

Photovoltaic systems operation and maintenance: A review and future directions

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ABSTRACT

The expansion of photovoltaic systems emphasizes the crucial requirement for effective operations and maintenance, drawing insights from advanced maintenance approaches evident in the wind industry. This review systematically explores the existing literature on the management of photovoltaic operation and maintenance. Through the integration of bibliometric analysis and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, 186 articles are selected for further comprehensive review. The selected articles are examined and categorized into four interconnected research domains: maintenance strategies, performance indicators, degradation modeling, and maintenance optimization and planning. The presented analysis underscores the importance of integrating maintenance strategies to enhance system effectiveness. It also emphasizes the necessity of a systematic approach that integrates reliability assessment with economic and technical considerations to optimize maintenance planning and enhance system availability and resource efficiency. This aligns with the Sustainable Development Goals for affordable, reliable, and sustainable energy, while also ensuring grid security. Furthermore, the study identifies gaps and proposes avenues for improvement, recommending a shift towards prognostic approaches and the advancement of predictive maintenance in photovoltaic systems. Key suggestions also include customizing metrics for large installations, implementing adaptive protocols that move away from traditional component-centric scheduling, and using reinforcement learning to prioritize risk and optimize long-term performance. Compared to previous reviews focusing on specific maintenance elements, this work provides a broader perspective by incorporating planning and organizational factors into the maintenance discussion.

1. Introduction

The depletion of traditional energy sources and the environmental impact of large carbon emissions have led to a growing shift towards renewable energy. According to the International Energy Agency (IEA), achieving net zero emissions by 2050 requires a 70% contribution from wind and solar power. The European Union has set more ambitious goals, with the aim of 80% reduction in greenhouse gas emissions (from a 1990 baseline) and 100% generation of renewable energy by 2050 [1]. Solar photovoltaic (PV) power generation, with abundant irradiance, stands out among various renewable energy sources. The global deployment of solar energy has experienced significant growth in the last 10 years. In 2022, a significant 231 GWdc of PV capacity was installed globally, resulting in a total cumulative PV installation of 1.2 TWdc [2]. There has also been a significant increase in the number of publications dedicated to solar energy in various regions. Fig. 1 illustrates this upward trend, highlighting the growing volume

of publications per region in the field of solar energy publications from 2013 to 2022.

It can be seen that the main growth of the publications comes from the Asia-Pacific and Middle East North Africa (MENA) regions. In 2022, China emerged as the leader in solar energy research, with a remarkable 8602 published articles. Similarly, in the MENA region, Saudi Arabia made significant progress in solar energy research, presenting 1367 articles that highlight its strong commitment to harnessing the solar potential of its desert landscape.

The expansion of the capacity of PV systems and the interdependencies among their components can complicate operation and maintenance (O&M) tasks, despite their relatively simple design. At the same time, the energy market for large-scale PV installations is characterized by low profit margins and intense competition, where even slight performance reductions can significantly affect the final

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Nomenclature			
Abbreviations			
<i>IEC</i>	International Electrotechnical Commission	<i>RT</i>	Response time
<i>RBD</i>	Reliability block diagrams	<i>SR</i>	Soiling ratio
<i>CPN</i>	Cost priority number	<i>Y_f</i>	Final yield
<i>CSP</i>	Concentrated solar power	<i>Y_r</i>	Reference yield
<i>DP</i>	Dynamic Programming	Units	
<i>DSS</i>	Decision support systems	<i>GWdc</i>	Gigawatt for direct current
<i>FMEA</i>	Failure modes and effect analysis	<i>h</i>	hour
<i>FMECA</i>	Failure mode, effects, and criticality analysis	<i>kW</i>	Kilowatt
<i>FTA</i>	Fault tree analysis	<i>kW/m²</i>	Kilowatt per square meter
<i>FV</i>	Fussel–Vesely	<i>kWh</i>	Kilowatt hour
<i>IP</i>	Integer programming	<i>kWh/m²</i>	Kilowatt-hours per square meter
<i>KPIs</i>	Key performance indicators	<i>kWp</i>	Kilowatt peak
<i>MCDA</i>	Multi-criteria decision analysis	<i>m²</i>	Square meter
<i>MENA</i>	Middle East North Africa	<i>MW</i>	Megawatt
<i>MIP</i>	Mixed integer programming	<i>MWp</i>	Megawatt peak
<i>ML</i>	Machine learning	<i>t</i>	time period
<i>O&M</i>	Operation and maintenance	<i>TWdc</i>	Terawatt for direct current
<i>PRISMA</i>	Preferred Reporting Items for Systematic Reviews and Meta-Analyses		
<i>PV</i>	Photovoltaic		
<i>RAM</i>	Reliability, availability, and maintainability		
<i>RL</i>	Reinforcement learning		
<i>TSP</i>	Traveling salesman problem		
<i>UAVs</i>	Unmanned aerial vehicles		
Notations/Symbols			
η_A	Array efficiency		
η_{inv}	Inverter efficiency		
η_{pv}	System efficiency		
A_t	Availability		
<i>CAPEX</i>	Capital expenditures		
<i>CF</i>	Capacity factor		
<i>CM</i>	Corrective maintenance ratio		
D_S	System degradation		
<i>EA</i>	Energy-based availability		
<i>ELC</i>	Equivalent labor cost		
<i>ESPC</i>	Equivalent spare parts cost		
<i>IRR</i>	Internal rate of return		
<i>LCoE</i>	Levelized cost of energy		
<i>MP</i>	Maintenance planning factor		
<i>MTBF</i>	Mean time between failures		
<i>MTTF</i>	Mean time to failure		
<i>MTTR</i>	Mean time to repair		
<i>NPV</i>	Net present value		
<i>OPEX</i>	Operational expenditures		
<i>PI</i>	Performance index		
<i>PM</i>	Preventive maintenance ratio		
<i>PR</i>	Performance ratio		
R_t	Reliability		

profit. Consequently, achieving maximum performance is essential to ensure long-term profitability. In the PV industry, a dominating “install and forget” mentality is observed, with operators performing minimal

maintenance beyond the essential periodic cleaning. This practice is driven by the belief in the reliability of the components. However, following this approach often leads to unexpected failures, production losses, higher costs, and compromised power quality [3]. Consistent management and maintenance of large-scale solar power plants are crucial to ensure grid stability, which goes beyond individual solar arrays.

The described challenge of O&M also applies to smaller-capacity distributed installations, such as PV fleets, which are often scattered across rooftops and hills, making them difficult to access. The importance of maintenance in PV systems has garnered significant interest, prompting research and initiatives from various institutions to establish “best practices” for the O&M of PV systems [4]. It has been reported that optimized O&M strategies can recover an average energy of 5.27% for a typical 16.1 MWp PV plant, equivalent to \$10 000 per MW annually. Without effective O&M strategies, the global PV industry could face an annual loss of \$14.5 billion by 2024 [5]. Therefore, maintenance management is essential for reliable and effective operation of PV power plants, ensuring uninterrupted system operation and minimizing downtime.

Compared to well-established technologies such as hydro, thermal, and wind, the O&M processes for PV systems are not yet fully structured in many operating companies [6]. In particular, the wind industry has made substantial progress in O&M, as evidenced by the extensive research landscape. For instance, Shafiee and Sørensen [7] emphasized the importance of developing optimal maintenance plans for wind farms considering factors such as inspection time, frequency, work preparation, and necessary resources. Ren et al. [8] highlighted the need for effective maintenance strategies for cost control and energy production optimization, covering elements such as strategy selection, schedule optimization, assessment criteria, recycling and environmental concerns. Furthermore, Tusar and Sarker [9] elaborated on efficient maintenance practices for offshore wind farms considering inventory management, transportation operations, and reliability improvement. The extensive body of research in wind energy O&M covers a wide range of aspects, indicating a higher level of depth compared to the existing literature on O&M for PV systems. To achieve a sustainable energy landscape, it is essential to recognize the crucial roles of wind and PV energy in the overall energy system. This requires concentrated research efforts and widespread sharing of best practices. Motivated by the substantial body of work in wind O&M, there is a need to systematically expand this knowledge to comprehensively review the current literature on PV O&M. The goal is to modify and implement

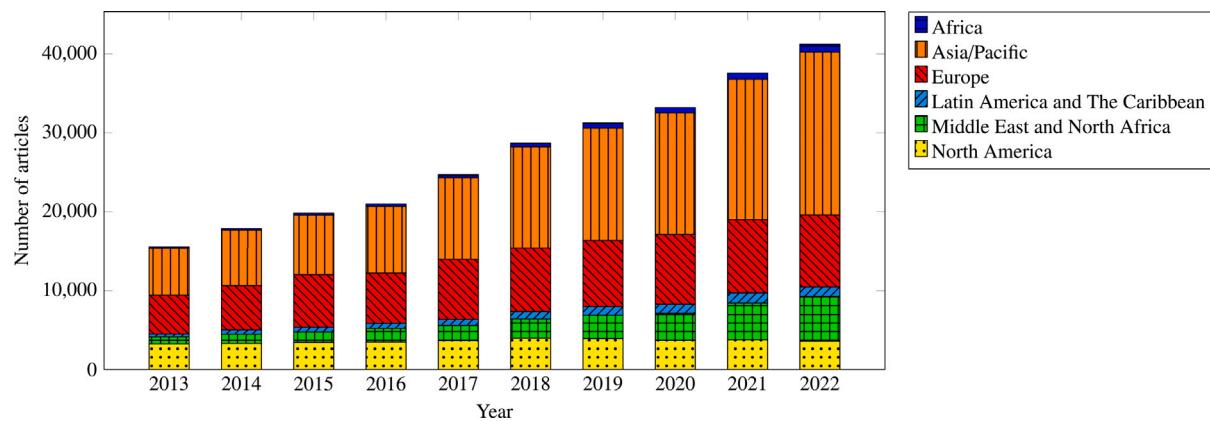


Fig. 1. Growth in solar energy publications across regions and years [<https://www.scopus.com>].

similar principles in the context of PV systems, thereby enhancing the understanding of effective O&M strategies.

