



Smart IoT-Enabled Efficient Optical Inspection of PV Modules Using Edge Detection Algorithms Enhanced with Ancillary Techniques

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Abstract- With the increasing demand for energy in both industrial and domestic sectors, the transition towards renewable energy sources has become imperative due to their environmental benefits. Among these, solar energy stands out, necessitating continuous optimization of its utilization, which heavily relies on the performance of photovoltaic (PV) modules. As PV modules typically operate autonomously, the absence of real-time monitoring can lead to undetected faults, adversely impacting overall system efficiency. This study introduces a smart IoT-enabled framework for real-time fault detection in PV modules, leveraging an efficient optical inspection algorithm. The proposed system integrates infrared thermography, utilizing a thermal imager strategically positioned to capture high-quality images of PV modules. A novel hybrid algorithm, combining edge detection with ancillary techniques, is developed to accurately identify and analyze various externally induced faults. The real-time experimental model demonstrates the capability of the smart IoT-based approach to enhance the reliability and operational performance of PV systems by enabling timely and precise fault detection, thereby supporting proactive maintenance and optimal energy yield.

Keywords- Renewable Energy, Solar Energy, PV modules, Fault detection, Performance.

1. Introduction

The Fourth Industrial Revolution (Industry 4.0) has significantly intensified energy demand across India's industrial and domestic sectors. With the rapid depletion of fossil fuels and the country's commitment to net zero carbon emissions by 2070, India's energy strategy is shifting decisively toward renewable sources, especially solar photovoltaic (PV), wind, and hydropower. Among these, solar PV stands out due to its scalability, cost-effectiveness, and the nation's abundant solar resources.

India's solar journey has been remarkable. By January 2025, the country's total non-fossil fuel-based energy capacity reached 217.62 GW, with solar energy accounting for 47% of the installed renewable capacity. In 2024 alone, India added a record 24.5 GW of solar capacity—a near threefold increase over the previous year—driven by government incentives, policy reforms, and robust investments in domestic manufacturing. Rajasthan, Gujarat, and Tamil Nadu are leading the solar revolution, contributing over 70% of the nation's utility-scale solar installations. The government's ambitious roadmap aims for 500 GW of non-fossil fuel-based capacity by 2030, positioning India as a global leader in clean energy. At the heart of PV power generation are solar cells, which convert sunlight into electricity through the movement of electrons. The efficiency of these modules depends on factors such as module composition, installation quality, and environmental conditions. One major challenge in India is the variability of solar irradiance, which leads to temperature fluctuations in PV modules. For instance, crystalline PV modules can lose about 0.5% efficiency for every 1°C rise in temperature—a significant concern given India's hot climate. Fluctuations in weather also impact voltage and frequency, complicating grid management and maintenance.

The widespread deployment of solar PV in India—spanning rooftops, utility-scale plants, and rural electrification—demands ongoing research and innovation to optimize energy output and investment returns while minimizing environmental impact. The rapid decline in PV module costs, coupled with government schemes like PM Surya Ghar Muft Bijli Yojana and PM-KUSUM, has accelerated adoption among consumers and businesses. However, maximizing system performance requires early detection and diagnosis of faults to prevent losses and safety hazards.

Common faults in Indian PV installations include delamination, junction box failures, hotspots from abnormal heating, and issues arising from poor installation or harsh environmental exposure. Infrared (IR) thermography has emerged as a vital tool for identifying such faults, enabling early intervention and reducing

maintenance costs. By capturing and analyzing thermal images, IR inspection can pinpoint hotspots and other anomalies that may otherwise go unnoticed, safeguarding both energy yield and system longevity.

Recent research and field deployments in India have leveraged advanced algorithms—including edge detection and hybrid image processing techniques—combined with smart IoT-based monitoring systems. These innovations enable real-time, remote fault detection and performance optimization, which are crucial for India's geographically dispersed and rapidly expanding solar fleet.

