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Review article

Maintenance techniques to increase solar energy production: A review

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ABSTRACT

This review explores advanced maintenance techniques aimed at improving solar energy production efficiency. The study analyzes the rapid growth of solar energy and the challenges posed by environmental factors such as soiling, harsh climate conditions and hotspots, which reduce photovoltaic (PV) and concentrated solar power (CSP) system performance. Predictive models for solar energy generation and soiling detection, including artificial intelligence (AI) and machine learning (ML) algorithms and Internet of Things (IoT), are discussed as means for optimizing energy production and reducing maintenance costs. It is also emphasized the role of Unmanned Aerial Vehicles (UAVs) to capture images for fault detection and failure prediction, enhancing maintenance accuracy and minimizing downtime. The study concludes by analyzing the role of these techniques to reduce water consumption in cleaning tasks, as well as solutions to increase the operational lifespan and performance of solar plants such as anti-soiling coatings, robotic cleaning systems and accurate predictive models.

1. Introduction

Renewable energy refers to energy derived from resources that are naturally replenished on a human timescale, such as sunlight, wind, rain, tides, waves, and geothermal heat. These energy sources are considered sustainable and environmentally friendly alternatives to fossil fuels, which are finite and contribute significantly to environmental degradation and climate change. The transition to renewable energy is critical for reducing greenhouse gas emissions, mitigating global warming, and achieving energy security [1]. Over the past few decades, there has been a significant global shift towards increasing the adoption and production of renewable energy, driven by technological advancements, policy initiatives, and growing environmental awareness [2]. Solar Energy has become the biggest source of renewable energy.

1.1. Solar energy production

Implementing solar energy as a sustainable energy source offers numerous advantages; it is a clean and renewable energy source that produces no greenhouse gas emissions or other pollutants during electricity generation, reducing reliance on non-renewable fossil fuels, promoting energy independence and security, and leading to significant cost savings over time [3]. Once installed, solar panels generate electricity at no additional cost, reducing utility bills and providing long-term financial benefits during panels' lifespan. The solar industry creates jobs in manufacturing, installation, maintenance, and research, and by investing in solar energy, countries can stimulate economic growth and create employment opportunities in the renewable energy sector [4]. Solar energy systems can be scaled to meet various energy needs, from small residential installations to large utility-scale solar farms, making solar energy a versatile solution for powering homes, businesses, and communities. Distributed solar energy systems can enhance grid stability and resilience by reducing strain on centralized power grids, helping to balance energy supply and demand, especially during peak usage periods [5]. Solar energy projects can benefit local communities by providing clean energy, reducing air pollution, and supporting sustainable development [6].

According to the latest report by the International Renewable Energy Agency (IRENA) in 2024 [7], there has been a continuous increase in the global production of renewable energy. Over the past decade, this rise has seen production capacity grow from 1,700,116 MW in 2014 to 3,869,705 MW in 2023, representing an increase of 227.6%.

Specifically, solar energy has shown significant growth over the last decade. Its production capacity has increased from 180,759 MW in 2014 to 1,418,969 MW in 2023, marking an increase of 785%. Indeed,

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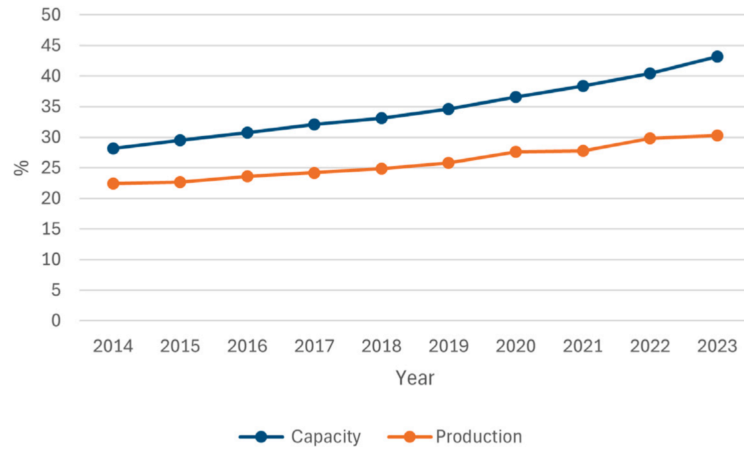


Fig. 1. Solar energy vs all renewable energies.

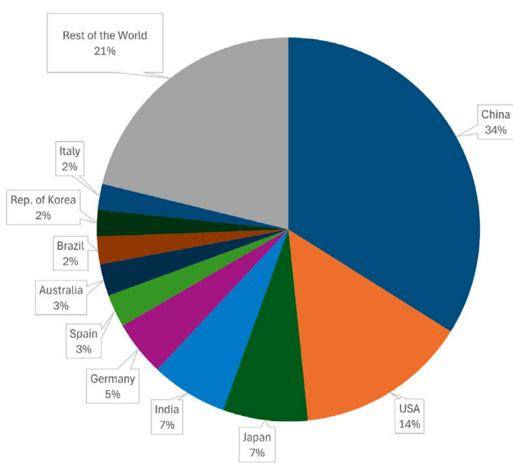


Fig. 2. Worldwide solar energy production.

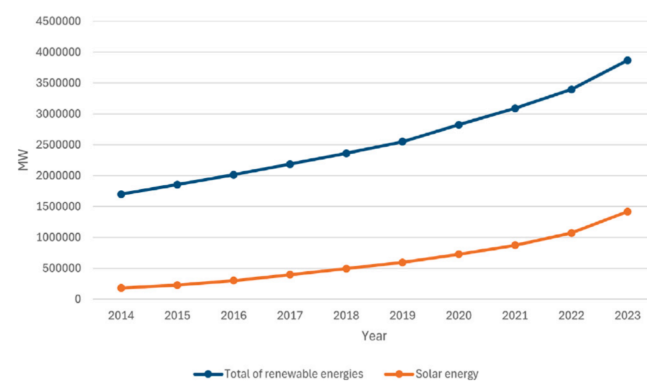


Fig. 3. Solar energy capacity vs production compared to all renewable energies.

solar energy has experienced tremendous growth, making it one of the renewable energy sources with the highest rate of increase [7]. It has gone from constituting 10.6% of the total energy capacity in 2014 to a 36.7% in 2023 (Fig. 1).

In terms of solar energy production, there has been a worldwide record of 1,294,481 GWh. As seen in Fig. 2, when data is analyzed by country, it is observed that China (34%), USA (14%) and Japan (7%) are the top three solar energy producers worldwide.

However, there is still a difference between the total capacity of the grid and the total amount of renewable energy production as seen in Fig. 3. In these terms, despite representing a 43.2% of the total electricity capacity, renewable energies only produce 30.3% of the total electricity consumption in the world in 2023 [8]. This difference is due to their inherent instability, as they rely on weather conditions to be fully efficient.

1.1.1. Photovoltaic solar energy

Photovoltaic (PV) solar energy works by converting sunlight into electricity through the photovoltaic effect. This process involves the use of solar panels, which are made up of photovoltaic cells that capture sunlight and convert it into electrical energy. When sunlight hits a photovoltaic cell, which is the building block of solar panels made of semiconductor materials, it excites the electrons in the cell, causing them to move and create an electric current (photovoltaic effect) [9]. They system usually consists of a mounting structure to support and position the solar panels to maximize sunlight exposure, in inverter to convert DC to AC electricity for several purposes and a battery storage for storing excess electricity generated during the day [10].

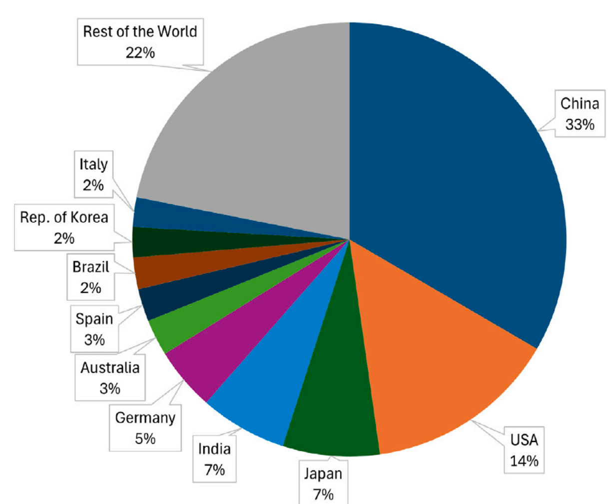


Fig. 4. Worldwide PV energy production.

There was a total production of 1,281,654 GWh in Solar Photovoltaic energy. According to the IRENA 2024 report [8], the three countries who produced more PV energy were China (34%), USA (14%) and Japan (7%), as seen in Fig. 4.

