Editorial

Autonomous Monitoring and Analysis of Photovoltaic Systems

Mohammadreza Aghaei [1,2,3]

1   Department of Ocean Operations and Civil Engineering, Norwegian University of Science and Technology (NTNU), 6009 Alesund, Norway; mohammadreza.aghaei@ntnu.no
2   Department of Sustainable Systems Engineering (INATECH), University of Freiburg, 79110 Freiburg, Germany
3   Department of Physics and Energy Engineering, Amirkabir University of Technology, Tehran 15119-43943, Iran

1. Introduction

At the beginning of 2022, photovoltaic (PV) installation exceeded 1 TWp which was an impressive milestone in the solar energy industry. In 2021, at least 183 GW was installed globally, which was almost 40 GW higher compared to PV installation in 2020. The PV capacity reached 788 GW and 971 GW at the end of 2020 and 2021, respectively. According to the current scenarios and recent strong growth, it is expected that the annual PV installation will exceed 200 GW for the first time [1]. Accordingly, it is predicted by the International Renewable Energy Agency (IRENA) that by 2050, over a third of the electricity throughout the world will be supplied by PV systems and reach up to 9 TW [2].

These statistics demonstrate that PV installation is dramatically increasing, and a huge amount of data are generated through PV systems. With such a large volume of PV systems, it will be a significant challenge to monitor the performance and diagnose failures during the operation of various systems. PV systems experience different unexpected faults due to human errors, temperature, humidity, mechanical load, UV irradiation, shading, irreversible equipment damage, environmental impacts, and degradation [3–6]. Therefore, fault diagnosis and comprehensive monitoring play a pivotal role in improving the service life of PV systems [7].

The rapid recognition of failures on PV components increases the reliability and durability of PV systems. PV system monitoring is essential to assure energy performance and the long-term reliability of PV systems. Early failure detection plays a significant role in optimizing PV systems' performance during their operation. The suitable monitoring method aims to detect the malfunctions and faults in PV systems precisely.

The increasing number of PV installations as well as related massive volumes of data which are collected from energy meters and sensors reveal the importance of developing new condition-monitoring technologies and procedures that can handle such large volumes of systems and data [8,9].

Recent advances in software and hardware, as well as platforms for large data acquisition and storage, aim to recognize the failures, faults, and malfunctions in PV components efficiently, quickly, and precisely as well as increase the reliability and durability of PV systems. In recent years, the evolution of reliable condition-monitoring and fault detection techniques based on enabling technologies, namely, artificial intelligence (AI), machine and deep learning, internet of things (IoT), unmanned aerial vehicles (UAVs), big data analytics (BDA), and satellite data, have seen dramatic development to automate PV monitoring. These technologies aim to develop innovative, autonomous, and smart condition-monitoring concepts for precise failure detection and classification as well as intelligent decision making for rapid remedial actions in PV systems.

