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Detection of Maximum Power Degradation in Photovoltaic Modules Using Support Vector Machines

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A B S T R A C T

In this paper, a Support Vector Machine (SVM) classifier is employed to analyze the degradation of photovoltaic (PV) modules in Algeria after five months of operation under moderate and humid climate conditions. The PV module examined has a nominal maximum power of 270 W. Using a comprehensive electrical and environmental dataset, the SVM model effectively classified the performance states of the module. The analysis of irradiance evolution over time shows that the peak power delivered during the day reaches approximately 249 W when solar irradiance ranges from 950 W/m² to 1050 W/m², representing about 92% of the module's nominal power, during peak irradiation hours, the module operated under cloudy conditions for nearly 30% of the time, resulting in noticeable power fluctuations and contributing to degradation effects. The SVM-based classification enabled the creation of heatmaps that intuitively highlight degradation patterns, offering a clearer and more interpretable diagnostic tool compared to traditional analytical methods. The results demonstrate that the proposed methodology is effective for detecting degradation in individual PV modules and scalable to PV power plants, thereby supporting improved monitoring, maintenance, and performance optimization in similar climatic environments.

1. Introduction

As a sustainable and renewable resource, sunlight provides an inexhaustible source of power. Solar panels convert this energy into electricity silently, and both residential installations and large solar power plants operate without emissions and with very little environmental impact [1]. Worldwide, the capacity of photovoltaic (PV) systems grew from nearly zero gigawatts (GW) in 1990 to 505 GW in

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2018, with an impressive 102.4 GW added in 2018 alone [2].

To ensure systems perform efficiently, regular monitoring of solar production is essential. Modern PV systems include a variety of monitoring tools, from basic energy-output tracking to advanced home-automation integrations, and some manufacturers offer additional customer service and technical support for solar professionals [3].

The increasing reliance on solar energy as a key component of sustainable energy solutions has led to a significant rise in the deployment of PV modules worldwide. These systems harness sunlight to generate electricity, contributing to reduced greenhouse gas emissions and fostering energy independence [4-6]. The performance and longevity of PV modules can be adversely affected by various degradation mechanisms. Identifying and classifying these degradation states is essential for effective maintenance and optimization of solar energy systems.

Recent advancements in artificial intelligence, particularly in neural networks, offer promising tools for analyzing complex datasets and extracting meaningful insights. Neural networks, especially deep learning models, have shown great potential in image and signal processing, making them suitable for analyzing visual and operational data from PV modules. By leveraging these technologies, we can develop sophisticated classification systems that accurately identify the degradation of PV modules [7,8].

In this study, we employed neural networks to analyze the degradation of a 270W PV module after five months of operation in Algeria's moderate and humid climate, and to apply neural network classification techniques to assess the degradation of a 270W PV module following five months of operation in Algeria's moderate and humid climate. We will investigate various factors influencing degradation, including environmental conditions and operational metrics, while utilizing both image data and numerical inputs. Our findings will contribute to enhancing maintenance strategies, extending the lifespan of PV systems, and ultimately improving the efficiency of solar energy production.

Through this research, we hope to demonstrate the effectiveness of neural networks in monitoring and analyzing PV module performance, paving the way for smarter and more responsive solar energy management systems [9,10].

The increasing reliance on renewable energy sources has underscored the importance of efficient PV systems. As these systems age, understanding their performance degradation becomes crucial for maintaining efficiency and maximizing energy output. Traditional methods of monitoring and analyzing PV module degradation often fall short in capturing the complexity of influencing factors, making advanced techniques necessary [11].

Neural networks, a subset of artificial intelligence, offer powerful tools for data classification and predictive modeling. Their ability to learn from vast datasets allows for more nuanced insights into the performance dynamics of PV modules. This study focuses on utilizing neural networks to classify data related to the degradation of PV modules, aiming to enhance monitoring processes and improve overall system performance [12].

The novelty of this work lies in the development of a comprehensive and data-driven framework that integrates electrical performance measurements with environmental operating conditions to evaluate the degradation of photovoltaic modules using SVM. Unlike many existing studies that focus solely on electrical parameters or rely on traditional performance ratio analysis, our approach captures the dynamic interaction between climate variability and PV behavior, enabling a more accurate and context-aware classification of degradation states. Another key innovation is the emphasis on maximum power degradation under real outdoor conditions, which remains insufficiently addressed in the literature, especially in moderate and humid climates such as those encountered in northern Algeria. The study introduces an interpretative layer based on heatmap visualization, which provides an intuitive representation of degradation patterns and significantly improves the diagnostic readability compared to conventional numerical outputs. The methodology is also designed to be scalable and adaptable, allowing it to be extended to larger datasets and large PV power plants without requiring complex instrumentation. This combination of detailed environmental modeling, machine-learning-based classification, and visual interpretability offers a novel contribution to the field of PV. By examining various operating conditions and isolating significant trends, this research aims to provide a comprehensive overview of PV module behavior. The findings can facilitate comparisons across different photovoltaic technologies and support optimized sizing for future installations. Ultimately, leveraging neural networks for this purpose not only enhances our understanding of PV degradation but also contributes to the advancement of renewable energy solutions.