There are several types of photovoltaic (PV) solar technologies, including monocrystalline silicon, which consists of solar panels made from a single crystal structure, offering high efficiency but at a higher

Fig. 5. Heliostats field for CSP in Plataforma Solar de Almería [17].

cost. Polycrystalline silicon panels, made from multiple silicon crystals, are less efficient but more affordable than monocrystalline options [11]. Thin-film solar cells are created by depositing thin layers of photovoltaic material onto a substrate, making them lightweight and flexible, which suits a variety of applications [11]. Concentrated photovoltaic (CPV) cells utilize lenses or mirrors to focus sunlight onto small, high-efficiency cells, though this technology is more complex and typically requires tracking systems to follow the sun's movement [12]. Organic photovoltaic cells use organic materials to generate electricity from sunlight and are lightweight, flexible, and hold promise for low-cost production [13].

1.1.2. Concentrated solar power

Concentrated Solar Power (CSP) technology converts solar radiation into both heat and electricity. It uses mirrors or lenses to concentrate sunlight onto a receiver to generate high temperatures that can produce steam to drive a turbine for electricity generation [14]. In Fig. 5 a Heliostats Field for CSP production is shown. By concentrating solar radiation onto a receiver, CSP systems can achieve efficiencies of 12%–30%, making them competitive with other renewable energy sources [15]. One of the key features of CSP is its ability to store heat energy, allowing for continuous electricity generation even when sunlight is not available. This energy storage capability sets CSP apart from other solar technologies and enhances its reliability as a power generation option [16] (see Fig. 5).

There was a total production of 12828 GWh in CSP in the year 2022. According to the IRENA 2024 report [8], the three countries who produced more Concentrated Solar Power were Spain (33%), USA (22%) and UAE (9%), as seen in Fig. 6.

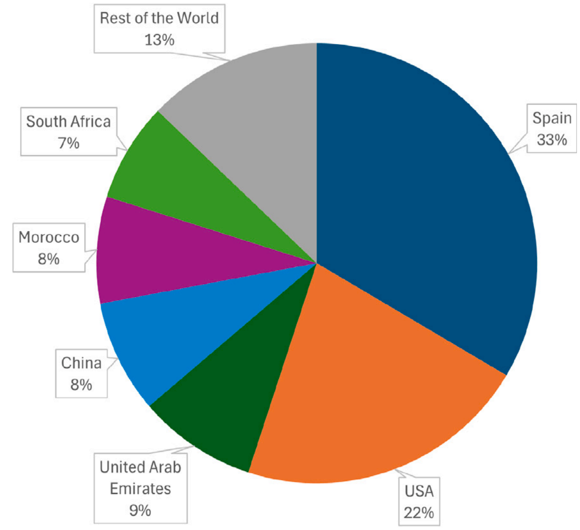


Fig. 6. Worldwide CSP energy production.

Despite its advantages, CSP also presents challenges that need to be addressed for widespread adoption [18]. The intermittent nature of solar irradiation poses a significant hurdle, requiring backup systems or energy storage solutions for uninterrupted operation [18]. Additionally, the initial capital costs of building CSP plants can be high, although advancements in technology are gradually reducing these expenses. The complexity of designing and operating CSP systems also necessitates specialized knowledge and maintenance, adding to the challenges of implementation [16].

In Fig. 7 (note there are two different scales) we can see a notably difference between the capacity of PV energy and CSP energy. By 2023, PV solar plants represented a capacity of 1,412,083 MW, while CSP plants only represented 6,876 MW. This means that PV represents 99.5% of the total capacity of solar energy produced worldwide, while only a 0.5% is contributed by CSP [7].

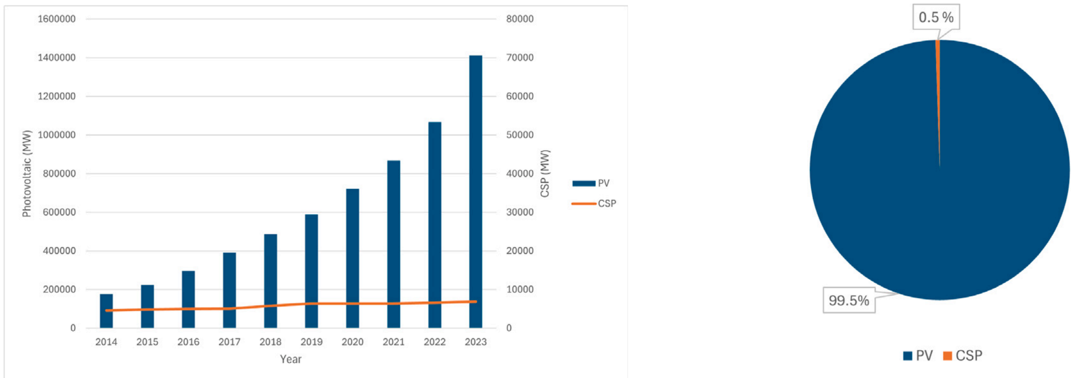
1.2. Deterioration factors

Solar panels are designed to operate for decades. However, several external conditions can reduce significantly their efficiency towards a 10%/year [19]. Some of these factors are:

Climate conditions can significantly impact the degradation of solar panels [20], and in desert regions, these effects may be exacerbated due to extreme environmental factors. Key climate conditions contributing to solar panel degradation include high temperatures, which can accelerate wear and induce thermal stress, affecting both performance and lifespan. High humidity can lead to corrosion and moisture ingress, potentially damaging the panels and reducing their efficiency over time [21]. Ultraviolet (UV) radiation from sunlight can degrade the materials used in solar panels, impacting their durability [22]. Extreme weather events like hailstorms (Fig. 8), strong winds, and heavy snowfall can physically damage the panels, causing cracks, breakages, or dislodgement of components. Desert environments also face soiling, where dust and sand accumulate on the panels [23], reducing the amount of sunlight reaching the cells and decreasing energy production. Ground reflectivity, or albedo [24], in desert areas can influence the performance of bi facial solar panels, which capture both direct sunlight and reflected light from the ground [25]. Shading from nearby structures, trees, or debris can create hotspots on the panels, leading to uneven heating and potential damage to the cells [26].

Analyzing soiling deeply, it is found a series of factors causing this phenomena. Desert climates are particularly prone to soiling due to the presence of dust particles that can travel long distances and deposit on solar panels [27]. Additionally, industrial activities emitting pollutants into the atmosphere can lead to deposition on solar panels, as seen in areas near industries like mining operations. Pollen and dirt from animal droppings are other sources of soiling that can affect the performance of photovoltaic systems,[28]. Dust accumulation on solar panels can have a significant impact on light transmittance and power generation efficiency [29]. When dust particles settle on the surface of solar panels, they create a layer that reduces the amount of sunlight reaching the photovoltaic cells. This reduction in light transmittance hinders the absorption of solar radiation by the cells, leading to a decrease in the efficiency of converting sunlight into electricity. In the case of heliostats in concentrated solar power plants, it reduces the reflectivity of the mirrors, thereby decreasing the amount of sunlight that can be efficiently captured and converted into energy [30]. This reduction in reflectivity leads to a decrease in the overall efficiency of the solar field, resulting in lower energy output and decreased productivity of the plant [31] (see Fig. 9).

Dust particles interact with the surfaces of solar collectors through processes such as generation, deposition, adhesion, and removal, each influencing maintenance and cleaning costs in distinct ways [33].



(a) MW (b) %

Fig. 7. PV production vs CSP production.

Fig. 8. Solar panels after a hail storm.

Fig. 9. Mirror surface after a strong soiling event [32].

Generation involves the creation and suspension of dust particles in the atmosphere, influenced by factors like wind speed, particle size, and composition, marking the initial step in the soiling process. Deposition follows, where airborne dust particles settle on solar collector surfaces due to gravitational settling, diffusion, and impact phenomena; this deposition rate varies based on wind conditions and surface characteristics. Once deposited, dust particles adhere to the surfaces through cohesive forces, with adhesion strength affected by factors like particle size, surface roughness, and environmental conditions; whether particles remain on the surface depends on the balance between adhesion and removal forces. This is why cleaning activities are essential to remove adhered dust particles, with the cleaning frequency and methods tailored to the level of soiling, surface type and operational needs to maximize panels' solar production [34]. In order to maintain optimal performance, regular cleaning of the heliostats and PV panels is required, which adds to the maintenance costs of the plant [35]. The cost of cleaning operations, including labor, equipment, and resources, can be substantial and needs to be carefully managed to balance the impact on productivity gains, creating in some cases a Key Performance Indicators (KPIs) matrix to evaluate the most relevant tasks to achieve this goal [36].

Another deterioration factor and one of the most common issues is the hotspot phenomenon. Its occurrence creates a localized high temperature, reducing the current output of the affected unit and, consequently, impacting the output of the entire string [37]. This substantially lowers the system's power generation efficiency and accelerates the aging of photovoltaic module materials, including the degradation of encapsulation materials and cracking of silicon wafers, leading to complete module failure and an unreliable system, increasing operation and maintenance costs [38].