The main objective of this review is to comprehensively examine the development of PV O&M over the past decade and systematically analyze key topics and their interconnections in the field. In Section 2.1, it is highlighted that the majority of existing research has focused primarily on individual aspects of O&M, neglecting the integration of crucial elements such as human resources, inventory, transportation, and supply network management. Maintenance of PV systems extends beyond addressing technical issues, including strategic allocation of resources, prioritization of tasks, and formulation of contingency plans. Understanding the interconnections between these aspects is essential for optimizing maintenance and making well-informed decisions.

The main contributions of this review, in comparison to existing reviews, include:

- A timely analysis of PV O&M evolution, considering recent advancements and challenges through a holistic approach.
- A broader scope by exploring often overlooked factors related to maintenance assessment, economic considerations, and logistical elements crucial for effective real-world management.
- An outlook of future research scopes in PV systems O&M management, aiming to contribute to the establishment of future standards and best practices.

To achieve a comprehensive review of PV system O&M management, a systematic methodology is employed, integrating bibliometric and content analyses. While bibliometric studies offer valuable quantitative insights, their limitations in providing a complete understanding of the field are acknowledged. To address this, systematic literature review methods are incorporated to evaluate the inherent characteristics of the O&M research landscape. A bibliometric analysis of research publications is initially performed from 2010 to 2023 to evaluate academic output and identify significant trends. Subsequently, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method is employed to extract relevant articles for systematic analysis and identification of research themes. These efforts aim to improve the understanding of PV O&M and establish a research agenda for future exploration by identifying gaps within the specified themes.

The remaining sections of this work are organized as follows. Section 2 presents a preliminary analysis, including an overview of existing review articles and bibliometric studies. This section also outlines the literature search strategy and selection process, and provides an overview of PV systems O&M management through analysis of bibliometric results. A PRISMA analysis is implemented to select relevant articles, which concludes with the classification of articles into research themes. Building on this, Section 3 presents an overview of PV maintenance strategies, Section 4 summarizes PV performance metrics, Section 5 discusses approaches for PV degradation modeling, and Section 6 reviews the existing literature on PV maintenance optimization

Table 1

Categorization of literature reviews on topics related to PV O&M and solar energy bibliometric research.

Article type	Scope	Related articles
Review articles	Monitoring and fault diagnosis techniques	[10–13]
	Performance degradation and mitigation approaches	[14–22]
	Impact of dust and soiling on PV panels and methods for cleaning	[23–26]
	Overview of maintenance strategies	[27–29]
	Predictive maintenance and energy forecasting techniques	[3,30–32]
Bibliometric analyses	Progression of concentrated solar power (CSP) and PV thermal systems	[33–36]
	Applications of PV systems such as rooftop installations or PV systems integrated into power networks	[37,38]
	Solar energy research trends in specific countries or regions	[39,40]
	Trends in PV energy management	[41]

and inspection planning. At the end of this review, Section 7 explores the identified gaps and proposes future research directions. Finally, Section 8 provides a concise summary of the main findings of the study, including limitations and future recommendations.

2. Preliminary analysis

2.1. Existing reviews

The literature reveals a wealth of review studies on topics related to PV O&M, as well as bibliometric studies within the solar PV research domain. Table 1 classifies the literature reviews on PV O&M-related subjects based on their scope and also categorizes the different bibliometric studies in the field of solar energy.

Several review articles have conducted comprehensive investigations on monitoring and fault diagnosis techniques in the field of PV systems. Specifically, Høiaas et al. [11] reviewed optics-based tools for large-scale PV module inspection, including fault classification and evaluations of infrared thermography and luminescence imaging technologies. These techniques are pivotal in aiding O&M operators in accurately identifying faults in PV plants. Similarly, Jaen-Cuellar et al. [12] investigated faults in solar PV and wind power systems, analyzing their causes and impact on efficiency and maintenance costs. The study emphasized the growing utilization of data-driven techniques, such as machine learning (ML), for fault detection and diagnosis. Investigating failure and degradation modes in PV systems has also

received considerable attention in the literature. Peinado Gonzalo et al. [19] analyzed failure and degradation mechanisms in PV modules, emphasizing the identification of root causes and prevention techniques for issues such as soiling, snow deposition, corrosion, cracks, and hot spots. The study emphasized preventive maintenance techniques such as surface modifications, coatings, and fatigue analysis. Another study by Hernández-Callejo et al. [20] discussed critical components, design factors, and O&M of PV systems, addressing energy control mechanisms, module degradation, and the influence of meteorological factors. Mitigation techniques such as uniform cooling were studied, and operational risk management was utilized to identify risks associated with electric current, fire hazards, natural events, and human factors.

Some reviews have focused on the effect of dust and soiling on PV panels and investigated various cleaning methods for enhanced performance. Conceicao et al. [26] examined the advancement of soiling research in solar energy, covering soiling characterization, modeling, and various cleaning techniques and their influence on O&M costs. Other studies have explored various maintenance schemes for PV systems. In their study, Keisang et al. [28] investigated O&M strategies in PV microgrid systems, including corrective, preventive, and predictive maintenance. The study focused on O&M challenges and solutions in PV microgrids in Sub-Saharan Africa, highlighting the importance of decentralized PV generation in addressing electricity access and poverty. Considerable focus has also been directed towards predictive maintenance and energy forecasting methods. For example, Ramirez-Vergara et al. [30] looked into predictive maintenance models as an economical option for solar PV systems. The article assessed forecasting methods for critical factors such as solar irradiance and temperature, particularly highlighting the potential of ML models.

It is evident that the O&M management of PV systems lacks comprehensive research that addresses the broader challenges and complexities of maintenance. As mentioned by Márquez [42], a comprehensive examination of maintenance management issues in solar energy systems is needed. Although Keisang et al. [28] recognized the importance of developing a maintenance itinerary and engaging stakeholders, their emphasis was primarily on managerial guidelines for O&M approaches. Furthermore, their assessment criteria overlooked essential technical system-related parameters, such as equipment reliability, failure rates, maintenance costs, and system availability. A successful maintenance program seeks to minimize failures, maximize production uptime, and reduce production loss through timely interventions. Once a maintenance strategy is determined, the focus shifts to scheduling, presenting an optimization challenge to ensure continuous and reliable operation of the PV system. However, there is a lack of comprehensive guidance on how to effectively coordinate the timing and sequencing of maintenance interventions and strategically integrate them within the broader operational context of a PV system. In addition, the effectiveness of O&M programs relies on the inclusion of factors such as staff coordination, required spare parts, and logistics and supply chain management, which have not received sufficient attention despite being crucial for effective maintenance.

There is also a stream of review articles that integrated bibliometric analysis in solar energy research to understand the development of the field, technological trends, and areas for further exploration. In a study by Azad and Parvin [35], an analysis was performed to monitor the progress of concentrated solar power (CSP) and PV thermal systems, highlighting key research themes such as performance analysis and nanofluid integration. Other bibliometric studies have investigated specific applications within PV systems, including rooftop PV systems [37] and the integration of PV systems into power networks [38]. These studies have identified trends in optimal design, power quality, and challenges such as voltage and frequency fluctuations. Furthermore, research has explored current solar energy trends in specific countries or regions. Zwane et al. [39] examined the evolution of solar forecasting in Africa, highlighting solar irradiance and ML algorithms in modeling

techniques. Madsuha et al. [40] analyzed solar research in Indonesia, covering semiconductors, simulation, and integration of technology and regulation. In addition, a comprehensive analysis conducted by David et al. [41] observed the evolving trends in PV energy management, discovering crucial aspects such as demand management, consumer behavior, and module materials. It is evident that the application of bibliometrics in the context of PV systems O&M management remains underexplored. The existing literature lacks detailed thematic descriptions of the management and planning of maintenance tasks, which are essential to ensure optimal performance. This gap calls for a more thorough and systematic analysis, tracking the evolving trends, and exploring key themes in PV O&M beyond the conventional domains. Embracing a holistic approach to O&M management enables a comprehensive understanding of the technical, operational, and financial elements involved. This ensures that maintenance practices are not limited to isolated tasks, but are integrated into a cohesive and efficient system.

2.2. Search strategy and initial data retrieval process

In the initial data retrieval phase, a draft protocol was developed, and an informal preliminary scan confirmed the research gap highlighted in Section 2.1. This scan helped determine potential review themes and exclusion criteria, as well as establish the time frame and keywords for the systematic search. Subsequently, an extensive literature search was conducted using the Scopus and Web of Science databases. A detailed description of the search strategy used in this study is presented in Table 2.

In the search strings, keywords related to “maintenance” and “operations” were carefully applied to the title, abstract, and keyword sections of the publications. The inclusion of the special character “*” at the end of specific terms enables the capture of variations and expansion of the search scope by accommodating different forms and extensions of the specified keywords. To ensure inclusiveness, the search focused on publications between 2010 and September 2023 (the date of the search). This time range was chosen to account for the remarkable technological advancements that have occurred within the solar PV industry over the past decade. The indicated search strings produced 3429 references (after removing duplicates) that were used for the bibliometric analysis. To perform the initial bibliometric analysis, several tools and software were employed. This includes the ‘Bibliometrix’ [43] package for the statistical programming language R [44], and the VOSViewer software [www.vosviewer.com, [45]]. These resources support exploration in various dimensions, such as publication trends, prominent journals, influential countries, and thematic evolution.

2.3. Basic bibliometric analysis

The obtained 3429 references contained 1920 journal articles and 1509 conference papers. Fig. 2 presents a further analysis of the collected references across years and sources where only sources with more than 50 publications in total are highlighted. Notably, there has been a significant rise in the number of publications, particularly in the last five years. This surge in publications reflects the industry’s recognition of the importance of efficient O&M practices and the growing significance of PV systems in the energy sector. It can also be noted that more than 55% of the collected references have been published in the last five years, highlighting the accelerated pace of research and innovation within the PV industry. Furthermore, Fig. 2 shows that “Energies”, “Solar Energy”, and “Renewable Energy” demonstrate the highest productivity, with 172, 102, and 94 publications, respectively. At the same time, the primary venue for conference papers was the “Conference Record of the IEEE Photovoltaic Specialists Conference”, with 62 papers.

Table 2

Overview of search strategy including search string, inclusion and exclusion criteria, and language considerations.

