decision-making approaches. Nevertheless, most of these studies are based primarily on simulation environments and do not provide comprehensive hardware-level validation, limiting their applicability in real-time photovoltaic monitoring systems [9]. In addition, many existing approaches do not integrate communication technologies for remote monitoring, which reduces their effectiveness in large-scale or distributed photovoltaic systems.

1.3. Monitoring of renewable energy via IoT and LoRa technology

In parallel with advancements in intelligent diagnosis, IoT technologies have been progressively integrated into photovoltaic monitoring systems. LoRa has gained significant attention due to its long communication range and low energy consumption. Numerous studies have utilized LoRa for transmitting photovoltaic environmental data, such as irradiance and temperature [22], while others have explored its application in converter-level fault notification [19]. However, most existing systems either lack intelligent fault diagnosis capabilities or are validated only under limited experimental conditions, without addressing real-time converter-level fault detection [29]. Furthermore, the integration of IoT communication with intelligent diagnostic algorithms such as fuzzy logic remains limited, particularly in systems designed for real-time fault classification.

Table 1. Comparative summary of related work

Ref. No.	Key method	Limitations addressed by our work	Detection accuracy/metric
[25]	Review of MPPT techniques for PV systems	Focuses on MPPT rather than fault detection; no IoT integration. In the proposed approach, LoRa enables real-time fault monitoring over long distances.	N/A review
[16]	Data-driven switch fault diagnosis	Simulation-based; no wireless monitoring. The proposed LoRa–Firebase system adds remote visualization within approximately 1 s.	90% accuracy; simulation-only
[30]	Digital twin + LoRa for fault notification	High computational cost and limited practical validation. The proposed low-cost PCB and LoRa architecture improve practical deployment.	91% recall; lab-scale
[10]	Review of AI techniques in PV systems	Broad review; no hardware implementation. The proposed Arduino-based prototype provides practical validation.	N/A review
[17]	Data-driven fault diagnosis	Limited scalability; no IoT integration. The proposed LoRa system improves scalability using low-power wireless transmission.	88% precision; no field tests
[16]	Hybrid model for applied technical assessment	Focuses on hybrid modeling in another technical field, not PV converter fault diagnosis. The proposed framework applies hybrid simulation–experimental validation to real-time PV boost converter monitoring.	N/A
[27]	Fuzzy logic for PV fault detection	Simulation-based; no LoRa communication. The proposed system combines fuzzy logic with wireless monitoring and detects faults within 1 s.	85% accuracy; simulation-based
[28]	Fuzzy rules for PV anomalies	Offline processing; no IoT integration. The proposed fuzzy–LoRa framework enables real-time alerts.	87% open-circuit; no IoT
[9]	Fuzzy logic vs. ANN for PV faults	Limited hardware validation. The proposed Arduino–Firebase system provides real-time experimental validation.	89% accuracy; lab-only
[21]	LoRa for PV health monitoring	Lacks intelligent fault detection. The proposed framework integrates fuzzy logic to improve diagnostic capability.	85% efficiency; restricted tests
[23]	IoT + ML for solar forecasting	Focuses on environmental data and forecasting, not converter faults. The proposed system targets converter-level fault diagnosis.	90% accuracy; no fault metrics

Table 1 compares the proposed approach with representative studies from the literature in terms of methodology, limitations, and reported performance.

This comparative analysis highlights that existing approaches often address fault detection, communication, or validation separately, whereas the proposed framework integrates these aspects into a unified real-time diagnostic and monitoring system.

1.4. Discrepancy assessment

Despite significant progress in intelligent fault diagnosis and IoT-based monitoring, several limitations remain in the existing literature. First, many studies rely primarily on simulation-based validation, lacking real-time experimental implementation under practical operating conditions. Second, IoT-based photovoltaic monitoring systems often focus on environmental parameters such as irradiance and temperature, while neglecting converter-level faults. Third, the integration of intelligent diagnostic algorithms with long-range communication technologies such as LoRa remains limited, particularly in real-time applications.

To address these limitations, this work proposes a hybrid simulation and experimental framework that combines fuzzy logic-based fault classification with LoRa-enabled IoT monitoring. The proposed approach is validated both computationally and experimentally, ensuring reliability, scalability, and applicability in real-world photovoltaic systems.

2. Methodology

2.1. System overview

The proposed framework unites photovoltaic (PV) energy harvesting, real-time fault detection, and long-distance wireless communication into a single intelligent monitoring system. A PV module delivers power to a purpose-built DC–DC boost converter whose input and output terminals are instrumented with voltage and current sensors [29]. These analogue signals are continuously sampled by an Arduino Mega microcontroller, which executes a fuzzy logic-based decision algorithm for local fault diagnosis [23].



