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Performance Analysis and Anomalies in Photovoltaic Solar Systems using Thermal Imaging Technology

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Abstract – *The rapid growth of photovoltaic (PV) solar systems has increased the need for efficient monitoring and maintenance techniques to ensure optimal performance. Faults such as hotspots, shading, cracks, and connection failures significantly degrade system efficiency. This paper presents a comprehensive performance analysis of PV systems using thermal imaging technology for anomaly detection. Infrared thermography enables non-contact, real-time monitoring of PV modules by detecting temperature variations associated with defects. The study analyzes various anomalies, evaluates their impact on system performance, and highlights the effectiveness of thermal imaging combined with image processing techniques. The results demonstrate that thermal imaging significantly improves fault detection accuracy, reduces maintenance time, and enhances overall system reliability. The proposed work was validated on 295kWp On-Gride Solar PV Rooftop Solar Plant at institute situated 21°00'53.6"N 75°30'10.7"E,Bambhori, Maharashtra, India, Lat N 21°00'53.4636" and Long E 75°30'10.7028"*

Keywords- Photovoltaic systems, thermal imaging, anomaly detection, hotspots, infrared thermography, fault diagnosis.

INTRODUCTION

The increasing demand for renewable energy has led to widespread adoption of solar photovoltaic (PV) systems. However, the performance of PV systems is affected by environmental conditions and internal faults. Issues such as partial shading, dust accumulation, and electrical defects can lead to reduced power output and long-term degradation. Traditional fault detection methods rely on electrical measurements, which may fail to detect localized faults. Thermal imaging (infrared thermography) has emerged as an effective non-invasive technique for detecting anomalies in PV systems. It identifies temperature variations that correspond to defects, enabling early fault diagnosis and preventive maintenance. Recent studies show that thermal imaging can detect faults such as hotspots and bypass diode failures, which directly impact energy efficiency and system lifespan.

Compared to other renewable energy sources, the PV system's installation has fewer drawbacks. While the current generated by a PV cell is directly proportional to the amount of solar radiation received by the PV cell surface, the power generated by a PV system depends heavily on solar radiation [3]. On the other hand, a variety of factors, some of which are diagnosable, such as partial shade, hotspots, diode failure, minor flaws, fractures, the burning of strings, PV cell failure, and others, restrict the amount of power that a PV system can produce. However, certain factors, such as hotspots and partial shading, are unavoidable [4]. PV systems commonly experience partial shade, which is the most prevalent occurrence. The uneven distribution of solar irradiation caused by this partial shade reduces power output by creating hotspots that raise the temperature of the PV panel. Additionally, due to the excessive current flow, this causes the PV cell to fail. The building-integrated PV system is more affected by partial shade. To increase the power conversion rate of a PV system, the effect of partial shade must be reduced. There are several strategies available to lessen the effects of partial shadowing. By obtaining the GMPP (global maximum power point), as explained in [5], maximum power point tracking (MPPT) can be one of the approaches that creates an equilibrium between the source resistance and load resistance. Conventional MPPT approaches, such as MPPT algorithms based on perturb and observe (P&O) [6] and incremental conductance (InC) [7], may fail to acquire the GMPP in a complicated partial shading situation because of the high cost of MPPT implementation on PV systems. Optimization techniques that make use of particle swarm optimization (PSO), neural networks (NNs), artificial neural networks (ANNs), ant colony optimization (ACO), the cuckoo search-based algorithm [8], and the musical chair-based algorithm [9] are integrated with conventional methods. The ability to precisely of produce the GMPP is slowly improving because of these strategies.

PV array configurations can also reduce the impact of partial shadowing by distributing light equally over the array. In the beginning, two array configurations were used: series (S) and series-parallel (Se-P). In certain situations, a complex type of partial shading may cause the available power output at the load terminal to be zero. In [10], the total-cross-tied (TCT) array configuration, which combines both series and series-parallel array design, was created. Although the TCT method lessens the impact of partial shade, it was ineffective in particular shading patterns. For increasing the power production, several PV array arrangements such as honeycomb, bridge-connected, and Sudoku pattern array configurations were discussed in [11]. The reconfiguration technique [12] is another method for reducing partial shadowing. In this method, the interconnections between the PV modules are switched based on the partial shading situation. The two types of reconfiguration procedures are static reconfiguration and dynamic reconfiguration. The reconfiguration strategy raises the cost of a PV system by requiring many sensors, switches, controlling units, and cables. Time is set aside during reconfiguration to measure the data and rearrange the interconnections of the modules. As mentioned before, the reconfiguration technique is highly complicated due to the numerous measurements, scanning time, and pattern construction time involved. The reconfiguration technique is the focus of much research aimed at reducing the amount of data needed, the scanning time, and the complexity.