2. SVM Classifier

SVM a type of artificial intelligence methods because they can learn patterns from data without requiring explicit, task-specific programming. Their performance improves with the availability of large and well-structured datasets, making them closely linked to Big Data applications [13]. In predictive modeling, SVM-based classification assigns a label to new input data by learning from previously observed examples.

An SVM is a linear model employed for both classification and regression. It works by finding an optimal line or, in higher dimensions, a hyperplane that separates data points belonging to different classes. This principle forms the core of the SVM methodology [14]. SVMs are part of a broader family of machine-learning algorithms used for tasks such as classification, regression, and anomaly detection. They are valued for their solid mathematical foundations, adaptability, and relatively simple implementation, which makes them accessible even to users with limited background in data analysis [15].

Figure 1 illustrates the architecture of the SVM classifier (Neuron model) as it relates to analyzing the performance of the PV module.

In PV module monitoring, machine-learning techniques play an essential role. SVM classifiers are particularly effective for identifying performance states, detecting abnormal behavior, and monitoring system conditions over time, especially when working with high-dimensional datasets or limited training samples. Compared to more complex learning algorithms, SVMs generally offer better interpretability and stronger resistance to overfitting. Selecting the appropriate technique ultimately depends on the monitoring goals, data availability, and computational constraints [13].

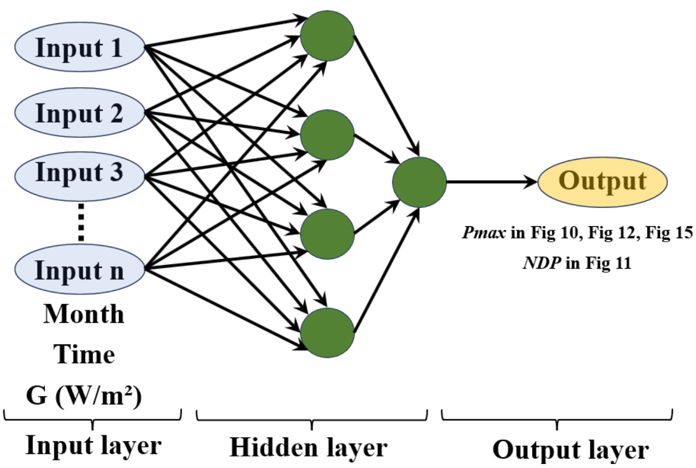

Figure 1. Architecture of SVM classifier (Neuron model)

3. Method of Measurement and Data Processing

This study focuses on the monitoring of PV modules in a laboratory setting, utilizing LabVIEW for data acquisition and integration. The objective is to assess the performance and efficiency of PV modules under controlled environmental conditions. Key parameters such as voltage, current, temperature, and irradiance are continuously monitored, enabling real-time analysis of the modules' behavior.

LabVIEW's graphical programming capabilities facilitate the integration of multiple sensors and data sources, allowing for comprehensive data visualization and analysis. By employing techniques such as IV curve tracing and thermal imaging, we evaluate the electrical performance and thermal characteristics of the PV modules. The collected data provides insights into efficiency losses, temperature effects, and degradation patterns over time.

This integrated monitoring system not only enhances our understanding of PV module performance but also supports the development of strategies for optimizing solar energy systems. The findings contribute to advancing research in solar energy technologies and promoting the reliability of PV systems in practical applications [15,16].

The outdoor data acquisition setup provides a wide variety of measurement conditions. All collected parameters from the different monitoring instruments are recorded and transferred into a centralized database, where they are converted into structured formats that allow fast and efficient data querying for subsequent analysis.

The photovoltaic modules used in this study are installed at the Renewable Energy Development Center (CDER) in Algeria. , is located at approximately 36.75° N latitude and 3.18° E longitude, as shown in Figure 2, Represents the CDER PV module monitoring platform. This platform contains everything we need to monitor our module. It contains: PV module; weather station; temperature sensors; irradiation sensors and the connection cables.


Figure 2. Outdoor platform

Various measurements in our laboratory were conducted using a data acquisition system (Keysight 34972 A), as depicted in Figure 3. This system collects data from multiple sensors, including Isc, Voc, Pmax, Imp, Vmp, Tm, T amb, G, WD, WS, Date, Time, and FF.

Figure 3. Data acquisition (Keysight 34972A)

Figure 3 shows the Keysight 34972A Data Acquisition System is a robust and versatile tool for monitoring PV modules in a laboratory setting. Its multi-channel capability allows for simultaneous measurement of critical parameters such as voltage, current, and temperature from various sensors, ensuring comprehensive analysis of PV performance. With high accuracy and resolution, it delivers reliable data crucial for evaluating efficiency and identifying performance issues. The seamless integration with LabVIEW facilitates automated data acquisition and real-time monitoring, streamlining the testing process. Additionally, its flexible configuration supports various input options, while built-in data logging enables long-term monitoring and storage of data for further analysis. The user-friendly interface and remote monitoring capabilities enhance accessibility and convenience, making the Keysight 34972A an excellent choice for precise and efficient data acquisition in PV module testing, ultimately contributing to advancements in solar energy research.