Database	Search string
SCOPUS	(TITLE (("Photovoltaic*" OR "PV") AND ("Maintenance" OR "Operations and Maintenance" OR "Operation and Maintenance" OR "O&M" OR "Operation & Maintenance" OR "Operations & Maintenance" OR "Maintenance Management" OR "Schedul*" OR "Plan*" OR "Decision")) AND ABS (("Photovoltaic*" OR "PV") AND ("Maintenance" OR "Operations and Maintenance" OR "Operation and Maintenance" OR "O&M" OR "Operation & Maintenance" OR "Operations & Maintenance" OR "Maintenance Management" OR "Schedul*" OR "Plan*" OR "Decision"))) AND PUBYEAR > 2009 AND PUBYEAR < 2024 AND (LIMIT-TO (SRCTYPE , "p") OR LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "ENER") OR LIMIT-TO (SUBJAREA , "DECI")) AND (LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp")) AND (LIMIT-TO (LANGUAGE , "English"))
Web of Science	(TI=(("Photovoltaic*" OR "PV") AND ("Maintenance" OR "Operations and Maintenance" OR "Operation and Maintenance" OR "O&M" OR "Operation & Maintenance" OR "Operations & Maintenance" OR "Maintenance Management" OR "Schedul*" OR "Plan*" OR "Decision")) AND AB=(("Photovoltaic*" OR "PV") AND ("Maintenance" OR "Operations and Maintenance" OR "Operation and Maintenance" OR "O&M" OR "Operation & Maintenance" OR "Operations & Maintenance" OR "Maintenance Management" OR "Schedul*" OR "Plan*" OR "Decision")))) AND (DT==("ARTICLE" OR "PROCEEDINGS PAPER") AND LA==("ENGLISH") AND SJ==("ENERGY FUELS" OR "ENGINEERING" OR "SCIENCE TECHNOLOGY OTHER TOPICS" OR "OPERATIONS RESEARCH MANAGEMENT SCIENCE"))
Inclusion criteria	
<input checked="" type="checkbox"/> Full-text accessibility <input checked="" type="checkbox"/> Publication in the final stage <input checked="" type="checkbox"/> Academic journals and conference papers <input checked="" type="checkbox"/> Published between 2010 and September 2023 <input checked="" type="checkbox"/> Subject areas related to engineering, energy, operations research and decision sciences	
Exclusion criteria	
<input type="checkbox"/> Abstracts, book chapters, dissertations, technical reports, and review papers <input type="checkbox"/> Papers covering non-renewable or alternative renewable energy sources, other than PV technologies <input type="checkbox"/> Papers that cannot be accessed	
Language	
<input checked="" type="checkbox"/> English	

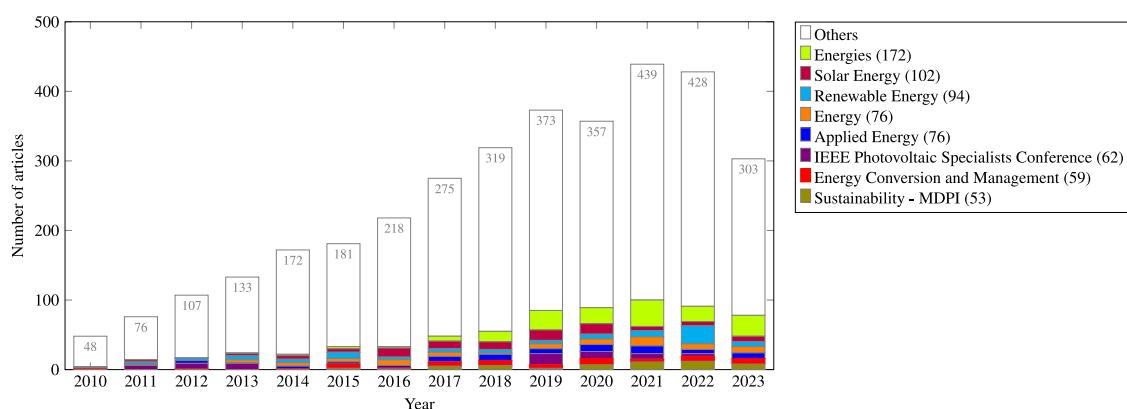


Fig. 2. Yearly distribution of publications between different sources.

The geographical distribution of publications across the world is shown in Fig. 3 with the density of the blue color indicating the relative degree of contribution for each country.

In particular, China had the highest number of publications, totaling 751 papers. This substantial publication count in China can be attributed to generous funding and sponsorship that supported research efforts in the country. The United States followed in second place with 329 articles, closely followed by India and Italy, with 295 and 289 papers, respectively. These findings highlight strong research activity in European, American and East Asian markets.

2.4. Keywords and thematic evolution

Keywords and thematic evolution analysis can help to understand the development of the most important research topics in the PV industry, and to highlight the essential research gaps. Fig. 4 displays

the heat map generated to identify significant keywords within the publications.

These keywords covered a range of topics, such as optimization, photovoltaic modules and plants, electricity generation, storage and distribution, efficiency and maintenance. Keywords “optimization” and “integer programming” are located in the most prominent areas of the map, indicating the importance of optimization among the collected references. This can be attributed to the general scope of the search strings. At the same time, “maintenance” and “efficiency” have relatively low weights in the obtained results. This highlights that the management of PV systems often focuses on closely monitoring energy production, neglecting the overall efficiency of the system affected by global operations such as preventive maintenance, cleaning, and relevant logistical tasks.

Following this, a thorough examination of the thematic evolution in PV O&M literature from 2010 to 2023 was conducted employing the

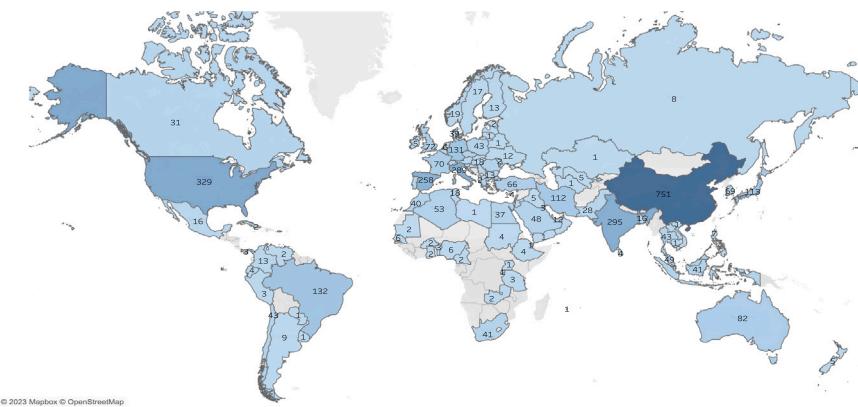


Fig. 3. Countries' scientific production.

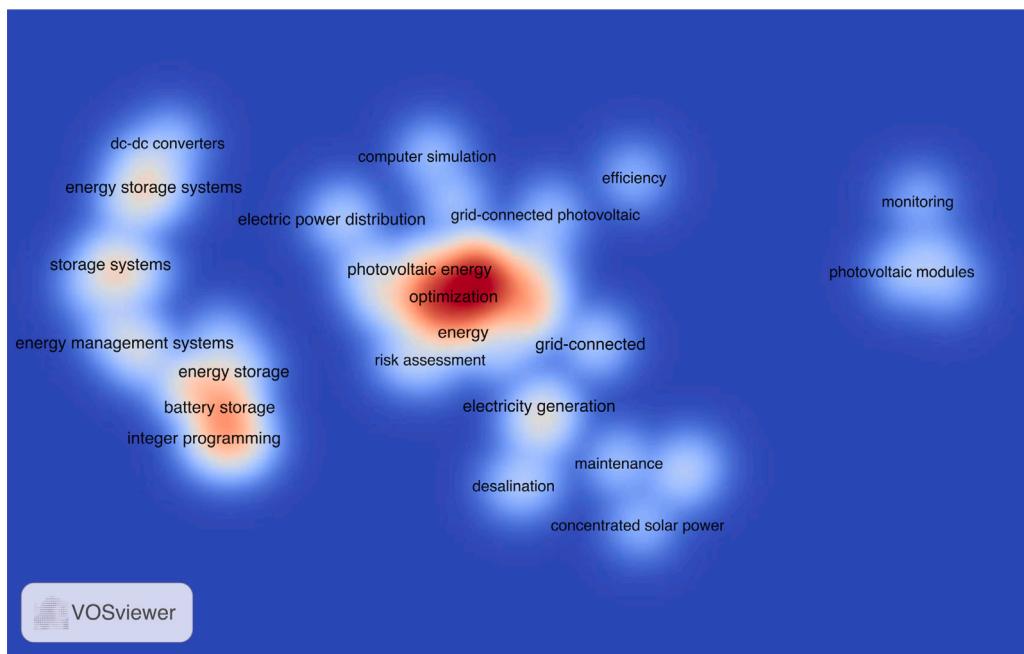


Fig. 4. Density diagram of the bibliographic coupling of keywords from VOSViewer.

“Bibliometrix” package. Four distinct time periods were identified, each marked by varying volumes of publication, which signified a dynamic change in research focus over time. This thematic evolution of the main keywords is visualized in Fig. 5.

In the initial period (2010–2014), research made pivotal contributions to the advancement of solar energy. This period focused on PV module technology, monitoring methods, and efficient power generation. Studies also investigated essential components, such as DC–DC converters and effective reactive power management. Collectively, these efforts established a robust foundation for understanding PV system fundamentals and significantly contributed to the progress of the solar energy sector in subsequent years.

During the second research period (2015–2017), there was a notable shift in the research landscape towards emerging thematic areas. While research continued on topics such as PV plants, reactive power, and PV module technology, there was a growing focus on new topics such as optimization and energy storage. In the domain of optimization, studies focused their attention on topology optimization methods, specifically

aiming to improve the efficiency and reliability of PV installations. This emphasis involved prioritizing optimal system design and strategic location selection to enhance overall performance.

In the subsequent period between 2018 and 2020, the research within the field continued to evolve, exploring new dimensions of PV systems. Studies focused their efforts on key topics, including scheduling, maximum power point trackers, energy storage solutions, and performance assessment methods. Scheduling related research during this period was aimed at optimizing the use of available resources, particularly solar irradiance. Additionally, there was considerable attention given to integrating PV power plants with charging stations, storage systems, and distribution networks. This emphasis revolved around the effective management of power generation and demand, marking a pivotal aspect of research during this time frame.