Fig. 1. Proposed system architecture integrating fuzzy logic diagnostics with LoRa-based monitoring

The processed data, consisting of real-time electrical measurements and categorized fault states, are transferred via a LoRa transceiver to a distant receiver (LoRa32) [24]. The receiver functions as a communication conduit, transmitting data to a Firebase cloud database using Wi-Fi [4]. A bespoke online interface displays data and fault notifications in real time, providing intuitive graphs of voltage and current trends.

This stratified design – integrating local sensing, cognitive processing, and cloud connectivity – attains fault recognition

within 1 s and web reporting in approximately 1 s [22]. This method provides energy efficiency, extensive communication range, and dependable functionality in remote solar installations, in contrast to traditional wired photovoltaic monitoring systems. Figure 1 illustrates the overall system architecture, integrating the local sensing, fuzzy-based diagnostic layer, and LoRa-enabled cloud reporting described above.

2.2. Converter and control functionality

The system features a non-isolated DC–DC boost converter that elevates a variable DC input voltage of 5–12 V to a regulated output voltage between 24 V and 50 V. The switching operation is controlled by a high-speed MOSFET driven by an ATtiny85 microcontroller, which generates a pulse-width-modulated (PWM) signal. In closed-loop operation, the controller dynamically adjusts the duty cycle to maintain the desired output voltage [6].

Two analogue feedback channels are used for regulation:

- A reference voltage V_{ref} supplied by a user-adjustable potentiometer.
- A feedback voltage V_{fb} measured at the converter output through a resistor divider network.

This configuration achieves effective voltage control with reduced hardware complexity, making it suitable for compact and cost-effective renewable energy applications. Figure 2 illustrates the PWM control architecture implemented in the ATtiny85 module.

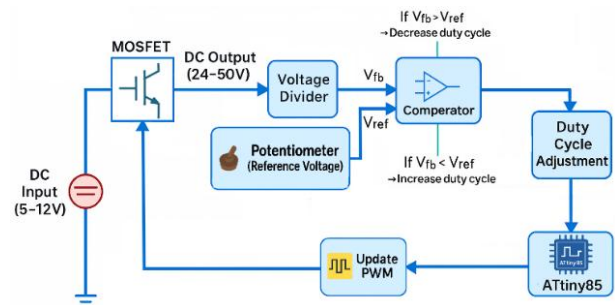


Fig. 2. Closed-loop PWM control implemented in the ATtiny85 microcontroller

2.3. Hardware configuration

The proposed system was implemented and validated using a physical hardware prototype to ensure reliability under real operating conditions [19]. The hardware configuration consists of four main layers: the photovoltaic source, the boost converter, the sensing units, and the control/communication modules. A custom PCB was designed to integrate the measurement and communication components, thereby improving compactness and reducing wiring complexity [2].

Photovoltaic Energy Source: A photovoltaic module rated at 50 W was used as the input source [8]. This module provides the variable DC power required to test the boost converter under real irradiance variations.

Boost Converter: The converter was designed using a switching MOSFET (IRF series), a fast-recovery diode (S560), and a high-frequency inductor (100 μ H) to increase the photovoltaic voltage [11]. The MOSFET duty cycle was controlled by a PWM signal to achieve stable output voltage and current.

Transducers: Voltage measurements were obtained using calibrated voltage divider circuits, while current measurements were performed using ACS712 Hall-effect current sensors [28]. The input and output sides of the converter were instrumented to enable real-time comparison between normal and faulty operating conditions.

Microcontroller: The Arduino Mega was selected as the main controller due to its multiple analog input channels and sufficient processing capability for real-time fuzzy inference execution [29]. The controller performed data acquisition, signal processing, and fault detection.

Communication Modules: A LoRa32 transceiver was integrated to provide long-range, low-power wireless transmission of fault and monitoring data [5]. The collected data were transmitted to a Firebase cloud database, from which a customized web dashboard retrieved and displayed real-time graphs and fault status alerts [3].

Customized Circuit Board: A custom PCB was produced to enhance system reliability and minimize noise interference. This PCB includes signal-conditioning circuits, microcontroller interfaces, and connectors for the LoRa module. Figure 3 illustrates the prototype hardware, including the solar panel, boost converter, and PCB assembly.