Figure 4. Weather station

Figure 4 shows the weather station used to measure and record various weather parameters, such as temperature, humidity, atmospheric pressure, wind speed, and direction. These data are essential for understanding and predicting local and regional weather conditions. The equipment can range from simple devices like thermometers and hygrometers to complex computerized systems with specialized sensors and online connectivity for real-time data sharing and Figure 5 depicts an anemometer, a component of our station that measures wind speed and direction.


Figure 5. Anemometer

Figures 6 and 7 show two different solar irradiation sensors that measure and record irradiation in real time. Both sensors were used to ensure the reliability of the measurements.

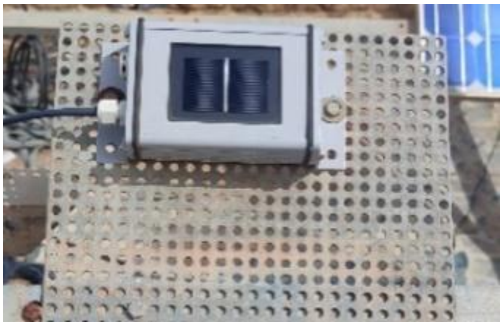

Figure 6. Reference cell

Figure 7. Pyranometer

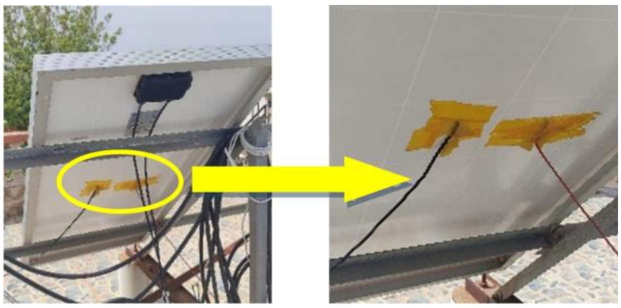

Figure 8. Tpv temperature measurement method

Figure 8 shows the two temperature sensors positioned in the middle of the rear face of the PV module in accordance with the IEC 61215 standard. These sensors measure the module temperature.

Figure 9 illustrates the proposed method's architecture, highlighting the processing and analysis stages that are central to our research on the performance of the PV module.

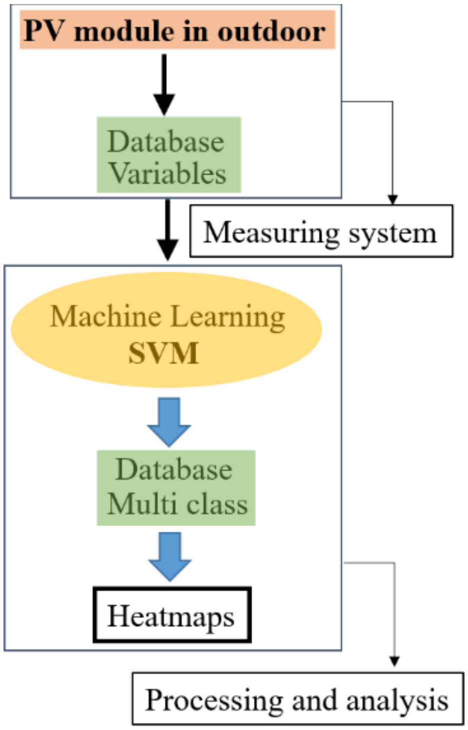

Figure 9. Diagram of method

4. Results and Discussion

The degradation of a 270 W photovoltaic (PV) module is examined using the classification by SVM, relying on a comprehensive monitoring dataset collected over a five-month period with measurements recorded every five minutes. The dataset incorporates detailed electrical characteristics of the module, including I–V curves and key performance indicators such as Pmax, Isc, Voc, Imp, Vmp and FF). Additional measurements were gathered from the module's rear-surface temperature sensors, complemented by environmental variables such as global solar irradiation on the inclined plane, ambient temperature, and wind speed and direction. Figure 10 presents the evolution of the module's maximum power throughout different times of the day and across successive months, highlighting the trend in daily average power output. The results show that the module typically reaches its highest production between 12h00 p.m. and 1h00 p.m., achieving approximately 68% of its rated power in February. As autumn approaches, this output gradually declines due to reduced sunlight availability, lower solar elevation, and increased cloudiness. The figure also illustrates the monthly changes in sunshine duration, providing additional context for the observed seasonal performance variations.

Recent studies demonstrate active progress on machine-learning methods for PV parameter estimation, degradation detection and forecasting. Batiyah et al. proposed a deep neural network framework to estimate PV parameters from datasheet and simulated datasets, illustrating strong performance for model-based parameter extraction but relying mainly on synthetic/board-level data rather than long-term field monitoring [17].