In the recent period from 2021 to 2023, research has notably shifted its focus towards forecasting and decision-making, reflecting a growing interest in enhancing the intelligence and adaptability of PV installations. Techniques such as artificial neural networks and stochastic

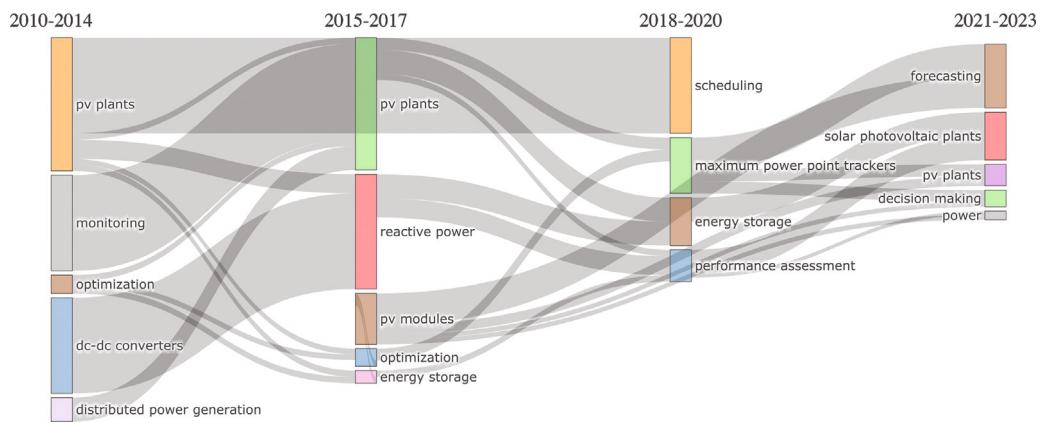


Fig. 5. Thematic evolution of keywords extracted using Bibloshiny.

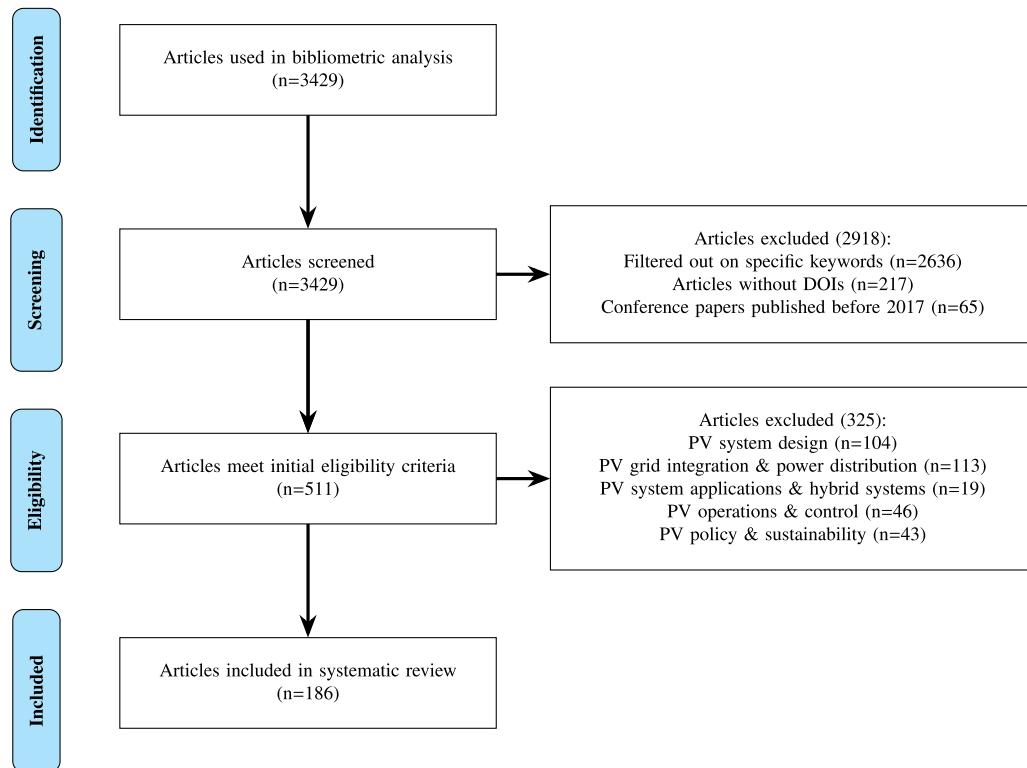


Fig. 6. PRISMA-based flowchart of the systematic selection of relevant studies.

optimization have been crucial for precise solar irradiance and PV system output forecasts, vital for efficient grid integration and energy planning. Studies have also examined decision-making frameworks and governance for utility-scale PV plant procurement, conducting thorough economic evaluations to ensure informed choices in the adoption and deployment of solar technology.

The presented thematic evolution analysis revealed a significant disparity within the academic literature, where O&M has gained less attention compared to other research areas. Despite the shift in research towards operational aspects such as control strategies, battery storage, energy dispatch, scheduling, and power forecasting, it is essential not to overlook the importance of maintenance considerations. Recognizing the complex connection between PV maintenance and these other themes is crucial. However, it is equally essential to acknowledge that the full potential of PV maintenance remains largely unexplored. This research gap serves as a clear indicator, which underlines the imperative need for future studies to thoroughly investigate the maintenance aspects of PV systems.

2.5. Article selection process for systematic and content analysis

The PRISMA 2020 flow diagram [46], depicted in Fig. 6, was employed to assess and choose articles for systematic review and content analysis. The initial dataset for bibliometric analysis, consisting of 3429 articles, was subjected to a screening and refinement process. This screening process utilized specific keyword filters that had been identified and confirmed during the preliminary literature scan. The filters included terms such as ((Optimization OR Cost OR Forecasting OR Economic analysis OR Performance OR Efficiency) AND (Maintenance OR Reliability)), applied to the titles and abstracts of the articles. Additionally, articles lacking digital object identifiers (DOIs) and those originating from conferences held before 2017 were excluded from the dataset. The decision was influenced by the rigorous peer review process associated with articles with DOI. Furthermore, it was assumed that conference papers before 2017 were subsequently published as journal articles. The focus on

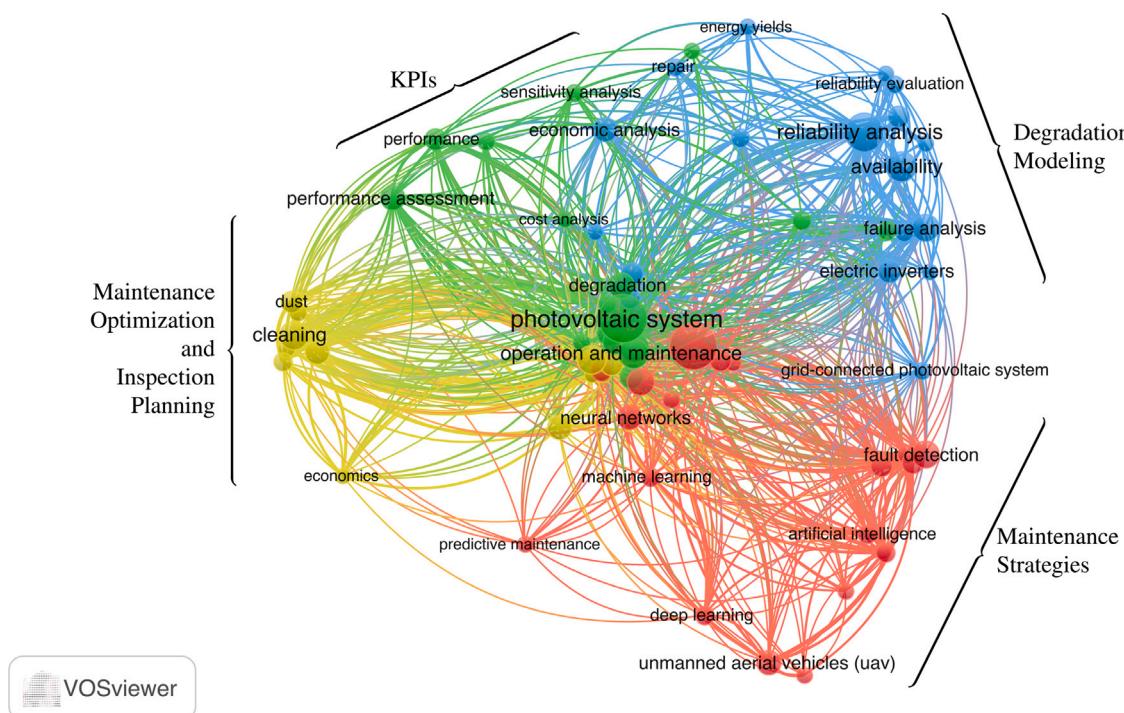


Fig. 7. Keyword clustering for selected 186 articles using VOSViewer (normalization: LinLog/modularity, attraction: 10, repulsion: 3, resolution 1.00, min.cluster size: 1).

conference papers after 2017 aligns with the latest developments in O&M management for PV systems, enabling the capture of recent progress in the field. As a result of these filtering measures, a total of 511 articles remained, meeting the initial eligibility criteria. To further narrow down the selection, exclusion criteria were established.

These criteria excluded articles related to engineering topics such as PV system design, installation, sizing, optimal configuration, component selection, material selection, and site location. Articles exclusively focusing on technical aspects of PV system integration into power grids, hybrid systems (e.g., CSP, PV-Wind), or specific PV applications (e.g., pumping systems, desalination plants, electric vehicles) without addressing maintenance-related topics were also excluded. Moreover, technical articles discussing PV system operations and control, such as battery operations, energy storage, and voltage stability, without incorporating maintenance practices were eliminated. Lastly, articles addressing PV system energy policies, sustainability, and government regulations were also excluded. Following this comprehensive examination, a total of 325 articles were removed from the dataset, resulting in 186 articles that remained eligible for systematic review and content analysis.

2.6. Article classification and research areas in PV systems maintenance

The selected articles were classified using the VOSViewer software, with the resulting clusters visually depicted in Fig. 7. This method enabled a comprehensive examination of the keywords, leading to the categorization of the articles into four main areas. Furthermore, the approach revealed the interconnected nature and highlighted the common themes evident in the papers.

