Wireless Fault Detection in Solar Panels

Ms. FATHIMATH RASHIHATH V. K
ASSISTANT PROFESSOR
EEE DEPARTMENT
VIMAL JYOTHI ENGINEERING COLLEGE

AJUWAID ANEESH, CHANDRAJITH K, DIYA C, N R KARTHIK
VIMAL JYOTHI ENGINEERING COLLEGE, KANNUR, INDIA EEE DEPARTMENT
Vimal Jyothi Engineering College, Kannur, India

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Abstract - Efficient monitoring of solar photovoltaic (PV) systems is essential to ensure sustained energy generation and long-term reliability. Conventional inverter-level monitoring methods are unable to detect and localize faults occurring at individual panel levels, resulting in unnoticed performance degradation. This paper presents the design and implementation of a distributed Internet of Things (IoT)-based monitoring architecture integrated with a Long Short-Term Memory (LSTM) neural network for intelligent panel-level fault detection. Voltage, current, and temperature parameters are continuously acquired using embedded sensors and transmitted wirelessly to a cloud-based database. The collected time-series data are processed using an LSTM model to identify abnormal operational patterns. Experimental evaluation under simulated fault conditions demonstrates effective detection performance with high accuracy and low latency. The proposed system provides a scalable, cost-effective, and practical approach for intelligent photovoltaic system monitoring.

Key Words: Solar photovoltaic systems, IoT monitoring, LSTM networks, fault detection, panel diagnostics, renewable energy systems.

1.INTRODUCTION

Solar photovoltaic installations have witnessed rapid growth in recent years due to increasing demand for clean and sustainable energy. Despite their reliability, PV modules are susceptible to environmental and operational stresses such as partial shading, dust accumulation, overheating, aging, and wiring faults. Even minor degradation at the panel level can reduce the overall efficiency of the system, particularly in string-connected configurations where one underperforming module affects the entire chain.

Most commercial monitoring systems operate at the inverter or string level. Although such monitoring provides aggregate power output, it does not allow precise localization of faults. As a result, minor abnormalities may remain undetected until they cause significant energy loss.

Recent advancements in embedded systems, wireless communication, and machine learning offer new possibilities for intelligent distributed monitoring. By equipping each panel with sensing capability and integrating time-series analysis algorithms, it becomes feasible to detect faults at an early stage. This work presents the development of such a system, combining IoT-based sensing with LSTM-based anomaly detection.

2. LITERATURE REVIEW

Fault detection in PV systems has been explored through electrical characterization, imaging techniques, and data-driven methods.

One common method for analyzing solar panel performance is I-V curve tracing,Which helps in understanding electrical behaviour, it requires manual equipment and offline testing, limiting its practicality for continuous monitoring.

Thermal imaging and electroluminescence techniques enable detection of cracks and hotspot formation. These approaches achieve high accuracy but involve expensive instrumentation and are less suitable for large-scale distributed deployment.

IoT-based monitoring systems have emerged as a cost-effective alternative, allowing real-time parameter acquisition and remote supervision. However, many existing systems rely on static threshold-based fault detection. Such approaches may fail to capture gradual degradation patterns or complex temporal dependencies.

Recurrent neural networks, particularly Long Short-Term Memory (LSTM) models, are well suited for time-series analysis due to their gated memory structure. LSTM networks can learn long-term dependencies in sequential data, making them effective for identifying subtle deviations in PV electrical behavior. This study integrates IoT-based sensing with LSTM-driven classification to enhance panel-level fault detection capability.

3. SYSTEM ARCHITECTURE

The methodology focuses on monitoring electrical and environmental parameters of solar panels using sensor-based data acquisition. Voltage, current, and temperature are continuously measured and transmitted to a central system.

The collected data is processed and used to train an LSTM model, which learns the normal operating behavior of the system. Any deviation from this behavior is treated as a potential fault condition.

The system is designed to work in real time, allowing early detection of faults and reducing performance losses.

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One of the key advantages of the proposed system is its ability to operate continuously without human intervention. Since each panel is monitored individually, faults can be localized accurately without affecting the analysis of other panels. This improves the overall reliability of the system and allows faster corrective actions.

