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Editorial

Prognostic Methods for Photovoltaic Systems' Underperformance and Degradation: Status, Perspectives, and Challenges

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The ongoing energy crisis and the rising prices of fossil fuels have accelerated the need for a renewable energy transition. Thanks to its low cost and versatility, photovoltaics (PV) is one of the renewable technologies expected to contribute most significantly to achieving this goal. In just a decade, PV capabilities have grown from 100 GW in 2012 to 1 TW, which was achieved in early 2022 [1]. This exponential increase is expected to continue, reaching 2 TW by the end of 2025.

The installation of new modules and systems is the essential contribution that PV makes toward achieving a more sustainable society. However, it should not be the only contribution. Indeed, installing new modules and systems can increase land competition between PV and other activities, such as agriculture, and pose risks to biodiversity [2]. For this reason, the community is already working on novel solutions to alleviate these issues, such as agriPV, building-integrated PV (BIPV), and floating PV. Additionally, the current regulatory framework concerning citizen and renewal energy communities [3] will foster the installation of shared rooftop or building-integrated PV systems in multi-apartment blocks and districts, which will be a valuable driver for the development of more decentralized forms of energy governance.

The optimization of the performance of the existing PV capacity may represent an additional step toward more sharing of renewable energy. In this way, resource efficiency can be maximized in terms of land, PV material, and electrical infrastructure usage. PV systems are indeed subject to several reversible and irreversible losses, hazardous and non-hazardous failures, and issues [4] (often triggered by exogenous or endogenous events) that affect their performance and eventually cause plants to shut down [5]. Preventive and corrective measures and troubleshooting can be put in place to maximize the energy yield of PV systems. They usually occur during regularly scheduled routine maintenance visits or, depending on the importance, according to an unscheduled procedure. However, these actions may require a long time for working on, testing, or inspecting components. Consequently, they are conditional based on the owner and contractual requirements, and site-specific cost–benefit analyses often determine whether they are warranted. Today, when properly applied, advanced monitoring [6], prognostic methods [7], and predictive maintenance [8,9], often supported by (data-driven) artificial intelligence approaches [10], can proactively facilitate seeking the fundamental causes that lead to failures. The objectives are (i) providing information in an autonomous way that can help to prevent the problem quickly, efficiently, and economically, and (ii) finding the fundamental cause of the problem, not just its outcome. These objectives allow the contributions of PV to increase in terms of market share, without considering any additional capacity that will be installed in the future. Moreover, if opportunely planned, these measures can also increase the profits for PV plant owners and operators, making PV even more appealing for further investments.

This editorial proposes a roadmap of prognostic methods for detecting PV systems' underperformance and degradation in alignment with current best practices and state-of-

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the-art research. Although several challenges need to be tackled, future perspectives of advanced monitoring strategies and technologies suggest that prognostic methods will provide significant cost-saving opportunities for the management of PV plants.

The article [11] reviews the causes of PV degradation provoking a steady rate of power loss while still meeting the warranty requirements. Hot spots represent the major cause of solar-module deprivation (covering approximately 33% of the cases), along with corrosion, delamination, and glass breakage. Lower degradation rates were found in sites with colder climate conditions, displaying an impactful influence of environmental factors. Due to the long operating life expected for PV modules, the assessment of the impact of different degradation modes on actual large scale field data is challenging. Hence, the authors of [11] discuss indoor accelerated testing (AT) of PV modules under different types of aging stress, based on techniques of pre- and post-characterization of the modules (e.g., thermal cycling, damp heat testing, UV tests). Breakages and microcracks due to mechanical loads are assessed through static and dynamic mechanical-loading tests (SML and DML). Results from tests show that higher power losses are expected with static (e.g., snow) rather than dynamic (e.g., wind) stresses. Mitigation strategies, such as adopting specific polymer and nanomaterials, increasing wafer thickness, and installing bypass diodes for hot spots, are indicated to reduce degradation rates and improve the performance of PV plants.

As aforementioned, the performance and the degradation of PV modules are affected by the environmental conditions of the site where the modules are installed. Historical values of various environmental factors are typically available on climate and weather databases. This means that if the correlation between environmental factors and PV degradation rates is known, these can be estimated for any location worldwide, even before PV systems are operational. This way, given a new PV site, one could choose modules and system designs that are less prone to degradation in those specific conditions. Moreover, knowing in advance the performance loss can help investors to better estimate the prospective PV systems' financial returns. In this light, the authors of [12] used the data available in the ERA5 database to map the PV loss due to three degradation mechanisms. They also plotted the total PV degradation rates as a function of temperature, humidity, and ultraviolet irradiation. They found that the degradation rates for mono-crystalline silicon modules can vary from $\leq$0.2%/year to $\geq$1.2%/year, depending on the location.