Further analysis of the proposed clusters suggests that the main research topics are related to maintenance strategies, key performance indicators (KPIs), degradation modeling, and maintenance optimization and inspection planning. It is also obvious that there are no clear boundaries between the areas, highlighting the need for a holistic approach in this field and emphasizing the importance of integrating maintenance practices, system performance evaluation, deterioration modeling, and strategic planning to achieve optimal maintenance outcomes.

Furthermore, it is clear that many of the selected papers fall into multiple categories. For example, a single paper might address various aspects, including different maintenance strategies for PV systems, assessing system performance using specific metrics, and exploring how maintenance decisions affect overall system conditions. It would be ideal to categorize these papers into multiple themes that correspond to their various research dimensions. As a result, articles were allowed to be associated with multiple subject areas, aligning with the methodology seen in previous bibliometric studies by Cosh et al. [47] and Leefmann et al. [48]. The detailed results of the keyword analysis, including research areas, primary keywords, and the top 10 cited articles, are presented in Table 3.

In the following sections, a more thorough and systematic analysis of the research areas will be presented.

3. Overview of PV maintenance strategies

Many studies have classified maintenance strategies in different ways [5,28,29,56,89]. In literature, three general maintenance strategies for solar PV systems are mentioned: corrective, preventive, and predictive maintenance. Fig. 8 shows the evolution of maintenance strategies over time, along with examples of maintenance activities for PV systems.

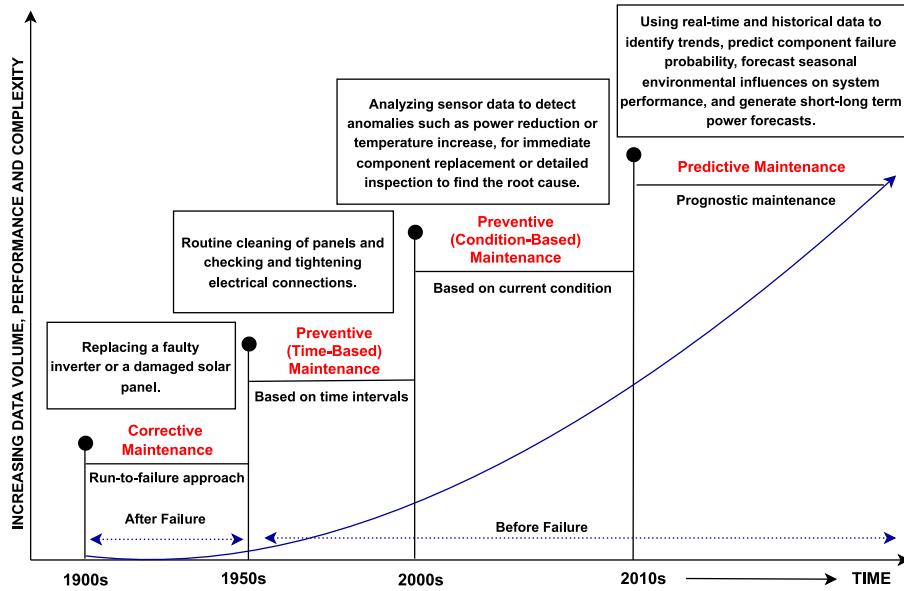
3.1. Corrective maintenance

Corrective maintenance involves addressing failures, malfunctions, or damages identified by remote monitoring or routine inspections. It is an unscheduled procedure aimed at resolving problems and restoring normal operation. However, it can be costly and cause power generation shortages and potential damage to critical components [89]. The accessibility challenges of remote sites further escalate the problem, as the need to dispatch personnel to these locations leads to increased maintenance costs. Reducing response times is crucial in corrective maintenance, involving acknowledgment, intervention, and repair times. Studies have explored decision support systems (DSS) to optimize the decision-making process, such as the work by Livera et al.

Table 3

Overview of research areas and frequency of main keywords.

Research area (color)	Main keywords (frequency)	Top cited articles
Maintenance strategies (red)	Artificial intelligence (8), Artificial neural network (6), Condition-based maintenance (7), Condition monitoring (7), Data acquisition (10), Deep learning (8), Environmental conditions (9), Fault detection (15), Forecasting (11), Image processing (5), Inspection (10), Machine learning (8), Maintenance (45), Maintenance management (5), Maintenance strategies (7), Neural networks (13), Preventive maintenance (8), Predictive maintenance (5), Unmanned aerial vehicles (12).	[49–58]
Key performance indicators (KPIs) (green)	Cost Analysis (13), Cost benefit analysis (8), Cost effectiveness (11), Degradation (16), Degradation rate (6), Efficiency (5), Energy productions (6), Operation and maintenance (19), Performance (10), Performance analysis (5), Performance assessment (13), Performance loss (7), Performance ratio (12), Photovoltaic modules (13), Photovoltaic system (48), Profitability (6), Sensitivity analysis (6).	[59–68]
Degradation modeling (blue)	Availability (20), Economic analysis (13), Electric inverters (11), Energy yields (5), Environmental conditions (9), Failure analysis (15), Failure modes (5), Failure rate (10), Grid-connected photovoltaic system (6), Markov chain (5), Markov processes (11), Reliability analysis (32), Reliability assessments (5), Repair (7), Risk assessment (6).	[69–78]
Optimal Cleaning (yellow)	Cleaning (17), Cleaning frequencies (6), Cleaning schedules (6), Decision making (6), Decision Support System (5), Dust (10), Dust accumulation (8), Economics (5), Energy efficiency (12), Optimization (18), Profit (5), Soiling (12), Scheduling (5).	[79–88]

**Fig. 8.** Evolution of maintenance strategies. Inspired by Lee et al. [90], modified specifically to PV systems, taking into consideration the current focus of literature in the field.

[5] that aimed to reduce the time between response and resolution of corrective activities. Reducing unnecessary maintenance visits and inspections improves the effectiveness of the corrective maintenance plan, leading to higher availability and minimal downtime. However, with increasing PV plant size, the number of components also increases and the failure rate increases. Thus, relying solely on corrective maintenance has been shown to be ineffective and undesirable for large-scale PV systems [56].

3.2. Preventive maintenance

Preventive maintenance strategies aim to prevent failures by addressing minor faults before they escalate. There are two main approaches: time-based and condition-based preventive maintenance [56]. Time-based preventive maintenance involves scheduled inspections, repairs, and adherence to operations manuals [29]. Studies have developed models for PV time-based preventive maintenance, such as the work by Baklouti et al. [91], which aimed to determine inspection intervals and optimize degradation thresholds. Although the time-based approach can enhance maintenance practices and reduce component failures, it can incur higher costs due to unnecessary and

inefficient site visits, particularly for large-scale PV systems in remote locations [68,92].

Condition-based preventive maintenance relies on monitoring systems and health analysis to detect early signs of failure or performance issues [28,93]. Swift fault detection and identification are crucial for preventing disruptions or damage in PV systems. Various methods are used for fault diagnosis, including visual inspections [92], electrical parameter evaluations [93], image processing [94,95], and statistical analysis [96]. However, manual or visual monitoring may be insufficient for large and complex PV systems, as it focuses primarily on panel performance rather than the entire system. Fault detection based on electrical measurements, such as current–voltage (I–V) characterization, is impractical for PV farms due to the requirement of extensive sensing and communication infrastructure. To address these challenges, advanced diagnostic and automated monitoring systems have been developed for fault identification and root cause analysis.

These systems use tools such as supervisory control and data acquisition (SCADA) systems [55,89,97–100], thermal imaging with unmanned aerial vehicles (UAVs) [51,53,58,94,95,101–105], and intelligent maintenance systems [5,106–113]. Artificial intelligence algorithms, such as support vector machine, k-nearest neighbors, decision

trees, and artificial neural networks, are integrated to analyze large datasets and detect anomalies in real-time [31,51,53,55,114–118]. This proactive approach enables the anticipation of failures, maintenance alerts, and recommendations to optimize performance and minimize downtime. However, implementing advanced monitoring techniques in large-scale PV systems can result in higher maintenance costs due to additional hardware installation, increased power demands, and the need for trained personnel.

3.3. Predictive maintenance

Condition-based maintenance and predictive maintenance are often used interchangeably in the research literature when discussing maintenance strategies [14,119,120]. However, there are important distinctions between the two approaches. Condition-based maintenance relies on sensors to collect real-time operational data from a system. The data is then analyzed to make informed decisions about the system's health. In contrast, predictive maintenance uses anomaly detection, fault diagnosis, and historical performance data to perform parametric analyses and employ forecasting models [3,110]. PV systems and their components are analyzed to generate forecasts, identify deterioration trends, and estimate the remaining useful life of the components [121]. This enables predicting when a component is likely to fail. Thus, condition-based maintenance is executed at the exact moment required, prior to significant failure. Predictive maintenance, on the contrary, involves anticipating equipment failure and deterioration in advance during normal operating conditions. This allows planned maintenance activities to be effectively implemented.

The use of artificial intelligence algorithms has gained popularity for fault prediction within a specific timeframe. In the PV industry, the primary emphasis on predictive maintenance has been on inverters [52, 122] and PV panels [54,123]. For example, Betti et al. [122] utilized artificial neural networks to predict faults, achieving a sensitivity of up to 95% and a specificity of around 80%. Their solution successfully predicted high-frequency inverter failures up to almost seven days ahead. Similarly, De Benedetti et al. [52] used an artificial neural network trained on historical data of solar irradiance, ambient temperature, cell temperature, and power output to accurately forecast inverter faults several weeks in advance.

Accurate forecasting of energy production is crucial for PV systems due to weather-related issues. The integration of predictive maintenance and power forecasting techniques has received significant attention, especially for large-scale PV systems [49,50,124–129]. Short-term power forecasting (0–72 h) helps in system operation planning and facilitates maintenance scheduling adjustments. Du Plessis et al. [126] developed neural network models for power forecasting within a six-hour horizon in a 75 MW PV system, while Gao et al. [127] used long-short-term memory networks for day-ahead power forecasting in a 10 MWp solar power plant. Accurate power forecasting enables operators to predict peak electricity production periods, allowing maintenance scheduling during low radiation periods without affecting power generation. This approach reduces system downtime and minimizes the risk of unexpected failures.