Autonomous monitoring and analysis is a novel concept for integrating various techniques, devices, systems, and platforms to enhance the accuracy of PV monitoring, thereby improving the performance, reliability, and service life of PV systems [9], see Figure 1.
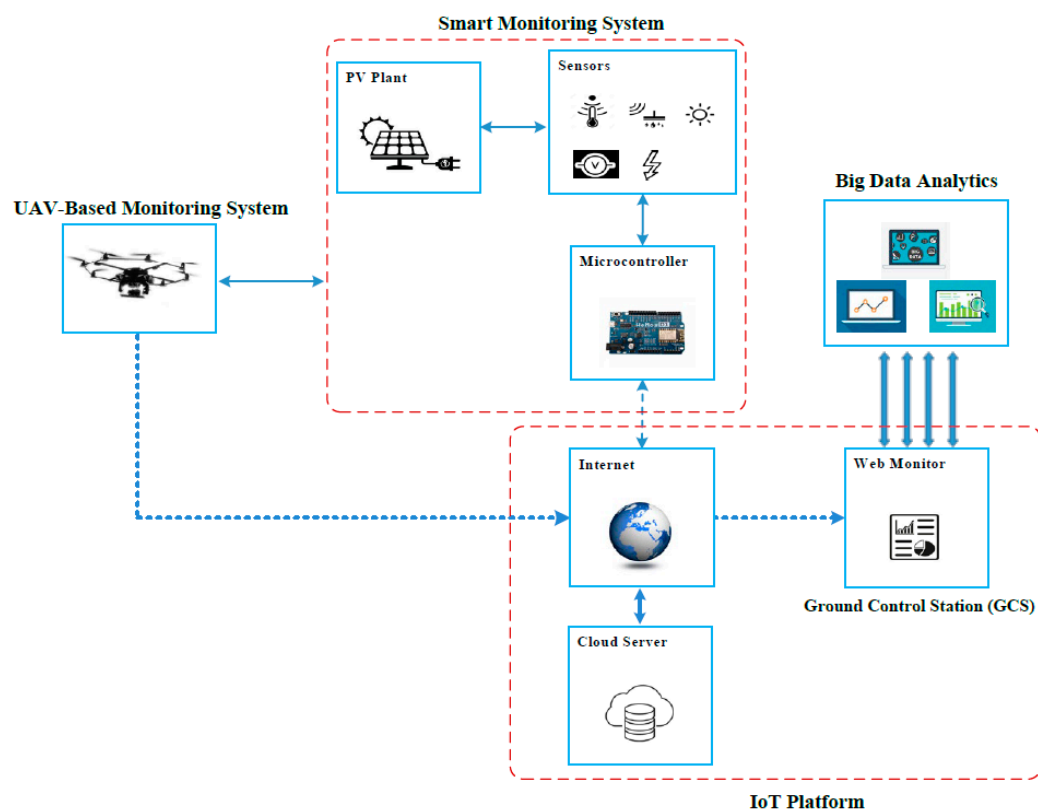
Figure 1. Concept scheme of autonomous monitoring and analysis of PV systems. Reprinted with permission from Ref. [9].

This editorial presents the collection procedure and the main achievement of the papers published in the Special Issue entitled ''Autonomous Monitoring and Analysis of Photovoltaic Systems'' in the MDPI *Energies* journal. The manuscripts were submitted on this topic between 2020 and 2022. A total of five papers were reviewed and published. In this Special Issue, five original research and review papers have been selected and published, related to autonomous-monitoring topics including, but not limited to: big data analytics (BDA), automatic failure detection and classification, internet of things (IoT), artificial intelligence (AI), unmanned aerial vehicles (UAVs), and reliability assessment for PV systems. Thanks to MDPI's *Energies* for supporting this Special Issue with a rigorous peer review procedure and with the aim of rapid and wide dissemination of research results, developments, and applications. The authors of the accepted papers are affiliated with various universities, research institutions, and companies from several countries as follows:

Lucerne University of Applied Sciences and Arts (Switzerland), SmartHelio Sarl (Switzerland), Amirkabir University of Technology (Iran), University of Freiburg (Germany), Norwegian University of Science and Technology (Norway), Concordia University (Canada), Instituto Tecnologico de Costa Rica (Costa Rica), Costa Rica Institute of Technology (Costa Rica), Anhalt University of Applied Sciences (Germany), and Universidade Federal de Santa Catarina (Brazil).

2. The Contribution of the Special Issue

This Special Issue had been formed based on a real scientific research project entitled ''Autonomous Monitoring and Analysis of PV System'' with numerous research outputs and dissemination [8–30], see Figure 1.

The aim of this Special Issue was to collect scientific manuscripts on the practical aspects and simulation models associated with the autonomous monitoring and analysis of PV systems. The key focus was to describe the emerging developments and advances in order to mitigate the challenges for autonomous PV-monitoring procedures in upcoming

years, especially in the terawatt PV installation era. The main contributions and outcomes of the accepted papers can broadly be categorized into the following main topics: (1) novel outdoor characterization techniques for PV modules, (2) autonomous fault detection and classification in PV arrays, (3) IoT-based monitoring systems, (4) machine and deep learning-based techniques, (5) UAV-based monitoring systems, (6) output power prediction. In the following, the synopsis of the papers published in this Special Issue are described.