In addition to degradation and aging mechanisms, the performance of PV modules can also be affected by reversible losses, such as soiling, which consists of the accumulation of dust, dirt, and contaminants. Soiling causes a drop in energy generation, which can be restored through corrective actions (e.g., cleanings) or mitigated through preventive measures, such as anti-soiling coatings [13]. These coatings are deposited on top of the PV glass to reduce the adhesion of soiling particles, facilitating their natural removal. They are required to last as long as the PV modules. This means that they have to be designed to face a 20–25-year outdoor exposure. These conditions can be reproduced through the aforementioned accelerated tests. In particular, the authors of [13] investigated the durability of hydrophobic anti-soiling coatings through damp heat and UV exposure tests, identifying degradation mechanisms and potential solutions. They reported, after the tests, loss of fluorine and heavy blistering. The first one reduced the hydrophobicity of the coating and was considered responsible for the severe degradation experimentally observed in previous outdoor studies. The second one caused the loss of coating materials. To limit this latter phenomenon, the authors recommended a careful curing of the coating.

Soiling has a nonuniform transmittance spectrum profile, which causes more losses in the blue region of the solar irradiance spectrum. This means that, under the same amount of soiling, the electrical losses are more significant for higher bandgap materials than silicon. This might lead to the conclusion that higher-bandgap materials are less appropriate for heavy soiling conditions. However, the authors of [14] pointed out that these materials are less sensitive to temperature (i.e., the absolute value of the temperature coefficient is lower) and analyzed the combined effect of the soiling and temperature losses on different PV module technologies. They developed a model validated using experimental data from soiling monitoring systems made of Si and CdTe cells. They concluded that temperature has a higher impact on the module performance than the spectral component of the soiling loss, especially for operating temperatures $\geq$40 °C.

In order to minimize losses and downtime, advanced inspection and maintenance strategies are necessary to identify failures and find the root issues for correction or mitigation. Any advanced reliability tool's objective consists in proactively detecting the largest classes of PV faults, intending to minimize the probability of occurrence of failure modes. These tools involve advanced on-site inspections, e.g., thermal (infrared) imaging with Unmanned Aerial Vehicle (UAV) technology, and artificial intelligence techniques, usually based on machine learning or deep learning, for automatic monitoring and diagnosis.

In [9], the authors provide a review of PV predictive maintenance. After justifying its need, they address the current approaches and opportunities, distinguishing between manual diagnostics, the failure modes and effects analysis (FMEA) approach, machine learning and forecasting, and real-time sensor analysis. PV maintenance approaches are classified by detection accuracy and cost. The authors conclude that methods that maximize accuracy are also the most expensive. On the other hand, manual diagnostic approaches, such as visual inspections or infrared thermography, are low-cost and can be mainly used to assess the PV panels' performance rather than the PV system as a whole. Using an FMEA approach or machine learning and forecasting can increase the accuracy but requires additional expenses. Last, the installation of specific sensors is found to be the most accurate yet the most expensive approach.

The number of field data to analyze increases as PV systems become larger, making manual PV monitoring more and more challenging. Aerial inspections and infrared thermography can be performed automatically, using manned survey aircraft or UAV (or drone) technology. The significant diffusion of UAV equipped with infrared cameras can support the fast supervision of PV plants and allows for identifying faults and malfunctions at module or cell levels for large surfaces; the quality of the assessment depends mainly on the imaging and post-processing systems that are used. Nonetheless, their utilization is limited based on geographic areas and authorizations [15].

In [16], the authors propose using optical and thermal infrared sensors simultaneously with different resolutions to produce accurate temperature spatial information. Based on orthographic thermal infrared images, the temperature-fluctuation characteristics and spatial distribution analysis can identify modules and cells with abnormally high temperatures. The authors conclude that the inspection method of the PV module using a UAV equipped with thermal infrared sensors can be helpful for safety inspection and monitoring. Following this approach, the authors of [17] propose providing multirotor UAVs with additional sensors to correct their flight path in real-time and move a further step toward autonomous monitoring techniques. The authors address the problem of direct and indirect visual servoing, i.e., the issue of controlling a vehicle using feedback information coming from vision sensors. Using a dynamic compensator (based on a combination of a Canny edge detector and a Hough transform) that works primarily on the data information provided by the cameras already installed onboard, the UAVs are able to correct the set-point position and reject errors with respect to the desired trajectory.

Artificial intelligence approaches have been used successfully in conjunction with UAV technology. As aforementioned, the quality of any UAV assessment depends on the selected post-processing techniques. In [18], the authors use deep neural networks to process the images acquired employing UAV. The approach (which uses a mask-region-based three-layers CNN) can precisely detect the location of anomalies in images. The method solves three tasks simultaneously: location, segmentation, and classification of objects in an image. The proposed method outperforms standard image-processing techniques, detecting faults that were not detectable. Given the good computational performances, the authors foresee an onboard integration in the UAV platform for automatic on-site inspection operations, with minimized personnel activities.