Despite these advances, challenges remain. Grid integration, energy storage, and the need for skilled maintenance are critical hurdles as India scales up its renewable ambitions. Addressing these issues through continued investment in technology, infrastructure, and human capital will be essential for sustaining India's clean energy momentum and achieving its 2030 targets.

Inspired by global and domestic advances, this work proposes an efficient, IoT-enabled optical inspection technique for fault diagnosis in PV modules, tailored to the Indian context. By integrating real-time thermal imaging, smart analytics, and automated fault detection, the approach aims to enhance the reliability, safety, and performance of solar PV systems across India's diverse energy landscape.

2. Materials and Methods

Figure 1 demonstrates the schematic illustration of the experimental setup. The system consists of a thermal imager to capture the PV module image instantaneously. The images obtained were processed using the MATLAB software employing fault diagnosis and detection algorithms in image processing and computer vision toolbox to detect the fault and identify the malfunctioned PV panels. The intended monitoring system is operating on the multicore CPU along with the parallel processing module using C++ programming. The crucial image processing algorithms were accommodated to find the PV module defect. The algorithm is robust with least error and deviation in identifying the fault.

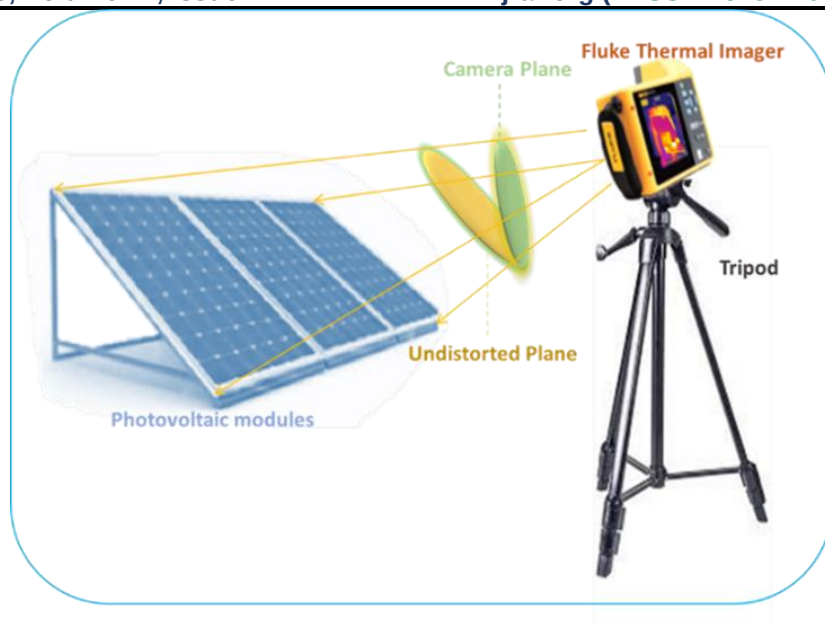


Figure 1. Schematic of the hardware employed in the experimental setup.

3. Segmentation by Canny edge detection algorithm and Bounding box technique

Initially, the input image is converted into grayscale where threshold values are adjusted that are held for binary image edge detection and to identify the regions of interest from the input thermal images. The solar cells of the defective kind are generally yellow or white in colors having sharp edges in thermal images, makes lucid to identify the region of interest. Threshold value, T_h is ascribed to a binary image. Convolution of the image is done by Gaussian filter coefficients. Later Non-Maximum Suppression is performed on the image. The Hysteresis Thresholding is depicted for the image followed by 8-connected components labeling. Furthermore, the morphological transformations also benefit from the kernel assignment, defining the structuring element. At first, the erosion technique is applied to the image, depending on the kernel kind, the pixels of the image are ascribed as such, else the erosion takes place in the image. Boundary pixels will be faded or discarded in the image based on the kernel size estimating the white color area reduction. The dilation is adopted later which is contradictory to the erosion, the pixel is 1 when at least any one of the pixels under the kernel is 1. This can be elaborated as the white region in the image grows or dimensions of the objects in the foreground enhances. Therefore, the Faulty solar cells in the modules can be identified by the optimal Canny's Algorithm accompanied by the region props and bounding box techniques.