LITERATURE REVIEW

Panthi et al. investigated methods for detecting anomalies in power distribution systems using machine-learning techniques and proposed effective methods for detecting anomalies in power systems by applying various machine-learning algorithms and data mining techniques [13-14].Furthermore, Imenes et al. combined thermal imaging with deep learning to detect faults in power systems. They used thermal cameras to automatically detect faults in power systems by analyzing images using deep-learning algorithms [15-16]. Syu et al. identified anomalies in power networks using AI algorithms and immediate actions to enhance the safety of power networks [17-18]. Additionally, studies have focused on developing data driven predictive models to detect equipment faults in power systems in advance and optimize maintenance schedules to enhance system reliability [19-20]. Moreover, notable research involves the utilization of the Internet of things and machine learning for real-time monitoring and anomaly detection in power systems [21].These related studies have proposed innovative approaches for the safety management and reliability enhancement of power facilities, contributing to strengthening the safety of power systems alongside this study.

SYSTEM CONFIGURATION METHOLOGY

The system comprises of 295kWp On-Grid Solar PV Rooftop power plants. The plant consists of two type of Solar PV modules of manufacturing technology Polycrystalline and Monocrystalline. The plants were commissioned in three stages in year 2018, 2020 and 2022. This different type of manufacturing technology and commissioning years give exposure for proposed Performance Analysis and Anomalies in Photovoltaic Solar Systems using Thermal Imaging Technology. The installed 09 Grid-tied inverters historical data from bidirectional energy meter along with thermal Image camera Fluck PTi120 is used for analysis and detection of thermal anomalies in solar PV modules. Thermal images of PV modules are captured periodically under operating conditions. Infrared thermography detects emitted radiation from PV panels. Faulty regions exhibit higher temperatures due to increased resistance or power dissipation. Thermal Anomalies in PV Systems are Hotspots due to localized overheating due to shading or cell damage. These significantly reduce efficiency and may cause permanent damage. Partial Shading due to occurs due to obstacles like trees or dust, leading to mismatch losses. Cracks and Cell Damage due to mechanical stress causes micro-cracks, detectable as temperature variations. Faulty Connections are due to lose or corroded connections result in abnormal heating. Bypass Diode Failure is Due to leads to uneven current distribution and thermal imbalance. Thermal imaging effectively identifies all these anomalies through temperature differences.

Table 1- Solar PV Module Specification

Capacity	100 kWp	95 kWp	100kWp
Type	On Grid Roof-Top	On Grid Roof-Top	On Grid Roof-Top
Number of Panels	318	295	247
Number of Inverter	03	03	03
Solar PV Module	Poly-crystalline	Poly-crystalline	Mono-crystalline
Nominal Maximum Power Pm (Wp)	315	325	405
Number of Cells	72	72	72
Power Tolerance	+5/-0 %	+5/-0 %	+3/-0 %
Open Circuit Voltage, Voc (V)	45.60	45.9	50.10
Short Circuit Current, Isc (A)	8.85	9.25	10.48
Voltage at Maximum Power, Vmp (V)	37.80	37.2	42.00
Current at Maximum Power, Imp (A)	8.34	8.76	9.65
Maximum System Voltage (V)	1000	1000	1500
Module Efficiency (%) Maximum	16.23	16.75	20.13
Temperature coefficient of current	+0.04 %/°C	+0.05 %/°C	+0.048 %/°C
Temperature coefficient of Voltage	0.32 %/°C	0.32 %/°C	0.28 %/°C
Temperature coefficient of Power	0.43 %/°C	0.39 %/°C	0.36 %/°C
NOCT (°C)	47°C ± 2°C	45°C ± 2°C	45°C ± 2°C

Operating temperature range	-40°C - +85°C	-40°C - +85°C	-40°C - +85°C
Date of Commissioning	March, 2018	Aug, 2019	March 2021

Here is a clear technical discussion of the three rooftop on-grid Solar PV systems based on the data provided. Three grid-connected rooftop photovoltaic (PV) systems with capacities of 100 kWp (2018), 95 kWp (2019), and 100 kWp (2021) are analyzed to compare their design parameters, module technologies, and performance characteristics. The comparative analysis clearly shows technological progression in PV systems over time:

- Reduction in number of modules with increased wattage.
- Transition from polycrystalline to monocrystalline technology.
- Significant improvement in efficiency and thermal performance.
- Adoption of higher system voltage (1500 V) for better system economics.