1.3. Objectives

The primary objective of this scientific review article is to systematically analyze and evaluate the current maintenance techniques utilized in solar power plants. It aims to identify and compare the various methodologies, technologies and algorithms applied in the detection, diagnosis, and prevention of faults in photovoltaic systems and maximize power in CSP plants. By examining state-of-the-art approaches, including machine learning algorithms, sensor data analysis, and aerial inspection methods, this review seeks to highlight the effectiveness, advantages, and limitations of each technique. Additionally, the article aims to provide insights into economic analysis and viability of these procedures, as well as future trends and potential advancements in maintenance techniques to extend their operational lifespan. An analysis on sustainability will be conducted to study how these techniques help to save resources and reduce water consumption.

2. Maintenance techniques based on the deterioration factor

We first want to analyze how research on maintenance techniques is distributed by country to establish a possible relationship between energy production and research on production improvement. According to Fig. 10, China, the United States, India, Spain, Germany, and Japan lead this research, which corresponds to Fig. 2, where it is shown

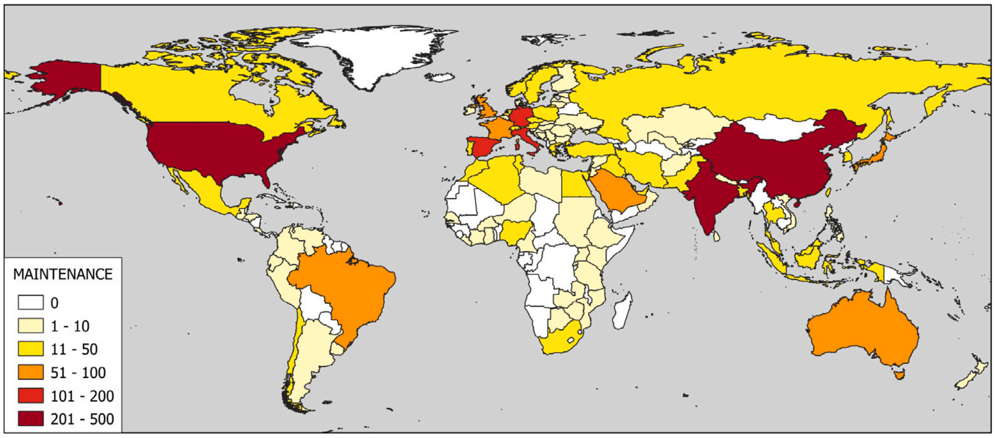


Fig. 10. Distribution of researches in maintenance techniques for solar plants per country.

that these countries are also leaders in solar energy production, while Australia and Japan fall behind in researches.

It is also interesting to show a division of studies between those countries who have published studies in maintenance techniques for PV plants vs CSP plants. In Fig. 11, it is shown that China, India and United States are leading the research in maintenance techniques for PV plants while Spain is leading the research for CSP plants, as it is the country with the highest production in CSP energy.

In this section, a deep research has been conducted to show and analyze the most cutting-edge techniques to maintain solar plants according to the root cause of the malfunctioning or lower production of the panels.

2.1. Soiling

As previously mentioned, soiling causes major loses due to a decrease in energy production and costly cleaning tasks [33]. Even under ideal cleaning conditions, soiling lowers current worldwide solar power production by at least 3%–4%, resulting in revenue losses of at least 3–5 billion € annually. By 2023, these losses could increase to 4%–7% and exceed 4–7 billion € [39]. In another study, after seven months without cleaning PV modules, production decreased by around 10% [40]. Therefore, predicting soiling events and its impacts becomes straightforward to the managers of the solar plant .

A survey has been conducted to analyze the countries who have the highest number of researches in soiling maintenance techniques, to investigate whether there is a correlation between the most arid countries and those that produce the most CSP energy. According to Fig. 12, Spain, Morocco, India and the United Stated are the countries with a higher number of researches, which have big arid areas and many hours of sunlight per day.

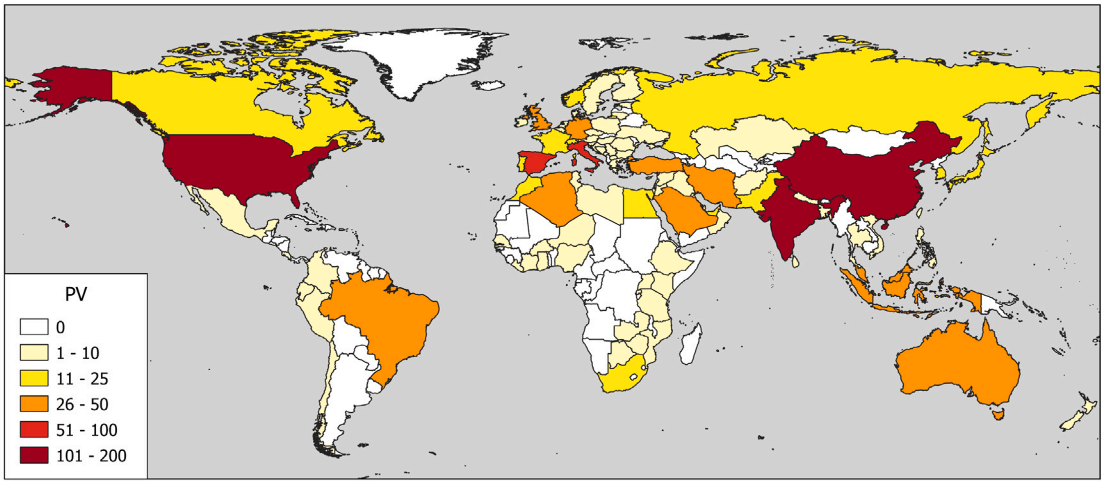
Analyzing the researches, several models are proposed to predict dust deposition on solar collectors [34]: The Brownian Diffusion Model accounts for the random motion of dust particles in the air due to Brownian motion, aiding in estimating the deposition of fine particles on surfaces. The Gravitational Settling Model considers the gravitational force acting on dust particles, causing them to settle on surfaces over time and predicting the deposition flux based on particle size and density. The Inertial Impaction Model focuses on the effect of airflow on dust particles, which leads to their impaction on surfaces and calculates the deposition rate by taking into account the aerodynamic properties of the particles. The Diffusion and Impaction Phenomena Model combines both diffusion and impaction processes to predict dust particle deposition on solar collectors, accounting for random particle movement and their collision with surfaces. The last model, the Threshold Friction Velocity Model determines the minimum wind speed needed to initiate dust particle movement on surfaces, helping to estimate the conditions under which particles can be removed from collectors.

Wu, S. et al. [29] use the Contact-Characteristics-Based Discrete Element Method to predict dust accumulation in solar panels. This enables researchers to simulate the deposition of dust particles on solar panels accurately. By incorporating factors such as solar panel inclination angles, wind speed, and direction, the model can provide realistic predictions of dust distribution on the panel surface. It predicts that winds higher to 5 m/s would help to reduce the soiling effect in panels.

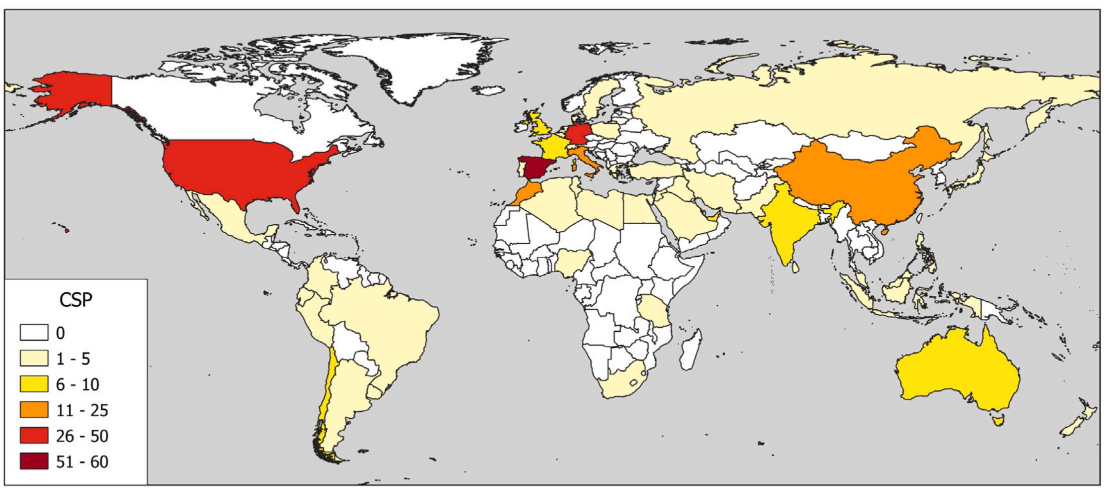
Nygard, M. et al. [41] propose the Combined Degradation and Soiling (CODS) algorithm. It works by decomposing the performance index time series data from PV systems into components related to soiling, degradation, and seasonality. The algorithm utilities a novel performance metric called CP-R (Clear-sky Performance Ratio) soiling, which provides a robust representation of daily performance by using the daily median performance index, in order to reduce the impact of outliers and noise in the data. By applying the CODS algorithm to the performance time series data, soiling and degradation rates can be accurately estimated. The CODS algorithm has been shown to provide more accurate estimates for degradation rates compared to other methods like the simple year-on-year (YOY) method and the YOY method corrected for soiling through the stochastic rate and recovery (SRR) method.