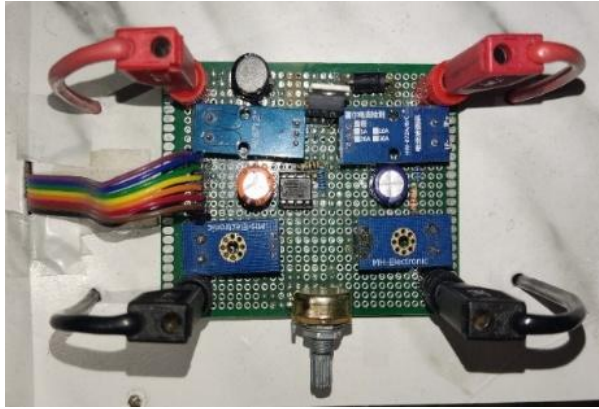


Fig. 3. Photograph of the fabricated DC-DC boost converter on custom

2.4. Software architecture and data flow

Embedded firmware

The control firmware was developed in C/C++ using the Arduino IDE. Input and output voltage and current signals were sampled at 1 kHz, processed through a moving-average filter for noise reduction, and normalized before fuzzy logic evaluation.

Fuzzy logic control

The fuzzy inference system was designed to classify the operating condition of the PV boost converter using six input parameters: input voltage V_{in} , output voltage V_{out} , input current I_{in} , output current I_{out} , voltage error e , and the rate of change of error Δe . These variables were selected because faults in the diode, MOSFET, and inductor produce distinguishable variations in the converter voltage-current behaviour.

The voltage error and its variation are defined as:

$$e(k) = V_{ref} - V_{out}(k) \quad (1)$$

$$\Delta e(k) = e(k) - e(k-1) \quad (2)$$

where V_{ref} is the reference output voltage, $V_{out}(k)$ is the measured output voltage at the current sampling instant, $e(k)$ is the current error, and $e(k-1)$ is the previous error value.

Before fuzzification, all input variables are normalized to improve numerical consistency and ensure reliable fuzzy inference under varying irradiance and load conditions. Each normalized input is mapped into linguistic categories, namely Low, Normal, and High, using triangular and trapezoidal membership functions. These membership functions were selected because they are simple, computationally efficient, and suitable for real-time implementation on the Arduino Mega platform.

The fuzzy rule base consists of expert-defined IF-THEN rules derived from the expected electrical behaviour of the boost converter under normal and faulty operating conditions. The system classifies the converter state into one of the following categories: Normal Operation, MOSFET Fault, Diode Fault, or Inductor Fault. In addition, a severity indicator is generated to distinguish between incipient and severe fault conditions.

The fuzzy inference system produces three outputs: a binary fault flag, a categorical fault type identifying the affected component, and a severity level indicating the seriousness of the detected fault.

Wireless communication and cloud integration

The LoRa transceiver transmits JSON-formatted packets at a data rate of 9600 bps. Field trials demonstrated communication ranges of up to 400 m in dense areas and approximately 1.2 km in open terrain, with packet loss below 5%. The receiver uploads the received packets to a Firebase cloud database with timestamps for continuous data logging and remote monitoring.

Web-based dashboard

The web-based dashboard provides real-time visualization of voltage, current, and PWM stability while displaying automatic fault notifications within approximately one second of detection. This allows remote operators to monitor PV system performance and fault status from any internet-connected device.

2.5. Fuzzy logic diagnostic layer

The fuzzy logic diagnostic layer represents the intelligence core of the proposed system. It interprets the measured electrical variables and classifies the operating condition of the PV boost converter in real time.

Fuzzification

During fuzzification, each measured input variable is normalized and converted into linguistic categories using triangular and trapezoidal membership functions. The main linguistic categories used in this work are Low, Normal, and High. For current-related variables, an additional Near Zero category is used to identify interruption or open-circuit-like behaviour.

The normalized membership functions are defined over the interval [0,1], which allows the fuzzy system to process voltage and current variables with different physical units in a unified manner. Table 2 lists the input variables used by the fuzzy inference system together with their diagnostic role in the classification process.

Table 2. Input variables and diagnostic meaning

Variable	Description	Diagnostic role
V_{in}	Input voltage of the boost converter	Indicates PV-side supply condition
V_{out}	Output voltage of the boost converter	Indicates boost conversion performance
I_{in}	Input current of the converter	Indicates current drawn from the PV source
I_{out}	Output current delivered to the load	Indicates load-side energy transfer
$e(k)$	Voltage error, $V_{ref} - V_{out}(k)$	Measures deviation from the desired output
$\Delta e(k)$	Change of error, $e(k) - e(k-1)$	Indicates dynamic variation of the output regulation

Table 3 presents the fuzzy rule base derived from these input variables, mapping combinations of error, change-of-error, and current conditions to the corresponding fault classification.