Furthermore, predictive maintenance techniques play a vital role in monitoring and managing environmental factors such as soiling and snow in PV systems, which significantly affect efficiency [130]. Analysts can forecast the seasonal impacts of these factors using readily available environmental data such as rainfall and particulate matter [131,132]. This forecasting is crucial for planning maintenance tasks such as snow removal and cleaning. Implementing predictive maintenance protocols enables the optimization of technician site visits and early fault notifications, leading to lower costs associated with unexpected corrective maintenance and excessive preventive maintenance. According to Benabbou et al. [133], predictive maintenance has the potential to reduce maintenance expenses from 10% to 40%. However, in situations where the consequences of failure are minor, when regular failures occur, or when parts replacement costs are low, implementing predictive maintenance may not be feasible.

4. Comprehensive analysis of key performance indicators (KPIs)

As PV plants age, O&M procedures become increasingly important for maintaining or improving performance. This involves evaluating metrics and indicators while creating action plans to address problems. KPIs play a critical role in evaluating and quantifying PV plant operation and management, providing comprehensible results for multiple stakeholders to monitor plant operation over time. Based on the classification scheme obtained from Rediske et al. [6], Table 4 categorizes PV system KPIs into operation, economic, and maintenance KPIs. This classification scheme is used to classify articles within this cluster, enabling a comprehensive evaluation of various aspects related to PV system performance.

4.1. Operation KPIs

Operation KPIs play a crucial role in assessing the performance of PV plants in generating and delivering electricity. The International Electrotechnical Commission (IEC) [181] has established the standard IEC 61724, which outlines the essential parameters for evaluating the performance of solar PV systems. These indicators define the performance of the plant and allow comparisons between plants based on factors such as location, solar irradiation, technology, energy generation, and system losses. For example, the soiling ratio (*SR*) quantifies the impact of dirt and debris on the performance of PV arrays. In addition, energy-based availability (*EA*) calculates the ratio between the actual energy produced by the system and the maximum potential energy that could be generated if the system operated continuously for a specific time frame [137]. It is important to differentiate between energy-based and time-based availability, a distinction that will be examined in Section 4.3. Both metrics are crucial for evaluating PV system performance and assessing the effectiveness of maintenance strategies.

Significant research has been conducted on the performance evaluation of large-scale PV systems, primarily focused on the MW range [59, 60,62–67,89,98,99,116,130,134–139]. Additionally, studies have shown interest in evaluating the performance of utility-scale PV fleets, which face specific operational challenges, by employing various operational metrics [140–147]. For example, Lindig et al. [142] conducted a comprehensive study in Europe, focusing on an extensive fleet of more than 8400 PV systems. Their main goal was to compute the annual final yield (Y_f) and performance ratio (*PR*) of these systems, offering valuable insights into managing vast PV performance data. The study underscored the significance of effective O&M practices in reducing system losses.

4.2. Economic KPIs

The financial aspects of a PV plant are based on different economic indicators. Capital expenditure (*CAPEx*) represents the initial costs of PV installations, while operational expenditure (*OPEX*) covers expenses related to site operation, maintenance, taxes, labor, and outsourced services, among others. These metrics are commonly used in the literature to assess the cost competitiveness of PV installations [68, 84,154–157]. For example, Muñoz-Cerón et al. [68] investigated the financial impact of *OPEX* on the performance and viability of a utility-scale PV plant in Spain. Their findings suggested that, in certain scenarios, it may be financially advantageous to prioritize corrective actions over preventive maintenance, rather than investing in regular O&M activities. However, relying solely on capital and operational expenses may not offer a complete insight into the profitability of the system.

Additional parameters, including the levelized cost of energy (*LCoE*), net present value (*NPV*), and internal rate of return (*IRR*), have been considered to provide a more comprehensive understanding [5,55,56,61,75,111,154,156,158–164]. These indicators incorporate factors such as the lifetime of the system and energy yield,

Table 4

Key performance indicators for O&M management of PV systems.

Group	KPIs
Operations [59,60,62–67,85,89,98–100,116,130–132,134–153]	$\text{Array yield } (Y_a) = \frac{\text{Actual array output energy (kWh) DC}}{\text{Rated power (kW)}}$ $\text{Final yield } (Y_f) = \frac{\text{Actual AC output energy (kWh) AC}}{\text{Rated power (kW)}}$ $\text{Reference yield } (Y_r) = \frac{\text{Solar radiation on PV panel (kWh/m}^2\text{)}}{\text{Standard test condition reference irradiance (kW/m}^2\text{)}}$ $\text{Performance ratio (PR)} = \frac{\text{Final yield (h)}}{\text{Reference yield (h)}}$ $\text{Performance index (PI)} = \frac{\text{Actual AC output energy (kWh) AC}}{\text{Global radiation (kWh)} \times \text{System efficiency (\%)} \times \text{Inverter efficiency (\%)}}$ $\text{Capacity factor (CF)} = \frac{\text{Energy production in period } t \text{ (kWh) AC}}{\text{Rated power (kW)} \times \text{Time interval (h)}}$ $\text{Soiling ratio (SR)} = \frac{\text{Soiled PV array power output (kWh)}}{\text{Clean PV array power output (kWh)}}$ $\text{Array efficiency } (\eta_A) = \frac{\text{Actual array output energy (kWh) DC}}{\text{Active array area (m}^2\text{)} \times \text{Total radiation on panel surface (kWh/m}^2\text{)}}$ $\text{Inverter efficiency } (\eta_{inv}) = \frac{\text{Actual AC output energy (kWh) AC}}{\text{Actual array output energy (kWh) DC}}$ $\text{System efficiency } (\eta_{pu}) = \frac{\text{Actual AC output energy (kWh) AC}}{\text{Active array area (m}^2\text{)} \times \text{Solar radiation on PV panel (kWh/m}^2\text{)}}$ $\text{Energy-based availability (EA)} = \frac{\text{Actual AC output energy (kWh) AC}}{\text{Energy potentially expected (kWh)}}$
Economics [5,55,56,61,68,75,84,111,154–164]	$\text{Capital expenditures (CAPEX)} = \text{Cost per peak power (\$/kWp)} \times \text{Total peak power (kWp)}$ $\text{Operational expenditures (OPEX)} = \frac{\text{Operational expenditures (\$)}}{\text{Rated power (kW)}}$ $\text{Levelized cost of energy (LCoE)} = \frac{\text{Total life cycle costs (\$)}}{\text{Total lifetime energy output (kWh)}}$ $\text{Net present value (NPV)} = \sum_{t=0}^T \frac{\text{Net cash flow during year } t \text{ (\$)}}{(1 + \text{Discount rate (\%)})^t} - \text{Capital expenditures (\$)}$ $\text{Internal rate of return (IRR)} = \sum_{t=0}^T \frac{\text{Net cash flow during year } t \text{ (\$)}}{(1 + \text{Internal rate of return (\%)}))^t} - \text{Capital expenditures (\$)} = 0$
Technical maintenance [56,57,70,119,134,138,142,165–178]	$\text{Mean time between failures (MTBF)} = \frac{\text{System operation time (h)}}{\text{Number of failures}}$ $\text{Mean time to repair (MTTR)} = \frac{\text{Total repair time (h)}}{\text{Number of failures}}$ $\text{Mean time to failure (MTTF)} = \frac{\text{System operation time (h)}}{\text{Number of non-repairable failures}}$ $\text{System degradation } (D_s) = \frac{\text{Current year power (kW)}}{\text{Previous year power (kW)}}$ $\text{Response time (RT)} = \frac{\text{Failure detection time (h)}}{\text{Failure intervention time (h)}}$ $\text{Reliability } (R_t) = e^{-\text{failure rate (failures/h)} \times \text{time (h)}}$ $\text{Availability } (A_t) = \frac{\text{System operation time (h)}}{\text{Expected operational time (h)}}$ $\text{Corrective maintenance ratio (CM)} = \frac{\text{Number of corrective interventions}}{\text{Total number of interventions}}$ $\text{Preventive maintenance ratio (PM)} = \frac{\text{Number of preventive interventions}}{\text{Total number of interventions}}$
Economic maintenance [56,75,111,159,179,180]	$\text{Equivalent labor cost (ELC)} = \frac{\text{Maintenance labor cost (\$)}}{\text{Total maintenance cost (\$)}}$ $\text{Equivalent spare parts cost (ESPC)} = \frac{\text{Spare parts cost (\$)}}{\text{Total maintenance cost (\$)}}$ $\text{Maintenance planning factor (MP)} = \frac{\text{Annual maintenance budget (\$)}}{\text{Total maintenance cost (\$)}}$

enabling a deeper analysis of the financial performance of the PV plant. The *LCoE* is particularly popular as a standard unit of energy cost measurement to evaluate the financial viability of PV installations. This metric calculates the total cost of constructing and operating a PV plant over its lifetime, as a ratio to the total electricity output. It is projected that the *LCoE* will decrease by 0.8% to 1.4% between 2015 and 2030, driven by advancements and innovations in O&M services within the PV industry [138,182]. This decrease drives global PV system adoption, emphasizing the need to prioritize system uptime and minimize O&M expenses to achieve a favorable *LCoE* value.

4.3. Maintenance KPIs

Efficient maintenance analysis is crucial to ensure the optimal performance and long-term reliability of PV systems. This involves selecting the appropriate maintenance strategy and evaluating its effectiveness using various measures. Maintenance KPIs play a vital role in

helping managers make strategic decisions to optimize the operation of PV plants. These KPIs assess maintenance quality based on factors such as intervention time and associated costs, classified as technical and economic indicators.

Maintenance-related technical indicators focus on assessing the reliability and availability of equipment, as well as the workforce responsible for repair procedures. In the context of PV systems, reliability (R_t) refers to the system's ability to operate efficiently without failures throughout its expected useful life, typically 25 years or more [183]. Availability (A_t), or time-based availability, is a reliability metric that assesses the uninterrupted power generation capability of a PV system. It measures plant operation time, including scheduled maintenance, repairs, and unexpected failures, without interruptions or limitations [184]. The industry employs various indicators to evaluate the reliability and availability of PV systems. The most commonly used indicators include mean time between failures (*MTBF*) and failure

Table 5

Methods for evaluating the reliability of PV systems and components.