Lee et al. developed an LSTM-based classifier for PV module degradation and compared it against SVM, random forest and CNN baselines, reporting improved temporal sensitivity for degradation events but focusing on moderate-sized datasets and short horizons [18].

Ebied et al. presented an advanced deep-learning pipeline for defect detection using electroluminescence images, which shows high accuracy for visual defects but does not combine electrical/environmental measurements with image data [19].

Song et al. integrated NGBoost with deep networks for probabilistic ultra-short-term PV power forecasting, showing value for uncertainty quantification in power prediction but not for long-term degradation assessment [20].

Recent practical overviews and datasets summarize observed degradation modes and emphasize the need for field-scale, reproducible monitoring studies [21].

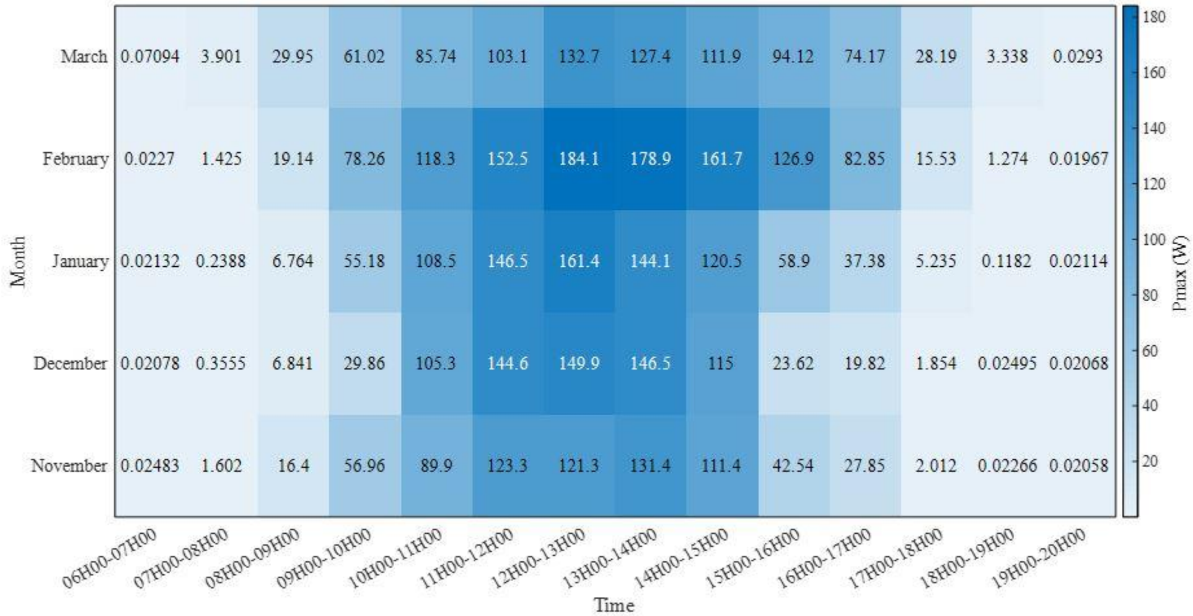

Figure 10. Maximum power supplied over a day in five (05) months

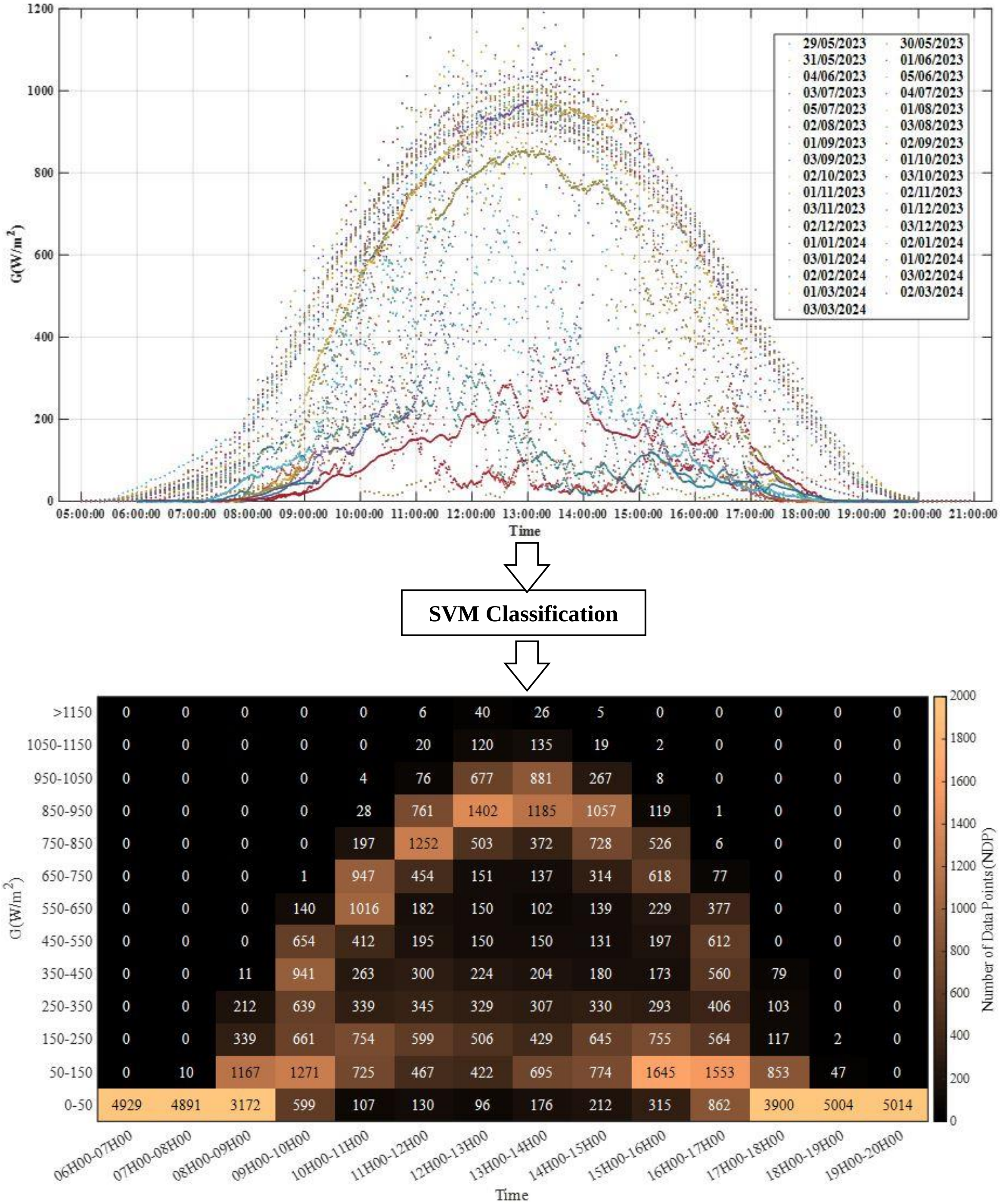

Figure 11. Number of Data points according to G (W/m^2) and Time in Five (05) months

Figure 11 shows the number of measurement points obtained as a function of time and irradiation before and after SVM classification. In the first figure (This is 33 days sampling) noted that the curve is difficult to read and analyze before SVM classification; however, after classification with 05 months, the heatmap we created is easier to interpret. This technique enables us to identify areas of interest for performance analysis as well as regions that represent non-essential values or isolated phenomena.

Figure 11 presents the number of daily measurements taken under different irradiation levels at specific times. This methodology helps identify key areas for performance analysis while filtering out non-representative data or isolated phenomena. Distinguishing these values is crucial for accurately assessing PV system performance. Notably, the dark yellow squares correspond to clear sky solar irradiation, while the data points within the bell curve mainly represent measurements taken under cloudy conditions. Additionally, values exceeding 1150 W/m² may indicate reflection phenomena. This visual analysis aids in defining the study area and minimizing potential errors in parameter calculations.

Figure 12 shows the evolution of solar irradiation over time and the maximum power achieved. It highlights that the peak power delivered during the day reaches approximately 249 W when irradiation ranges from 950 W/m² to 1050 W/m², equating to about 92% of the module's nominal power. During peak hours, the PV module operates under cloudy conditions roughly 30% of the time. This data can serve as a valuable reference for sizing PV systems, particularly in selecting the appropriate inverter.

