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Review

Current Challenges in Operation, Performance, and Maintenance of Photovoltaic Panels

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Abstract: The installed solar capacity in the European Union has expanded rapidly in recent years. The production of these plants is stochastic and highly dependent on the weather. However, many factors should be considered together to estimate the expected output according to the weather forecast so that these new PV plants can operate at maximum capacity. Plants must be operated in coordination with maintenance operations and considering actual energy market prices. Various methods have recently been developed in the literature, ranging from the most impactful artificial-intelligence-based generation estimation methods to various diagnostic and maintenance methods. Moreover, the optimal operational and maintenance strategy usually depends on market regulation, and there are many concerns related to the distribution system operator. This review article aims to summarize and illustrate the challenges of operating and maintaining solar power plants and the economic and technical importance of these problems.

Keywords: photovoltaic; power generation; maintenance; ROI; artificial intelligence

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1. Introduction

The Paris Agreement aims to keep the global temperature increase below 2 °C above the preindustrial level. Decarbonizing electricity generation based on renewable energy sources is one of the pillars of this aim. Applying renewable energies to the European Union's (EU) energy mix has been crucial in recent years. A significant, more than 25% annual growth of the built-in renewable energy is needed to reach zero emissions by 2050 [1–3]. Photovoltaic (PV) energy is one of the most successful renewable energies in EU countries because this technology is relatively cheaper and more mature than other renewable sources [4]. Before the introduction of the first European Renewable Energy Directive (2009), the installed PV capacity was only about 11.3 GW in the whole European Union, while this amount exceeded 175 GW at the end of 2021, which means a more than 15-times increment in fewer than 15 years [5–7]. The difference in the increment rate of some selected countries is plotted in Figure 1, where 100% represents the built-in capacities status at the end of 2021.

However, there are differences between the different EU member states regarding their climate, ecological, social, economic, and political factors, and not every country is equally capable of implementing this kind of technology [8–13] (Table 1). The short selection of countries based on the authors' origin may confirm various factors. Spain is one of the EU's pioneers in implementing PV systems, thanks to its good climate, hot and dry summers, and many hours of sunshine [14]. Despite its great potential, installed capacity growth until 2019 remained below the EU average due to areas for improvement in the PV market's Spanish regulatory and support system. After all, at that time, the German and French markets were more profitable [15–17]. Despite poorer weather and geographical conditions, Estonia and the Nordic countries have grown significantly recently. According to [18–21], Hungary and Poland produced the most significant growth in the built-in PV capacity in the last years. In 2020, Hungary's Innovation and Technology Ministry published the new National Energy Strategy that outlines priorities until 2030. According to this strategy, the decarbonization of electricity generation is based on the radical increase in built-in PV capacity, it should exceed 6500 MW built-in capacity, which is essential for the long-term energy-independence goals of the country [22,23]. At the end of 2023, the built-in PV capacity reached 5500 MW in Hungary [24]. This is a relatively high number, nearly equal to the average electrical energy demand of the country if we are calculating this number from the maximal electric energy demand, which was not more than 125 GWh in January of 2024 [25].

Table 1. Built-in PV capacities [MW] in the European Union, Hungary, Spain, and Estonia.

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021
Hungary	13	31	73	148	205	327	741	1441	2161	2949
Spain	4561	4639	4646	4656	4669	4688	4707	8711	11,669	15,286
Estonia	0.2	2	3	7	10	15	32	121	208	395
European Union	68,640	80,330	86,850	95,020	101,110	106,690	114,810	131,020	149,640	175,700

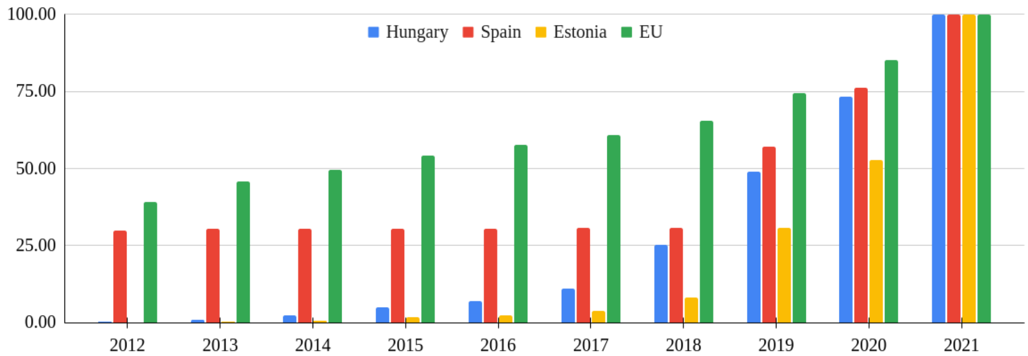


Figure 1. Built-in relative increase in the PV capacity in the EU, Hungary, Spain, and Estonia. The reference of the calculation is the 2021 data, which represent 100% in the image.

It can be seen in the previous part of the introduction that the PV industry has significantly increased in all of the EU member states since the last decade [3]. The high growth rate means that more than half of the solar power plants are relatively new, younger than three to five years old, and usually built with a "set it and forget it" philosophy. Although the PV power plants have a relatively low maintenance need [26–29], it does not mean modern and novel predictive maintenance methods can not increase the profitability of these PV panels. Iftikhar et al. [3] have shown in a case study that simple operation and maintenance practices, intended mainly for the tracker system, can increase the energy output by 4%, which meant 170,000 EUR/year at the investigated, 18 MW power plant. Bosman et al. [30] have shown that it is necessary to coordinate and maintain the different technologies and operation methods to gain the maximal benefit from a solar power plant. They expressed the need to develop modern predictive maintenance methods for the different subsystems. The reason is simple: these PV power plants are relatively large constructions far from the cities and the populated zones. Identifying the reason for the failure and fixing the problem usually requires many working hours while a significant part of the PV park is not operating. Due to the increasing size of the PV parks, many researchers proposed advanced techniques for monitoring the status of the panels because finding a problem and tracking down issues in a huge system can be even more difficult [31–34].