Table 2- Thermal Image Camera Specification

Thermal Image Camera	Make	Fluke , Model :PTi120
	IFOV (spatial resolution)	7.6 mRad
	Infrared resolution	120 x 90 (10,800pixels)
	Field of view	50° H x 38° V
	Distance to spot	130:1
	Temperature measurement range	-20 ° C to 150 ° C
	USB , Wifi	Mini USB used to transfer image to PC, Yes

Fig. 1- Solar PV Modul array under analysis

RESULT AND DISCUSSION

Thermal imaging (also called infrared thermography) is a powerful non-contact diagnostic technique used to monitor the performance and health of solar photovoltaic systems. It detects temperature variations across PV modules and components to identify faults, inefficiencies, and degradation. Thermal imaging uses infrared cameras to capture heat patterns emitted by objects. Since defective PV components often generate excess heat, thermal images help locate issues quickly.

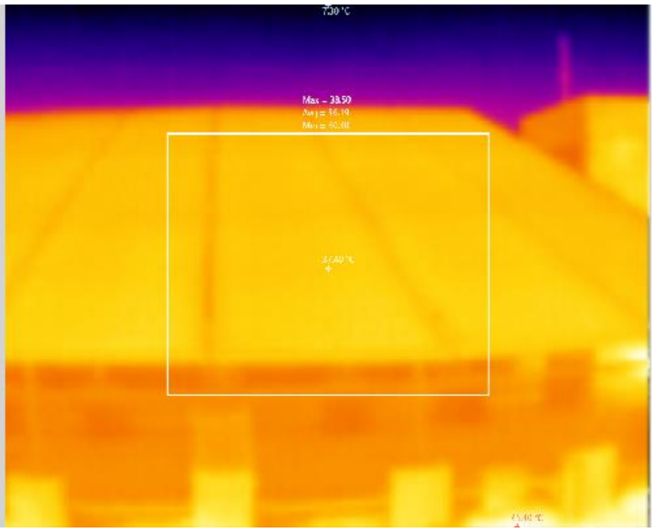


Table 3- Thermal Image data

Background Temp.	22.00ºC
Emissivity	0.95
Transmission	1.00
Average Temp.	31.00ºC
Calibration Range	-10.00ºC to 400.00ºC
Camera Model	PTi120
Camera Make	Fluke Corporation
Date	10/03/26

Fig. 2 Thermal Image for Mono-crystalline PV Module

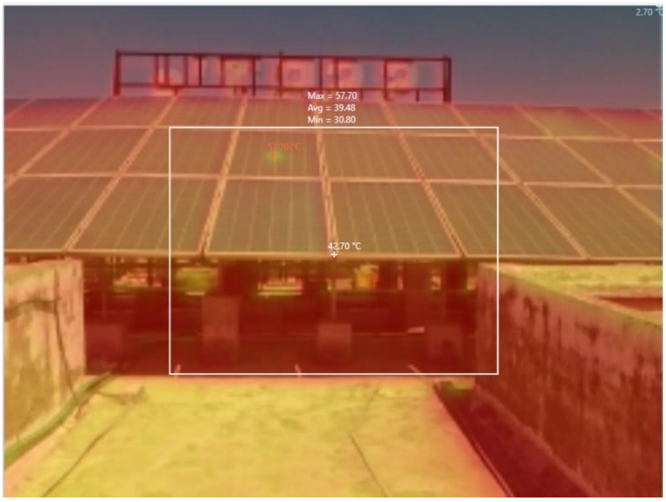
Thermal Performance Analysis

The thermal image data was recorded on Mono-crystalline Solar PV modules using the Fluke PTi120 manufactured by Fluke Corporation provides valuable insights into the operating condition of the solar PV system.