Olivares, D. et al. [42] propose a technique to simulate soiling evolution in solar panels in indoors environments. Spin-coating allows for the deposition of homogeneous layers of soil on photovoltaic glass, providing a controlled environment to study the effects of soiling on PV devices. It also enables accelerated indoor testing of soiling effects on PV modules, reducing the time required for research compared to outdoor exposure studies, being a cost-effective alternative to complex climate chambers, and researchers can replicate real-world soiling conditions in a controlled laboratory setting. It facilitates the use of analytical techniques such as X-ray diffraction and scanning electron microscopy to analyze the physicochemical aspects of soiling and its impact on PV devices.

Masoom, A. et al. [43] study's methodology involves a structured approach to assess the influence of dust on solar energy prediction. Initial data gathering includes information from surface based on Aeronet measurements, satellite data from MODIS and CALIPSO, and the MIDAS database. The MIDAS dataset aids in determining Aerosol Optical Depth (AOD) and Dust Optical Depth (DOD) during dust occurrences, while CALIPSO profiling is utilized to examine the vertical structure of aerosols. Solar irradiance prediction is carried out through the Weather Research and Forecasting (WRF) model, configured with input from the Global Forecast System (GFS). The WRF model integrates dust dynamics through assimilation techniques and incorporates AOD data from



(a) PV



(b) CSP

Fig. 11. Maintenance studies for PV plants vs CSP plants.

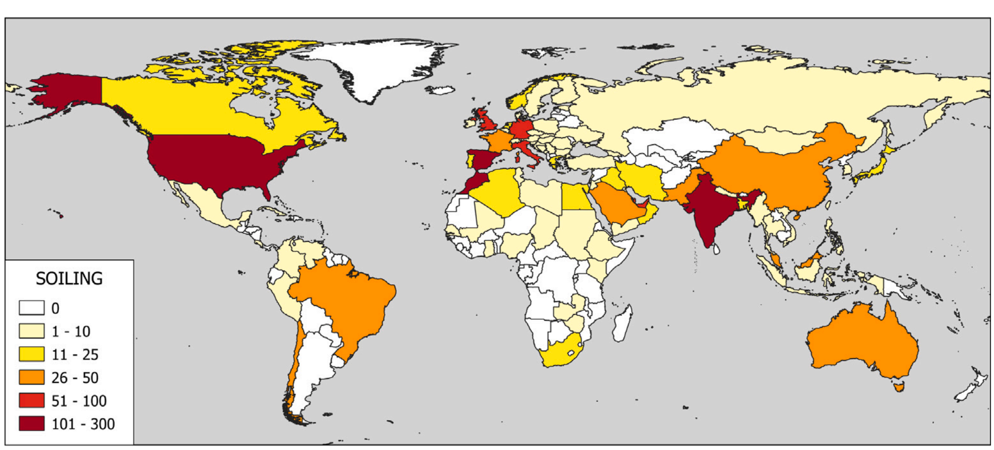


Fig. 12. Distribution of researches in maintenance techniques for soiling per country.

the Copernicus Atmosphere Monitoring Service (CAMS) to improve the assessment of dust impact on solar irradiance.

Perez, N.S. et al. [27] focused on estimating soiling losses in photovoltaic plants using artificial intelligence techniques, particularly ANN, to optimize maintenance schedules and enhance the economic performance. By analyzing meteorological variables and installation parameters, the research successfully modeled soiling losses and validated the models with statistical indicators like nRMSE, and the correlation coefficient "r". The models showed high accuracy, with normalized root mean square error below 7% and a strong correlation coefficient above 0.9. These results were achieved when Isc (short circuit current) was included, enhancing the results compared to when only module temperature, irradiance of the array panel, relative humidity and solar altitude was included.

Heimsath, A. et al. [44] introduce a model based on the Lambert–Beer law to quantify the incidence angle dependent attenuation due to dust on reflector Surface. The reflectance of soiled glass reflectors diminishes significantly with increasing angles of incidence. Clean mirrors typically show little variation in specular reflectance with changing angles of incidence. However, for soiled mirrors, the angle of incidence has a significant impact on specular reflectance. As the angle of incidence increases, the reflectance of soiled mirrors decreases. The study reflects that at an acceptance angle of 15 mrad, the specular reflectance of a soiled mirror can decrease by 7%, going from 91% at an 8° incidence angle to 84% at a 70° incidence angle. The study highlights that not considering angle-dependent reflectance can lead to an overestimation of the annual plant performance by up to 2%.

Javed, W. et al. [45] carried out a study analyzing the seasonal evolution of soiling in PV panels in the dessert environment of Qatar. PV soiling rates varied significantly across different seasons: cooler seasons had the highest soiling rates, followed by summer months with higher PM10 concentrations due to dust storms and lack of rain. High wind speed and low humidity levels were linked to lower soiling levels. Approximately 3 mm of rain was found to be necessary to fully clean the PV modules. Rainfall less than 2 mm resulted in partial cleaning, while very light rain (≤0.2 mm) exacerbated soiling. The impact of dust storms during the winter season was found to be more severe than in summer. Dust storms caused an 8% attenuation of solar radiation reaching the PV panels and increased the annual average soiling rate by 23% compared to non-dust storm days.

The results of the study by Picotti, G. et al. [46] on the optimization of cleaning strategies for heliostat fields in solar tower plants suggest that the use of a Mixed Integer Linear Programming (MILP) model allows for the identification of optimal cleaning schedules for different sectors of the solar field, considering factors such as soiling impact, cleaning frequency, and cleaning costs. The research shows improvements in Total Cleaning Costs (TCC) ranging from 0.7% to 19.6% across various scenarios and cost structures, leading to significant savings in annual costs for the solar power plants.

2.1.1. Anti-soiling strategies to increase solar energy production

Soiling is an inevitable event that will occur at some point due to the factors explained in Section 1.2. This is why materials and coatings have been developed to reduce the accumulation of soiling on the panels.

Ammari, N. et al. [47] conducted an experiment under hot arid climate conditions, where three types of PV solar technologies were used to see how they were impacted by soiling. Cadmium Telluride (CdTe) was the least affected technology, with a daily Soiling Ratio (SR) loss of 23.6%, followed by Multi-crystalline Silicon (m-Si) with a daily SR loss of 24% and finally Monocrystalline Silicon (mono-Si) with a daily SR loss of 28%.

Coatings for solar panels are specialized materials applied to the surface of photovoltaic cells to enhance their efficiency and durability. This is of vital importance to prevent dust and other materials to adhere to panels' surface [48]. Several researches, addressed from now on, have been conducted worldwide to address this issue and improve coating technology [49].

Papadopoulos, N.D. et al. [50] concluded that the quaternarized silica hybrids demonstrated strong anti-soiling performance, with the ability to resist contamination and dust buildup. The Si-QUAT molecules in the hybrid coatings formed a robust structure with marked anti-soiling properties, and the coatings exhibited self-cleaning properties due to their antistatic behavior. The quaternarized silica hybrids showed similar anti-soiling performance to commercial coatings for extended periods. The compact quaternarized silica structures promoted the formation of a silica matrix surrounded by anchor sites, allowing the quaternary ammonium silane molecules to graft on them, further enhancing their anti-soiling capabilities.

The hydrophilic anti-soiling coating for solar reflectors tested in CSP plants by Wette, J. et al. [32] demonstrated a significant improvement in cleanliness, reducing soiling rates and extending cleaning intervals. The study found a mean cleanliness gain of up to 1.0 percentage points, with higher gains of 2.4 percentage points under stronger soiling conditions. The coating also reduced water usage by up to 11.7% through fewer cleaning cycles, while maintaining its durability and optical properties over two years of exposure. This technology offers a solution for reducing operational costs and conserving water, essential for arid regions where CSP plants are typically located.

Abdallah, A.A. et al. [25] carried out a study on the performance of monofacial and bifacial silicon heterojunction modules in a desert, where that bifacial SHJ modules outperformed monofacial modules, showing a 15% higher energy yield attributed to the rear-side power contribution and high albedo utilization. The bifacial modules exhibited lower sensitivity to PV soiling, as a consequence of a lower soiling impact in the rear side. This also helped to reduce cleaning tasks in the bifacial module.

Anderson, C.B. et al. [30] suggest that stowing heliostats in the horizontal position at night increased daily soiling rates by 114% and total cleaning costs by 51% compared to vertically stowed heliostats. Moreover, performing cleaning tasks during day is 7% more expensive that doing it during night due to the necessity of parking operational heliostats during this process. The study was performed in Mount Isa. Australia. A model was also developed to predict a soiling rate of 0.12pp/d for low dust seasons and 0.22pp/d for high dust seasons.