The current study is focused on PV panels. However, we understand that there are many issues that might be related to the entire PV system, including solar trackers and inverters. The main issues for solar trackers might be related to undulating terrain, the large format of the modules, layouts, etc., while inverters may have issues related to power electronics, insulation, overheating, control, and communication failures, etc.

This study aims to provide an overview of the current challenges in operating and maintaining PV power plants. In Section 2, the need for predictive maintenance strategies is discussed. The typical maintenance problems and current solutions for detecting underperforming PV panels (or other devices in a solar power plant) are reviewed, as well as some specific maintenance areas that require more attention than currently, such as the aging and maintenance of power cables in a solar PV environment. Section 3 highlights the challenges of PV integration from the perspective of the distribution system operator (DSO). Section 4 reviews the commercial and performance optimization methods based on artificial intelligence, which are of great importance in maximizing energy production and financial profit. Lastly, in Section 5, the main conclusions are outlined.

2. Predictive Maintenance of PV Systems

The inevitability of wear and maintenance needs for production machines, equipment, and devices persists despite the industry's progression. Hence, the evolution of maintenance techniques aligns with the advancement of industry. Industry 4.0 is a term used to describe the ongoing digital transformation of the manufacturing industry. One important aspect of Industry 4.0 is predictive maintenance, which uses data analytics to identify and prevent potential equipment failures before they occur.

There are several approaches to industry maintenance within PV systems, each with benefits and drawbacks. Some of the most common approaches include the following:

- Reactive maintenance: This approach involves repairing equipment only when it breaks down or malfunctions. While it may seem cost-effective in the short term, reactive maintenance can lead to increased downtime and more significant repair costs in the long run [35].
- Preventative maintenance: In contrast to reactive maintenance, preventative maintenance involves regularly scheduled maintenance activities to prevent equipment breakdowns and extend the lifespan of the system. This approach can be more cost-effective over the long term, but it requires a significant investment of time and resources upfront [36].
- Predictive maintenance: This approach uses data analytics and monitoring tools to predict when maintenance will be necessary, allowing for repairs before significant breakdowns occur. Predictive maintenance can be highly effective in reducing downtime and maintenance costs, but it requires a significant investment in data collection and analysis tools [37].
- Condition-based maintenance: This approach involves monitoring equipment performance and condition in real time and scheduling maintenance activities based on that data. Like predictive maintenance, condition-based maintenance can be highly effective in reducing downtime and maintenance costs, but it requires a significant investment in monitoring tools and sensors.

From the above mentioned, predictive maintenance, referred to as PdM 4.0 in modern times, represents the highest form of maintenance within the context of the Fourth Industrial Revolution, an ongoing phenomenon. The approach involves converging big data analytics and artificial intelligence techniques to prevent asset failure. Through the analysis of production data, the technique aims to detect patterns and predict impending issues before they occur. A study by L. Koschikowski et al. (2020) [38] found that predictive maintenance can reduce downtime and maintenance costs by up to 25% and increase energy production by up to 3%. Another study by S. K. Sahoo et al. (2019) [39] showed that predictive maintenance can improve the reliability of PV systems and reduce the risk of equipment failure.

In the case of PV systems, predictive maintenance can help improve system efficiency and reliability, reducing downtime and maintenance costs. PV systems are becoming increasingly important in transitioning to renewable energy sources, and their efficiency is critical to meeting energy demand.

- From the perspective of a single PV plant, predictive maintenance can help identify and prevent equipment failures, reducing downtime and maintenance costs. This approach can help minimize downtime, reduce maintenance costs, and increase the lifetime of the PV system [39].
- From the perspective of a virtual power plant, the main goal is to minimize the difference between the scheduled and the current production. This can be achieved by aggregating several small-scale PV systems and using predictive maintenance algorithms to optimize their output. By monitoring the performance of individual PV systems and predicting potential failures, virtual power plants can optimize energy production and reduce costs [39].

2.1. Typical Maintenance Issues

Faults in PV power plants reduce their efficiency, durability, and reliability. Solar panel failures can be categorized as optical degradation, electrical inadequacy, and unclassified faults [40,41]. Many recent papers on reliability analysis have found that a solar farm's reliability is proportional to its size, i.e., smaller solar farms are more reliable. However, after ten years, even these smaller solar parks have reliability approaching zero, i.e., at least one of its main components (e.g., inverter, transformer, solar panels, wiring systems) needs to be replaced at this time [42,43]. Figure 2 illustrates typical PV panel failures and maintenance problems in the different power plants. It can be seen from these images that the typical problem of a dedicated PV power plant depends on the climate of the installation area. The first Figure 2a image shows that grass cutting is a general maintenance issue; in extreme cases, some plants, high grass shrubs, or trees can grow in the abandoned plants. These plants can shade the panels or degrade the cable systems and inverters, leading to decreased power output. This maintenance job is usually outsourced to a third-party company. Some of them have ideas to use the PV park area for some connecting agricultural activity, like sheep grazing [44].

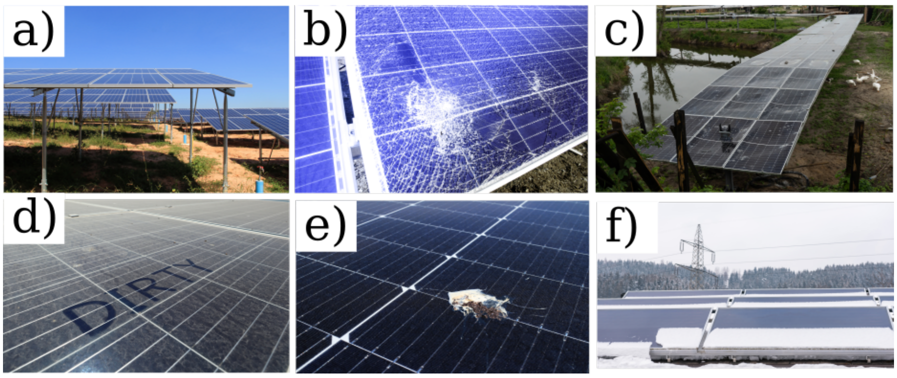


Figure 2. Some typical maintenance issues are illustrated in this image: (**a**) grass cutting, (**b**) PV panel cracks, (**c**) hailstorms, (**d**) pollution, (**e**) bird droppings, (**f**) snow.