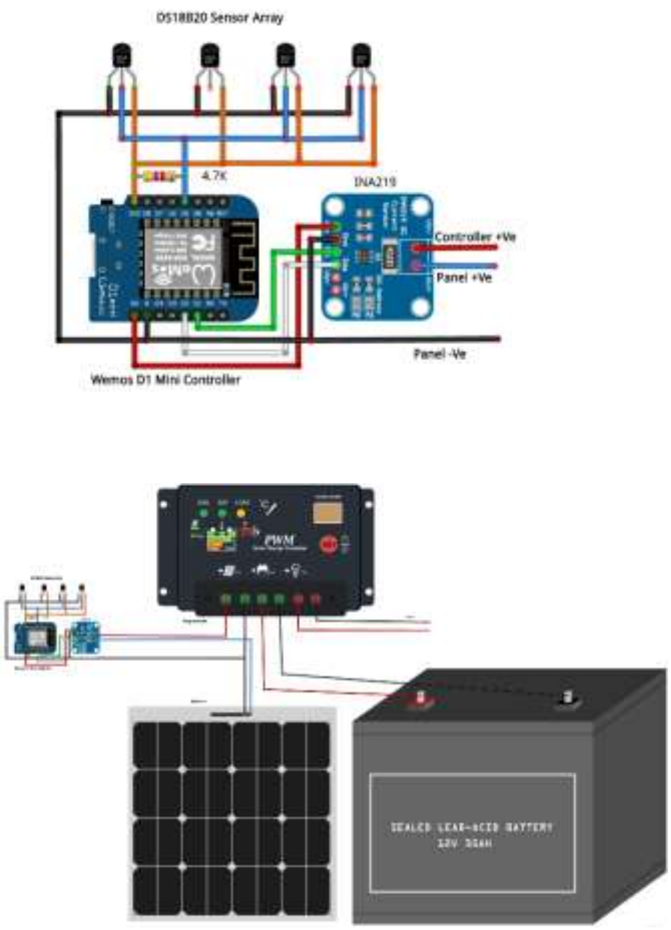

Fig -1: System Architecture

4.HARDWARE IMPLEMENTATION

Each photovoltaic panel is equipped with:

- INA219 sensor for voltage and current measurement
- DS18B20 temperature sensor
- Wemos D1 Mini (ESP8266) microcontroller

The microcontroller collects sensor readings through I2C and digital interfaces and prepares structured data packets for wireless transmission.

5.COMMUNICATION FRAMEWORK

The ESP8266 module transmits data via WiFi to a Firebase real-time database. Each sensing node is assigned a unique identifier to enable panel-level tracking and localization.

6.SYSTEM BLOCK DIAGRAM

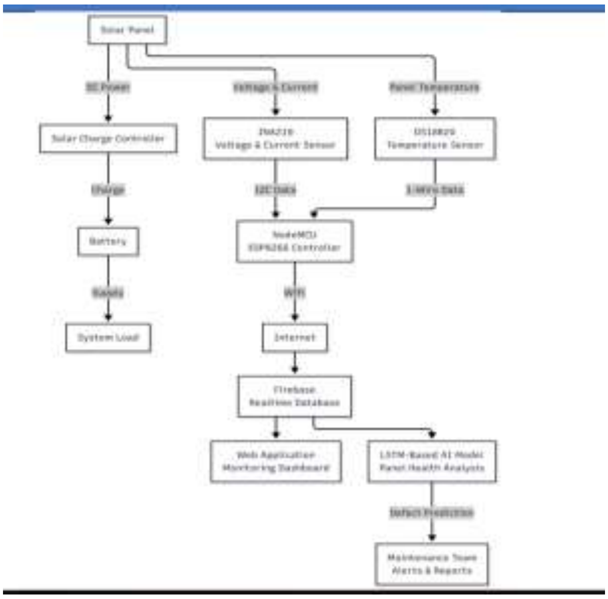

Fig -2: block diagram

7. METHODOLOGY

Data Acquisition

In this system, data is collected directly from solar panels using sensors that measure voltage, current, and temperature. These sensors are connected to a microcontroller, which continuously reads and processes the values.
The collected data represents the real-time operating condition of each panel and is transmitted wirelessly to a cloud database for further analysis.

Data Preprocessing

The collected sensor data may contain small fluctuations due to environmental variations and measurement noise. To improve data quality, basic preprocessing techniques such as filtering and smoothing are applied.
The data is then normalized to maintain consistency across different parameters. This ensures that all input values are within a similar range, which helps improve the performance of the learning model.