Table 3. Fuzzy rule base for converter fault classification

Rule No.	Input Conditions	Detected Condition
1	IF V_{out} is Low AND I_{out} is Low AND I_{in} is High	Inductor Fault
2	IF V_{in} is Low AND V_{out} is Low AND I_{out} is Near Zero	Diode Fault
3	IF $V_{in} \approx V_{out}$ AND $I_{in} \approx I_{out}$ AND Duty Cycle is High	MOSFET Fault
4	IF V_{in} , V_{out} , I_{in} , and I_{out} are within nominal ranges	Normal Operation
5	IF V_{out} is moderately reduced AND I_{out} is unstable	Incipient Fault
6	IF V_{out} is very low AND current behavior is abnormal	Severe Fault

Inference and decision criteria

The Mamdani inference method is used to evaluate the rule base defined in Table 3. The logical AND operation is implemented using the minimum operator, while the outputs of activated rules are aggregated using the maximum operator. The final fuzzy output is converted into a crisp diagnostic value using centroid defuzzification:

$$y^* = \frac{\int y\mu(y) dy}{\int \mu(y) dy} \quad (3)$$

where y^* is the crisp diagnostic output and $\mu(y)$ is the aggregated membership function.

The final decision is made according to the crisp diagnostic output and the activated rule combination. If all electrical variables remain within their nominal ranges, the converter is classified as operating normally. If abnormal voltage-current behaviour is detected, the system identifies the most probable faulty component as MOSFET, diode, or inductor. The severity level is determined according to the magnitude of voltage deviation, current variation, and persistence of the abnormal condition.

Performance

Hardware testing confirmed that the diagnostic algorithm identifies converter faults within approximately 1 s, while fault alerts appear on the web dashboard in under one second. This response time is suitable for real-time monitoring and remote supervision of photovoltaic boost converter operation.

2.6. Simulation framework

A Python-based simulation environment was established to evaluate the fuzzy diagnostic algorithm before hardware deployment. The model was implemented using NumPy and Matplotlib, enabling numerical analysis and graphical visualization of converter behaviour under different operating conditions. The simulation reproduced the transient voltage-current characteristics of the DC–DC boost converter in both healthy and faulty states [5].

The converter dynamics were expressed using the standard averaged equations of a boost converter operating in continuous conduction mode (CCM):

$$V_{out} = \frac{V_{in}}{1-D} \quad (4)$$

$$I_{in} = \frac{I_{out}}{1-D} \quad (5)$$

where V_{in} and V_{out} denote the converter input and output voltages, I_{in} and I_{out} denote the corresponding input and output currents, and D represents the PWM duty cycle. These relations served as the theoretical basis for generating time-domain data in Python.

To simulate transient behaviour, each voltage or current signal was represented by an exponential rise function:

$$x(t) = x_{ss} \left(1 - e^{-\frac{t}{\tau}}\right) \quad (6)$$

where $x(t)$ is the instantaneous value of the simulated signal, x_{ss} is the steady-state value, and τ is the time constant, approximated as 50 μ s based on the typical LC parameters of the converter. This formulation captures the smooth transition from start-up to steady state observed experimentally.

2.7. Fault modelling

Component-level faults were independently modelled to evaluate the diagnostic performance of the proposed fuzzy logic system.

Diode faults: Diode faults were represented as open-circuit, short-circuit, and partially degraded conduction states.

Inductor faults: Inductor faults were simulated by altering the inductance L or introducing saturation effects.

The inductor voltage-current relationship is expressed as:

$$V_L = L \frac{di_L}{dt} \quad (7)$$

where V_L is the inductor voltage, L is the inductance, and i_L is the inductor current. A reduction in L directly increases the current slope and reduces the energy storage capability of the converter.

MOSFET faults: MOSFET faults were modelled by varying the effective duty cycle D_{eff} , representing open-gate operation, short-circuit behavior, and degraded switching efficiency.

2.8. Fuzzy logic simulation validation

The fuzzy inference system was reproduced in Python using trapezoidal membership functions for the normalized input variables V_{in} , V_{out} , I_{in} , and I_{out} . The degree of membership of each input x in a linguistic set A_i was calculated as:

$$\mu_{A_i}(x) = \begin{cases} 0, & x \leq a_i \\ \frac{x-a_i}{b_i-a_i}, & a_i < x \leq b_i \\ 1, & b_i < x < c_i \\ \frac{d_i-x}{d_i-c_i}, & c_i \leq x < d_i \\ 0, & x \geq d_i \end{cases} \quad (8)$$

where a_i , b_i , c_i , and d_i define the trapezoidal membership boundaries.