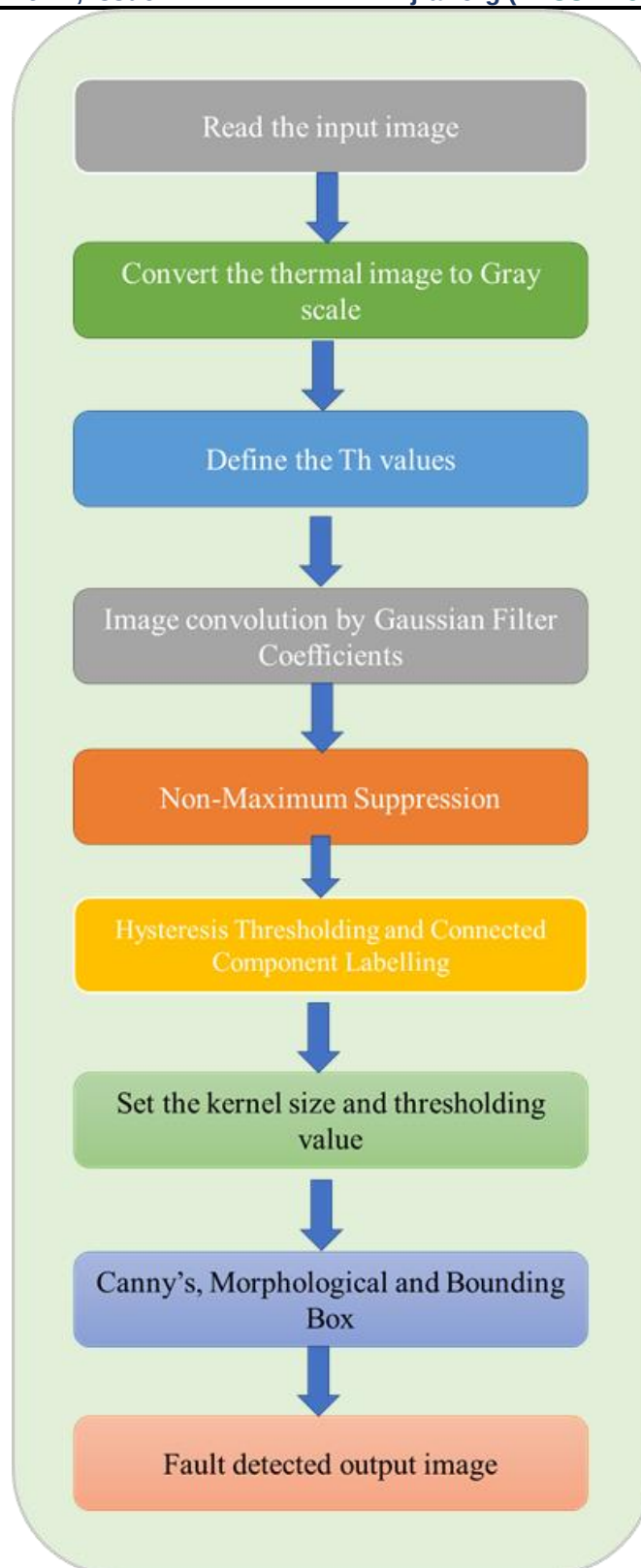


Figure 2. The flow of algorithm for fault detection

3. Results and discussions

The input images for our PV modules were captured at the research facility of JIS College of Engineering (JISCE), Kalyani, West Bengal, India (Latitude and Longitude: 22.9750° N, 88.4345° E) to validate our proposed methodology. The experimental setup consists of multiple hardware components, as detailed in Table 1. The complete system was developed within the JISCE research center, as illustrated in Figure 3, incorporating all necessary elements of connectivity, calibration, and system scalability. This setup leverages the institute’s advanced infrastructure and expertise to enable real-time monitoring and fault diagnosis of PV modules, aligning with India’s growing focus on renewable energy technologies and smart IoT-enabled solutions.