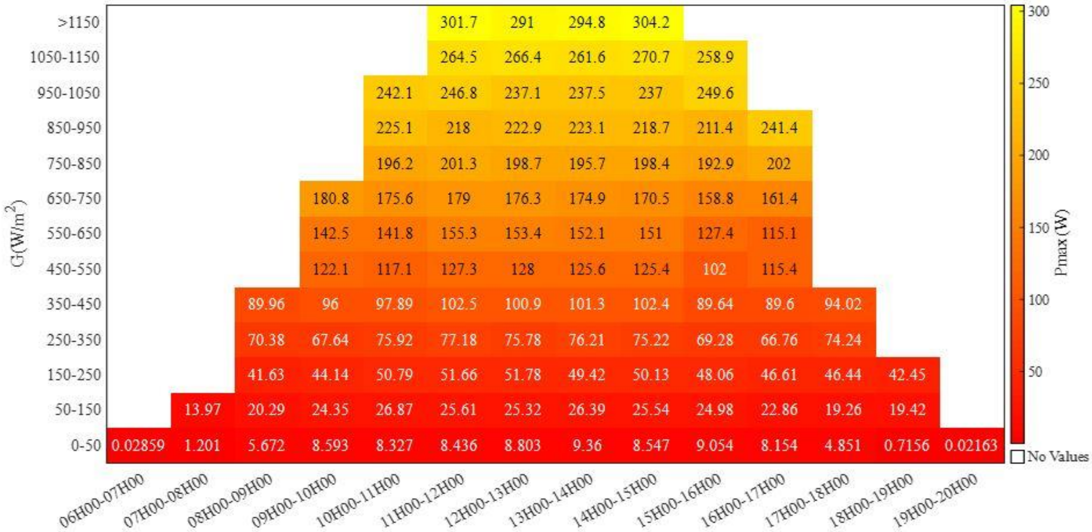

Figure 12. Pmax (W) according to G (W/m^2) and Time in Five (05) months

4.1. Example of Data Analysis and Fault Detection at the 1.7 MW PV Power Plant of Oran International Airport

Oran is located on the Mediterranean coast, about 400 km west of Algiers. The Ahmed Ben Bella Airport is equipped with a PV power plant covering an area of 15,900 square meters see Figure 13 and 14. It is the second largest photovoltaic plant rooftop in Africa, with a peak capacity of 1.7 MWp, built in 2022 by the Renewable Energy Development Center of Algeria. The plant consists of 5,540 photovoltaic modules. It supplies 40% of the airport's electricity needs and helps reduce greenhouse gas emissions by approximately 1,000 tons of carbon dioxide per year.

The plant includes 46 inverters rated at 27 kW each, connected to 46 junction boxes. Each junction box is connected to 6 strings, and each string contains 21 or 22 PV modules.

Figure 13. Image satellite PV Power Plant of Oran International Airport

Figure 14. Image PV Power Plant of Oran International Airport

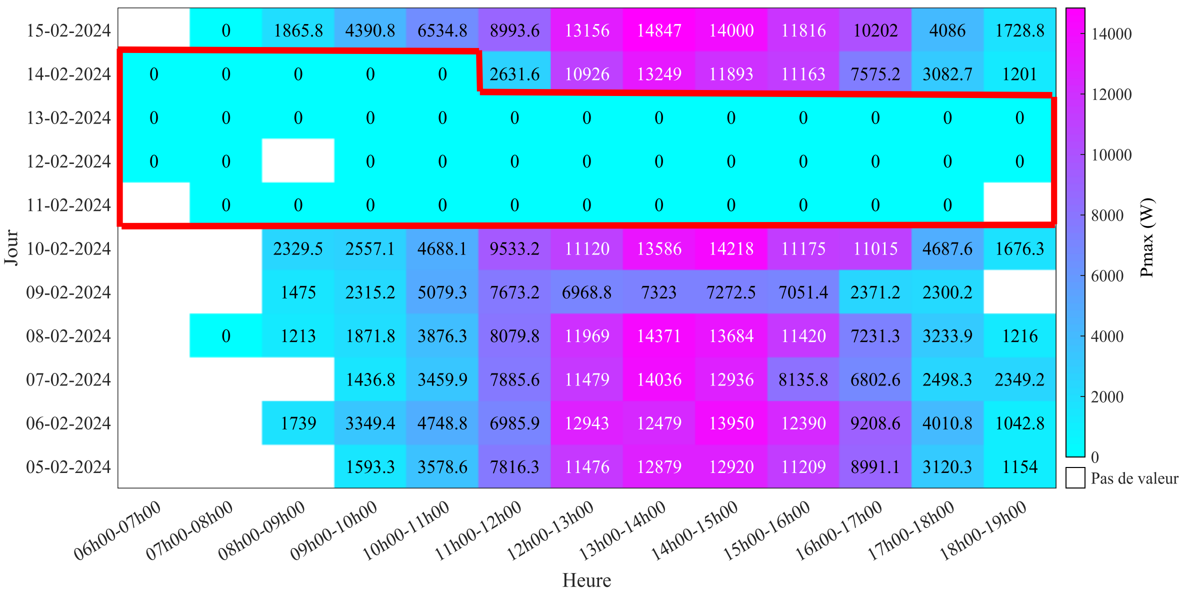

Figure 15. Evolution of Pmax (W) provided for the month of February over 11 days

Figure 15 shows the evolution of the maximum power output over a single day, from February 5, 2024 to February 15, 2024, of inverter No. 22 of the Oran airport photovoltaic installation. It can be seen that the inverter produced no power output for four days, from the morning of February 11, 2024 to the morning of February 14, 2024, due to a failure of the PV module to detach caused by wind, as indicated by the area highlighted in red. Figure 16 shows the detachment failure of a PV module caused by wind on the PV installation of the Oran airport power plant.

The importance of applying SVM to facilitate the analysis of PV system data. We used SVM to classify data from a PV module as well as data from a 1.7 MW PV power plant. We obtained very clear and easy-to-interpret heatmaps. This method allowed us to analyze performance and detect faults in PV power plants.