The impact of PV power plants on wildlife is significantly smaller, often by several hundred percent, compared with fossil-fuel-based power plants. However, the core mechanisms regarding how solar facilities impact wildlife still need to be fully understood [45]. Many researchers have shown that these facilities are key in the increased bat and bird fatality rate. Walston et al. published a paper stating that approximately 140,000 bird fatalities were caused by solar plants in 2016 [46]. Smallwood has shown that in 2020, approximately 250,000 bird and 11,000 bat fatalities occurred due to solar projects in California [47]. The scale of these numbers can be considered similar if the growth rate in the built-in PV capacity during the period between the two studies is considered. The lake effect hypothesis is one of the most probable reasons for these mortalities; this theory drives back to the maintenance problems that birds can cause in the PV panels. The lake effect hypothesis is one of the most probable reasons for these mortalities. The birds can mix up the PV plants with lakes from high altitudes and collide with the panels from high altitudes. The collisions can cause cracks in the solar panels, as shown in Figure 2. At the same time, bird droppings (Figure 2e) can also create significant shading on the panels [48], which can significantly decrease the generated power. Some chemical and IoT-related technologies have been developed to keep birds far away from PV panels. The most advanced technologies can use artificial intelligence with radar technology to monitor and keep the birds flying away from the PV panels. The chemical solution is a gel, which looks normal for humans, but in the UV spectrum, the birds can see it as a firing object and will maintain a distance from the panel [49,50].

The performance of a PV panel is usually measured under standardized test conditions in laboratories, where the temperature is set to 25 °C, and the solar irradiance is 1000 W/m^2, which passes through a 1.5-thickness atmosphere [51]. However, the performance of the panels can vary depending on the pollution, wind, rainfall, humidity, and many other environmental factors during outdoor operations (Figure 2d). Wind and rainfall usually promote the removal of the dust; it was shown that quite heavy rain (more than 38 mm/h) is necessary to remove the dust from the panels [52]. Many researchers examined the effect of cleanliness on the panels [53]. Salimi et al. [54] performed a 135-day-long experiment where some selected PV panels were cleaned every day, while others with different schedules, e.g., every third day, while some of them were never cleaned during the experiment. It was shown that the appropriate cleaning of the solar panels can increase the outcome by 8–12%. Other studies in different climates have also shown that energy losses can be reduced by 25% by applying proper cleaning methods [55].

Besides the cracks, there is another type of failure, which is called snail trails or snail tracks (Figure 3). This problem usually occurs on panels installed outside after 3–5 months of the installation [56]. This problem means a discoloration of the silver paste used for the gridlines on the cells, which can be easily seen after the visual inspection of the panel [57,58]. This problem can decrease the panel's performance by 20% [59]. Similar failure problems are the delamination of the panels and the discolorization. The delamination of the panel means that the adhesive bonds in the encapsulant or the substrate of the PV cell modules allow some moisture from the environment, and this causes detachments inside the panel [58,60]. The reason for the discolorization is the bad quality of the applied polymers in the PV panel, which creates browned, discolored areas, which reduce the quantity of the entrancing sunlight [56,58].

Hail has significant damage on PV panels (Figure 2c), which can cause a 30% performance loss on the panels. The damage is typically 3 cm on the panels, and larger hailstones, which can be larger than 4 cm, can cause greater damage. In 2016, a hail storm damaged almost one-third of the solar panels at OCI Solar Power's Alamo 2 [61]. Experiments with the protective glasses have shown that applying 4 mm or more of glass can protect the panels without significantly impacting the performance [61]. However, connecting is sometimes not visible after the hail, but the monitoring system shows some panels are underperforming. Nondestructive techniques use UV–fluorescence images or thermocameras to locate the impacted PV panels in a facility [62,63].

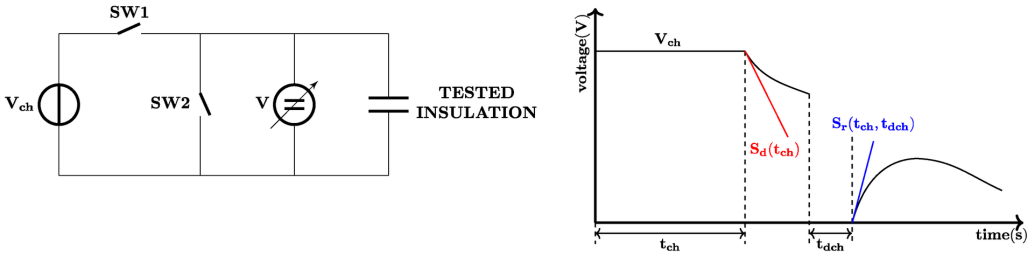
Northern countries have the highest energy requirements for heating during the winter; however, in these times, snow can cover the PV panels (Figure 2f), which can reduce their annual energy generation by 35% [64], and some PV parks can reduce their production by 90–100% daily. Understanding the climatic conditions and finding possible solutions to increase performance during these times is important. Simple solutions include setting an appropriate tilting angle, using thermal absorbers, and using electrostatic forces to remove the snow from the PV panels [65,66].

Figure 3. Snail trail in a PV cell [57,58].