The cleaning robot proposed by Megantoro, P. et al. [51] is equipped with sweeper rollers and nylon tassels optimized for effective removal of dirt and dust from the solar array surface, enhancing the system's performance and efficiency. Moreover, the robot integrates proximity sensors, IMU sensors, and gyroscope sensors to detect and follow the sweep path over the entire PV array area.

Pradhan, A. et al. [52] designed a solar dust cleaner for PV modules that incorporates several key features to effectively remove dust and maintain the performance of the panels. The system utilizes a microcontroller to control the cleaning process, including sensors to detect dust levels and vibrators to dislodge dust particles uniformly. It includes a power inverter with a boost device to power an air compressor for cleaning and cooling purposes. The design ensures that the cleaning process is automated and efficient, with switches controlled by the microcontroller to manage operations based on cleaning requirements. It utilizes membrane vibrators strategically placed on the corners of the panels. These vibrators are used to shake a transparent plastic sheet that is placed on the upper layer of the PV panel, where dust gets deposited. The vibrators operate at the resonant frequency of the shield to create a standing wave that efficiently dislodges dust particles from their positions.

The dust cleaning machine designed by Walaman-I, I. et al. [53] for solar PV panels in Ghana operates by employing a combined wet and dry brush-based cleaning approach. The machine translates over the panels, spraying water onto them before the cleaning brush rotates to wash and remove the accumulated dust. This process ensures effective cleaning without water wastage. The machine is strategically positioned at a distance from the panels when not in operation to prevent shadowing, optimizing its efficiency.

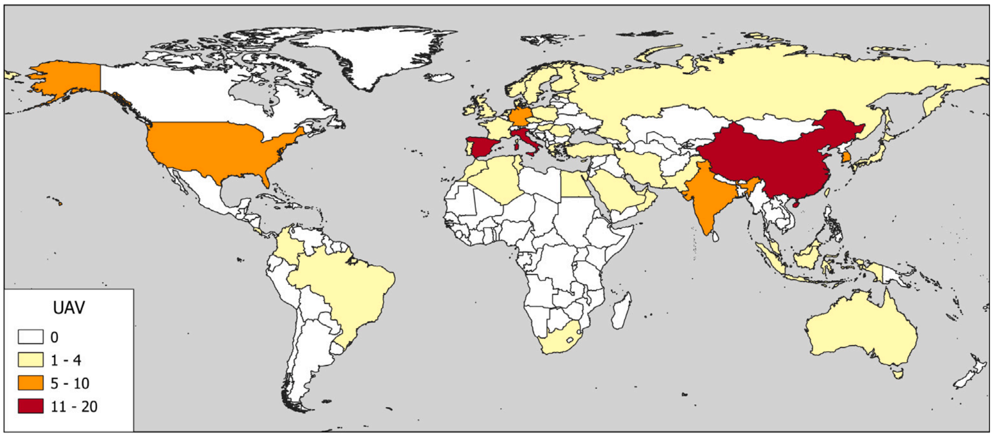


Fig. 13. Distribution of researches in UAV maintenance techniques per country.

2.2. Panel faults detection: hotspots, cracks and other defects

As mentioned in Section 1.2, hotspots and cracks are a main issue for PV panels and a major failure cause. Fast detection help to minimize long-lasting defects that may cause the malfunction and the removal of the panel. Thanks to technological advancements, it is now possible to detect and anticipate this failures thanks to UAVs, AI and IoT. The combination of these three technologies help to capture images of the panels faster, analyze them with artificial intelligence and detect and prevent failures more accurately than with visual inspection. IoT helps to transfer the data and set alarms when a failure is detected in real time.

2.2.1. UAV images

Several researchers have been studying in the incorporation of Unmanned Aerial Vehicles (UAVs) equipped with high-resolution imaging cameras to operate and maintain solar power plants [54]. According to Fig. 13, China is leading the researches in UAVs for solar plants along with Spain.

Some of the advantages in the use of UAVs include efficient inspections, as UAVs can quickly and cost-effectively survey large-scale solar power plants, covering vast areas in a short time. By utilizing UAVs for these inspections, labor costs are reduced, resulting in operational and maintenance savings. UAVs also enable fast data acquisition, capturing high-resolution optical and infrared images that provide detailed information on the condition of PV modules and potential defects. Moreover, UAVs enhance safety by eliminating the need for personnel to access hard-to-reach or hazardous areas of solar plants. The data collected by UAVs can be used to identify defects, anomalies, and other issues in PV modules, facilitating proactive maintenance and minimizing downtime [55]. Advanced analysis of UAV-captured images using computer vision techniques allows for the detection, segmentation, and classification of PV module defects, supporting more precise and efficient maintenance strategies. UAVs combined with infrared technology enable the detection of soiling and shading on panels [56,57].

Zefri, Y. et al. [58] introduce an analysis of overheated regions within PV arrays using Long-Wave Infrared (LWIR) UAV imagery with a novel two-layer end-to-end inspection solution that combines georeferenced orthomosaics with deep semantic segmentation. This innovative approach eliminates the need for module extraction and enhances the efficiency of defect detection and achieves a mean Intersection over Union (mIoU) of 93.44% and an F1-score of 96.39% on the test set.

By using Red, Green and Blue (RGB) and Infrared Thermography (IRT) images with drone photogrammetry, Hernandez Lopez, D. et al. [59] developed an application called SunMap to fully automate the process of detecting hotsports in PV plants. It creates 3D model and geolocalize the failures with an error lower than 15%.

A similar technique is used by Chen, H. et al. [60] to capture images with UAVs. An adapted generative adversarial network (GAN) is employed to augment the size of the limited visible aerial images. This process involves generating new images based on the existing dataset to increase the diversity and quantity of training data. An automatic algorithm is implemented to remove images with poor quality among the augmented datasets. A deep learning-based model, such as a convolutional neural network (CNN), is utilized to classify the photovoltaic modules based on the visible images. The algorithm can identify hotspots, glass breakage, shading, snail trails and gridline corrosion.

Lee, D. and Park, J.H. [61] presented a novel inspection methodology for solar energy plants utilizing thermal infrared sensors on UAVs. By combining optical and thermal infrared sensors, the study produces accurate spatial information and orthographic images of temperature distributions of PV panels. Through this approach, it identifies abnormal heat generation in solar panels and cells, distinguishes between normal and faulty modules based on temperature fluctuations, and utilizes spatial temperature distribution for precise detection of abnormal phenomena. Other studies like [62] also use infrared technology to detect failures.

Setiawan, E.A. et al. [63] utilize adaptive thresholding and modified noise filtering approaches to analyze the captured images and detect objects, such as hot spots, on the PV modules. These techniques help in accurately identifying areas of partial shading that could lead to power loss. By combining thermal and visual data, the system pinpoints regions of concern on the solar panels, enabling maintenance activities to be targeted towards resolving these issues promptly. This method has an accuracy of 94,74% for hot sports detection and 100% for modules detection.

Oliveira, A.K.V.D. et al. [64] developed an automatic fault detection algorithm that uses aerial infrared thermography images to identify faults in large-scale PV power plants. A dataset of infrared images capturing various faults such as disconnected substrings, short-circuited strings, and hot spots was created and annotated with ground-truth segmentation to highlight faulty modules, facilitating algorithm training and validation. Orthomosaicking techniques which combines multiple images to create a comprehensive and detailed orthophoto of the PV system was used, providing a broader view of the modules and their surroundings.

Bemptosa Rosende, J. et al. [65] designed a UAV fleet which operates by utilizing a distributed communication system, enabling remote and automated control of drones. Each UAV is equipped with sensors and cameras — visible, infrared, or multispectral — used for inspecting solar panels, detecting defects, and performing surveillance task, with flight paths and tasks controlled from a processing center via a web interface. Each UAV can inspect about 35 square meters of solar panels

Table 1
UAV methods for solar plant maintenance.

Method	Function	Accuracy/Performance
UAVs with high-resolution optical and infrared cameras	Quick inspection of large solar fields, detecting faults, soiling, and shading	High efficiency for fast and cost-effective inspections (no specific metrics)
UAV Long-Wave Infrared (LWIR) with semantic segmentation	Detects overheated regions in PV arrays using deep learning segmentation	93.44% mIoU, 96.39% F1-score
SunMap application with UAV RGB and IRT images	Detects hotspots and geolocates failures in PV plants	Localization error < 15%
UAV with GAN (Generative Adversarial Network)	Augments visible image datasets for training, detects multiple panel issues	Improved dataset diversity and classification accuracy
UAV with thermal and optical sensors	Identifies abnormal heat generation and spatial temperature anomalies in PV modules	High accuracy in identifying abnormal panels
Infrared thermography with UAVs	Fault detection in PV systems, covering larger areas	Effective detection (specific metrics not always provided)
UAV fleet with distributed communication	Automated inspection of large solar arrays, real-time data transfer	Inspects 1 hectare in 5 min, covering 35 square meters/second
UAV with YOLOv5 and CNN for thermal imaging	Fast detection of clean/dirty panels and other faults	Reduced inspection time by 99.93% (e.g., 120 h to 5 min)

per second, covering one hectare in just 5 min.

