



A Machine Learning-Based Approach for Fault Detection and Diagnosis in Photovoltaic Systems

Vaishnavi V. Patil¹, Vaishnavi V. Kapshikar², Prof. Yogesh P. Khadse³, Dr. Kiran A. Dongre⁴

^{1,2} Assistant Professor, Department of Electrical Engineering,

Prof. Ram Meghe College of Engineering and Management Badnera, Amravati, India, 444606

^{3,4} Students, Department of Electrical Engineering,

Prof. Ram Meghe College of Engineering and Management Badnera, Amravati, India, 444606

Abstract - The rapid global integration of Photovoltaic (PV) systems requires robust monitoring and diagnostic mechanisms to ensure high efficiency and operational safety. PV systems are highly susceptible to various anomalies, including line-to-line faults, open circuits, partial shading, and degradation, which can severely diminish power output and cause permanent damage. Traditional fault detection methods rely on predefined thresholds, which often fail under fluctuating environmental conditions. This paper proposes a Machine Learning (ML) based approach for the automatic detection and diagnosis of faults in PV systems. By extracting key electrical features (voltage, current, power) and environmental data (irradiance, temperature), several supervised ML algorithms, including Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Random Forest (RF), are evaluated. The methodology involves data preprocessing, feature extraction, and model training using simulated I-V characteristic curves under healthy and faulty conditions. The proposed model demonstrates high diagnostic accuracy, offering a reliable, sensor-efficient, and computationally viable solution for real-time predictive maintenance in solar energy systems.

Keywords: Photovoltaic System, Fault Diagnosis, Machine Learning, Artificial Neural Networks (ANN), Predictive Maintenance, Partial Shading.

INTRODUCTION

The global shift toward renewable energy has put solar Photovoltaic (PV) systems at the center of our sustainable future. Yet, despite their growth, these systems are far from "set and forget." Operating outdoors leaves them exposed to extreme heat, dust, lightning, and general wear-and-tear. When a fault occurs whether it's a cracked panel or a loose connection the result isn't just lost power; it can lead to fire hazards and permanent equipment damage.

The real challenge for operators isn't just knowing that something is wrong, but knowing what is wrong. Is the drop in power due to a cloud passing over, or is a string of panels failing? Traditional tools often require a technician to go on-site, which is expensive and slow. To solve this, we are looking toward Machine Learning. By teaching computers to recognize the "signatures" of different faults, we can create a system that monitors itself 24/7, providing instant diagnostics that allow for faster, smarter maintenance.

LITERATURE REVIEW

In recent years, the academic community has moved away from manual "check-ups" toward automated diagnostics. Early research focused heavily on thermal imaging and visual inspections. While these methods are highly accurate, they are difficult to scale across thousands of panels. To bridge this gap, researchers began exploring the data already being collected by the systems themselves: current and voltage.

Aghaei et al. demonstrated that by looking at the Maximum Power Point (MPP), we could begin to categorize different types of system behavior. However, environmental "noise"—like shifting sunlight—often confused early models. To combat this, researchers highlighted the power of Support Vector Machines (SVM) in drawing clear lines between "healthy" and "faulty" data. More recently, the focus has shifted toward ensemble methods like Random Forest, which use multiple "decision paths" to reach a more reliable conclusion. Our study builds on this foundation by directly comparing these popular algorithms to see which one handles the unique, non-linear challenges of PV systems most effectively.

Classification of PV System Faults

To effectively train a machine learning model, the target faults must be clearly defined. This study focuses on the DC side of the PV array, categorizing conditions into one normal state and four primary fault states:

1. **Normal Operation (NO):** The system operates at its Maximum Power Point (MPP) under given irradiance and temperature.
2. **Open-Circuit Fault (OC):** A disconnection within a string or between strings, often caused by broken cables or loose contacts.
3. **Short-Circuit / Line-to-Line Fault (LL):** An accidental low-impedance connection between two nodes of different potentials within the array.
4. **Partial Shading (PS):** A temporary or permanent condition where sections of the PV array receive unequal irradiance due to dust, bird droppings, or structural shadows.
5. **Degradation Fault (DF):** Long-term aging of the modules leading to increased series resistance (R_s) or decreased shunt resistance (R_{sh}).

COMMON PV SYSTEM FAULTS

In this study, we focus on identifying five specific conditions that commonly affect solar arrays:

- Normal Operation (NO): The baseline where everything is working as intended.
- Open-Circuit Fault (OC): Usually caused by a broken wire, stopping current flow entirely.
- Short-Circuit Fault (LL): A dangerous condition where current bypasses part of the array, often leading to hotspots.
- Partial Shading (PS): When trees or dust block panels, creating a "dip" in the power curve.
- Degradation (DF): The natural "aging" of the panels which slowly saps efficiency.

METHODOLOGY

Our approach was built on a three-step pipeline: gathering data, refining that data, and training the models.

Since it is impractical to intentionally damage a solar farm to collect data, we used a high-fidelity MATLAB/Simulink model. We simulated thousands of scenarios across different weather conditions (irradiance from 200 to 1000 W/m²). We performed "Feature Engineering," extracting specific markers like Open-Circuit Voltage (V_{oc}) and Short-Circuit Current (I_{sc}). We then tested three primary "brains" for our system: SVM, Random Forest, and ANN.

Table 1: Performance Metrics of ML Algorithms

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
SVM	94.5	93.8	94.1	93.9
Random Forest	96.2	96.0	95.8	95.9
ANN	98.1	97.9	98.2	98.0

RESULTS AND DISCUSSION

After testing our models on "unseen" data, the results were clear. While all the machine learning models outperformed traditional threshold methods, the Artificial Neural Network (ANN) was the standout performer, achieving an accuracy of 98.1%.

The most interesting finding was how the models handled "Partial Shading." This is the hardest condition to diagnose because it looks very similar to a panel that is simply wearing out. The ANN was able to spot the tiny differences in the "knees" of the I-V curve that a human eye—and many simpler algorithms—would likely miss.

CONCLUSION

The future of solar energy isn't just about building more panels; it's about managing the ones we have more intelligently. This study confirms that Machine Learning, particularly Neural Networks, can take the guesswork out of PV maintenance. By accurately identifying faults before they become failures, we can ensure that solar power remains a reliable energy source.

ACKNOWLEDGEMENTS

The authors would like to give their heart-felt thanks to Prof. Yogesh P. Khadse sir , Assistant Professor of Electrical Engineering Prof. Ram Meghe of Engineering and Management, Badnera, Amravati as the mentor of this study and the corresponding author. The success of Fault Detection and the creation of this manuscript was primarily due to his professional guidance, feedback in a timely manner, and unremitting encouragement.

The authors also acknowledge the faculty and staff of the Department of Electrical Engineering Prof. Ram Meghe College of Engineering And Management, Badnera as having provided the required resources and a conducive environment of the research.

REFERENCES

1. Aghaei, M., et al. (2020). "Fault Detection and Classification for Photovoltaic Systems..."
2. Kurukuru, V.S.B., et al. (2019). "Fault classification for photovoltaic modules..."
3. Mellit, A., & Kalogirou, S. A. (2021). "Artificial intelligence and machine learning advances..."
4. Hwang, H. P. C., et al. (2021). "Detection of Malfunctioning Photovoltaic Modules..."

