TELKOMNIKA Telecommunication, Computing, Electronics and Control
Vol. 23, No. 1, February 2025, pp. 258∼266
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v23i1.26155

PV solar anomaly detection using low-cost data logger and ANN algorithm

Younes Ledmaoui[1], Adila El Maghraoui[2], Mohamed El Aroussi[1], Rachid Saadane[1], Abdellah Chehri[3], Ahmed Chebak[2]
[1]Laboratory Engineering System-SIRC-(LaGeS), Hassania School of Public Works (EHTP), Casablanca, Morocco
[2]Green Tech Institute (GTI), Department and Organization, Mohammed VI Polytechnic University (UM6P), Benguerir, Morocco
[3]Department of Mathematics and Computer Science, Royal Military College of Canada, Kingston, Canada

Article Info

Article history:

Received Mar 11, 2024
Revised Oct 28, 2024
Accepted Nov 26, 2024

Keywords:

Artificial intelligence
Edge device
Energy management system
Energy monitoring
Predictive maintenance
Renewable energy
Solar energy

ABSTRACT

This paper presents an innovative edge device architecture that significantly enhances solar energy management systems. By integrating advanced functionalities such as generation prediction, maintenance alerts, and solar anomaly detection, this architecture transforms solar energy management. Through edge computing, it enables real-time analysis and decision-making at the network edge. Leveraging machine learning algorithms and accurate predictive models, these edge devices provide precise energy generation forecasts, facilitating optimal energy utilization and strategic planning for stakeholders. Additionally, the architecture incorporates anomaly detection techniques to proactively identify deviations from normal operation, minimizing downtime, and enabling timely maintenance. This approach ensures uninterrupted energy generation, enhancing the reliability and efficiency of the entire monitoring system. The integration of these features within edge devices improves the performance and reliability of energy monitoring systems. Implementing this cutting-edge architecture empowers stakeholders to achieve superior energy management, substantial cost reductions, and unparalleled system reliability.

Corresponding Author:

Younes Ledmaoui
Laboratory Engineering System-SIRC-(LaGeS), Hassania School of Public Works (EHTP)
Casablanca, 8108, Morocco
Email: ledmaoui.younes.cedoc@ehtp.ac.ma

1. INTRODUCTION

Solar photovoltaic (PV) plant systems have been deployed on a large scale. However, older PV systems suffer from high failure rates of modules (3-10% of active PV systems have at least one anomalous module). Due to this high number, automatic anomaly detection in PV modules has become necessary. Module performance is often monitored by current-voltage (I-V) curves, but typically, only strategies using specialized hardware such as micro-converters, data acquisition, and digital signal processors are reliable but economically infeasible for small residential system applications. Therefore, low-cost modular technologies are increasingly being used for large-scale installations that can be integrated easily into residential systems [1]. Although it is common to use communication infrastructure to gather information from selected PV systems, such commercially available systems do not usually offer intelligent anomaly detection [2]-[4]. As solar installations continue to proliferate, effective monitoring systems are crucial to ensure optimal performance [5]-[7], maintenance, and overall system reliability. The advent of edge computing has opened up new possibilities for enhancing energy monitoring by enabling real-time analysis and decision-making at the network edge. Moreover, the utilization of artificial intelligence (AI) technology in the domain of renewable energy, particularly in solar power systems, has presented numerous novel possibilities for the identification and resolution of various challenges. These data-based decision-making systems possess an inherent capability to facilitate efficient energy management [8]-[10]. In this context, numerous studies have been undertaken on monitoring solar energy, Table 1 provides an overview of solar power monitoring using internet of things (IoT) and artificial neural network (ANN) algorithm.

Table 1. IoT and ANNs applied for solar systems

Paper	Year	Summary
[11]	2022	Edge-based individualized anomaly detection in large-scale distributed solar farms, based on Siamese-twin neural networks.
[12]	2017	System for online display of the power usage of solar energy.
[13]	2017	Employment of Raspberry Pi to monitor the solar output.
[14]	2022	Usage of data-logger based on ESP32 to monitor inverter output.
[15]	2023	Usage of the ANN algorithm to predict the PV system's current and voltage.
[16]	2019	Deployment of the ANN model in which internal parameters are formulated to effectively map the inputs to the outputs.
[17]	2018	Correlation coefficients between the ANN predictions and actual solar radiation intensities.
[18]	2021	Comparison between the ANN and type 2 fuzzy logic system to detect the anomaly of the PV.
[19]	2022	Employment of machine learning (ML) algorithms in the RapidMiner tool, using real-time data from a smart grid in an experimental open-pit mine.
[20]	2021	Various solar plant configurations and the ideal solar energy monitoring criteria.
[21]	2019	A system with a data gateway with a 98.49% success rate.
[22]	2023	Monitoring PV system for fault detection in solar systems.
[23]	2021	Advancements in solar PV monitoring.