Besides inspection procedures, predictive approaches are gaining significant interest (they are explicitly cited in the IEC TS 63265 Photovoltaic power systems–Reliability practices for operation). Predictive maintenance is a condition-based intervention carried out following a forecast derived from the analysis and evaluation of the significant parameters of the PV plants and their components (e.g., modules, inverters). The objective is to forecast the plant performance and degradation rate to detect anomalies before they become failures and estimate the plant's remaining useful lifetime.

Generally, predictive monitoring systems need high-quality information, i.e., measured data processed through preliminary filtering and conditioning actions, consisting of fixing missing data and synchronization issues, data aggregation, and outlier management. In [19], quality issues relative to measured data of temperature, irradiance, and power outputs are assessed. Nominal Operating Cell Temperature model and different regression models are compared with temperature data fixing. In-plane irradiance data with different degrees of accuracy might be measured directly on-site or inferred from neighboring weather stations or satellite information on global horizontal irradiance. Imputation or transposition models and machine-learning algorithms are suggested to fill in the irradiance data gaps. Simple visual approaches are indicated to first detect data issues, such as similarity checks between time series of irradiance and power. Different preliminary data filtering approaches are discussed. Nevertheless, the authors state the necessity of establishing common guidelines to ease comparability and reliability of results.

Once reliable data sets are available, predictive approaches can be used. In [20], the authors use long short-term (LSTM) neural networks on a multivariate set of input data: they use publicly available weather reports and measured PV power output. Unlike other methods, a black box approach is proposed that does not rely on any technical information about the specific PV system. The dataset with the measured values is regularly updated to ensure continuous learning of the predictive model and address concept drift. Interestingly, the study shows that, despite commonly perceived opinions, air temperature and humidity have a stronger relationship with PV power than the current cloudiness. The predictive model shows better accuracy when using solar irradiance data; in this case, it can forecast single power peaks and drops in the PV system production. These predictive tools may be easily integrated into energy management systems.

In [21], the authors use a hybrid model based on the combination of convolution neural networks (CNN) with the LSTM. The combined architecture uses five CNN layers for feature extraction on input data, acting as a filter, combined with an LSTM model to support temporal sequence prediction. The authors assess the performance of the hybrid model through comparison with a single LSTM model, a CNN–LSTM hybrid model with two layers, and two well-known popular benchmarks, i.e., the Lasso regression and the Ridge regression. The proposed model accurately predicts PV power generation with reasonable computational times.

However, meteorological data might not always be available. The author of [22] handles this issue, presenting a method to monitor PV systems lacking environmental parameter data. The method is based on comparing the average energy of the various arrays and the average energy of the whole PV plant. The variability of the energy produced by each array is monitored using a statistical tool known as the Bollinger Bands (BB) method. The novelties with respect to the standard BB method are the use of the exponential moving average instead of the simple moving average and the increased size of the width of BB, set to three times the standard deviation instead of four times. An array is considered to be working well if the spread is lower than 3%. A spread greater than 5% is a clear signal of an anomaly, whereas a spread within 3–5% is an alert. The author concludes that the BB method can provide valuable support for detecting even low-intensity anomalies.

Day-ahead PV production forecasting can be crucial not only for energy allocation in the day-ahead market, allowing the direct participation in markets of PV power plants and aggregated systems, but also for predictive maintenance. In [23], the authors compare three machine learning models for day-ahead forecasting: Bayesian neural network, support vector regression, and regression tree. The authors conducted a valid comparison by employing the same dataset to train the models and perform verifications of performances. The authors show that training the models with calculated input data (e.g., through numerical weather prediction methods, instead of on-site measured data), training based on larger time frames, and irradiance filtering improve the prediction accuracy. Overall, the authors claim that a Bayesian neural network outperforms all the other investigated models.

The growing need for renewable energy sources and the increasing PV capacity are making downtime and failures in PV more and more critical. For this reason, O&M strategies are becoming a crucial component of PV systems not only during their operation but also their design. The ongoing energy crisis and the currently high electricity prices are also pushing toward preventive and predictive maintenance strategies, in addition to the typical corrective approach. These allow maximizing the energy yields and the revenues, minimizing costly downtimes and failures. In this editorial, recent studies and research findings are illustrated, involving preventive loss mitigation solutions, predictive algorithms for power production, and prognostic methods to detect underperformance and degradation of PV. In light of European policies favoring energy transition, these are recognized as essential tools to exploit available energy resources by enhancing PV plants' performance.

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