If you want, I can also help you draft a more detailed description of the experimental setup or include specific hardware components relevant to JISCE’s facilities.

Table1. Components of the experiment

Component	Specifications
Solar PV Panel	Waaree WS-50 W
Battery	Eternity Technologies 12 VDC, 56 AH
Charge Controller	Morning Star SS-MPPT-15L
Thermal Imager	Fluke Ti-45
Clamp Meter	HEME Analyst 2050
Tripod	BOSCH BS280
Multimeter	Fluke 176
IR Light	250 W IR
Load	2 x 24 W DC Motors

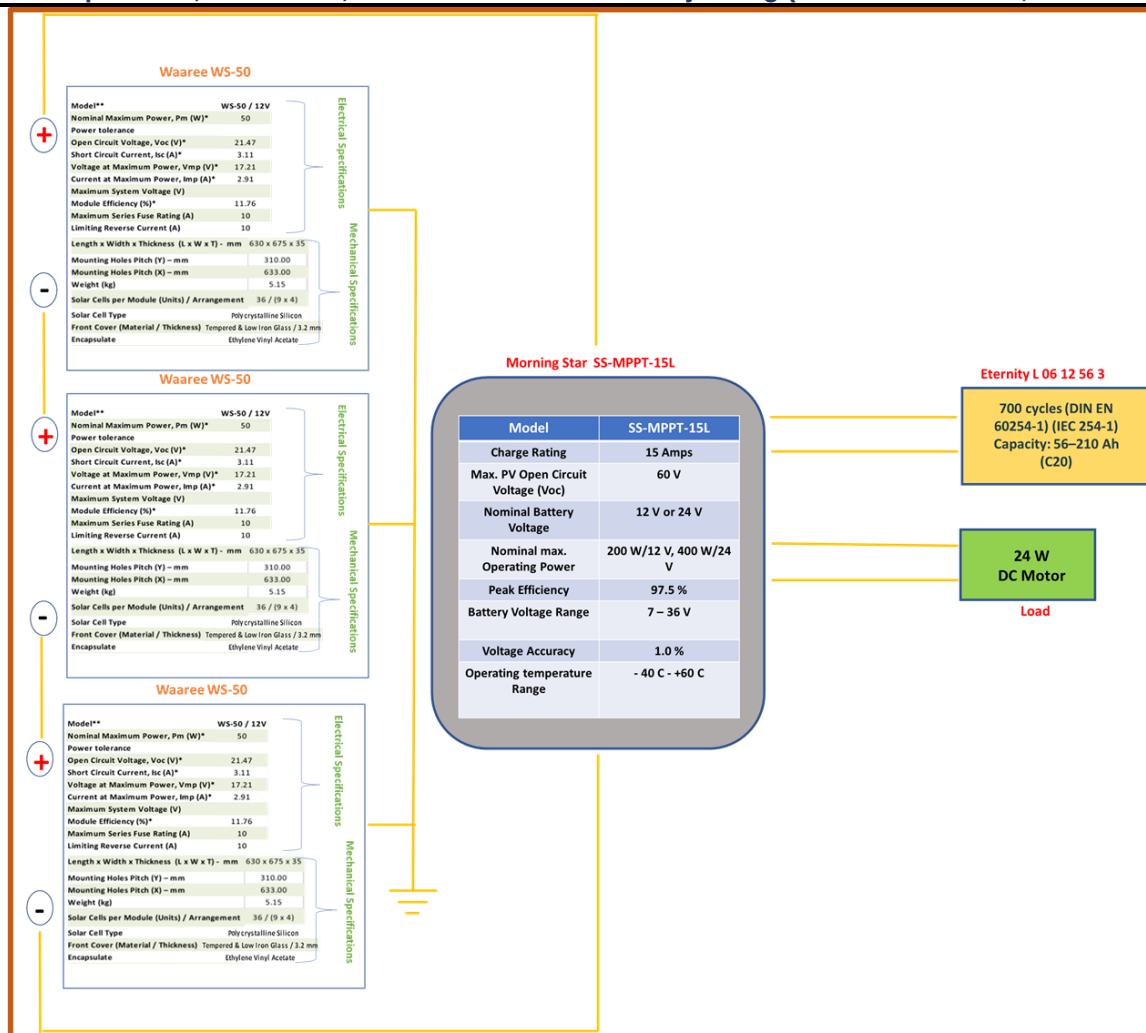


Figure 3. Scheme of PV module setup at RAKRIC

The Fluke Ti-45 thermal imager, featuring a 160 x 120 VOx detector and high thermal sensitivity ($\leq 0.08^\circ\text{C}$ at 30°C), was utilized to capture high-resolution thermal images of the PV modules, ensuring accurate data for subsequent image processing in MATLAB¹³⁶. The BOSCH BS 280 tripod provided stable mounting, with the thermal imager positioned at an optimal distance facing the solar PV module to acquire clear images.

To extend the analysis to indoor conditions, 250 W IR light sources were mounted on two additional tripods to simulate illumination, enabling comprehensive fault detection. For defect simulation, polystyrene sheets were strategically placed on the PV panel surface to act as minimal defects.

Image acquisition and processing were managed using MATLAB R2020b on a workstation equipped with an ASUS Tek Computer Inc. X556UB, Intel Core i7-6500U processor (2.59 GHz), 12 GB RAM, and a 64-bit Windows 10 Professional operating system. The MATLAB environment included the Image Processing and Computer Vision Toolboxes, along with relevant extensions, facilitating advanced analysis. A C++ program was accessed via the MATLAB Command Prompt to perform specific operations on the thermal images, ensuring efficient and flexible workflow integration.

4. Algorithm implementation for edge detection

The application of morphological transformations and the Canny edge detection algorithm proved effective for identifying faults in PV modules under both indoor and outdoor experimental setups. Morphological operations—such as dilation, erosion, opening, and closing—were first applied to the thermal images to enhance feature extraction and suppress noise. These steps help emphasize relevant structures like cracks or hotspots, connect fragmented fault regions, and eliminate small artifacts that could otherwise interfere with accurate fault identification⁴.

In the outdoor setup, two out of three PV panels were intentionally made defective in random patterns, while the third panel remained unaltered as a control. In the indoor setup, a single PV panel was used and manually induced with defects. The thermal images of all panels, as shown in Figure 5a, were processed using the aforementioned techniques.

The Canny edge detector was then employed to delineate the boundaries of fault regions—such as cracks, hotspots, or delaminated areas—by identifying sharp intensity gradients in the processed thermal images. This combination of morphological transformations and edge detection provided clear visualization and accurate localization of faults, even in the presence of noise or varying lighting conditions⁴⁶.

The results demonstrate that this approach is robust for both indoor and outdoor scenarios, enabling reliable detection of faults in PV modules and supporting efficient maintenance and monitoring strategies⁴.