As PV solar installations expand to remote areas and power capacity increases, the likelihood of damaged panels due to temperature and degradation rises. Maintenance costs and losses also escalate with the number of panels and distance from the capital. Fitness degradation rates fail a 10% reduction in operating power. There are no guarantees exceeding this level or universal periodic maintenance programs. Possible faults include low cleanliness, panel aging, broken or soiled cells, shading, bay effect, electrical issues, and anomaly of the IV curve [24], [25]. The proposed architecture integrates advanced functionalities, including generation prediction, maintenance alerts, and solar anomaly detection [26], [27]. Voltage, current, power, and energy data from PV modules are collected and transmitted to a custom-developed IoT platform for analysis and storage. The structure of the paper is as: section 2 describes the methodology, focusing on the proposed edge device architecture, including its components and data processing capabilities, as well as a detailed explanation of the edge computing framework. In section 3, we present the experimental results and provide a thorough description of how the architecture performs in real-world scenarios. The findings of the paper and future work to further enhance the system's capabilities are encapsulated in section 4.

2. METHOD

The following is a framework of the suggested approach. Figure 1 illustrates the structure of the implemented methodology, the utilization of a Raspberry Pi-based edge device connected to the inverter via Modbus protocol for solar energy monitoring, incorporating ML and monitoring data for solar plants to make anomaly detection, the edge device extends its functionality by incorporating image analysis techniques. By processing solar plant images, the edge device can detect faults or anomalies.

2.1. Description of the proposed architecture

The methodology used in the solar energy monitoring system begins with acquiring and transmitting data. This data is then stored and processed to enable accurate energy generation prediction. The system also includes anomaly detection, maintenance alert features, and data visualization tools. Compliance with industry standards and continuous system improvement are integrated to ensure the delivery of reliable energy forecasts and real-time alerts.

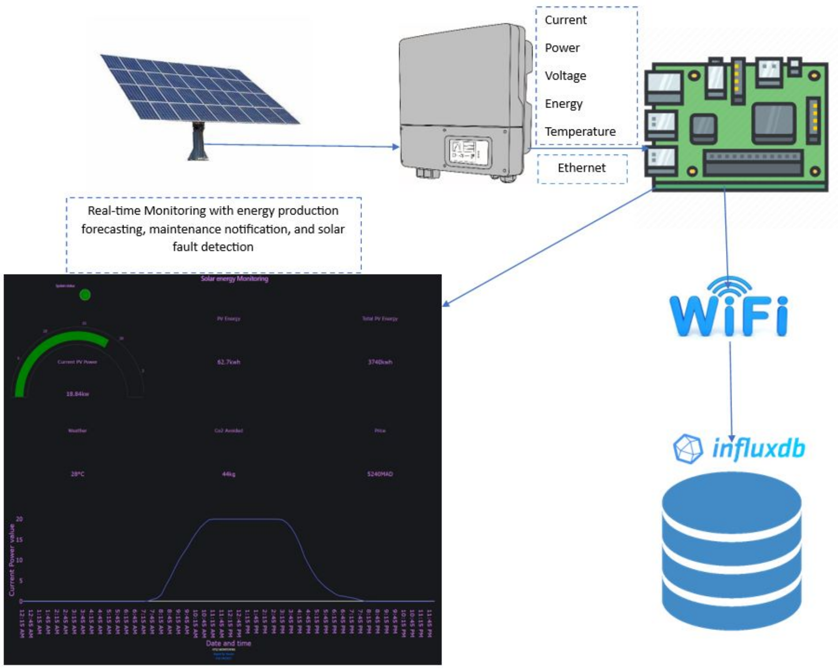


Figure 1. The proposed architecture of the edge device

2.1.1. Hardware components

The core hardware component of the architecture is the Raspberry Pi, a compact and low-power single-board computer. The Raspberry Pi acts as the central processing unit for data collection, analysis, and communication. It is connected to the inverter with the Modbus protocol to get the necessary data to monitor the solar plant and make future predictions and anomaly detection.