The previous use cases explained only the failures or performance losses related to the PV panels. However, most PV plant outages are related to inverter and combiner box failures [3,67]. Many papers deal with the investigation of the different inverter failure modes and topologies, and simple and advanced mathematical statics-based models are applied to examine which string topology can improve PV power plant reliability [68–70]. Markov-formulation-based approximations can suggest that some central inverter string configurations have the highest return-on-investment (ROI) values [43,68]. Besides inverters, PV parks contain a power transformer connecting to the grid. The size of this transformer depends on the capacity of the PV park and their regulation, as well as the general power transformer types in different countries [71–74].

Condition monitoring and prediction of the lifetime of high-voltage power systems have a crucial role in the case of nuclear or fossil power plants [75,76]. Not only because these cables are relatively expensive assets but also because their functions lead to power plant outages during maintenance.

The last component of the PV parks is the cables, which account for 1–2% of the overall cost of the PV system and also have excessive stress during the operation [77]. Condition monitoring and prediction of the lifetime of high-voltage power systems have a crucial role in the case of nuclear or fossil power plants [75,76], not only because these cables are relatively expensive assets but also because their functions lead to power plant outages during maintenance. This problem needs to be examined in the case of PV farms. One reason is that the nominal capacity of these parks is much smaller than a fossil or a nuclear power plant. Secondly, these PV plants are relatively young, and these problems will arise in older power plants. The maintenance and outage time is not independent of the previous factors. Mainly, the improper installation procedure of the PV systems can significantly extend maintenance times [30,78]. Ref. [78] stated that a significant part of the PV park installations can be underrated, which will lead to operational and maintenance issues. Due to the insulation capability of these plastic-coated (XLPO [79,80]) DC cables depending mainly on environmental temperature, humidity, and load, there is a high risk that these shortcuts and maintenance issues will appear mainly in summertime, where the temperature is hot and the cables are working with maximal utility. Parise [81] suggested a special "brush-distribution" layout for connecting the strings to reduce the maintenance need of PV parks due to cable problems. Then, he proposed a life loss tool for the optimal management of cables [82]. Tamus et al. [79,80,83] proposed a nondestructive measurement methodology using the voltage response methodology (Figure 4). This measurement is based on a simple test device, which firstly applies a long-duration DC current on the cables and then measures the slopes of the different decay voltages (S_d) after given times. These slopes correlate with the internal polarization processes of the examined materials, making it possible to estimate the condition of the cables. The thermal and mechanical stresses can be considered, which are subjected to the cable during the assembly process [77,84]. Due to the spread of the agrivoltaics, the proper sizing of the wires and DC cables can be more important to reduce the potential damage to PV plants and grazing animals [85,86].



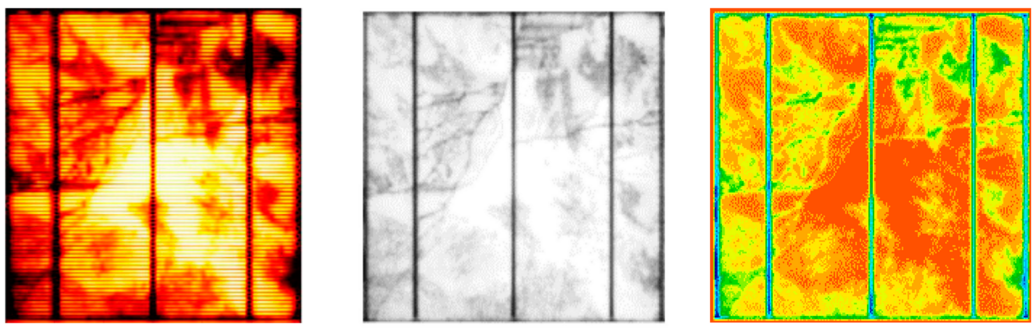
(**a**) (**b**)

Figure 4. The image shows the voltage response method-based nondestructive testing of the polymer cables. Where (**a**) shows the realized electrical circuit, while (**b**) is the time function of the voltage response [83]. Where SW_1 and SW_2 represent the switches in the circuit, V_{ch} is the applied DC current for charging the cable for t_{ch} time, S_d represents the decay, while S_r is the slope of the measured voltage response after the different t_{dch} charging times.

Additionally to the above-mentioned problems, Potential-Induced Degradation (PID), Light-Induced Degradation (LID), and general degradation are indeed crucial concerns in the realm of PV technology, especially with the advent of modern advancements like the half-cut Passivated Emitter Rear Cell (PERC) [87,88] or Top Contact (TopCon cells) [89,90]. It may take a long time to detect the PID through traditional data analysis methods, resulting in an undetected energy loss [91]. LID, on the other hand, involves a temporary decrease in efficiency upon initial exposure to light, which stabilizes over time but can still impact long-term performance [92]. Both phenomena require careful consideration and mitigation strategies to ensure optimal module performance and longevity. However, with the emergence of half-cut PERC and TopCon cells, which offer improved efficiency and performance characteristics, it becomes even more critical to address potential degradation factors to maximize the benefits of these advanced technologies.

2.2. Tools and Devices for Predictive Maintenance

There are many techniques developed to help identify the different malfunctions of PV panels (Figure 5).



(**a**) (**b**) (**c**)

Figure 5. Different photovoltaic panel crack inspection methods: (**a**) photoluminescence, (**b**) electroluminescence, (**c**) thermal imaging [93].

Garcia et al. [4] presented a low-cost DSP-based application that performs a voltage–current (V-I) test to check the solar panel parameters continuously. This device should be connected to a dedicated PV panel to measure different operation points. It is a simple, cost-effective way to identify shading, soiling, or module degradation issues. Moreover, its usage does not need an industrial PLC; it is only this simple device. This device costs about EUR 40, which is very cheap; however, it should be applied to every panel, which can result in a significant cost for a large PV power plant.

A more advanced predictive maintenance method is PV string-level monitoring [94]. Usually, such methods include current and voltage ratio comparison with thresholds and parameter ratio comparison for the whole string. This reduces the number of sensors used in maintenance but reduces the fault localization. However, the main disadvantage of that type of tool is the fact that they need regular maintenance to ensure the accuracy and reliability of the monitoring equipment. Moreover, they produce a significant amount of data, which need to be managed and analyzed.