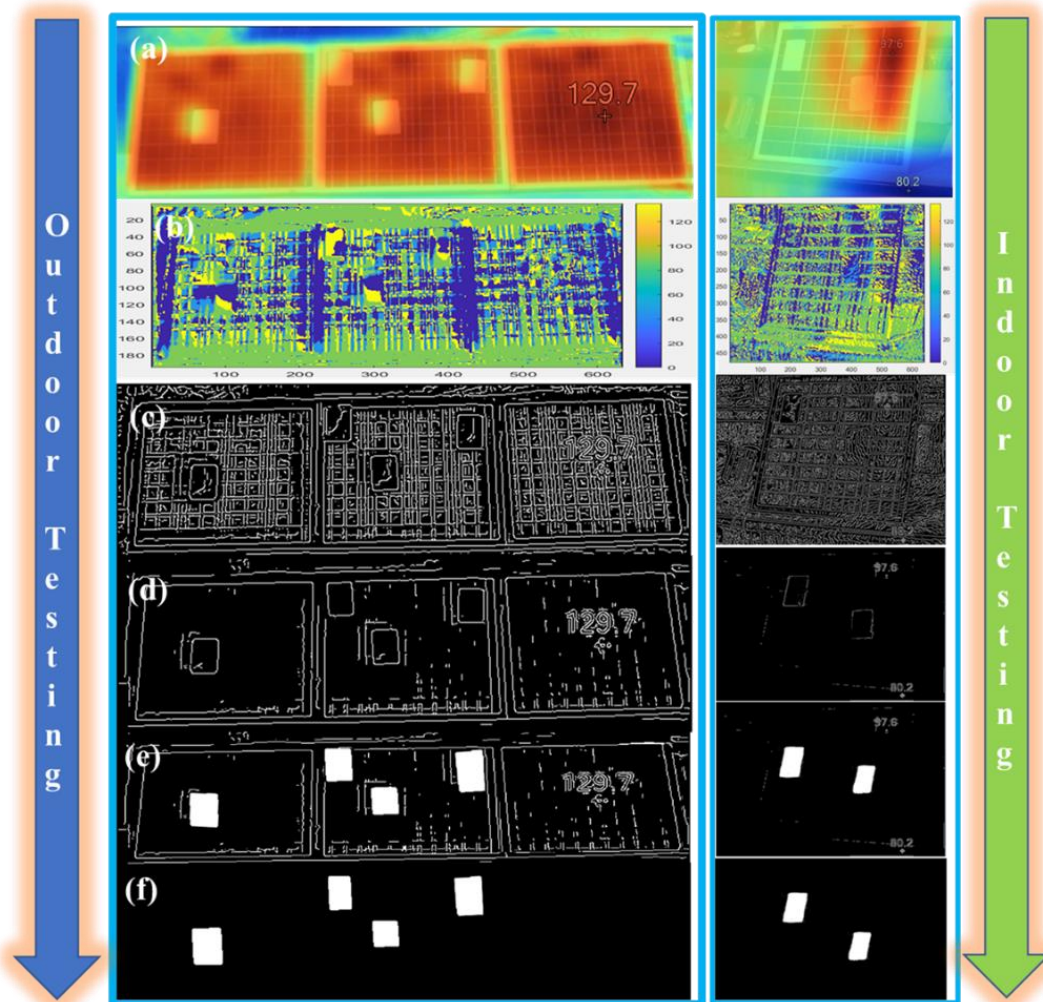


Figure 5. (a) Input thermal image (b) Scaling Colored Image (c) Non-Maximum Suppression (d) Hysteresis Thresholding (e) Morphological transformations (f) Bounding Box Techniques

The image processing workflow begins by loading the input thermal image and converting it to grayscale, which simplifies further analysis by reducing computational complexity and focusing on intensity variations relevant to fault detection²⁵. Next, thresholding is applied with lower and upper bounds set at $T_{low}=0.075$ and $T_{high}=0.175$, respectively, to segment regions of interest based on pixel intensity.

A Gaussian filter is then employed for convolution in both X and Y directions. As a linear filter, the Gaussian is primarily used to blur the image and suppress noise, thereby enhancing the reliability of subsequent edge detection steps. This filtering not only smooths the image but also reduces contrast, which is beneficial for both edge detection and unsharp masking, making the process robust and computationally efficient due to its straightforward operations of multiplication and addition²⁵.

The output, visualized with color scaling (Fig. 5b), provides an intuitive representation of temperature gradients and potential fault regions. Following this, non-maximum suppression is performed (Fig. 5c), which refines the detected edges by preserving only the local maxima in the gradient direction and setting all other pixels to zero. This step effectively suppresses non-relevant information and sharpens the edge map, ensuring that only the most significant features are retained².

Subsequently, hysteresis thresholding is applied (Fig. 5d), using the previously set threshold values to further refine the edge map. This technique compares two binary images, each thresholded at different levels, and combines them to produce an intermediary image where only the most relevant pixels—those in the higher threshold region—are retained, accurately depicting real edges².