2.1.2. Data collection, processing, and analysis

The edge device includes real-time measurements from the inverter, such as energy generation readings, voltage, current, CO_2 avoided, and temperature. The collected data is processed and analyzed within the edge device using advanced algorithms and ML techniques. The data is preprocessed to remove noise, outliers, and inconsistencies.

2.1.3. Prediction with artificial neural network

The architecture incorporates an ANN model for energy generation prediction with the best hyperparameters got from related works studies. The trained ANN model takes input data such as historical energy generation patterns, and time of day to forecast future energy generation. This prediction capability helps in optimizing energy utilization and planning.

2.1.4. Communication and connectivity

The edge device has versatile connectivity options, including Ethernet and wireless technologies like Wi-Fi, to ensure seamless communication with the cloud. These connectivity features enable the device to transmit data in real-time, facilitating continuous updates and enhancing system responsiveness. By leveraging these technologies, the device ensures minimal latency, which is crucial for time-sensitive applications such as predictive maintenance and energy optimization. This robust design ensures reliability and consistent performance in diverse environments.

2.1.5. User interface

The solar edge device includes a user-friendly interface, accessible through a web-based dashboard using the dash framework. This seamless integration with the Python ecosystem allows easy incorporation of data analysis, ML models, and predictive algorithms into dashboards. The dashboard provides interactive visualizations and real-time data updates, enabling users to effectively monitor system performance. This framework ensures compatibility with numerous libraries and tools, making it easier to customize features and extend functionality based on user requirements.

2.2. Raspberry Pi-based edge device

The utilization of Raspberry Pi-based edge devices, combined with the power of ML and monitoring, presents a compelling approach to edge computing. These devices offer an affordable and accessible platform for deploying intelligent edge solutions. By integrating ML and monitoring into the Raspberry Pi, edge devices can perform data analysis and decision-making [28]. It enables autonomous and self-learning edge devices that can adapt to changing conditions.

Figure 2 depicts the data logger, based on the Raspberry Pi 4 model, integrated into the proposed architecture. It serves as the central hub for data acquisition, transmission, and preprocessing. Equipped with sufficient processing power, the Raspberry Pi 4 enables efficient handling of large datasets collected from various sensors. In addition, the data logger ensures reliable communication with the IoT platform, supporting real-time monitoring, and analysis of the collected information.

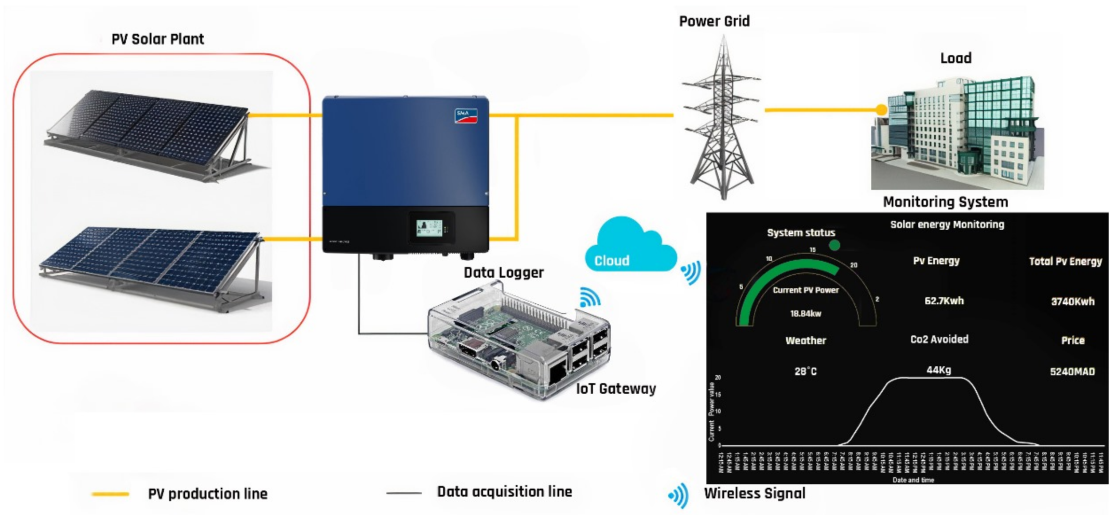


Figure 2. Proposed architecture based on a Raspberry Pi 4 model as the data-logger

2.3. InfluxDB database

InfluxDB is a widely adopted open-source time-series database that manages and analyzes time-stamped data. Designed specifically for time-series data, InfluxDB offers a range of features and capabilities that make it a preferred choice for various industries and applications. It provides a dedicated query language called InfluxQL. InfluxDB also supports high write and query throughput, ensuring efficient handling of large volumes of real-time data. Its lightweight design and scalability make it suitable for edge computing scenarios, enabling seamless integration with IoT devices.