Reference(s)	Methods used for reliability evaluation				
	RBD	FTA	Markov chains	Monte Carlo	Others
[73,168,185]	✓				
[154]	✓			✓	
[186]	✓		✓		
[70,72,78,167,187–190]		✓			
[191]		✓	✓		
[192]					✓Petri networks
[69,193,194]					✓State enumeration
[195]			✓		✓Bayesian networks
[74–76,165,196]			✓		
[197,198]			✓	✓	
[56,199–202]				✓	

rate, mean time to repair (*MTTR*) and repair rate, and mean time to failure (*MTTF*) [70,165–171,176].

In addition, system degradation (D_S) measures the decrease in efficiency of a PV system over time, quantifying the annual decrease in production as a percentage of the total annual output [57,134,142,172–175]. For example, a degradation rate of 0.5% per year means a 5% reduction in generation capacity each year compared to the previous year. Other maintenance metrics such as response time (*RT*) and the proportions of corrective maintenance (*CM*) and preventive maintenance (*PM*) have been utilized for both the entire PV plant and specific subsystems with multiple arrays and inverters [56,119,138].

Maintenance-related economic indicators are vital to assess the financial viability of the PV plant [56,75,111,159,179,180]. Indicators such as equivalent labor cost (*ELC*) and equivalent spare parts cost (*ESPC*) evaluate labor and spare parts costs as percentages of the total maintenance cost. These indicators help optimize resource allocation and enhance maintenance strategies to improve performance and cost control. The maintenance planning (*MP*) factor is determined by assessing the efficiency of the total maintenance cost in relation to the annual maintenance budget. This evaluation ensures that maintenance costs are adequately covered while optimizing the planning process.

In their study, Peters and Madlener [56] compared the economic feasibility of preventive and corrective maintenance strategies for PV plants of different sizes in Germany. The authors found that preventive maintenance is more cost-effective, as it reduces downtime and increases energy yield. However, it was highlighted that the optimal maintenance strategy depends on factors such as plant size, PV module type, and local climate conditions. Thus, a systematic approach to maintenance planning and optimization can help maximize economic benefits.

5. Analysis of degradation modeling approaches

The evolving nature of PV system deterioration and fault progression presents a significant challenge in creating precise models and assessing the overall reliability of the system. The reliability of PV systems has been a concern for more than a decade due to their complexity, making it challenging to evaluate the overall reliability. Until recent years, reliability assessment was focused on individual components, mainly modules and inverters, using failure data [203, 204]. Accurate measurement of reliability is crucial for evaluating energy output, O&M expenses, and estimating *LCoE*, as evidenced by the numerous publications on this topic.

The growth of PV installations has intensified the focus on assessing and quantifying the reliability of large-scale PV systems [69,70,72, 75,78,167,168,186,188,189,192,197,198,201,205]. This involves evaluating the reliability of subsystems and individual components and understanding their impact on the overall system reliability. Additionally, it is essential to identify critical components that are more prone to failure or malfunction to implement suitable maintenance measures. In the analysis of larger PV systems, factors such as weather conditions,

maintenance schedules, and overall system performance need to be considered in the reliability assessment. For example, Altamimi and Jayaweera [198] conducted a comprehensive analysis of a 1 MW PV farm, identifying critical components and subsystems prone to climate-related failures. Their reliability model incorporated geographical and environmental factors, such as cloud shading and climate change, to provide a comprehensive analysis.

5.1. Reliability modeling techniques

Studies have used different techniques to assess the reliability and availability of PV systems and their components. Table 5 illustrates the most common reliability analysis techniques, such as reliability block diagrams (RBD), fault tree analysis (FTA), Markov chains, Monte Carlo simulations, among others.

Although various reliability analysis techniques have been employed, certain methods have inherent limitations. For example, FTA is suitable for small-scale systems, but it struggles to handle interconnected modes effectively [116]. To accurately represent PV systems, a multi-state model is necessary to account for the intermittent nature of solar radiation. This requires a modeling approach that captures the stochastic behavior and dynamic characteristics of the components. It is important to note that the failure of PV modules does not necessarily result in a complete system failure, but rather a partial failure that leads to reduced power output. FTA and RBD are restricted to handling only binary states (down or functional) [116]. To address these limitations, alternative stochastic methods such as Markov models have been extensively utilized in the literature. These approaches enable the accurate characterization of MTTF in PV systems, providing a more comprehensive understanding of system performance.

5.2. PV reliability and effects on economics

Several articles have integrated reliability models in their cost analysis to estimate or minimize the effect of component failure on the economics of PV systems [56,74–76,78,166,200,202,206]. Shin et al. [206] developed a reliability-centered approach to O&M scheduling of PV components and evaluated the scheduling plan considering the duration of failure. Their results suggested that it is more cost-effective to implement corrective replacement instead of preventive maintenance, due to the low failure rate. Similarly, Baschel et al. [78] concluded that while certain components could theoretically be repaired sooner, arranging a maintenance visit is often not cost-effective when the failure has only a minimal impact on the system's energy yield. These studies aimed to assess and mitigate the financial consequences that arise from component failure within PV plants, allowing stakeholders to make informed decisions about maintenance strategies, component selection, and overall system design.

Table 6
Utilized methods for criticality analysis and quantification of technical risks in PV systems.

Reference(s)	Criticality and risk analysis method				
	FMEA/FMECA	RAM	MCD	FV	CPN
[71,84,112,119,128,159,175,207,208]	✓				
[77]	✓		✓		
[5]	✓		✓		✓
[73,168,171,180]		✓			
[176]		✓		✓	
[111]			✓		
[190]				✓	
[18,209]	✓				✓

5.3. PV reliability and criticality analysis

Integration of reliability, criticality analysis, and technical risk quantification has led to the development of prioritization functions that support O&M teams in efficient and cost-effective maintenance scheduling. With limited resources, the optimal selection of components for maintenance becomes crucial. Reliability-centered maintenance is a crucial process that incorporates reliability analysis and identification of critical components. It assesses the economic implications to tailor maintenance strategies, facilitating effective prioritization and scheduling of corrective actions [84]. PV research has introduced various approaches to assess component criticality and mitigate maintenance incident risks, aiming to minimize energy generation losses. Table 6 presents an overview of these methods.

These methods include failure modes and effect analysis (FMEA)/failure mode, effects, and criticality analysis (FMECA), reliability, availability, and maintainability (RAM) analysis, multi-criteria decision analysis (MCPA), Fussel-Vesely (FV) importance, and cost priority number (CPN). For example, Bansal et al. [175] used FMECA to analyze degradation and failures in a 5 MW PV plant operating in a hot semi-arid climate. The study focused on O&M practices, module degradation, and reliability assessment, identifying dark encapsulant discoloration as a significant and damaging defect that accelerated plant deterioration. Similarly, Barkhouse et al. [209] employed a cost-based FMEA with CPN to prioritize risks based on their economic impact, highlighting major failures in PV modules and inverters. These methods provide valuable insights for decision-making and resource allocation to minimize energy generation losses.

6. Review of maintenance optimization and inspection planning approaches

In recent years, there has been a growing interest in the field of optimization of maintenance policies and inspection planning for PV systems. Table 7 offers a comprehensive compilation of studies related to PV maintenance optimization, highlighting optimization outcomes and influential factors.

In addition, a detailed description of the key elements used in the formulation of optimization models within the studies has been included. This comprehensive overview, depicted in Fig. 9, provides a thorough understanding of the current focus and methodologies used to optimize and plan PV maintenance activities.

6.1. Objectives in PV maintenance optimization

Maintenance schedules for PV systems are usually based on best practices and heuristics [4], lacking structured optimization models. Aboagye et al. [57] examined the impact of design, installation, and O&M practices on PV system performance in different climatic zones in Ghana. The authors used data from measurements, interviews, photography, and visual inspections to propose maintenance schedules. However, these schedules may not be optimal as they are heavily based on subjective recommendations from system owners. Most PV plants employ a combination of corrective and preventive maintenance

according to the manufacturer's guidelines and best practices [4]. Although immediate corrective maintenance ensures high availability, it may not always be cost-effective. Hence, it is essential to adopt a systematic approach to optimize the maintenance strategy and achieve a balance between various objectives in PV systems.

The primary focus of PV maintenance optimization has been to achieve various crucial objectives, including maximizing reliability and availability, minimizing expected costs, optimizing scheduling operations, and efficiently allocating resources. In their studies, Mahani et al. [88] and Baklouti et al. [91] proposed optimization strategies to minimize the overall expected maintenance cost in solar PV systems. The first study considered penalty costs resulting from performance degradation or failure, while the second study highlighted the importance of the reliability threshold in identifying components that require maintenance. Similarly, Sa'ad et al. [180] developed an algorithm to optimize the selection and cost of preventive maintenance actions in PV systems. This algorithm led to the implementation of five maintenance actions performed in multiple streaks, targeting components based on their reliability index.

Research has also explored the integration of maintenance considerations into the design of renewable energy systems. Jiménez-Fernández et al. [87] conducted a study on a standalone PV-hydrogen facility. Their objective was to determine an optimal maintenance plan considering system size and maintenance visits, with the aim of minimizing the total annual cost. Other studies have focused on prioritizing system reliability and availability. For example, Sa'ad et al. [210] proposed an optimal preventive maintenance strategy that takes into account environmental conditions to achieve maximum availability. Research has shown a growing interest in utilizing a multi-objective optimization approach for PV maintenance. This approach aims to maximize the reliability and availability of the system while minimizing overall maintenance costs. The studies conducted by Li et al. [222], Sa'ad et al. [180], Chen et al. [223], and Qi et al. [224] have explored this approach, recognizing the interdependencies between these objectives and seeking a balanced solution.