While V-I tests are commonly used to characterize PV system performance, these types of tests are also used in efficiency evaluation, performance monitoring, and optimization. The disadvantages of such methods are that they depend on environmental conditions, measurements are time-consuming, and high-precision measurement equipment is expensive.

Several decades ago, spectral imaging was introduced for remote sensing applications, mainly satellites. Since its inception, it has gained a wide range of scientific and industrial uses. Hyperspectral Imaging (HSI) is a branch of spectral imaging that deals with hundreds of image bands on a single-image datacube. An HSI provides much greater spectroscopic information than a traditional RGB (red–green–blue) image, allowing many uses. PV condition monitoring involves assessing panels' performance, health, and potential issues. According to Lombez et al. [95], HSI can provide valuable insights into the condition and performance of PV systems. By leveraging its detailed spectral information, HSI enables fault detection, performance analysis, cell characterization, assessment of environmental factors, predictive maintenance, and quality control during PV manufacturing.

HSI can include infrared wavelengths within its spectrum. However, infrared thermography (IT) can be a specific technique or subset focused on capturing thermal information within the infrared range. It plays a crucial role in the preventive maintenance of PV systems by using infrared cameras to capture and analyze thermal images of PV modules and associated components. Such techniques might be useful for detecting transportation-induced failures [96] and provide information on the health state of the PV module [97]. Usually, nonintrusive diagnostic techniques are implemented using unmanned aerial vehicles (UAVs) [59,96]. That increases the price of already expensive imagining equipment.

HSI has advantages over V-I methods: they are noninvasive techniques, and it is possible to identify materials to provide valuable data for understanding the spectral response and efficiency of emerging materials and designs. On the other hand, they are more expensive and complex, require significant storage and computational resources, and cannot be used in all environmental conditions.

Recent advancements in predictive maintenance strategies have paved the way for maximizing the efficiency and reliability of PV systems. Several studies that explored innovative approaches to predictive maintenance for PV systems, ranging from model predictive control (MPC) for PV modules to AI-driven algorithms, might be highlighted. The integration of predictive maintenance strategies holds immense potential for enhancing the performance and reliability of PV systems. Operators can proactively manage maintenance activities and optimize system operation by leveraging methodologies, such as model predictive control, AI-driven algorithms, and machine learning techniques. Through continuous monitoring, analysis, and intervention, the longevity and efficiency of PV systems can be maximized, contributing to the widespread adoption of renewable energy sources and the transition towards a sustainable future.

One significant contribution to the field is the development of a novel Maximum Power Point Tracking (MPPT) method based on model predictive control (MPC) for PV modules [98]. This method offers superior tracking performance and dynamic response compared with conventional MPPT techniques. By considering factors such as spectral wavelength and module temperature, the proposed approach aims to optimize power generation, thereby enhancing the overall efficiency of grid-connected PV systems. Furthermore, integrating finite control set model predictive current control (FCS-MPCC) algorithms for inverters [99] ensures precise control over the power output, contributing to improved system stability and performance.

While not directly focused on PV systems, AI-based predictive maintenance strategies have shown promising results in enhancing the efficiency and reliability of electrical equipment and power networks [100]. By leveraging predictive analysis techniques, such as machine learning algorithms, insights can be gained into the health status of critical components within PV systems. This proactive approach enables the early detection of potential faults or degradation, facilitating timely intervention and preventive maintenance activities. Consequently, the operational lifespan of PV systems can be prolonged, ensuring sustained energy generation over time.

Specifically targeting PV systems, researchers have developed predictive maintenance algorithms utilizing synthetic datasets [101]. These algorithms can predict maintenance requirements and optimize system performance by simulating various operating conditions and failure scenarios. Through continuous monitoring and analysis of system parameters, potential issues can be identified in advance, allowing for timely maintenance interventions. Moreover, the utilization of synthetic datasets enables extensive testing and validation of the algorithms under diverse conditions, ensuring robustness and reliability in real-world applications.

A comprehensive review of maintenance strategies for PV systems acknowledges the significance of ground fault detection interrupters (GFDI) and overcurrent protection devices (OCPD) [102]. These devices play a pivotal role in predictive maintenance by detecting potential faults or abnormalities in the system. By implementing advanced sensing technologies and intelligent algorithms, GFDIs and OCPDs can preemptively identify deviations from normal operating conditions, mitigating equipment failure or electrical hazard risks. This proactive approach aligns with the overarching goal of predictive maintenance: optimizing system reliability and performance while minimizing operational disruptions.

In the domain of battery management, which might be related to PV energy storage systems, the integration of machine learning algorithms has emerged as a powerful tool for predictive maintenance [103]. While the focus lies primarily on lead–acid batteries, the principles extrapolate to PV systems, where battery storage plays a crucial role. By analyzing historical data and patterns, machine learning algorithms can forecast potential failure modes or performance degradation in batteries, enabling preemptive measures to be taken. This proactive maintenance approach minimizes the risk of unexpected downtime and optimizes the utilization of energy storage resources within PV systems.

3. Operation of PV Plants from the DSO Perspective

Energy markets are evolving towards a significant decentralized-generation paradigm, with a wide penetration of renewable energy sources (RESs). For this new paradigm, the cost minimization of technologies such as PV and energy efficiency awareness, as well as directives focusing on sustainability, flexibility, and diversification of energy markets, have contributed decisively [104–106].

3.1. The Role of a DSO

The vast majority of DSOs are committed to regulatory frameworks and focused on the decarbonization of the electrical energy sector. Therefore, it is a core mission of DSOs to provide a friendly integration of RES into the electric grid, benefiting from it by finding efficiencies in their grid operation [106–108].