2.4. Machine learning

2.4.1. Definition

ML encompasses a collection of advanced algorithms and methods aimed at exploring and analyzing databases to uncover hidden patterns, associations, trends, and specific structures within the data [29]. By leveraging these techniques, ML extracts valuable insights that might otherwise remain undetected, offering a deeper understanding of complex datasets. It transforms raw data into concise and meaningful representations of essential and actionable information.

2.4.2. Artificial neural network

ANNs also known as neural networks, are a type of ML model inspired by the structure and functioning of the human brain. ANNs consist of interconnected nodes, organized into layers that work collaboratively to solve complex problems. Each neuron receives input signals, processes them through a weighted sum and an activation function, and produces an output signal that is passed on to other neurons in subsequent layers. This layered structure allows ANNs to learn and model intricate patterns in data, making them effective for tasks such as classification, regression, and image recognition.

2.5. Dash applications

The Dash framework, developed by Plotly, is a powerful Python-based open-source tool designed for building interactive web applications tailored for data visualization and analysis. It streamlines the development process by enabling developers to create dynamic, feature-rich web interfaces using Python, along with HTML and CSS for customization. Dash's architecture integrates seamlessly with Plotly's visualization libraries, allowing for the creation of highly interactive graphs and dashboards.

3. RESULTS AND DISCUSSION

The ANN model in our proposed architecture was implemented with parameters in Table 2, determined from experience and using the Scikit-learn library in Python. The table includes key parameters for configuring and training the models. Data from a year-long operational solar plant was used, providing valuable insights into the system's performance and behavior under different conditions and factors. These results confirm the efficacy of using ANN for prediction tasks and highlight its position as a powerful tool in the field of data analysis and forecasting. Through evaluation and analysis, it is evident that the ANN prediction model surpasses alternative methods by capturing and predicting complex patterns within the data.

Table 2. ANN models' parameters used in the proposed edge-device

Typer-parameter	Value
Activation	Identity
Alpha	$1e-5$
Iidden-layer-size	100
Learning-rate	adaptive
Solver	Lbfgs
validation-fraction	0.1
Max-iteration	1000

Figure 3 presents solar energy monitoring outcomes using Raspberry Pi-connected inverter data. The system continuously collects and analyzes data, including energy production levels, voltage, power, CO_2 saved, and other relevant parameters. Alerts are triggered for output decrease, indicating potential faults or energy generation drops. Quick intervention and troubleshooting are enabled by promptly detecting and alerting output decreases. This proactive maintenance ensures optimal energy generation and utilization, minimizing downtime and maximizing efficiency.