Using drones for monitoring solar photovoltaic (PV) power plants offers several key advantages, including improved operation and maintenance, time savings during inspections, enhanced energy productivity, and greater accuracy in fault detection. This technology also helps boost returns on investment, increases inspection efficiency, and allows for wide integration and multitasking capabilities, along with long-term data maintenance [66].

In Table 1, a summary of the methods discussed above is presented:

UAV methods underscores the versatility and efficiency of these technologies in maintaining solar plants. UAVs equipped with high-resolution optical and infrared cameras offer rapid and cost-effective inspection solutions for detecting faults, soiling, and shading in extensive solar fields. Advanced techniques like Long-Wave Infrared (LWIR) with semantic segmentation achieve high precision in identifying overheated regions, while the SunMap application combines RGB and IRT imagery to geolocate failures with minimal error. Distributed UAV fleets improve scalability by automating inspections over large areas (e.g., 1 hectare in 5 min). Each method excels in specific domains, but challenges like dependency on advanced algorithms, high equipment costs, and integration complexities are aspects to take into account when designing the strategy for the maintenance of a specific solar plant.

2.2.2. Artificial intelligence

Artificial Intelligence (AI) plays a pivotal role in detecting failures in solar panel modules, enhancing efficiency and reliability. AI and Machine Learning (ML) [67] algorithms analyze data from sensors and imaging technologies to identify issues such as cracks, hotspots, and degradation in real-time [68]. This predictive maintenance approach reduces downtime, lowers repair costs, and extends the lifespan of solar panels, ensuring optimal performance and energy production [69].

According to Fig. 14, China is leading the researches in the use of AI for solar plants maintenance.

Segovia Ramirez, I. and Garcia Marquez, F.P. [70] present a groundbreaking approach for fault detection in photovoltaic solar plants using aerial thermographic images and an Internet of Things (IoT) platform. This includes the development of a novel methodology that combines two consecutive artificial neural networks (ANNs) for panel and hot spot detection, resulting in enhanced accuracy and reliability in fault identification of false regions. The first ANN is dedicated to panel detection, while the output data from this initial network serves as input data for the second ANN, which is designed for hot spot detection. The platform's integration of advanced machine learning techniques, such as Faster-RCNN, demonstrates high performance with 100% accuracy for panel detection and over 93% accuracy for hot spot detection.

Other studies like [71–73] provide a similar approach but also focused on cleaning methods, reducing time and maintenance costs.

Rocha, D. et al. [54] highlight the use of UAVs equipped with high-resolution optical and infrared imaging for efficient inspections in solar power plants. The study focuses on creating a dataset of IR images from a 10-MW solar power plant and compares the performance of mask R-CNN and U-Net algorithms for defect segmentation and classification. The results show that the mask R-CNN algorithm achieved a mean average precision at intersection over union (IoU) of 0.96 for defective module segmentation and 0.88 for segmentation and classification of failure types.

In order to detect broken tubes in CSP plants, Perez-Cutino, M. A. et al. [74] created the first public dataset, RTSet, specifically for this problem, which includes data from seven real CSP plants. By addressing the challenge of class imbalance in fault detection, they significantly improved the accuracy of identifying broken glass envelopes in receiver tubes. Notably, their approach using a machine-learning dual optimization with dense-sparse-dense (DSD) training and random under-sampling techniques boosted recall by up to 8%, making the detection process more reliable and efficient.

Bendale, H. et al. [75] propose a system focused on achieving high accuracy in detecting faults in solar panels using deep learning Convolutional Neural Network (CNN). By using a training dataset, the system takes a .csv file as input, generated by the solar panel system monitor, recording energy generation and storage data in terms of Voltage, Current, Capacity, etc. The machine learning model predicts fault types based on these recorded values. The system achieved an accuracy of 97.5% and it outperformed the existing system by detecting more types of faults (over 7 types) compared to the previous system that focused on only 2-3 types of faults.

Kaligambe, A. and Fujita, G. [76] used a VGG16 fine-tuned model, which is deep learning architecture that has been pre-trained on a large-scale dataset (ImageNet) for image recognition tasks and then further trained or "fine-tuned" on a limited dataset of electroluminescence (EL) images of solar photovoltaic (PV) cells for the purpose of defect detection. Another important key feature of this study is the use of electroluminescence imaging (also used in [77]), as it provides high-resolution images and it is highly sensitive to defects within solar cells, such as micro-cracks, broken cells, and interconnect faults. These defects alter the EL emission pattern, making them easily detectable and allowing for precise localization of the issues. This model achieved a performance of 95.2%.

Ahmed, S.U. et al. [78] proposed a model where drones and YOLOv5 are used for detecting clean and dirty panels in solar power plants due to its high accuracy and speed of detection. In the context of inspecting

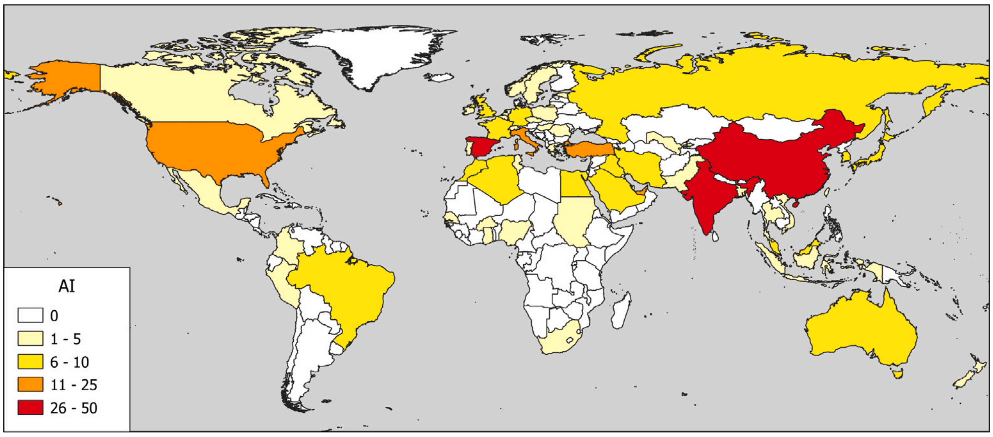


Fig. 14. Distribution of researches in AI maintenance techniques per country.

solar panels, the YOLOv5 algorithm is known for its expeditious detection capabilities, processing images with a speed of 2 ms per image on NVIDIA Tesla V100. This rapid processing speed is essential for real-time performance, especially when dealing with images captured from drones at different heights and angles. The system significantly reduces the inspection timeline from 120 h to just five minutes. This automation ensures timely maintenance for the efficient and safe operation of solar arrays, saving 99.93% of the inspection time through vision and robust automation techniques.

Tyagi, S. et al. [79] compared predicted and actual power output values using several machine learning models like linear regression, Bayesian regression, and non-linear regression, successfully identifying faulty PV modules based on significant differences in performance. While linear regression models were effective in detecting severe failures, non-linear regression models outperformed in explaining variance in power yield, pinpointing modules requiring maintenance.

Fan, F. et al. [80] conducted a study on hotspot detection. By developing a five-layer CNN model and employing image enhancement techniques like cropping and restoration, the research substantially improves the classification accuracy of both CNN and naive Bayes classifier models. The comparison between the two classifiers demonstrates the superior performance of CNN in accurately identifying and classifying hot spots within photovoltaic modules, achieving a classification accuracy of 96.58%.

Masita, K. et al. [81] propose a comprehensive approach to enhance the accuracy of anomaly detection in Solar PV Plants using drone-captured thermal images. By introducing the Res-CNN3 framework, which incorporates concatenated CNNs and residual networks, the authors aim to improve the efficiency and accuracy of detecting PV module defects. Implementing logistic regression as the loss function and utilizing the Selective Search algorithm further contribute to identifying and localizing anomalies with high confidence scores. Through experiments on a consolidated dataset, the authors demonstrate the superior performance of the Res-CNN3 framework compared to existing methods. The strategy of scale transformation and augmentation addresses the challenge of detecting complex anomalies like burn marks and encapsulant delamination, achieving a mean average precision of 76.4% across all PV module defects.

The model developed by Fonseca Alves, R.H. et al. [82] utilize a CNN architecture, which includes convolutional layers, pooling layers, and fully connected layers. The convolutional layers are responsible for extracting features from the input images, while the pooling layers help reduce the spatial dimensions of the features. The fully connected layers then process these features for classification. Based on the extracted features, the model classifies the input images into specific fault categories such as soiling, cracking, vegetation, diode failure, and others. This classification allows for the identification of the type of fault present in the PV module, achieving a detection accuracy of 92% for healthy PV modules and 93% for damaged modules.