Inference was performed using Mamdani's min-max composition. The final crisp output, expressed as the fault index, was computed using the centroid defuzzification method:

$$z^* = \frac{\int z\mu(z) dz}{\int \mu(z) dz} \quad (9)$$

where z^* is the crisp fault index and $\mu(z)$ is the aggregated output membership function.

The resulting fault index enabled classification of the converter operating condition as Normal, Open-Circuit Fault, Short-Circuit Fault, or Degraded Fault. Therefore, the simulation framework established a digital twin of the hardware prototype, providing a validated computational platform for tuning and verifying the fuzzy logic diagnostic algorithm before experimental testing.

3. Simulation model

3.1. Simulation and fault analysis

The Python-based simulation was developed to validate the proposed fuzzy logic fault detection framework for the DC–DC boost converter integrated within the photovoltaic (PV) system. The simulation environment reproduced both normal and faulty operating conditions, enabling controlled observation of converter behaviour under component-level degradation. Each simulation employed exponential time-domain models for voltage and current transients, with a time constant of approximately 50 μ s, reflecting the practical response of the converter's inductor–capacitor network.

3.2. Standard converter simulation

During standard operation, the boost converter increased the input voltage (V_{in}) from 12 V to an output voltage (V_{out}) of 24 V, sustaining input and output currents of 1.5 A and 0.6 A, respectively. The transient response demonstrated a steady exponential increase devoid of overshoot or oscillation, affirming consistent and efficient performance. Figure 4 illustrates the simulated voltage and current waveforms that establish the nominal behaviour utilized as a benchmark for subsequent fault investigation for the diode, inductor, and MOSFET components.

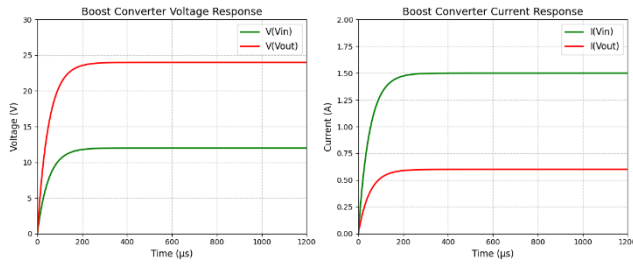


Fig. 4. Simulated input-output voltage and current characteristics of the boost converter during nominal operation, showing stable voltage boosting from 12 V to 24 V and steady current behaviour under healthy conditions

3.3. Diode fault simulation

The diode facilitates unidirectional current flow in the boost converter, and three failure modes were examined: open circuit, short circuit, and poor conduction. In the open-circuit scenario, the current pathway was disrupted, resulting in the output voltage (V_{out}) dropping to 0 V and the current diminishing to around 0.1 A, thereby ceasing energy transfer. The short-circuit scenario resulted in the failure of both input and output voltages, generating elevated transient currents typical of converter shorting. The compromised diode demonstrated partial conduction, with V_{out} stable at approximately 15 V and the output current near 0.4 A, indicating diminished efficiency owing to elevated forward resistance. Figure 5 depicts the respective voltage-current responses, each exhibiting a unique signature precisely categorized by the fuzzy diagnostic method.

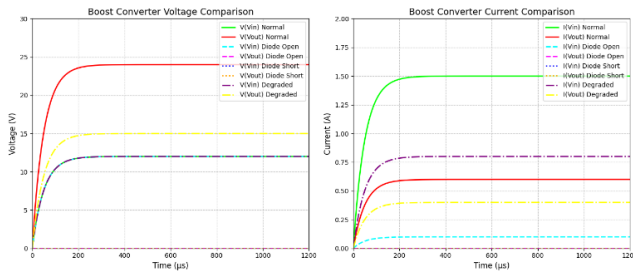


Fig. 5. Simulated input-output voltage and current profiles of the boost converter under diode fault scenarios, including open-circuit, short-circuit, and degraded conduction conditions

3.4. Inductor fault simulation

The inductor, as the main energy storage element, was tested under open-circuit, short-circuit, and reduced-inductance faults. The open fault halted energy transfer, driving V_{out} to 0 V and I_{in} nearly to zero. The short fault negated the boost effect, equalizing voltages near 12 V and raising both currents to about 1.5 A. Reduced inductance yielded $V_{out} \approx 15$ V, $I_{in} \approx 1.0$ A and $I_{out} \approx 0.5$ A indicating efficiency loss. Figure 6 shows the distinct waveforms, each fault clearly identified by the fuzzy diagnostic system.