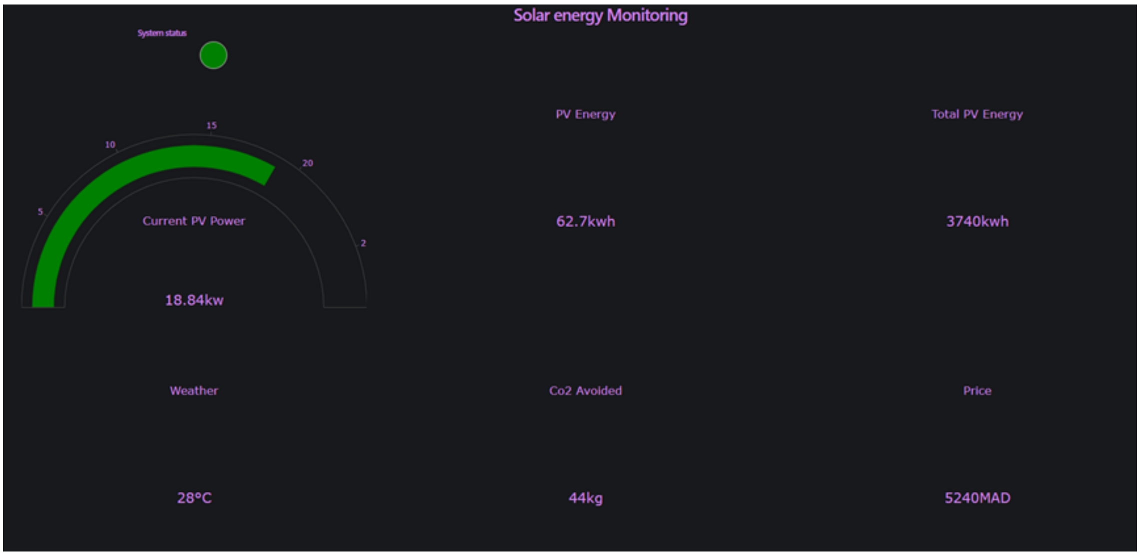


Figure 3. Edge device monitoring system

An alert is displayed when the power generated by the solar energy system falls below expected levels as shown in Figure 4. This alert compares real-time and expected power generation data and triggers when there is a significant drop. It can be visual or a message to the system administrator. The purpose is to identify and address issues affecting power generation, such as faults in solar panels or wiring issues. By monitoring deviations in real-time, the system can operate more efficiently and minimize potential losses.

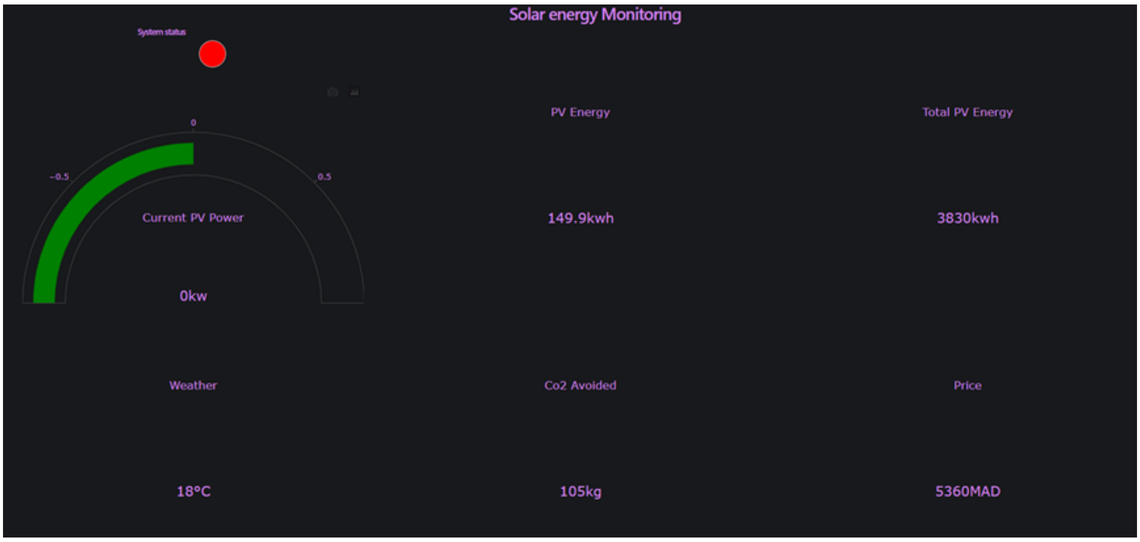


Figure 4. Edge device alert

Figure 5 shows the daily power output of our solar system. The graph represents power generated over time, typically measured daily. The x-axis denotes time intervals, while the y-axis represents power output in kilowatts (kW). This visualization helps identify trends in energy production, including peak generation periods and potential anomalies. In addition, the graph provides valuable insight into system performance, enabling better analysis and optimization of energy generation. Such data is crucial for evaluating the efficiency of solar installations and planning energy usage effectively.