The proposed deep learning approach by Han, S.H. et al. [83] utilize a UAV equipped with a thermal camera and GPS to detect faults in solar panels. The UAV captures thermal images in real-time, covering a wide area where the deep learning model operates intelligently to identify faults within the solar panels. Additionally, the GPS mounted on the drone helps determine the location of the damaged panel. It uses the improved version of YOLOv3-tiny, which incorporates additional convolution layers to extract complex scenes like those encountered in solar panel fault detection. The transmission of fault information to a remote server using Long-Term Evolution (LTE) plays a vital role in the visualization and monitoring of solar panel faults in real-time.

Kuzlu, M. et al. [84] use XAI (Explainable Artificial Intelligence) tools to enhance the transparency, interpretability, and efficiency of AI models in the context of solar PV forecasting. By applying XAI tools such as LIME, SHAP, and ELI5 to interpret the random forest AI model, this research provides an insight into the impact of different input features on solar PV power generation predictions, such as weather conditions, temporal variability or data quality. It helps to understand why IA takes some decisions, as it usually works as a black box without understanding which parameters are more decisive for its predictions.

A summary of the most relevant AI algorithms is presented in Table 2, providing a quick insight on their purpose and efficiency:

The algorithms analyzed each excel in their specific domains but also present unique limitations. Faster-RCNN offers exceptional precision but requires significant computational resources, while YOLOv5 prioritizes speed, drastically reducing inspection time, yet depends heavily on large datasets. Mask R-CNN is highly accurate for defect segmentation but computationally intensive. VGG16 specializes in electroluminescence analysis but demands advanced setups. Res-CNN3 targets thermal anomalies with moderate accuracy.

2.2.3. IoT networks

The use of IoT contributes significantly to improving maintenance management for photovoltaic solar power plants [85]. IoT allows for the connection of sensors and devices, enabling real-time monitoring of various parameters such as energy production, system performance, and environmental conditions in solar power plants [86]. The use of Big Data is closely linked to IoT, as this technology enables the analysis of huge amount of information in real time thanks to AI algorithms, improving the overall performance of the system [87].

In terms of IoT research within the maintenance techniques scope in solar plants, India is leading this field, as seen in Fig. 15.

Ledmaoui, Y. et al. [3] used IoT and evaluated six machine learning algorithms for forecasting energy production, including Support Vector Regression (SVR), Random Forest (RF), Decision Tree (DT), Generalized

Table 2
AI Algorithms for predictive maintenance and fault detection.

Algorithm	Purpose	Accuracy/Performance
YOLOv5 [78]	Fault detection	99.93% accuracy, moderate cost/complexity, high-speed detection
Mask R-CNN [54]	Defect segmentation	96% IoU, high cost/complexity, precise segmentation
VGG16 fine-tuned model [76]	Defect detection in electroluminescence images	95.2% performance, high cost/complexity, moderate ease of implementation
Res-CNN3 [81]	Anomaly detection in thermal images	76.4% mean average precision, high cost/complexity, requires advanced techniques
Faster-RCNN [70]	Fault detection in solar panels	100% panel detection, 93% hot spot detection, high cost/complexity, highly precise

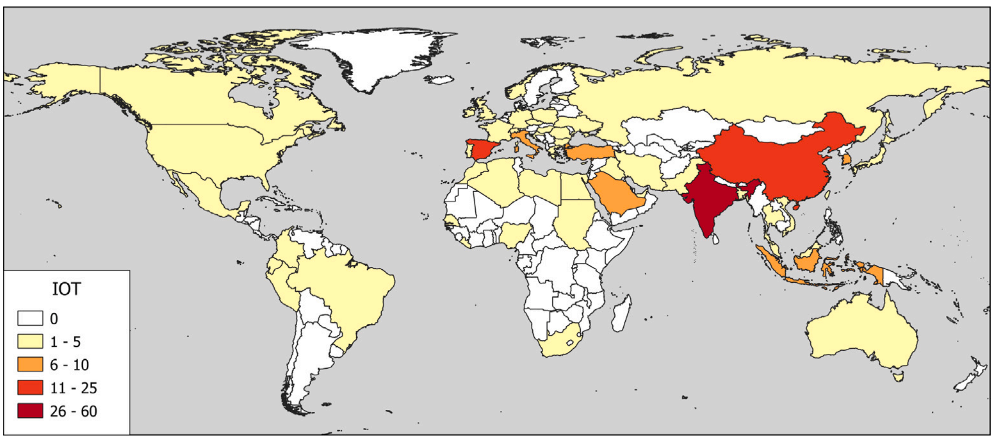


Fig. 15. Distribution of researches in IoT maintenance techniques per country.

Additive Model (GAM), and Extreme Gradient Boosting (XGBOOST), in addition to ANN. Among these models, ANN provided the best results.

Ramirez, I.S. et al. [88] focus on utilizing thermal images obtained from unmanned aerial vehicles (UAVs) to analyze the superficial state of PV panels. By employing advanced machine learning algorithms, particularly convolutional neural networks, the platform aims to enhance the accuracy and efficiency of fault detection processes. For this purpose, it designed an IoT platform that uses CakePHP, HTML, CSS, and JavaScript to create a user-friendly interface for managing the system. Users can easily upload thermal images, create datasets, and access different training functionalities.

Priya, S. et al. [89] developed of an IoT-based monitoring system that enhances the performance and reliability of solar photovoltaic (PV) installations, especially those in remote areas. The system integrates sensors with a central controller to monitor key parameters such as voltage, current, and temperature, allowing for real-time monitoring, problem identification, and preventative maintenance. This IoT solution ensures continuous updates of system data, significantly improving efficiency while minimizing human intervention.

The study presented by Del Rio, A.M. et al. [90] focus on improving maintenance management for photovoltaic solar power plants by integrating Internet of Things (IoT) and Machine Learning (ML) techniques. A real case study using SCADA data from a solar plant in Spain demonstrates the successful application of classification algorithms, specifically Shapelets and K-nearest neighbors, to detect patterns indicating a decrease in the Performance Ratio (PR) over time. While both algorithms proved effective in pattern recognition (average accuracy of 0.9882 for K-nearest neighbors and 0.9674 for Shapelets in pattern recognition), K-nearest neighbors emerged as the preferred choice for implementation on the IoT platform due to its reduced execution time and superior performance in detecting irregularities in time series data.

Mellit, A. and Kalogirou, S. [91] focused on designing smart monitoring systems that combine AI-based fault detection and IoT-based remote sensing capabilities. By implementing these technologies into simple hardware, such as low-cost chips, the study aims to make fault detection and diagnosis more accessible and cost-effective, especially for PV plants located in remote areas.

3. Forecasting solar energy production in facilities

Once the main causes of failure and lower production in solar plants have been addressed, these tools and methods can be used to forecast the solar energy a solar plant is expected to produce according to the existing circumstances on the day or over a time period. Accurate forecasts are essential for optimizing the integration of solar energy into the power grid, enhancing the reliability and efficiency of energy supply, and supporting grid stability. These predictions rely on a combination of meteorological data, historical solar output, the current state of the solar panels and advanced modeling techniques [92].

Vyas, S. et al. [93] developed a comprehensive forecasting model based on a Vector Auto Regression (VAR) approach, integrating the total power generation, maintenance activities (such as grid failures, inverter failures, and module cleaning), weather conditions (such as temperature, solar radiation, humidity, wind speed and pressure or UV radiation) and aging factors (PV cell shedding, cleaning issues, elevated air temperature, high system voltages, broken interconnects, hot spots, corrosion, encapsulant issues, discoloration, and delamination). These are considered as time series data to improve the accuracy of solar power generation predictions. The study's findings indicated that the forecasting model could track peaks in total power generation effectively by utilizing daily unscheduled and scheduled maintenance activities and weather conditions.

On the other hand, Fan,T. et al. [94] use a Spatial-Temporal Genetic-based Attention Networks (STGANet) model to forecast short-term energy production in a solar plant. The STM is designed to predict missing solar irradiance data by incorporating a graph convolutional neural network to learn the spatial and temporal dependencies between historical meteorological data. It utilizes dilated convolution as the nonlinear part to simplify the network structure and improve efficiency. The Genetic-based Attention Module combines the predicted solar irradiance and historical power generation data to forecast the power generation of PV plants. It employs an attention mechanism to efficiently explore potential relationships in the input features. It uses genetic-based operations and LSTM to find globally optimal solutions.

Lin, P. et al. [20] propose a hybrid improved Kmeans–GRA–Elman model to enhance short-term power prediction for PV power plants by integrating advanced techniques. Firstly, it utilizes an optimized K-means clustering method to group historical power datasets, identifying patterns for more accurate predictions. Secondly, Grey Relational Analysis (GRA) is employed to determine similarity days and optimize forecasting accuracy. Thirdly, the Elman neural network captures complex relationships between meteorological factors and power data. By considering diverse meteorological factors, the model accounts for weather influences on PV power generation.

4. Sustainability and water saving

Because of their typical desert, hot, and dry setting, CSP plants (and PV plants to a lesser extent) are also confronting the additional problem of being water-efficient. In actuality, a CSP plant may use up to 2500 m3/GWh of water [95]. Seeking solutions is necessary to deal with the limitation of declining water supplies in the affected areas. About the various water-use items (steam generation and solar field cleaning, up to 5% each, and power block cooling 90% of the overall water use).