Morphological transformations are then utilized with appropriate structural elements to enhance and connect edge features (Fig. 5e). Finally, bounding box techniques are applied to the processed image (Fig. 5f), drawing rectangles around detected defects. These bounding boxes serve as reference points for object detection, allowing precise localization and annotation of faults within the PV module²⁵. This comprehensive approach ensures accurate, efficient, and automated fault detection, which is essential for large-scale PV system monitoring and maintenance.

5. Conclusion

With rapid industrialization, the need for alternative energy sources has intensified, making renewable resources like solar photovoltaic (PV) technology increasingly vital for meeting energy demands. Achieving optimal PV plant performance requires careful consideration of design, construction, and ongoing evaluation, with fault detection playing a critical role in maintaining efficiency, reliability, and safety.

This work introduces a new hybrid algorithm for real-time PV fault detection, utilizing an infrared thermal camera mounted on a tripod to capture module images. The proposed approach leverages advanced image processing and edge detection techniques to identify faults—such as hotspots, cracks, and delamination—directly from thermal imagery, enabling early intervention and minimizing hazardous effects during PV operation. Experimental results demonstrate that the algorithm offers fast processing times and is well-suited for real-time applications in PV plants, supporting both energy savings and economic benefits.

Recent research highlights the effectiveness of combining thermal imaging with artificial intelligence and image processing for PV fault detection. Techniques such as deep learning, fuzzy logic, and hybrid models have shown high accuracy in identifying and classifying faults, further enhancing system reliability and

reducing maintenance costs. Additionally, methods based on electrical parameter monitoring—such as voltage and current analysis—remain essential, especially for detecting faults under varying environmental conditions.

Looking ahead, integrating IoT technology with the current system is a key focus. IoT-enabled solutions will allow real-time performance monitoring and fault alerts via mobile devices, providing operators with instant access to system status and enabling prompt maintenance actions. This aligns with global trends in smart PV plant management, where remote monitoring and automated diagnostics are becoming standard practice.

References

1. How Solar Cells Work. Available online: <http://science.howstuffworks.com/environmental/energy/solarcell.htm> (accessed on 01 March 2021).
2. Zsiborács, H.; Pintér, G.; Bai, A.; Popp, J.; Gabnai, Z.; Pályi, B.; István, F.; Nóra, H.B.; Christian, G.; Heidelinde, T.; et al. Comparison of thermal models for ground-mounted south-facing photovoltaic technologies: A practical case study. *Energies* Vol 11, No 1114. 2018.
3. Chen, T.; Alsafasfeh, Q.; Pourbabak, H.; Su, W. The Next-generation retail electricity market with customers and prosumers—A bibliographical survey. *Energies* Vol 11, 2018.
4. Adetokunbo, A.A.; Luo, J.; Liang, Z.; Qais, A.; Su, W. Intelligent Home Energy Management System for Distributed Renewable Generators, Dispatchable Residential Loads and Distributed Energy Storage Devices. In *Proceedings of the 2017 8th IEEE International Renewable Energy Congress (IREC)*, Amman, Jordan, 21–23 March pp. 1–6. 2017.
5. Louy, M.; Tareq, Q.; Al-Jufout, S.; Alsafasfeh, Q.; Wang, C. Effect of dust on the 1-MW photovoltaic power plant at Tafila Technical University. In *Proceedings of the 2017 8th International Renewable Energy Congress (IREC)*, Amman, Jordan, 21–23; pp. 1–4. March 2017.
6. Liang, Z.; Alsafasfeh, Q.; Jin, T.; Pourbabak, H.; Su, W. Risk-Constrained Optimal Energy Management for Virtual Power Plants Considering Correlated Demand Response. *IEEE Trans. Smart Grid*, Vol 12, no 1. 2017.
7. Arfoa, A.; Alsafasfeh, Q.; Al, S.M. Evaluation of Electric Energy Losses in Southern Governorates of Jordan Distribution Electric System. *Int. J. Energy Eng.* Vol 5, No 2. 2015.