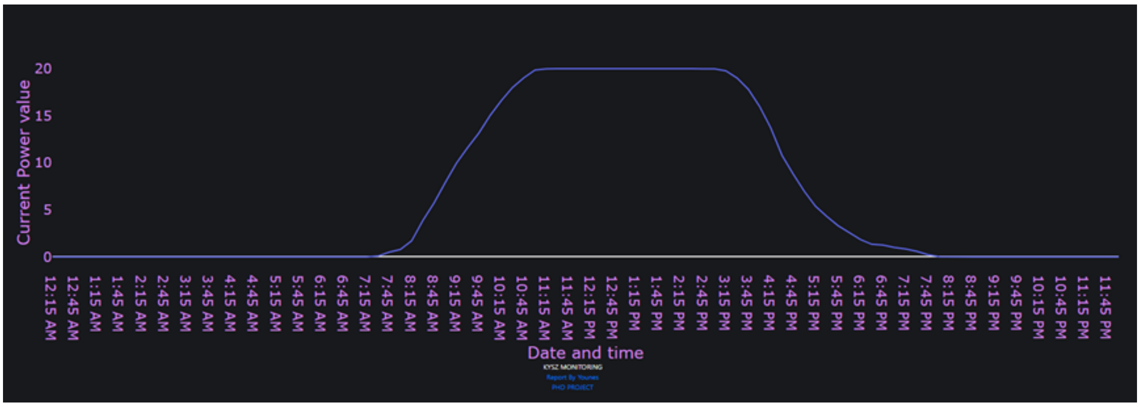


Figure 5. Daily power of our system

The research demonstrates that the fusion of ANN and IoT within an edge device framework can offer significant information for forecasting, overseeing, and sustaining solar energy. Utilizing historical solar energy data and environmental factors to train the ANN allows for precise predictions, leading to improved energy efficiency and strategic decision-making. Nevertheless, obstacles such as data reliability and accessibility, as well as the expansion and adaptability of the edge device framework, require additional investigation and confirmation, across multiple solar facilities. However, the study also identifies key challenges that need further exploration. Ensuring the reliability and accessibility of the data is crucial for maintaining the accuracy of predictions. Additionally, scaling the edge device framework to accommodate larger and more diverse solar facilities poses a significant challenge. The adaptability of this framework to different operational conditions across various solar installations also needs rigorous testing. Addressing these challenges is essential to fully realize the potential of this technology in supporting sustainable and efficient solar energy systems on a broader scale.

4. CONCLUSION

The proposed edge device architecture presents a compelling solution to enhance solar energy management systems. By leveraging the capabilities of edge computing, advanced functionalities such as generation prediction, maintenance alerts, and anomaly detection are seamlessly integrated into this device. This integration empowers energy stakeholders with accurate energy forecasts, proactive maintenance alerts, and improved overall system efficiency. Embracing this advanced architecture enables improved energy management, reduced operational costs, and heightened system reliability. The adoption of edge computing in energy monitoring systems is a significant step towards sustainable and efficient energy. Future work includes extensive testing of the prototype across multiple solar sites to gather data for comprehensive analysis and monitoring. Testing in diverse environments will assess scalability, adaptability, and performance across different solar installations.

REFERENCES

[1] W. Kandeal *et al.*, "Infrared thermography-based condition monitoring of solar photovoltaic systems: A mini review of recent advances," in *Solar Energy*, 2021, pp. 33–43. doi: 10.1016/j.solener.2021.05.032.

[2] P. S. Lakshmi, S. Sivagamasundari, and M. S. Rayudu, "IoT based solar panel fault and maintenance detection using decision tree with light gradient boosting," *Measurement: Sensors*, vol. 27, p. 100726, Jun. 2023, doi: 10.1016/j.measen.2023.100726.

[3] K. Obaideen *et al.*, "On the contribution of solar energy to sustainable developments goals: Case study on Mohammed bin Rashid Al Maktoum Solar Park," *International Journal of Thermofluids*, vol. 12, p. 100123, Nov. 2021, doi: 10.1016/j.ijft.2021.100123.

[4] K. R. Padiyar and A. M. Kulkarni, "Solar Power Generation and Energy Storage," in *Dynamics and Control of Electric Transmission and Microgrids, Wiley*, 2019, pp. 391–414, doi: 10.1002/9781119173410.ch11.

[5] F. Jacome, L. D. Andagoya-Alba, H. Osorio, and E. Paredes, "Real-Time Fault Identification of Photovoltaic Systems Based on Remote Monitoring with IoT," *International Journal of Electrical and Computer Engineering Systems*, vol. 15, no. 3, pp. 225–234, 2024, doi: 10.32985/ijeces.15.3.2.

[6] D. Saravanan and T. Lingeshwaran, "Monitoring of solar panel based on IOT," *in 2019 IEEE International Conference on System, Computation, Automation and Networking, ICSCAN 2019, IEEE*, Mar. 2019, pp. 1–5, doi: 10.1109/ICSCAN.2019.8878814.

[7] Y. Ledmaoui, A. El Maghraoui, and A. Chebak, "Solar Charging Station for Electric Vehicles with IoT Solution for Monitoring Energy Production," *International Conference on Smart Applications and Data Analysis*, 2022, pp. 63–77, doi: 10.1007/978-3-031-20490-6_6.

[8] J. Li, M. S. Herdem, J. Nathwani, and J. Z. Wen, "Methods and applications for Artificial Intelligence, Big Data, Internet of Things, and Blockchain in smart energy management," *Energy and AI*, vol. 11, p. 100208, Jan. 2023, doi: 10.1016/j.egyai.2022.100208.