Over or under reparation of technical equipment in solar plants is a constant challenge to increase the economic revenue. Therefore, accurate predictive models based on weather conditions and historical data are of vital importance to reduce maintenance operations and cleaning tasks [96]. Some studies have proved that these models can decreased the maintenance costs by more then 15% [97].

To address the growing competition for water resources in regions where CSP plants operate, regional water demand scenarios have been developed based on socioeconomic analyses [98]. Using a participatory multi-criteria approach, water-saving measures are evaluated by Terrapon-Pfaff, J et al. [98] to balance the needs of communities, agriculture, industry, and power plants. This approach identifies specific strategies to avoid critical development pathways that might compromise water availability.

A study conducted by H. Truong Ba, M.E. et al. [21] suggests the importance of a favorable weather conditions and regular rain to keep the solar panels clean, reduce costs and save water. In order to increase accuracy De, S. et al. [99] use a noise filter (1-sigma Hampel filter) to remove outliers from weather forecast. As this is unpredictable and not always possible, it is of vital importance to have efficient water distribution looped networks [100] to reduce the water consumption used in cleaning the solar panels and to promote sustainability.

The WASCOP project [101] highlights innovative strategies to reduce water consumption in CSP plants, which is critical due to their location in arid and desert regions. In cooling systems, WASCOP develops hybrid wet–dry systems that optimize the balance between energy efficiency and water use. This includes thermal storage to delay heat dissipation, enhanced dry cooling systems with water sprays to increase air enthalpy, and advanced techniques for the intelligent management of hybrid systems. For cleaning, the project integrates physical barriers to minimize dust accumulation, antisoiling coatings applied to mirrors and absorber glasses to reduce particle adhesion, soiling level sensors to monitor dirt accumulation, and cleaning devices such as ultrasonic cleaners that use thin water layers and exploit cavitation properties. Other studies have focused on reducing the operating temperature in PV panels to increase sustainability in solar plants [102].

A revolutionary plasma-based technology is being developed by Bennett, A. et al. [103] to clean CSP mirrors without the use of water. This system employs a plasma array attached to the end of a robotic arm, which generates a plasma jet capable of vaporizing dust and sand adhered to mirror surfaces. This process not only removes dirt but also modifies the surface energy of the mirrors, making them superhydrophilic. This property enables the mirrors to self-clean when exposed to high levels of humidity or precipitation, eliminating the need for additional water.

Zaoui, F. et al. [104] combined cleaning methods, such as brushing (CBB) and water-based cleaning (CBW) to offer sustainable solutions to mitigate soiling effects. CBW improves the electrical performance of modules by up to 3.09%, while CBB significantly reduces water consumption by relying more on mechanical methods. Non-traditional techniques like dew, melting snow, and natural gravity are proposed as complementary methods.

Antisoiling coatings have proven to be an effective tool for mitigating soiling in regions with high solar irradiance and dust storms. These innovative coatings not only reduce cleaning frequency but also protect the surfaces of mirrors and solar modules from permanent damage [105]. Recent research shows significant advances in developing more durable and effective materials that maintain high levels of reflectance and transmittance even under adverse conditions. These technologies are essential for maintaining solar system efficiency while reducing water usage in maintenance operations.

One example are self-cleaning aluminum nitride coatings [106]. Manufactured using magnetron sputtering, these coatings can restore the initial reflectance of mirrors after dust accumulation. Their self-cleaning property significantly reduces the amount of water required for cleaning compared to conventional glass mirrors.

Another study propose a hydrophilic antisoiling coatings applied to CSP mirrors under real-world conditions over two years [107]. The results showed an improvement in cleanliness of up to 7% in high-soiling conditions and a reduction in cleaning cycles by 11%. The coatings maintained higher cleanliness levels compared to conventional mirrors, both before and after cleaning, demonstrating their capacity to reduce dirt accumulation and water requirements while showing minimal degradation.

5. Discussion and future lines

The reviewed article thoroughly examines advanced maintenance techniques to optimize the performance of solar energy plants, incorporating cutting-edge technologies like artificial intelligence, Internet of Things and Unmanned Aerial Vehicles. However, there are still some limitations, challenges and future work to address towards a more sustainable and efficient system to enhance solar facilities performance, which will be discussed below.

5.1. Limitations of solar energy

Despite its enormous potential, solar energy faces several inherent limitations. The intermittency of power generation, which depends on the availability of sunlight, varies with weather conditions and time of day, requiring energy storage solutions or back-up systems that increase costs. Dust, sand and other particles significantly reduces energy production, and although cleaning solutions are available, they often involve additional costs and increased resource use. In addition, the high upfront costs of photovoltaic (PV) and concentrating solar power (CSP) plants represent a considerable barrier due to the necessary investments in infrastructure and technology. Land use also poses challenges, as large-scale solar installations require large areas, competing with other land uses and leading to possible ecological disturbances. Finally, environmental factors, such as high temperatures, ultraviolet radiation and extreme weather events like hail storms, can degrade solar panel materials, reducing their efficiency and lifetime.

5.2. Challenges in solar plants maintenance

The maintenance of solar plants faces several major challenges. Fouling due to the accumulation of dust and pollutants on solar panels reduces their efficiency and requires frequent cleaning, which can be resource-intensive, especially in water-scarce regions. Hot spots and cracks represent localized problems that cause energy losses and long-term damage to panels. Although advanced detection methods such as infrared imaging and artificial intelligence algorithms exist, their implementation requires significant investment. Moreover, the lack of standardization in maintenance techniques and technologies leads to inconsistencies in efficiency and effectiveness between different plants. Water scarcity, particularly in arid locations, challenges traditional water-intensive cleaning methods. The complexity of advanced technologies such as artificial intelligence, the Internet of Things and unmanned aerial vehicles, while offering significant benefits, requires specialized knowledge and training, which increases operational complexity.

5.3. Future lines

The future of solar plant maintenance must focus on several key directions. Research into innovative materials, such as durable, self-cleaning and anti-soiling coatings, must continue to reduce maintenance needs. Predictive models based on artificial intelligence (AI) and machine learning (ML) must be refined to improve accuracy in energy prediction and fault detection. It is essential to develop scalable and cost-effective solutions that facilitate more widespread adoption of these technologies. The integration of unified systems, combining AI, IoT and UAVs, will optimize maintenance and monitoring processes. Sustainability should be prioritized, promoting innovations that minimize water use and energy consumption during maintenance tasks. Some studies propose the collection of the water used in cleaning tasks, by means of gravity filters and in-field deposits.

6. Conclusions

This article highlights significant advancements in solar plant maintenance technologies, emphasizing predictive models, innovative cleaning solutions, and operational optimization techniques. The analysis begins by highlighting the rapid growth of renewable energy, particularly solar power, which has expanded significantly over the past decade. Despite this progress, solar energy generation is still hindered by environmental challenges like soiling and climate conditions, which affect photovoltaic systems and concentrated solar power plants.

Climate conditions like high temperatures, UV radiation, and extreme weather events, significantly affect the lifespan and performance of solar panels. Soiling (accumulation of dust, sand, and other materials) can reduce energy output, making cleaning essential but costly. Therefore, a series of technological advances have been proposed to address this issue and enhance energy production.

Specifically, algorithms like artificial neural networks (ANN) and convolutional neural networks (CNN) have demonstrated outstanding results in fault detection, achieving up to 100% accuracy in panel detection and 93% in hotspot identification. YOLOv5, a state-of-the-art object detection algorithm, has significantly improve inspection efficiency, reducing time by 99.93%. Meanwhile, Mask R-CNN and U-Net have shown exceptional precision in defect segmentation and classification.

For cleaning innovations, plasma-based cleaning technology has emerged as a water-free solution, modifying mirror surface properties for self-cleaning under humid conditions. Antisoiling coatings and robotic cleaning systems have further optimized cleaning processes by reducing water usage and extending cleaning intervals, crucial for plants located in arid regions. Hybrid wet–dry cooling systems and enhanced water management techniques have effectively minimized resource consumption while maintaining operational efficiency.

Despite these remarkable advancements, there are still some challenges to address, including the complexity of integrating advanced technologies, high implementation costs, and the lack of standardization across maintenance practices. Nonetheless, these technologies show immense promise in improving solar energy production, enhancing asset durability and promoting sustainability.

CRediT authorship contribution statement

Fernando Martinez-Gil: Writing – review & editing, Writing – original draft, Resources, Methodology, Investigation, Data curation, Conceptualization. **Christopher Sansom:** Validation, Supervision, Resources, Methodology, Conceptualization. **Aránzazu Fernández-García:** Writing – review & editing, Validation, Supervision, Data curation, Conceptualization. **Alfredo Alcayde-García:** Validation, Supervision, Resources, Investigation, Conceptualization. **Francisco Manzano-Agugliaro:** Writing – review & editing, Writing – original draft, Validation, Resources, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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