8. Zsiborács, E.; Pályi, B.; Pintér, G.; Popp, J.; Balogh, P.; Gabnai, Z.; Pető, K.; Farkas, I.; Baranyai, N.H.; Bai, A. Technical-economic study of cooled crystalline solar modules. *Sol. Energy*, Vol 140, pp. 227–235. 2016.
9. Pintér, G.; Baranyai, N.H.; Williams, A.; Zsiborács, H. Study of Photovoltaics and LED Energy Efficiency: Case Study in Hungary. *Energies*, 11, 790. (2018).
10. Zsiborács, H.; Baranyai, N.H.; Vincze, A.; Háber, I.; Pintér, G. Economic and Technical Aspects of Flexible Storage Photovoltaic Systems in Europe. *Energies*, Vol 11, pp. 1445. 2018.
11. Review of Failures of Photovoltaic Modules. Available online: <http://www.solarquarter.com/index.php/resources/82-white-papers/6051-review-of-failures-of-photovoltaic-modules-final> (accessed on 03 March 2021).
12. Munoz, M.A.; Alonso-García, M.C.; Vela, N.; Chenlo, F. Early degradation of silicon PV modules and guaranty conditions. *Sol. Energy* Vol 85, pp. 2264–2274. 2011.
13. T. Potthoff, K. Bothe, U. Eitner, D. Hinken, and M. Köntges, “Detection of the voltage distribution in photovoltaic modules by electroluminescence imaging,” *Prog. Photovoltaics Res. Appl.*, vol. 18, no. 2, pp. 100–106, Mar. 2010.
14. T. Fuyuki, H. Kondo, T. Yamazaki, Y. Takahashi, and Y. Uraoka, “Photographic surveying of minority carrier diffusion length in polycrystalline silicon solar cells by electroluminescence,” *Appl. Phys. Lett.*, vol. 86, no. 26, pp. 262108, Jun. 2005.
15. B. Kubicek, T. Schlager, and M. Halwachs, “Outdoor Lock-In Thermographie von PIDModulen,” in 31. Symposium Photovoltaische Solarenergien, 2017.
16. “IEC 61215 Terrestrial photovoltaic (PV) modules - Design qualification and type approval.” 2016.
17. S. K. Thompson, *Sampling*, 3rd edition. Wiley, 2012.
18. Anwar, S.; Efstathiadis, H.; Qazi, S. *Handbook of Research on Solar Energy Systems and Technologies*; IGI Global: Hershey, PE, USA, 2012.
19. Gao, X.; Munson, E.; Abousleman, G.; Si, J. Automatic solar panel recognition and defect detection using infrared imaging. *Proc. SPIE* 2015, 9476. (2015).
20. Tsanakas, J.A.; Chrysostomou, D.; Botsaris, P.N.; Gasteratos, A. Fault diagnosis of photovoltaic modules through image processing and canny edge detection on field thermographic measurements. *Int. J. Sustain. Energy*, Vol 34, pp. 351–372 2015.

21. Chouder, A.; Silvestre, S. Automatic supervision and fault detection of PV systems based on power losses analysis. *Energy Convers. Manag.*, Vol 51, pp. 1929–1937, 2010.
22. Alexander Neubeck, Luc Van Gool, Efficient Non-Maximum Suppression, <http://lars.mec.ua.pt/public/LAR>.(Accesses on 03 March 2021).
23. Joe Smith, EE Affiliate, Assignment 3: Edge Detection, <http://www.homepages.ucl.ac.uk>. (Accessed on 03 March 2021).
24. K.Sreedhar, B.Panlal, Enhancement Of Images Using Morphological Transformations, *International Journal of Computer Science & Information Technology (IJCSIT)* Vol 4, No 1, Feb 2012.
25. Mostafa S. Ibrahim, Amr A. Badr, Mostafa R. Abdallah, Ibrahim F. Eissa, Bounding Box Object Localization Based On Image Superpixelization, *Proceedings of the International Neural Network Society Winter Conference (INNS-WC 2012)* *Procedia Computer Science* Vol 13 pp.108 – 119, 2012.