In the first published paper [31], L.D. Murillo-Soto and C. Meza have proposed an automated fault management system based on a reconfiguration approach to managing two faults (i.e., short-circuit to ground and the open wires in the string) in any position inside the PV arrays. The proposed reconfiguration system can detect and locate the faults, and switch the distributed commutators to recover most of the power loss. Moreover, the system can return automatically to the previous state when the fault has been repaired. The main contributions of this paper were: (1) developing a switch matrix that is built in a modular and distributed way as close as possible to the PV panel; (2) detecting, locating, and isolating the electrical faults in the PV array; (3) reconfiguring the PV array in simulation time when a critical electrical fault occurs, and when the electrical faults are repaired; (4) proposing lightweight diagnostic algorithm and also reconfiguration solution which is based on a multiple finite state machine and receives the diagnosis information to take a control action. The simulation results demonstrated that the recovery of power is more than 90%, and the diagnosis accuracy and sensitivity are both 100% according to the numerical experiment.

In the second research paper, L. Cardinale-Villalobos et al. [32] have compared multiple characterization techniques, namely infrared thermography (IRT), visual inspection (VI), and electrical analysis (EA) in detecting soiling, partial shadows, and electrical faults in the PV system. The main contributions of this paper were (1) proposing quantitative indicators of effectiveness for failure identification methods, which are very limited or do not exist at the experimental level; (2) describing a more detailed experimental characterization of each method, identifying strengths and limitations under different types of conditions; and (3) defining the objective selection of the methods to be used for a more efficient operation and maintenance of PV plants. The outcomes of this study demonstrated that the visual inspection (VI) was the best at detecting soiling and partial shading with an accuracy of 100%. The other two methods, namely infrared thermography (IRT) and electrical analysis (EA), showed an effectiveness of 78% and 73%, respectively, for detecting electrical failures, partial shading, and soiling. The authors have also proven that it is not possible to obtain a maximum accuracy to detect the failure using only one of the techniques, and also that the visual inspection (VI) technique must be performed with infrared thermography (IRT) or electrical analysis (EA) methods in order to provide a detailed overview of the failure mechanism.

The third published paper is a review article in which the authors presented a comprehensive review on automatic inspection of PV power plants using aerial infrared thermography (aIRT) [33]. This review covered several related aerial PV inspection topics, including infrared thermography (IRT), unmanned aerial vehicles (UAVs), aerial infrared thermography (aIRT), aerial inspection algorithms (e.g., digital image processing (DIP), machine learning (ML), deep learning (DL)), and applications of automatization algorithms (e.g., automatic path planning, detection of PV systems and modules, orthomosaicking, fault detection and classification). In recent years, these topics have been intensely investigated by scholars. In this review article, the authors reviewed around 177 articles. Among these articles, 77 studies focused on autonomous fault detection and classification in PV plants using visual, IRT, and aIRT techniques. The authors found that the use of DL algorithms provided good results with an accuracy of up to 90% in the detection and classification of faults in ten different anomaly types detected in module segments using aIRT. The authors also reported that only a few studies have explored the automation of other parts of the procedure of aIRT, namely, the optimization of the path planning (9 articles) for the aerial inspection; the orthomosaicking of the PV plant (14 articles) that is performed to facilitate the localization of the faults in the field and the detection of soiling;

and its differentiation from actual faults on PV modules (8 articles). Moreover, the authors concluded that the algorithms for the detection and segmentation of PV modules were presented in 38 papers with a maximum F1 score (harmonic mean of precision and recall) of 98.4%. The authors also discussed the automation of the aIRT procedure by reporting different algorithms, including DIP filters and methods such as Canny edge detection and thresholding; DL algorithms such as Fast R-CNN, ImageNET, and VGG16; and other ML-based algorithms used for classification tasks such as SVMs, KNNs, and RFs. The main conclusion of this review article demonstrated that the autonomous procedure and classification task must still be explored to enhance the accuracy and applicability of the aIRT method.