Measurement Conditions and Parameters

- **Background Temperature:** 22°C Indicates ambient environmental conditions during inspection. This is important as PV module temperature is influenced by surrounding air temperature.
- **Emissivity:** 0.95 This is appropriate for solar PV modules (typically 0.90–0.96), ensuring **accurate temperature measurement** from the module surface.
- **Transmission:** 1.00 Assumes no atmospheric interference (ideal condition), meaning thermal radiation reaches the camera without losses.
- **Average Temperature:** 31°C Represents the mean operating temperature of the PV module surface.
- **Calibration Range:** -10°C to 400°C Confirms that the camera is capable of detecting a wide temperature range, suitable for PV diagnostics.
- **Date of Inspection:** 10/03/2026
- A **9°C rise** above ambient is generally **normal under moderate solar irradiance**. This suggests that the PV module is **actively generating power** and no severe overheating is present at the macro level

Table 4- Thermal Image data



Background Temp.	22.00ºC
Emissivity	0.95
Transmission	1.00
Average Temp.	35.08ºC
Calibration Range	-10.00ºC to 400.00ºC
Camera Model	PTi120
Camera Make	Fluke Corporation
Date	10/03/26

Fig. 3 Thermal Image for Mono-crystalline PV Module

The thermal inspection of the solar PV module was carried out on Poly-crystalline using the Fluke PTi120 developed by Fluke Corporation. The recorded parameters provide insight into the thermal performance and possible anomalies in the PV system.

Measurement Parameters Interpretation

- Background Temperature: 22°C Represents ambient conditions during inspection.
- Average Module Temperature: 35.08°C Indicates the operational temperature of the PV module.
- Temperature Rise (ΔT): $\Delta T = 35.08 - 22 = 13.08^{\circ}C$ The observed ΔT ≈ 13.08°C indicates a moderate temperature increase above ambient. Interpretation is higher than normal (compared to ideal <10°C) . This indicates possible minor inefficiencies or early-stage faults

The given diagram presents the specific energy generation (kWh per kWp) of solar PV plants across different months for three years: 2018, 2020, and 2025. The energy generation in all three years shows a seasonal pattern. There is a decline from January to around April–May, followed by a steady increase towards the end of the year (November–December). This trend corresponds to solar irradiance variation, where peak summer and post-monsoon periods yield higher output. Low generation (March–May) may be due to high module temperature and dust accumulation or soiling losses. The drop in 2025 could be correlated with thermal anomalies, which aligns with the need for thermal imaging diagnostics in PV systems.