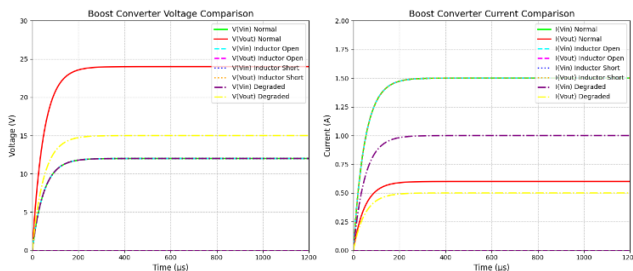


Fig. 6. Simulated input-output voltage and current characteristics of the boost converter under inductor fault conditions, showing the effects of open-circuit, short-circuit, and reduced-inductance faults

3.5. MOSFET fault simulation

The MOSFET, serving as the converter's primary switching component, was examined under open, short, and degraded conditions. In standard operation, the converter boosted 12 V to 24 V with nominal current ratios. The open-fault scenario halted switching, resulting in $V_{out} = 12$ V and reduced current ($I_{in} = I_{out} = 0.5$ A). Under short-circuit conditions, continuous conduction equalized voltages ($V_{in} = V_{out} = 12$ V) and increased currents to 1.5 A. The degraded case exhibited partial switching, yielding $V_{out} = 18$ V, $I_{in} = 1.2$ A and $I_{out} = 0.5$ A indicating increased on-state resistance and efficiency loss. Figure 7 depicts the voltage-current responses, where each condition produced a distinct signature accurately recognized by the fuzzy diagnostic system.

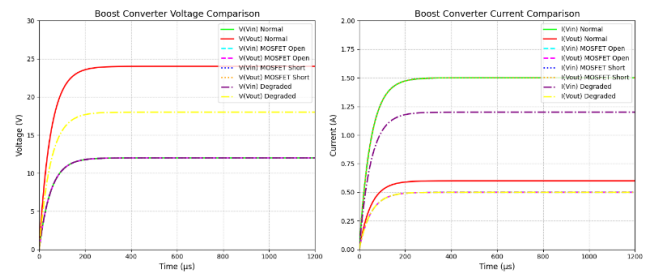


Fig. 7. Simulated input-output voltage and current behaviour of the boost converter under MOSFET fault scenarios, including open-gate, short-circuit, and degraded switching conditions

4. Experimental setup and validation

4.1. DC-DC boost converter with conventional functionality

The experimental prototype of the photovoltaic-fed boost converter was first evaluated under normal operating conditions to establish a performance baseline. The converter consistently increased the input voltage from 11.8–12.2 V to a stabilized output voltage of 24.0–24.3 V, delivering an average output current of 1.6 A and an output power of approximately 38.5 W. The measured voltage and current responses confirmed stable energy conversion with minimal ripple. The current waveforms also demonstrated stable operation of the switching MOSFET and inductor. No anomalies or false fault triggers were observed during this phase, confirming the reliability of the sensing and diagnostic layers under fault-free conditions, as shown in Figure 8.

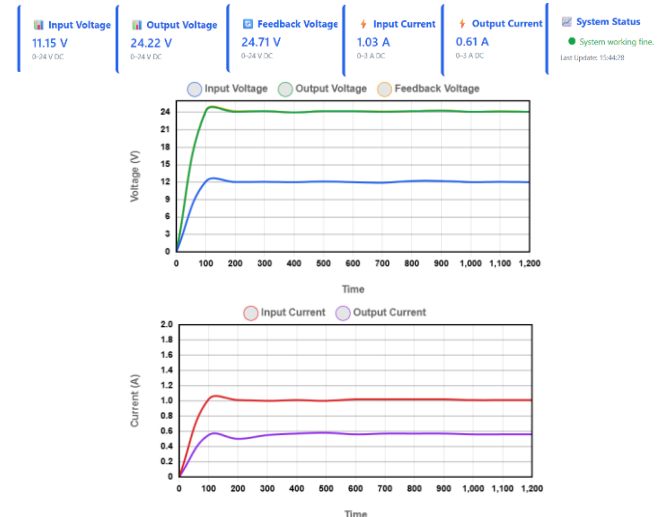


Fig. 8. Experimental voltage and current characteristics of the photovoltaic-fed boost converter under normal operation, showing stable conversion from approximately 12 V input to 24 V output without false fault detection

4.2. Fault injection in the boost converter

To evaluate the reliability of the proposed fuzzy diagnostic system, several hardware-level faults were deliberately introduced into the boost converter. Each fault scenario was analysed in terms of voltage and current behaviour, power degradation, detection latency, and fault visualization on the IoT-enabled web dashboard.