One of the major benefits of RES integration, from the DSO perspective, is grid flexibility. With increased flexibility, several local problems can be mitigated [105]. In [109], the authors investigated a real-time energy congestion management platform using market-based flexible procurement. It was found that distribution transformer overload can be significantly reduced with a dominant share of distributed energy resources. Other benefits include the following [110]:

- More entities participating in the energy market.
- Innovative solutions.
- More awareness concerning energy efficiency.
- Reduction in greenhouse gas emissions.
- Improvement of grid reliability.
- Reduction in technical distribution losses.
- Reduction in outage times.

Many projects have been developed focusing on integrating PV sources in the grid. In recent years, the European Union has been funding large projects with the participation of DSOs, such as EU-SysFlex [111], INTERRFACE [112], and OneNet [113].

In the EU-SysFlex project, in which one of the authors has participated, the project intended to identify constraints and viable solutions to allow the large-scale integration of renewable sources, maintaining and optimizing, whenever possible, the current levels of quality of service. The project implemented several pilots and showed many valuable flexibility solutions to operate the power system with high levels of variable generation (more than 50%) [114,115].

Concerning the INTERRFACE project, the objective was focused on the design, development, and operation of an Interoperable Pan-European Network Service Architecture to act as an interface between the energy system (Transmission System Operators (TSO) and DSOs) and customers to allow an integrated and coordinated operation of all interested parties in the use and acquisition of network support services [116].

The OneNet project is intended to create the conditions for a new generation of grid services that can fully exploit demand response, storage, and distributed generation while creating fair, transparent, and open conditions for the consumer. The project aims to build a customer-centric approach to grid operation, proposing new markets, products, and services. Creating unique IT architecture to support innovative mechanisms is proposed [117,118].

Besides the funded projects where many DSOs are involved with specific objectives, they are also providing several open datasets available to all in order to democratize access to energy data. One example can be found in [119], from where several datasets related to the distribution grid of the major Portuguese DSO (E-REDES) can be explored. Other examples from other countries can be found in [120,121]. The datasets can be explored online, exported to a file, or collected via API. The available datasets have been developed focusing on four major stakeholders, i.e., developers, academia, municipalities, and producers. There are several thematic datasets, such as Consumed Energy, Electric Mobility, Networks, Renewables, and Operation and Quality of Service. For instance, it is possible to collect the geographical distribution of production units by municipality, installation date, and connection power. Another example is the scheduled energy interruptions by zip code, which can be incorporated, for example, in forecasting algorithms.

3.2. Integration of PV Sources

The DSO is responsible for maintaining the distribution grid as stably and reliably as possible. To do so, there are several capital costs (such as redundant lines and systems of control and protection) and operational costs (such as O&M operators and resilient dispatch centers). In many regions, the classic business model of a DSO to recover costs is based on tariffs charged to consumers according to their network usage (typically, two components are charged, one fixed according to the contracted power and another that is proportional to the energy consumed). Despite the emergence of more and more prosumers, which tend to reduce network usage (thus not contributing to compensate grid investments), the decarbonization and electrification of industry, as well as mobility, are expected to increase energy flows and more investments in the distribution grid.

PV integration will play an important role not only in the reduction in greenhouse gas emissions but also in the reduction in the transmission of electricity over long distances, thus improving technical losses. Currently, the Levelized Cost of Energy (LCOE) generated from the PV utility scale (and even PV rooftops depending on their size and location) is lower than wind generation technologies (onshore and offshore), whereby it is expected to observe growing levels of PV penetration over the next decades [122].

The integration of PV sources will also benefit the most remote places. In less-meshed networks, the availability of backup lines is reduced. Thereby, in the occurrence of an abnormal failure event or even during maintenance activities, the operation in island mode (provided by locally distributed generators) contributes to reducing unavailability periods of electricity delivery.

3.3. Obstacles and Solutions

The increased penetration of distributed production brings more complexity to grid management and operation. The main obstacles are grid stability, grid congestion, and even potential market volatility. However, it is expected that the grid will become more flexible and resilient against massive power outages [123,124]

As the installed capacity of PV sources increases, combined with the intermittency of production, the voltage and frequency stability of the grid can be affected [125,126]. One of the main challenges concerning the increased penetration of PV plants is voltage regulation, particularly when in low demand. Network incidents are higher in less-meshed networks, typically in rural areas. Near real-time monitoring of the energy generated and injected in the grid utilizing smart metering, along with forecasting of generation and consumption, will be a key factor in avoiding voltage fluctuations and maintaining frequency within normal operating ranges. Besides the well-known light flickering, the negative consequences of voltage fluctuations include torque variation in machinery and the potential reduced service life of connected loads [127]. In critical lines, installing grid batteries mitigates network incidents and increases the network's flexibility.

On the other hand, grid overcurrent protection should be properly sized to accommodate increased penetration of distributed sources. Prior to distribution grid connection, DSOs first evaluate the impacts of such sources on the stability of the grid and the adequate overcurrent protections. Due to the potential impact on grid stability, even smaller self-consumption units (e.g., small rooftop PV plants) are subjected to evaluation in case of grid connection. For instance, in Portugal, self-consumption units above 30 kWp are required to be certified by their DSO before grid connection [128]. Depending on the location and connection power, it is usual to perform smart meter installation (if not previously installed) and overcurrent protection updates. In order to avoid the overload of Distribution Transformers, grid updates are also considered, not only due to distributed generators but also to the electrification of industry and transportation, such as EV charging. However, since grid upgrades are generally capital-intensive, attention is given to the optimization of the existing infrastructure. The development of smart grids and intelligent markets is often the preferred way to increase flexibility in the grid [129–131]. Smart grids, particularly with the support of smart meters, allow customers to manage their own consumption and production in near real time. With increased awareness about energy consumption and production, customers become more energy efficient and, therefore, reduce their electricity bill, not only by reducing their consumption (as well as maximizing their production in the case of prosumers) but also by participating in dynamic markets where the tariffs are time-dependent [132].