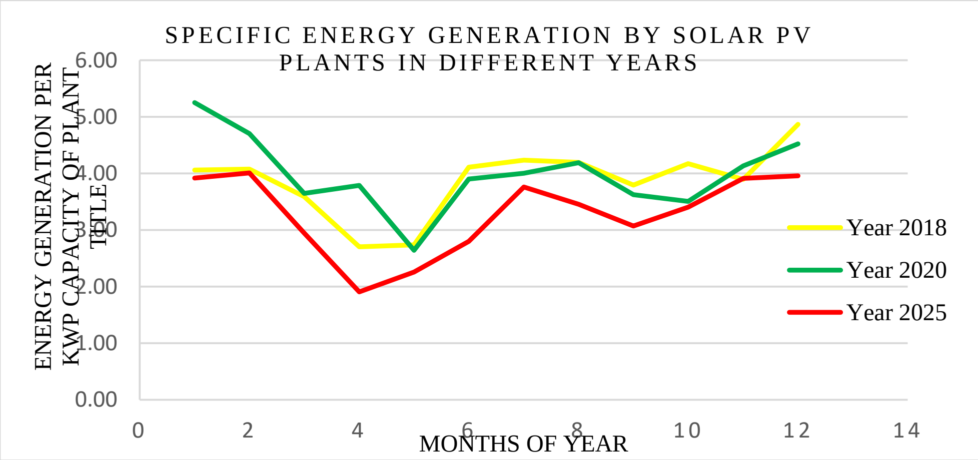


Fig. 4 Specific energy generation by solar plants in different years

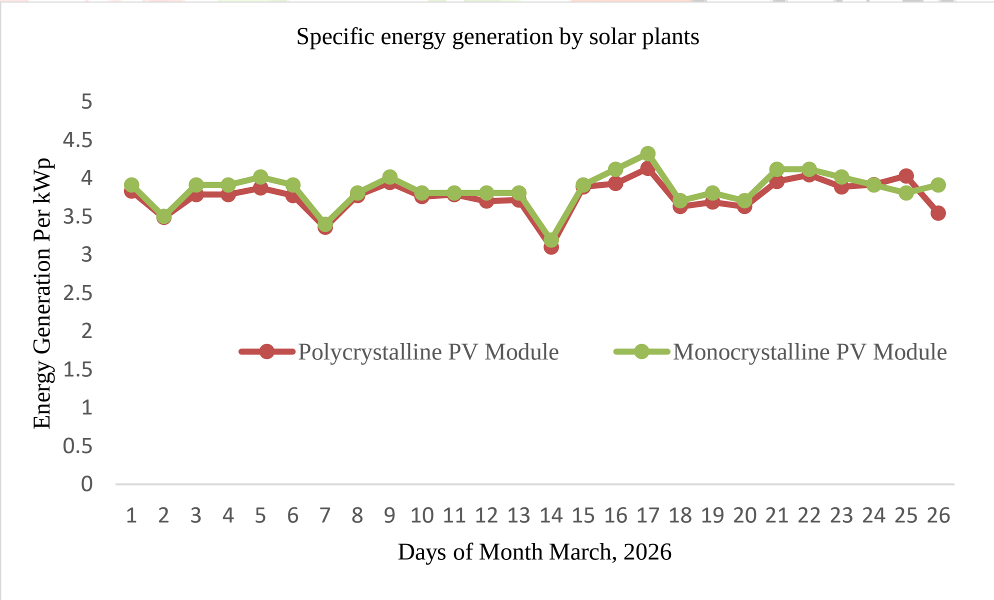


Fig. 5 Specific energy generation by solar plants in same climatic and geographical condition

The given diagram illustrates the daily specific energy generation (kWh/kWp) of polycrystalline and monocrystalline PV modules for the month of March 2026. Both polycrystalline (red) and monocrystalline (green) modules exhibit similar daily generation patterns, indicating they are subjected to the same environmental conditions. Energy generation remains mostly in the range of 3.5 to 4.3 kWh/kWp, showing stable system performance throughout the month. The monocrystalline PV module consistently performs slightly better than the polycrystalline module on most days. The difference is typically around 0.05 to 0.2 kWh/kWp, which reflects higher efficiency of monocrystalline modules and better performance under low irradiance conditions. The thermal anomalies are more dominant are observed in poly-crystallin as compared to Mono-crystallin solar PV modules.

CONCLUSION

This paper presents a comprehensive performance analysis of PV systems and investigates anomaly detection using thermal imaging technology. Infrared thermography enables non-contact, real-time detection of defects such as hotspots, faulty cells, and connection failures. The study evaluates system efficiency, identifies thermal irregularities, and correlates them with power losses. Thermal imaging technology plays a crucial role in the performance analysis and fault detection of photovoltaic systems. It enables early identification of anomalies such as hotspots, cracks, and connection failures, thereby improving system efficiency and reliability. The integration of thermal imaging with machine learning and drone technology offers a promising future for automated and large-scale PV monitoring. The future Scope of the work by incorporating AI-based real-time monitoring systems, integration with IoT and smart grids and automated drone inspection systems