In the fourth paper, M.Hojabri et al. investigated, simulated, implemented, and tested eight different PV faults in a real PV system [34]. The purpose of the study was to identify the performance of module-level fault detection and classification to allow the development of a low-cost IoT-based sensor that could be deployed at a large scale in low-power-output PV arrays. This dataset, including current, voltage, and temperature acquired at the module level, was used to develop machine-learning (ML) models that can be used for automatic fault detection and classification at the grid edge. The authors demonstrated that the best model was the nearest neighbors (NN) compared to other proposed models. The NN was able to detect six PV faults, and also the normal condition with a classification accuracy of 93% on the unseen test datasets. The main contributions of this paper were (1) investigating, simulating, classifying, and implementing a combination of important physical and environmental faults that affect PV modules; (2) identifying the main features for module-level classification by analyzing the variations in the I-V and P-V characteristics under normal and fault events using a Simulink-based model; (3) developing a PV fault detection process at the PV module level using ML techniques and based on measured data; (4) training, evaluation, and comparison of several supervised-learning algorithms to define the best one to use for the edge computation of PV fault detection; (5) performing a comparative study to further demonstrate the superiority of the proposed method for the detection and classification of faults; (6) selecting the best algorithm for testing on the real PV systems.

The fifth published paper proposed an intelligent monitoring system (IMS) for PV systems using affordable and cost-efficient hardware and also lightweight software [35]. M. Emamian et al. used the IoT platform for handling data as well as interoperability and communication among the devices and components in the IMS. The IMS included a personal cloud server for computing and storing the acquired data of PV systems. The IMS also consisted of a web monitor system via some open-source and lightweight software that displays the information to multiple users. The IMS used deep ensemble models for fault detection and power prediction in PV systems. A remarkable ability of the IMS was the prediction of the output power of the PV system to increase energy yield and identify malfunctions in PV plants. The authors also developed a long short-term memory (LSTM) ensemble neural network to predict the output power of PV systems under different environmental conditions. The IMS is able to detect numerous faults in PV systems using ML models, namely ensemble learning models, including naive Bayes (NB), k-nearest neighbors (KNN), and support vector machine (SVM). In this study, the authors applied the feature selection approach in order to improve the performance of the fault detection and classification process. The IMS was implemented, tested, and validated under real conditions for a PV system. In summary, IMS is an interoperable, scalable, and replicable solution for holistic monitoring of PV plants from data acquisition, storing, and pre- and post-processing to malfunction and failure diagnosis, performance and energy yield assessment, and output power prediction. The authors demonstrated that the proposed monitoring solution can be used in remote, urban, and rural regions. The results of this study showed that the LSTM ensemble network has unique accuracy compared to other models for output prediction, failure identification, and decision making for remedial actions. The proposed method was able to detect and classify the faults with

an average accuracy of 96.56% and 96.89%, respectively. Moreover, the proposed LSTM ensemble algorithm demonstrated a very small forecasting error compared to the other proposed algorithms. The authors plan to further investigate diagnosing entire electrical faults, including the bypass diode problem, line-ground, shading, etc. To this end, the authors will apply further learning algorithms that can be difficult to choose in ensemble learning models. Therefore, optimization methods such as the genetic algorithm or particle swarm optimization algorithm can be used to select the best learning algorithms.

3. Summary

The papers published in this Special Issue have demonstrated that the autonomous monitoring and analysis approach is highly crucial in the performance monitoring, operation, and maintenance of PV systems. This Special Issue has provided a novel concept for addressing the current and future challenges of enabling the PV terawatt transition. The importance of this approach has shown that the rapid recognition of failures on PV components efficiently, quickly, and precisely led to increasing the reliability and durability of PV systems. The autonomous monitoring and analysis approach is based on enabling technologies, namely, artificial intelligence (AI), machine and deep learning, internet of things (IoT), unmanned aerial vehicles (UAVs), big data analytics (BDA), and satellite data, which aim to automate the entire monitoring procedures of PV systems. These technologies aim to develop innovative, autonomous, and smart condition-monitoring concepts for precise failure detection and classification as well as intelligent decision making for smart remedial actions in PV systems.

Conflicts of Interest: The author declares no conflict of interest.

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