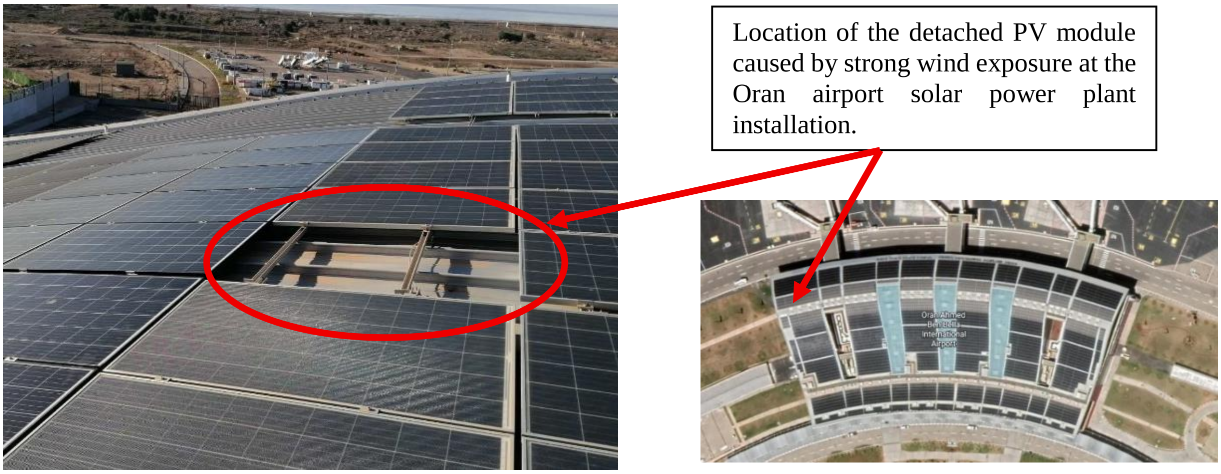

Figure 16. Location of the detached PV module caused by strong wind exposure at the Oran airport solar power plant installation

Figure 16 shows the detachment failure of a PV module caused by wind on the PV installation of the Oran airport power plant.

5. Conclusion

This study demonstrates the effectiveness of an SVM-based classification framework for assessing the degradation of photovoltaic modules operating for five months under moderate and humid climatic conditions in Algeria. By leveraging a comprehensive combination of electrical and environmental data, the model successfully identified degradation patterns, particularly in relation to the decline in maximum power. The analysis revealed that although the module has a nominal power of 270 W, the maximum power measured during peak irradiance reached approximately 249 W equivalent to 92% of its rated output indicating measurable degradation during the monitoring period, the results showed that nearly 30% of peak-irradiance hours occurred under cloudy conditions, contributing to irregular power delivery and reinforcing the need to account for weather-related influences in outdoor degradation studies.

The application of heatmap visualization strengthened the interpretability of the classification results, allowing clear identification of performance transitions that are not easily captured by traditional analytical methods. The findings confirm that SVM offers a reliable and scalable tool for real-time or near-real-time PV performance assessment, supporting both early detection of degradation and improved maintenance planning. The methodology is practical, non-invasive, and adaptable to larger PV installations, making it suitable for deployment across different climatic regions.

Future work should aim to extend the dataset to include longer monitoring periods and multiple module technologies, as well as compare SVM performance with other modern machine-learning methods. Incorporating physical diagnostic techniques such as infrared thermography or electroluminescence imaging would further validate the classification outputs and strengthen the robustness of the approach, the proposed framework contributes a valuable and interpretable tool for enhancing PV system reliability, optimizing field performance.

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Nomenclature

Imp	Current at maximum power point [A]
Isc	Short-circuit current of PV module [A]
G	Measured in-plane irradiance [W/m^2]

NDP	Number of Data Points
PNN	Probabilistic Neural Networks
Pmax	Maximum power of PV module [W]
PV	Photovoltaic
SVM	Support Vector Machine
Tamb	Ambient temperature [°C]
Tm	Temperature of PV module, measured at the backshet [°C]
Vmp	PV module voltage at maximum power poit [V]
VOC	Open-circuit voltage of PV module [V]
WD	Wind direction
WS	Wind speed [m/s]

References

[1] Doyle, T., Erion‐Lorico, T., & Desharnais, R. (2020). PV module reliability scorecard. Relatório técnico, PVEL and DNV GL. [2] Seme, S., Sredenšek, K., Štumberger, B., & Hadžiselimović, M. (2019). Analysis of the performance of photovoltaic systems in Slovenia. Solar Energy, 180, 550-558. doi.org/10.1016/j.solener.2019.01.062

[3] Quansah, D. A., & Adaramola, M. S. (2019). Assessment of early degradation and performance loss in five co-located solar photovoltaic module technologies installed in Ghana using performance ratio time-series regression. Renewable energy, 131, 900-910. doi.org/10.1016/j.renene.2018.07.117

[4] Achour, Y., Berrada, A., Arechkik, A., & El Mrabet, R. (2023). Techno-economic assessment of hydrogen production from three different solar photovoltaic technologies. *International Journal of Hydrogen Energy*, *48*(83), 32261-32276. doi.org/10.1016/j.ijhydene.2023.05.017

[5] Chiteka, K., & Enweremadu, C. (2025). A Review on Modeling and Prediction of Soiling on Solar Photovoltaics and Thermal Collectors. *Journal of Solar Energy Research*. 10(1), 2135-2160 doi.org/10.22059/jser.2025.392093.1544