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REFERENCES

1. *Serna-Garcés, S.I.; Bastidas-Rodríguez, J.D.; Ramos-Paja, C.A. Reconfiguration of Urban Photovoltaic Arrays Using Commercial Devices. Energies 2015, 9, 2.*
2. *Kumar, S.; Sharma, A.; Roy, B. Solar energy market developments in India. Renew. Sustain. Energy Rev. 2016, 62, 121–133.*
3. *Parida, B.; Iniyan, S.; Goic, R. A review of solar photovoltaic technologies. Renew. Sustain. Energy Rev. 2011, 15, 1625–1636.*
4. *Abdullah, M.; Mamun, A.; Selvaraj, J. Experimental investigation of the effect of partial shading on photovoltaic performance. IET Renew. Power Gener. 2017, 11, 912–921.*
5. *Zhou, T.; Sun, W. Study on maximum power point tracking of photovoltaic array in irregular shadow. Int. J. Electr. Power Energy Syst. 2015, 66, 227–234.*
6. *Mohapatra, A.; Nayak, B.; Das, P.; Mohanty, K.B. A review on MPPT techniques of PV system under partial shading condition. Renew. Sustain. Energy Rev. 2017, 80, 854–867.*
7. *Podder, A.K.; Roy, N.K.; Pota, H.R. MPPT methods for solar PV systems: A critical review based on tracking nature. IET Renew. Power Gener. 2019, 13, 1615–1632.*
8. *Eltamaly, A.M. An improved cuckoo search algorithm for maximum power point tracking of photovoltaic systems under partial shading conditions. Energies 2021, 14, 953.*
9. *Eltamaly, A.M. A novel musical chairs algorithm applied for MPPT of PV systems. Renew. Sustain. Energy Rev. 2021, 146, 111135.*
10. *Sai Krishna, G.; Moger, T. Optimal SuDoKu Reconfiguration Technique for Total-Cross-Tied PV Array to Increase Power Output under Non-Uniform Irradiance. IEEE Trans. Energy Convers. 2019, 34, 1973–1984.*
11. *Pendem, S.R.; Mikkili, S. Modeling, simulation and performance analysis of solar PV array configurations (Series, Series–Parallel and Honey-Comb) to extract maximum power under Partial Shading Conditions. Energy Rep. 2018, 4, 274–287.*
12. *Srinivasan, A.; Devakirubakaran, S.; Meenakshi Sundaram, B. Mitigation of mismatch losses in solar PV system—Two-step reconfiguration approach. Sol. Energy 2020, 206, 640–654.*

13. M. *Panthi, "Anomaly detection in smart grids using machine learning techniques," 2020 First International Conference on Power, Control and Computing Technologies (ICPC2T), pp. 220-222, 2020. DOI: 10.1109/ICPC2T48082.2020.9071434.*
14. *J. Mulongo, M. Atemkeng, T. Ansah-Narh, R. R. Rockefeller, G. M. Nguegnang, and M. A. Garuti, "Anomaly detection in power generation plants using machine learning and neural networks," Applied Artificial Intelligence, vol. 34, no. 1, pp. 64-79, 2020. DOI: https://doi.org/10.1080/08839514.2019.1691839.*
15. *A. Gholami and A. K. Srivastava, "Comparative analysis of ml techniques for data-driven anomaly detection, classification and localization in distribution system," 2020 52nd North American Power Symposium (NAPS) IEEE, pp. 1-6, 2021. DOI: 10.1109/NAPS50074.2021.9449712.*
16. *M. Ibrahim, A. Alsheikh, F. M. Awaysheh, and M. D. Alshehri, "Machine learning schemes for anomaly detection in solar power plants," Energies, vol. 15, no. 3, p. 1082, 2022. DOI: https://doi.org/10.3390/en15031082.*
17. *A. G. Imenes, N. S. Noori, O. A. N. Uthaug, R. Kröni, F. Bianchi, and N. Belbachir, "A deep learning approach for automated fault detection on solar modules using image composites," 2021 IEEE 48th Photovoltaic Specialists Conference (PVSC) IEEE, pp. 1925-1930, 2021. DOI: 10.1109/PVSC43889.2021.9518540.*
18. *N.H. Ishak, M. A. I. Halim, and I. S. Isa, "Detection of Power Distribution Fault in Thermal Images Using CNN," in Intelligent Multimedia Signal Processing for Smart Ecosystems, Cham: Springer International Publishing, pp. 267-287, 2023. DOI: https://doi.org/10.1007/978-3-031-34873-0_11.*
19. *B. V. Charitha and T. Ananthan, "Machine learning based fault detection in induction motor using thermal imaging," 2022 3rd International Conference on Electronics and Sustainable Communication Systems (ICESC) IEEE, pp. 929-936, 2022. DOI: 10.1109/ICESC54411.2022.9885282.*
20. *C. Wei, "Power grid facility thermal fault diagnosis via object detection with synthetic infrared imagery," 2021 3rd International Conference on Electrical Engineering and Control Technologies (CEECT) IEEE, pp. 217-221, 2021. DOI: 10.1109/CEECT53198.2021.9672631.*
21. *J. H. Syu, J. C. W. Lin, and G. Srivastava, "AI-Based Electricity Grid Management for Sustainability, Reliability, and Security," IEEE Consumer Electronics Magazine, 2023. DOI: 10.1109/MCE.2023.3264884.*