MOSFET fault

The shutdown of the MOSFET gate caused an immediate interruption of the switching process. As a result, the output voltage decreased from 24.2 V to 12.3 V, while the output current decreased to 0.9 A. Consequently, the delivered power dropped from 38.7 W to 11.1 W. The fuzzy logic algorithm detected this fault in 0.75 s and triggered the alert "Converter MOSFET Fault!" on the web dashboard, as illustrated in Figure 9.

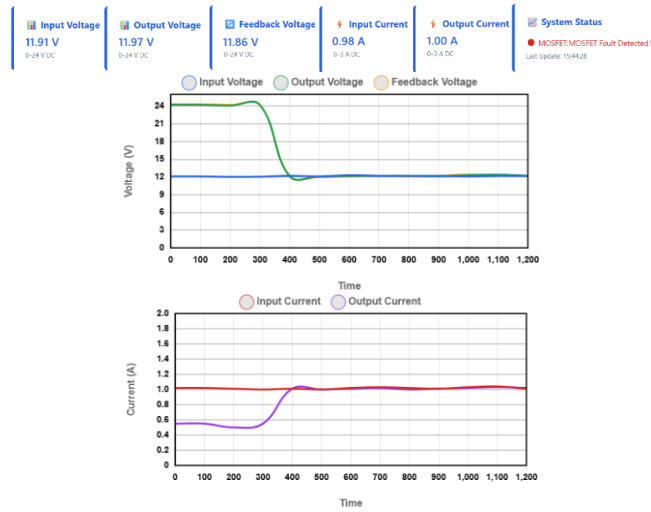


Fig. 9. Experimental response of the boost converter under MOSFET fault condition, showing the reduction of output voltage from 24.2 V to 12.3 V and the corresponding decrease in delivered power

Diode fault

The converter exhibited significant instability when the freewheeling diode was bypassed, causing the output voltage to fluctuate between 10 V and 16 V and the output current to oscillate between 0.6 A and 1.2 A. As a result, the output power varied between 6 W and 19 W. The diagnostic system detected the fault in 1.0 s and displayed the alert "Converter Diode Fault!" on the web dashboard, as shown in Fig. 10.

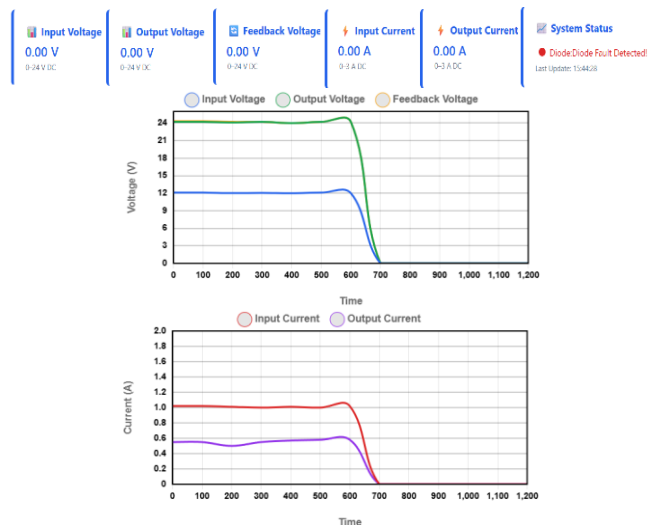


Fig. 10. Experimental voltage and current response of the boost converter under diode fault condition, showing output voltage fluctuation between 10 V and 16 V and current oscillation between 0.6 A and 1.2 A

Inductor fault

A partial short-circuit in the inductor winding reduced the inductance, leading to unstable current behaviour. The converter output voltage decreased to 15.2 V, while the output current increased to 1.9 A, causing the delivered power to drop to 28.9 W. The diagnostic system detected the fault in 0.9 s and displayed the alert "Converter Inductor Fault!" on the web dashboard. The elevated inductor temperature confirmed the abnormal stress condition caused by the fault, as illustrated in Figure 11.

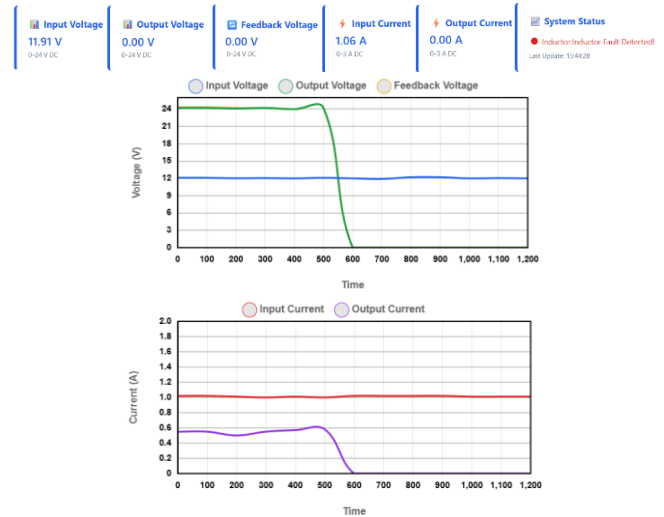


Fig. 11. Experimental response of the boost converter under inductor fault condition, showing reduced output voltage, increased current, and unstable energy-transfer behaviour caused by partial inductance degradation

Table 4 summarizes the key experimental results obtained for each fault scenario, including detection time and cloud-reporting latency.