[9] T. Ahmad et al., "Artificial intelligence in sustainable energy industry: Status Quo, challenges and opportunities," *Journal of Cleaner Production*, vol. 289, p. 125834, Mar. 2021, doi: 10.1016/j.jclepro.2021.125834.

[10] K. Mahmud, S. Azam, A. Karim, S. Zobaed, B. Shanmugam, and D. Mathur, "Machine Learning Based PV Power Generation Forecasting in Alice Springs," *IEEE Access*, vol. 9, pp. 46117–46128, 2021, doi: 10.1109/ACCESS.2021.3066494.

[11] A. R. Sajun, S. Shapsough, I. Zualkernan, and R. Dhaouadi, "Edge-based individualized anomaly detection in large-scale distributed solar farms," *ICT Express*, vol. 8, no. 2, pp. 174–178, Jun. 2022, doi: 10.1016/j.icte.2021.12.011.

[12] S. M. Patil, M. Vijayalashmi, and R. Tapaskar, "IoT based solar energy monitoring system," in *2017 International Conference on Energy, Communication, Data Analytics and Soft Computing, ICECDS 2017, IEEE*, Aug. 2018, pp. 1574–1579, doi: 10.1109/ICECDS.2017.8389711.

[13] A. Gupta, R. Jain, R. Joshi, and R. Saxena, "Real time remote solar monitoring system," in *Proceedings - 2017 3rd International Conference on Advances in Computing, Communication and Automation (Fall), ICACCA 2017*, IEEE, Sep. 2017, pp. 1–5, doi: 10.1109/ICACCAF.2017.8344723.

[14] Y. Ledmaoui *et al.*, "Enhancing solar power efficiency: Smart metering and ann-based production fore casting," *Computers*, vol. 13, no. 9, p. 235, 2024, doi: 10.3390/computers13090235.

[15] M. Jlidi *et al.*, "An Artificial Neural Network for Solar Energy Prediction and Control Using Jaya-SMC," *Electronics*, vol. 12, no. 3, p. 592, Jan. 2023, doi: 10.3390/electronics12030592.

[16] S. Al-Dahidi, O. Ayadi, J. Adeeb, and M. Louzazni, "Assessment of Artificial Neural Networks Learning Algorithms and Training Datasets for Solar Photovoltaic Power Production Prediction," *Frontiers in Energy Research*, vol. 7, Nov. 2019, doi: 10.3389/fenrg.2019.00130.

[17] K. Anwar and S. Deshmukh, "Use of Artificial Neural Networks for Prediction of Solar Energy Potential in Southern States of India," in *Proceedings - 2018 2nd International Conference on Green Energy and Applications, ICGEA 2018, IEEE*, Mar. 2018, pp. 63–68, doi: 10.1109/ICGEA.2018.8356321.

[18] R. Janarthanan, R. U. Maheshwari, P. K. Shukla, P. K. Shukla, S. Mirjalili, and M. Kumar, "Intelligent detection of the pv faults based on artificial neural network and type 2 fuzzy systems," *Energies*, vol. 14, no. 20, p. 6584, Oct. 2021, doi: 10.3390/en14206584.

[19] A. El Maghraoui, Y. Ledmaoui, O. Laayati, H. El Hadraoui, and A. Chebak, "Smart Energy Management: A Comparative Study of Energy Consumption Forecasting Algorithms for an Experimental Open-Pit Mine," *Energies*, vol. 15, no. 13, p. 4569, 2022, doi: 10.3390/en15134569.

[20] A. Rasheed and F. Al-Turjman, "IOT Based Energy Monitoring of PV Plants - An Overview," in *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST*, 2021, pp. 57–64, doi: 10.1007/978-3-030-69431-9_5.

[21] W. Priharti, A. F. K. Rosmawati, and I. P. D. Wibawa, "IoT based photovoltaic monitoring system application," *Journal of Physics: Conference Series*, vol. 1367, no. 1, p. 012069, Nov. 2019, doi: 10.1088/1742-6596/1367/1/012069.

[22] F. S. M. Abdallah, M. N. Abdullah, I. Musirin, and A. M. Elshamy, "Intelligent solar panel monitoring system and shading detection using artificial neural networks," *Energy Reports*, vol. 9, pp. 324–334, Oct. 2023, doi: 10.1016/j.egyr.2023.05.163.

[23] S. Ansari, A. Ayob, M. S. Hossain Lipu, M. H. Md Saad, and A. Hussain, "A review of monitoring technologies for solar pv systems using data processing modules and transmission protocols: Progress, challenges and prospects," *Sustainability (Switzerland)*, vol. 13, no. 15, p. 8120, Jul. 2021, doi: 10.3390/su13158120.