LSTM Model Design

Fig -3: Live panel monitoring

The LSTM model is used to analyze the time-series sensor data. Since solar panel parameters change over time, LSTM helps in capturing these sequential patterns effectively.

The model is trained using historical data representing normal and faulty conditions. By learning these patterns, the system can identify deviations and classify them as fault conditions.

This approach allows early detection of faults and helps in maintaining the efficiency of the solar panels.

Fault Detection Logic

The system classifies the operating condition of the panel as either normal or faulty based on the output of the LSTM model.

The fault classification function is defined as:

y = {1, Fault condition; 0, Normal operation}

Electrical power is calculated using the relation:

$$P=V\times I$$

Efficiency can be estimated as:

$$\eta = Pout / (G \times A)$$

where "G" represents solar irradiance and "A" denotes panel area. Deviations in these parameters over time indicate abnormal operating conditions.

8.EXPERIMENTAL EVALUATION

The system was tested under simulated fault scenarios including:

- Partial shading
- Elevated temperature conditions
- Load disturbances

The LSTM model successfully identified abnormal temporal patterns corresponding to fault conditions.

9. COMPARATIVE ANALYSIS

The proposed system provides real-time operation, intelligent detection capability, and panel-level localization, making it suitable for scalable deployment.

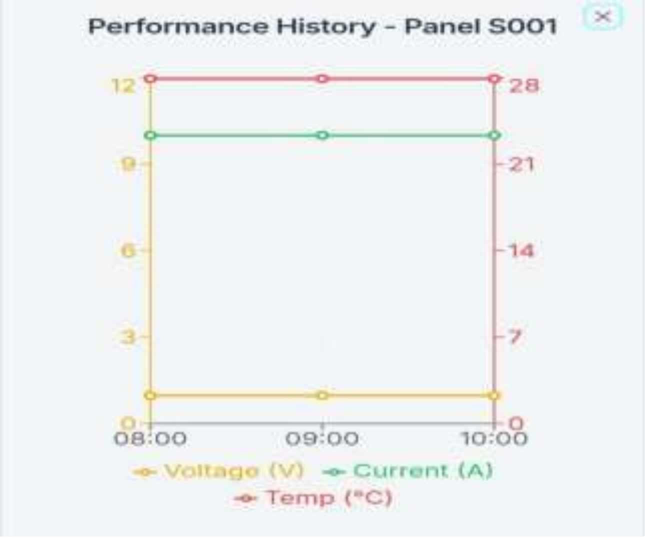

Fig -3: Performance graph

10.DISCUSSION

The integration of distributed IoT sensing with LSTM-based analysis enables early detection of subtle anomalies that may not be captured by threshold-based methods. The system demonstrates robustness under normal environmental variations. However, sensor accuracy and network stability influence performance, highlighting the importance of calibration and reliable connectivity.

11.FUTURE WORK

The proposed system demonstrates effective fault detection in solar panels using IoT-based monitoring and LSTM analysis. However, there is still room for improvement to enhance its performance in real-world conditions. One important direction is to expand the dataset by collecting data from different environmental conditions and locations. A more diverse dataset will allow the model to better understand variations in solar panel behavior and improve its overall accuracy. In addition, incorporating extra parameters such as solar irradiance, humidity, and wind speed can provide a more complete understanding of panel performance and lead to more reliable fault detection.

Another area for improvement is optimizing the LSTM model to reduce computational complexity and improve processing speed. This becomes especially important when the system is deployed in large-scale solar installations. Implementing edge computing can further enhance system efficiency by enabling data processing closer to the hardware, reducing dependence on cloud services and minimizing latency. These improvements can make the system faster, more efficient, and better suited for real-time applications.

Furthermore, the system can be enhanced by integrating user-friendly features such as real-time alert notifications and performance dashboards. This would allow users to quickly identify faults and take necessary actions without delay. Developing a clear visualization platform for monitoring panel performance and fault history can improve usability for operators. Finally, testing the system under real industrial conditions and scaling it for larger deployments will help evaluate its reliability, robustness, and long-term effectiveness.

12. CONCLUSIONS

This paper presented the development of a distributed IoT-based panel-level fault detection system using LSTM networks. The proposed approach enables real-time monitoring and intelligent classification of photovoltaic operating conditions. Experimental results demonstrate reliable detection performance, supporting the feasibility of scalable intelligent solar monitoring systems

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