Table 4. Summary of experimental fault-detection results

Operating condition	Main observed behaviour	Quantitative result	Detection time
Normal operation	Stable boost conversion	$V_{in} = 11.8\text{--}12.2\text{ V}$ $V_{out} = 24.0\text{--}24.3\text{ V}$ $I_{out} = 1.6\text{ A}$ $P_{out} = 38.5\text{ W}$	No fault
MOSFET fault	Switching interruption	V_{out} decreased from 24.2 V to 12.3 V $I_{out} = 0.9\text{ A}$ P_{out} decreased from 38.7 W to 11.1 W	0.75 s
Diode fault	Output voltage instability	$V_{out} = 10\text{--}16\text{ V}$ $I_{out} = 0.6\text{--}1.2\text{ A}$ $P_{out} = 6\text{--}19\text{ W}$	1.0 s
Inductor fault	Reduced inductance and unstable current	$V_{out} = 15.2\text{ V}$ $I_{out} = 1.9\text{ A}$ $P_{out} = 28.9\text{ W}$	0.9 s

As summarized in Table 4, the experimental results demonstrate that the proposed fuzzy logic-based diagnostic system successfully identified the three tested converter faults using their voltage-current signatures. Under MOSFET fault conditions, the output voltage decreased from 24.2 V to 12.3 V, and the fault was detected in 0.75 s. Under diode fault conditions, the output voltage fluctuated between 10 V and 16 V, while the output current oscillated between 0.6 A and 1.2 A, and the fault was detected in 1.0 s. Under inductor fault conditions, the output voltage decreased to 15.2 V, while the output current increased to 1.9 A, and the fault was detected in 0.9 s. These results confirm that the proposed framework provides real-time fault diagnosis and cloud-based alert reporting within approximately one second.

The fuzzy inference method provided stable fault classification under the tested operating conditions, while LoRa connectivity enabled reliable low-latency fault reporting

to the cloud interface for continuous remote monitoring. This integration of local intelligent diagnosis with IoT-based communication addresses two key limitations identified in the literature: limited real-time experimental validation and insufficient communication scalability. Therefore, the proposed framework supports improved operational reliability for photovoltaic systems in remote applications.

5. Conclusion

This study introduced an intelligent and practical framework for real-time fault diagnosis and monitoring in photovoltaic (PV) boost converters by integrating fuzzy logic diagnostics with LoRa-based IoT communication and cloud-based visualization. Hardware validation confirmed the system's effectiveness in identifying critical converter faults, namely MOSFET, diode, and inductor failures. The experimental results showed that the MOSFET fault was detected in 0.75 s, the diode fault in 1.0 s, and the inductor fault in 0.9 s, while fault alerts were displayed on the web dashboard within approximately one second. These findings confirm that the proposed framework provides reliable real-time diagnosis and remote monitoring under practical operating conditions.

The originality of this work lies in the integration of three key elements within a single framework:

1. a fuzzy logic inference system designed for photovoltaic boost converter fault diagnosis;
2. a LoRa-based communication network suitable for remote monitoring applications;
3. cloud-based visualization enabling real-time data access and fault notification.

Unlike conventional approaches that address these elements separately, the proposed framework combines local intelligent diagnosis, experimental validation, and scalable IoT communication. These elements collectively provide a cost-effective, scalable, and experimentally validated diagnostic platform for improving the operational reliability of photovoltaic energy systems.

Future research will extend the proposed design to larger multi-converter photovoltaic arrays, investigate hybrid artificial intelligence approaches by combining fuzzy inference with machine learning and digital twin modelling, and improve energy-efficient IoT communication protocols. Predictive maintenance strategies will also be explored to enable earlier fault identification and preventive action. In addition, data privacy and protection mechanisms should be considered to support the wider deployment of IoT-enabled renewable energy monitoring systems. The demonstrated effectiveness of the proposed framework provides a solid foundation for future intelligent and self-diagnosing photovoltaic monitoring systems.

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