[24] L. Malka, A. Kuriqi, and A. Haxhimusa, "Optimum insulation thickness design of exterior walls and overhauling cost to enhance the energy efficiency of Albanian's buildings stock," *Journal of Cleaner Production*, vol. 381, p. 135160, Dec. 2022, doi: 10.1016/j.jclepro.2022.135160.

[25] R. Pandey, S. Uziel, T. Hutschenreuther, and S. Krug, "Towards Deploying DNN Models on Edge for Predictive Maintenance Applications," *Electronics*, vol. 12, no. 3, p. 639, Jan. 2023, doi: 10.3390/electronics12030639.

[26] 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, Feb. 2022, doi: 10.3390/en15031082.

[27] M. Le, V. S. Luong, D. K. Nguyen, V.-D. Dao, N. H. Vu, and H. H. T. Vu, "Remote anomaly detection and classification of solar photovoltaic modules based on deep neural network," *Sustainable Energy Technologies and Assessments*, vol. 48, p. 101545, Dec. 2021, doi: 10.1016/j.seta.2021.101545.

[28] T. Gizinski and X. Cao, "Design, Implementation and Performance of an Edge Computing Prototype Using Raspberry Pis," in *2022 IEEE 12th Annual Computing and Communication Workshop and Conference (CCWC), IEEE*, Jan. 2022, pp. 0592–0601, doi: 10.1109/CCWC54503.2022.9720848.

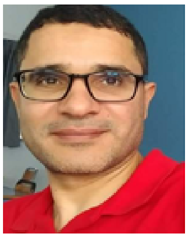
[29] Y. Ledmaoui, A. El Maghraoui, M. El Aroussi, and R. Saadane, "Enhanced fault detection in photovoltaic panels using cnn-based classification with pyqt5 implementation," *Sensors*, vol. 24, no. 22, p. 7407, 2024, doi: 10.3390/s24227407.

BIOGRAPHIES OF AUTHORS

Younes Ledmaoui received B.S. and M.S. degrees in Electrical Engineering from the Polytechnic Mohamed VI University in 2022. Currently a Ph.D. student at the Hassania School of Public Works in Casablanca, his expertise includes smart grids, IoT, artificial intelligence, electrical engineering, renewable energy, and IT. He can be contacted at email: ledmaoui.younes.cedoc@ehtp.ac.ma.

Adila El Maghraoui holds a Bachelor's degree in Computer Science, Electronics, Electrical Engineering, and Automation (2019) and an Engineer's degree in Electrical Engineering (2021). She is a Ph.D. student at Mohammed VI Polytechnic University, specializing in smart grids and optimal power flow to enhance energy efficiency. She has a strong interest in the field of machine learning and deep learning. She actively contributes to projects focused on energy consumption monitoring and forecasting, and renewable energy integration. She can be contacted at email: adila.elmaghraoui@um6p.ma.

Mohamed El Aroussi received his B.S. (2005) and M.S. (2006) from Mohamed V University and his Ph.D. (2007) from Mohamed V University jointly with the Eurecom Institute. He is currently a Full Professor in the Department of Electrical Engineering at the Hassania School of Public Works. He is the head of the LaGeS Laboratory. He can be contacted at email: Mohamed.elaroussi4@gmail.com.



Rachid Saadane is a Full Professor at Hassania School of Public Works (HSPW) and deputy director for research, cooperation, and partnership. His expertise spans wireless communication systems, AI, machine learning, smart grid, renewable energy, and smart city applications, with over 139 publications and significant contributions to UWB communication systems. He leads the LaGeS laboratory and was honored with the SCA'19 Award for the best paper in 2019. He can be contacted at email: saadane@ehtp.ac.ma.

Abdellah Chehri is an Associate Professor at the Department of Mathematics and Computer Science at the Royal Military College of Canada (RMC), Kingston, Ontario. Before joining the RMC, he served as an Associate Professor in Electrical and Computer Engineering at the University of Quebec (UQAC) from 2018-2022. He can be contacted at email: chehri@rmc.ca.

Ahmed Chebak received his B.S. (2003) and M.S. (2008) from Mohamed V University and his Ph.D. (2007) from Mohamed V University jointly with the College Royal in Canada. He is currently a Full Professor in the Department of Electrical Engineering at Polytechnic Mohamed VI University/Benguerir. He can be contacted at email: ahmed.chebak@um6p.ma.