3.4. Optimization

Since grid-connected PV plants influence the distribution grid, the optimization of PV plants is relevant to ensure that such plants are compatible with the operation of the grid and do not cause problems such as voltage fluctuations, frequency instability, or harmonic distortion.

On the one hand, there is the optimization of PV plants by itself, ensuring the optimal operation of components such as inverters, wiring, and PV modules to ensure that such plants operate at their maximum efficiency, producing the highest amount of energy from the available solar irradiance. This contributes to a better exploration and planning of distribution grids since it reduces the uncertainty about the expected production. In low-demand and high solar availability, PV plants can also feed energy storage systems, such as ion-lithium batteries or electrolyzers.

On the other hand, considering the flexibility that can be offered to the grid, PV plants can also be aggregated in a portfolio to participate in energy markets [133]. In this scenario, commonly denominated as virtual power plant (VPP), different generation plants are virtually pooled to provide flexibility to the system via frequency regulation and balancing reserve. In this scenario, only reliable and optimized PV plants are eligible.

VPPs use advanced systems to monitor and control the output of each contributing source, ensuring a stable and reliable power supply to the grid. Generally, VPPs are controlled with stochastic optimization algorithms [134,135]. Further, the operation is orchestrated by workflows that execute the necessary periodic tasks, such as the creation of market bids (both capacities and prices), the calculation of dispatch schedules, and the data transfer between inner and outer data sources involved in the market.

Since the concept is still far from its maturity level, several studies and projects have been developed to test and prove the concept of VPPs, such as EU-SysFlex [111], GOFLEX [136], DRES2Market [137], and InterFlex [138]. In EU-SysFlex, the concept of a VPP composed of several decentralized sources, including a windfarm, PV, and a grid battery storage system, was successfully implemented in a French grid [111].

Besides the technical proof, several studies have been performed to evaluate the economic aspects of VPPs. For instance, a cost–benefit analysis of the integration of VPPs in the German energy market has been performed in [139]. In [140], the technical–economic impact of the integration of a VPP in the Spanish electricity system was assessed. Hence, it is expected that optimization will play an important role in the further development of distributed generation and grid connection [141].

4. AI-Based Solutions to Increase PV System Performance and Trading

4.1. Forecasting PV Generation

In the context of artificial intelligence algorithms, predicting solar irradiation and the resulting PV power of each generator remains crucial. The generator with the best forecasting performance has an advantage in reduced balancing costs and a better understanding of actual power system conditions. The eminent generator usually has information about the generally expected error in the schedules of less accurate PV plants. This knowledge makes it possible to submit profitable bids on ancillary service markets with optimal prices and accurate quantities.

Many different machine learning tools have been utilized to forecast PV generation. The exhausting review of the related literature is beyond the scope of this paper, but a selection of recent relevant studies is briefly inspected in Table 2.

Table 2. Machine learning tools for PV generation forecasting.

Source	Machine Learning Tool	Note
[142]	eXtreme Gradient Boosting, Light Gradient Boosting, MultiLayer Perceptron, Elman Neural Network, Long Short-Term Memory	comparative study
[143]	MultiLayer Perceptron	metaheuristic training
[144]	Deep Neural Network	auxiliary irradiation forecast
[145]	Random Forest, Neural Networks, Support Vector Machines	comparative study
[146]	MultiLayer Perceptron, Deep Neural Network	comparative study
[147]	Convolutional Neural Network	combined with load forecasting
[148]	Transfer Neural Network, Convolutional Neural Network	hybrid model with enhanced data preprocessing
[148]	Radial Basis Function Neural Network	integrated Grey Theory System

As Table 2 illustrates, the forecast of PV generation is a well-known challenge with many proposed answers. Nonetheless, the accuracy of PV forecasts is still limited because the architecture of forecasting algorithms (including those applying AI) is built on inherently inaccurate weather forecasts. The improvement of input quality regarding meteorological variables—especially solar irradiation—is a promising research direction already recognized, e.g., in [144].

The weather forecast inputs of PV generation forecast algorithms usually originate from Numerical Weather Prediction (NWP) models. NWP is a mature technology based on refined meteorological knowledge and the application of differential equations. However, image-based predictors can often provide more accurate results in the short-term and ultra-short-term horizon (with lead times of less than 4 to 6 h [149]).

The simplest way to generate the images for irradiation forecasting is to use of ground-based total sky imagers (TSIs). TSIs can provide images with high spatial and temporal resolution, and these images can be effectively used to detect, classify, and predict clouds. Multiple TSIs can provide enough information to construct a three-dimensional cloud model of the sky [150]. The pictures can also be directly mapped to the solar irradiation on the site of PV plants (e.g., through the use of Convolutional Neural Networks [151] or a combination of AI techniques [152]). Remarkable prediction accuracy has also been achieved using simple fish-eye lens cameras following the same general approach [153]. On the other hand, the lead time of prediction is severely limited by the distance the images can show. The effective forecasting horizon of this technique is typically less than two hours [154].

For forecast lead times between 4 and 2 h, a different image-based cloud prediction method appears to be the most promising [155]. Instead of TSIs, this method uses satellite imagery. Satellite data have become more commercially available in visible and infrared images in recent years. Besides being available for longer lead time forecasts, the satellite-based method poses new challenges as well. Firstly, the temporal resolution of satellite images is usually much smaller compared with TSIs, and therefore, prediction requires a nontrivial interpolation between images. Secondly, since the position of the Sun is not captured in the images (as they show Earth instead of the sky), the exact area of cloud shadows has to be calculated in a separate algorithm. After the consideration of these additional steps, AI can be successfully applied to create PV power forecasts with XGBoost [155], Support Vector Machines, and Gradient Boosting Decision Trees [156], as well as deep learning [157] and Long Short-Term Memory networks [158].