[6] Ameur, A., Berrada, A., Bouaichi, A., & Loudiyi, K. (2022). Long-term performance and degradation analysis of different PV modules under temperate climate. *Renewable Energy*, *188*, 37-51. doi.org/10.1016/j.renene.2022.02.025

[7] Mohamed, M. (2022). Comparison between P&O and SSO techniques based MPPT algorithm for photovoltaic systems. International Journal of Electrical and Computer Engineering (IJECE). doi.org/10.11591/ijece.v12i1

[8] Bayrak, F., Oztop, H. F., & Selimefendigil, F. (2020). Experimental study for the application of different cooling techniques in photovoltaic (PV) panels. Energy Conversion and Management, 212, 112789. doi.org/10.1016/j.enconman.2020.112789

[9] Parsa, H. R., & Sarvi, M. (2024). Analysis of Intra-String Line-Line Fault in Photovoltaic System. Journal of Solar Energy Research, 9(1), 1780-1793. https://doi.org/10.22059/jser.2024.367117.1352

[10] Ruiz-Gonzalez, R., Gomez-Gil, J., Gomez-Gil, F. J., & Martínez-Martínez, V. (2014). An SVM-based classifier for estimating the state of various rotating components in agro-industrial machinery with a vibration signal acquired from a single point on the machine chassis. Sensors, 14(11), 20713-20735. doi.org/10.3390/s141120713

[11] Hichem, H., & Djamel, B. (2015). Identification of Acoustics Microwaves (Bulk Acoustic Waves) in Piezoelectric Substrate (LiNbO3 Cut Y–Z) by Classification Using Neural Network. Journal of Nanoelectronics and Optoelectronics, 10(3), 314-319. doi.org/10.1166/jno.2015.1767

[12] Hafdaoui, H., Bouchakour, S., & Belhaouas, N. (2022). Use an artificial intelligence method (Machine Learning) for analysis of the performance of photovoltaic systems. Journal of Renewable Energies, 25(2), 199-210. doi.org/10.54966/jreen.v25i2.1082

[13] Hafdaoui, H., Bouchakour, S., & Belhaouas, N. (2022). Using machine learning for analysis a database outdoor monitoring of photovoltaic system. International Journal of Integrated Engineering, 14(6), 275-280. doi.org/10.30880/ijie.2022.14.06.024

[14] Belhaouas, N., Hafdaoui, H., Nunzi, J. M., Khatir, S., Ernst, D., Mehareb, F., ... & Saheb-Koussa, D. (2025). Comprehensive analysis and insights into the relationship between temperature coefficients, PV failures, and investigating their correlation with other PV parameters. Solar Energy, 301, 113891. doi.org/10.1016/j.solener.2025.113891

[15] Herteleer, B., Huyck, B., Catthoor, F., Driesen, J., & Cappelle, J. (2017). Normalised efficiency of photovoltaic systems: Going beyond the performance ratio. Solar Energy, 157, 408-418. doi.org/10.1016/j.solener.2017.08.037

[16] Hafdaoui, H., Belhaouas, N., Assem, H., Hadjrioua, F., & Madjoudj, N. (2023). Compare between the performance of different technologies of

PV Modules using Artificial intelligence techniques. Journal of Renewable Energies, 99-106. doi.org/10.54966/jreen.v1i1.1166

[17] Batiyah, S., Al-Subhi, A., Elsherbiny, O., Aldosari, O., & Aldawsari, M. (2025). Deep neural networks model for accurate photovoltaic parameter estimation under variable weather conditions. *Solar Energy*, *299*, 113734. doi.org/10.1016/j.solener.2025.113734

[18] Lee, C. H., Lim, S. K., Park, S. J., & Kim, B. H. (2025). Photovoltaic Module Degradation Detection Using V–P Curve Derivatives and LSTM-Based Classification. *Sensors*, *25*(20), 6475. doi.org/10.3390/s25206475

[19] Ebied, M. A., Munshi, A., Alhuzali, S. A., El-Sotouhy, M. M., Shehta, A. I., & Elborlsy, M. S. (2025). Advanced deep learning modeling to enhance detection of defective photovoltaic cells in electroluminescence images. *Scientific Reports*, *15*(1), 31640. doi.org/10.1038/s41598-025-14478-y

[20] Song, Z., Xiao, F., Chen, Z., & Madsen, H. (2025). Probabilistic ultra-short-term solar photovoltaic power forecasting using natural gradient boosting with attention-enhanced neural networks. *Energy and AI*, *20*, 100496. doi.org/10.1016/j.egyai.2025.100496

[21] Hameed, M. A., Gottschalg, R., Scheer, R., & Alias, Q. M. (2025, February). Performance analysis with risk identifications and its economic impact on PV plant in harsh climates: Baghdad site case. In *AIP Conference Proceedings* (Vol. 3169, No. 1, p. 040136). AIP Publishing LLC. doi.org/10.1063/5.0254682