4.2. Advanced Trading Algorithms

The development of improved trading strategies is critically important for PV generators' endeavor to enhance their profitability. In earlier years, the ramp-up of PV generation received substantial government subsidies in many countries (e.g., in Belgium [159], Germany [160], the UK [161], and China [162]), but this state of affairs is starting to change. Subsidies to PV generators have been eliminated in the UK [161] and China [162]. The Chinese experience provides ample opportunities to investigate the effects on generation companies [162,163] and potential other incentive mechanisms for the adoption of PV technology [164]. Initial PV support schemes are also (partially) retracted or substantially modified in several countries in continental Europe (see the lists in [165,166]). It has to be recognized that the PV generation sector is heavily reliant on government programs, and therefore, sudden changes represent considerable financial risk. Furthermore, the economic feasibility of PV projects without subsidies is still not guaranteed for a few more years (even with widespread peer-to-peer trading [167]). PV plants that are already operating have to prepare for the corresponding economic challenges. Even if they operate in a jurisdiction with intact subsidy schemes, they can expect changes to encourage gradually stepping out to electricity markets directly. However, the electricity market is a complex configuration of many trading platforms for several products (e.g., energy and ancillary services) with different lead times and technical requirements. Competent trading requires a deep understanding of its components and the construction of an appropriate strategy.

An especially crucial decision for PV generators is the choice between energy and control reserve markets. This is a relevant question for electricity producers in general because energy and reserve products utilize the same production capacity of their units. The two kinds of markets can be cleared simultaneously using unit commitment algorithms (see, e.g., [168]), a setting that makes bidding easier for generators. In Europe, the sequential clearing of energy and reserve markets is prevalent (the day-ahead energy market is not coupled to reserve trading platforms [169]), although there are proposals for coallocation in a common algorithm without unit commitment [170]. The consideration and comparison of providing energy and reserves are especially important for PV plants for two general reasons. The first one is that the growing penetration of weather-dependent generation—including PV—has substantial effects on the expected behavior of reserve market demand [171]. The second reason is that due to their connection to the grid through power electronics devices, PV plants are capable of providing quick regulation services—including automatic frequency regulation reserve (aFRR)—in their available power range, i.e., between their available output and zero. The combination of these observations holds the promise of advantageous business opportunities in the future. Nonetheless, the trading decisions of PV generators have their own difficulties. Most importantly, the uncertainty of the PV generation, as well as the price levels of energy and reserve markets, has to be taken into account. All of these factors are suitable for prediction with artificial intelligence algorithms. For PV generation, Section 4.1 provides a summary, while price prediction has its own extended literature, e.g., with ensemble learning methods [172], long and short-term memory networks with the sparrow search algorithm [173], transfer learning [174], and integrated long-term recurrent convolutional networks [175]. Several comparative studies are also available inspecting multiple machine learning models, e.g., for applications in Spain [176] and Iran [177]. Most of the relevant studies focus on energy prices, mainly because reserve markets are substantially more complex and can be quite different in different regions. Nonetheless, their key indicators can be predicted and utilized during the construction of trading strategies using statistical and machine learning models [178] or mathematical programming [179].

Determining optimal PV generator trading strategies and the best structure of the trading management tool remain important research questions. The control of power electronics can be adapted to the trading strategy, a step towards better economic performance and flexibility of PV applications.

5. Conclusions

Since adopting the Europe Green Deal in 2019, installed solar capacity has grown rapidly in the EU countries. The rate of growth varies from country to country. Poland and Hungary have seen the fastest growth in installed solar capacity over the last three years. With fewer than 15 MW of installed solar capacity in 2012, the latter country increased to 5500 MW by the end of 2023, comparable to the country's current maximum energy demand. One of the drawbacks of this rapid expansion may be that solar farms are being built with more installation and design problems and need to be better thought out in terms of operation and maintenance. However, as the second part of this article pointed out, maximum profit can only be achieved through an adequately coordinated maintenance and operation strategy. Inappropriate maintenance can result in losses of up to 20–30% for solar farm owners.

Another valuable finding of the review is that some of the problems encountered in the operation of solar parks depend on the installation environment. While in a northern country, the quick detection of snowfall and the quick removal of snow from the solar panels are the biggest problems, in a southern or sandy desert environment, the cleaning of the solar panels is the most significant general maintenance problem. Predictive maintenance-based methods can simplify and speed up the detection of faulty solar panels and significantly increase the yield of solar farms. It is not only the maintenance of solar panels that needs attention; it is also essential to monitor the condition of inverters and switchgear, which are responsible for a significant part of the outages in solar parks. Monitoring the cable systems of aging solar parks can also significantly increase the availability of solar parks in the future.

Most solar generation capacity is connected to the grid on the distribution level. Therefore, DSOs have a significant role in answering the technical and institutional questions regarding its integration. In line with the goals of reduced carbon emission, market liberalization, and improved grid efficiency, DSOs participate in several large-scale research projects on solar energy and provide curated, open data sources for other scientific studies. Projects such as EU-SysFlex, INTERRFACE, and OneNet are examples of projects funded by the European Union, where DSOs have been involved in the development of innovative mechanisms intended to create new markets, products, and services. The most essential technical issues include the effects of intermittent solar generation on voltage quality and grid stability, as well as the protection arrangements and sizing. Meanwhile, the new institution type of VPP has been invented to aggregate and represent solar producers in the environment of the power sector, including DSOs, TSOs, regulators, and various market platforms.

The forecast of solar irradiation and the corresponding PV power is a well-established field of research and practice with ever shorter lead times and innovative new prediction methods. However, to achieve maximum profit for solar farms, it is necessary to consider the weather and the regulation of the energy exchange in the country concerned. One of the main tasks is deciding which market, e.g., the day-ahead market or an intraday market, is the most suitable one to sell the electricity generated during a given hour. Many solutions, including artificial intelligence, have been and are being developed in the literature to solve these problems. It is essential to note that a country's regulation and energy consumption habits also play a significant role in these solutions. It seems from the review that due to the operation algorithm highly depending on weather forecasting and many other country-specific parameters, the applied artificial intelligence methods need some customization before applying them from one region to another.

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