6.2. Approaches for PV maintenance optimization

Once O&M objectives and strategies are set, the decision-making process for maintenance parameters can be enhanced through the application of modeling and optimization techniques. These techniques can be broadly categorized into qualitative analysis, which relies on subjective judgments [57], and quantitative analysis, which utilizes mathematical and statistical methods. The quantitative methods used in optimizing PV maintenance studies are presented in Table 8, and include operations research models such as integer programming (IP), mixed integer programming (MIP), dynamic programming (DP), and problem-specific models such as the traveling salesman problem (TSP). In addition, stochastic models focus on probabilistic modeling and simulation, including Markov chains and stochastic simulation tools. Analytical models offer precise closed-form solutions for the prediction of PV system behavior through mathematical equations. Intelligent algorithmic models, such as ML and deep learning, predict PV system performance and guide maintenance planning. Metaheuristic search

Table 7

Classification of papers on PV maintenance optimization and inspection planning based on outcomes and factors considered.

Reference(s)	Outcome		Factors affecting PV maintenance optimization and planning						
	Assessment of maintenance alternatives	Optimal maintenance strategy	Optimal component grouping for maintenance	Optimized resources	Reliability indicators	Economic parameters	Weather factors	Resource logistics management	Route planning
[111]	✓		✓			✓	✓	✓	✓
[113]	✓		✓		✓	✓			
[5,112]	✓		✓		✓	✓	✓		
[206]	✓	✓			✓	✓			
[180]		✓			✓	✓			
[210]		✓	✓		✓		✓		
[211]		✓				✓		✓	✓
[131,149,212]		✓						✓	
[80–83,85–87,132,139,148,151,153,213–220]		✓				✓	✓		
[150]		✓			✓	✓	✓		
[221]		✓				✓	✓		
[222,223]		✓			✓	✓	✓	✓	
[88,91,224]		✓			✓	✓			
[56]	✓				✓	✓	✓	✓	
[165]					✓	✓			
[225,226]					✓				
[155,157]					✓	✓	✓	✓	
[159]					✓	✓			
[227]					✓	✓			
[228–236]					✓			✓	✓

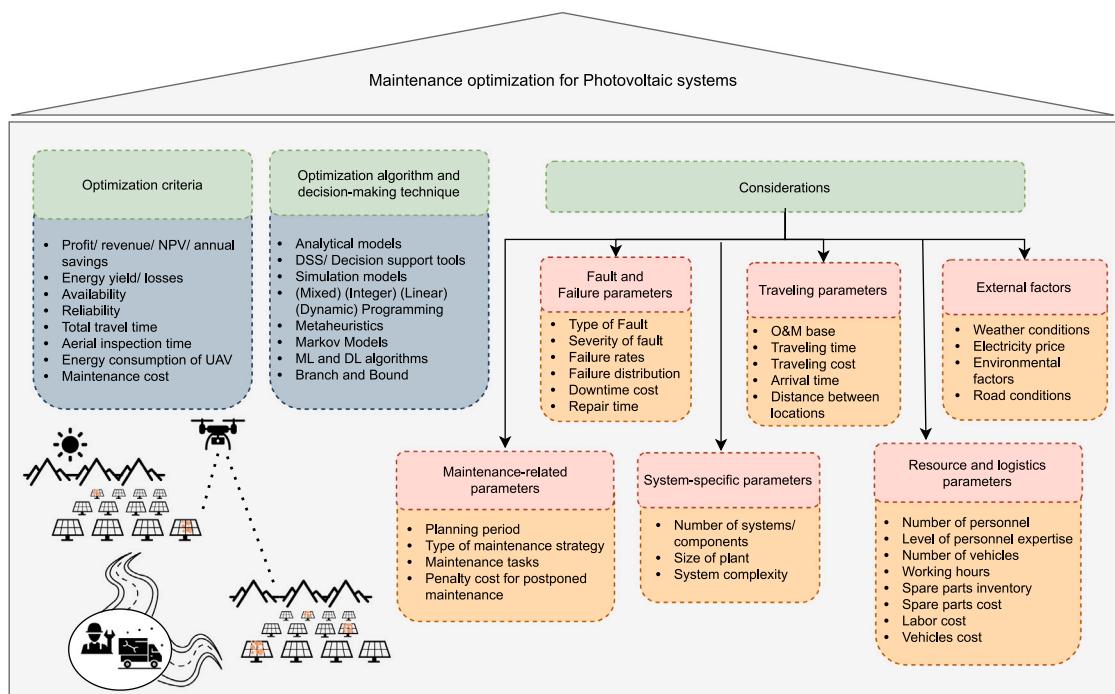


Fig. 9. Key elements in PV maintenance optimization. Note: NPV — net present value, UAVs — unmanned aerial vehicles, DSS — decision support system, ML — machine learning, DL — deep learning, O&M — Operation and maintenance.

algorithms, such as genetic and evolutionary algorithms also play a role. Some studies combined elements from these various methodologies, while others relied on experimental analysis to inform their maintenance optimization approaches.

Research has also developed decision tools for PV system O&M scheduling, guiding operators on timing, frequency, and task sequencing. In a study by Kothona et al. [111], MCDA was used to rank maintenance plans for six PV plants in Türkiye, considering criteria such as personnel expertise, fault severity, and travel time. The model also assessed maintenance costs, including fuel and labor, and the costs associated with energy losses caused by faults. Additionally, DSS as demonstrated by Livera et al. [5,112,113] and Lindig et al. [237],

provided data analysis, reporting, and visualization features, offering quantitative assessments of issues and recommending O&M actions for performance optimization. For instance, Livera et al. [5] discovered that implementing extra cleaning for a PV plant was not cost-effective, and their DSS recommended deferring the cleaning event until the next periodic maintenance.

6.3. PV cleaning scheduling

Regular cleaning is crucial for optimal energy production in PV systems due to the negative impact of dirt accumulation on solar panels, known as “soiling” [79]. In the United States, the cost of cleaning a

Table 8

Overview of literature approaches for optimizing PV maintenance and inspection planning.

Reference(s)	Operations research models (IP, MIP, DP, TSP)	Stochastic models (Simulation, Markov chains)	Analytical models	Intelligent algorithmic models	Metaheuristic Search algorithms	Decision support systems (DSS) and tools	Experimental analysis
[155,157,218,220,225,233]	✓						
[131,139,159,165,206,216,217,220]		✓					
[56,80,83,85,86,91,132,148–151,153,180,210,215,219,226]			✓				
[81,214,230,232,235] [87,211,227–229,231,236]				✓			
[111–113]					✓		
[213,222,223]		✓	✓			✓	
[88]		✓	✓				
[224]		✓	✓				
[221,234]		✓					
[82,212]							✓

10 MW system with 365 Watt-rated modules would exceed \$5000 for one-time cleaning. Therefore, careful consideration of the economic benefits and associated costs is important when planning the cleaning schedule [131]. The MENA region, with its dusty environment and frequent sandstorms, presents significant challenges for solar panels. In the worst-case scenario, these conditions can cause an 80% reduction in panel efficiency [212]. Soiling in the PV field has gained attention as an optimization problem, with the aim of finding the best cleaning strategy (frequency or interval) to minimize expenses and maximize productivity.

Numerous studies have focused on determining cleaning schedules for soiled PV plants, especially large-scale systems [80–83,85,86,132,139,148–151,153,213–218,220,221]. While some studies relied on operational experience or predetermined power loss thresholds to recommend cleaning schedules [132,139], neglecting site-specific factors such as local climate and geographical location can result in financial losses. Many research efforts utilized empirical methods incorporating meteorological parameters to create models that quantify performance reduction due to soiling. These models were then combined with factors such as cleaning costs, revenue generation, electricity prices, and *LCoE* to determine the optimal cleaning frequency. Although Wang et al. [219] focused on a small-scale PV plant, they successfully developed a cleaning schedule that leverages environmental forecasts, PV power generation, and dust deposition. This approach improves resource utilization, reduces costs, and optimizes PV system performance. The methodology showed great potential and can be extended to large-scale PV systems.

Stochastic approaches have also been investigated to determine the optimal cleaning frequency for utility-scale PV plants [213,216,217,220]. For instance, Cheema et al. [213] introduced an innovative method for optimizing PV system cleaning schedules. This method uses virtual scenarios to predict dust accumulation and actively adjusts cleaning schedules based on changing conditions, outperforming fixed schedules. In a study by González-Castillo et al. [220], a stochastic Markov decision process was employed to handle environmental uncertainty, especially concerning rainfall and irradiance, in maintenance scheduling. This approach treated the problem as a stochastic optimization problem, factoring in various weather scenarios to make optimal cleaning decisions under uncertainty.

6.4. Optimizing maintenance resources

Resource optimization strategies involve identifying critical components and maintaining spare parts inventories to minimize downtime and maximize system performance. Efficient resource optimization is crucial for managing multiple O&M bases and PV systems, particularly in remote areas. Conventional preventive maintenance policies aim to reduce system downtime, but relying solely on subjective risk assessment and operator expectations for spare parts can be problematic. In

practice, critical spare parts are stored near the site to minimize losses caused by delayed deliveries [238]. However, the dynamic nature of PV systems introduces uncertainties and unexpected failures. Accurate risk assessment and spare parts management require a systematic, data-driven approach that considers equipment reliability, failure patterns, historical data, and predictive maintenance techniques.

Several research studies have explored the integration of maintenance resources, such as personnel management and spare parts inventory, in the evaluation of energy yield and operational costs of PV systems [56,111,154,155,157,159,165,211,225–227,239]. Logistic delay time, including spare parts replenishment and crew arrival, is critical for evaluating PV system availability and functionality restoration. The resulting downtime greatly impacts plant performance and productivity [56,154]. In their study, Peters and Madlener [56] considered component reliability, operational costs, and the driving time of the service team to the PV plant, with the objective of determining an optimal maintenance strategy that minimizes total maintenance costs.

Other studies have expanded their focus beyond the deterministic delay time of PV spare parts, emphasizing the stochastic nature of spare parts inventory and maintenance activities. These studies used probabilistic models, Markov chains, and optimization techniques to provide valuable insights into spare parts inventory planning and optimization [159,165]. Guo et al. [159] developed an optimization model that integrated spare parts inventory policies for micro-inverter PV systems, combining continuous-time Markov chains with stochastic inventory theory to optimize the energy yield of the system. Similarly, Oprea et al. [165] utilized a probabilistic model based on Markov chains to calculate the reliability index. This index guided the proposal of maintenance activities that optimized spare parts inventory, ensuring a timely response to equipment failures.

The provision of electricity to remote areas with limited access to traditional electrical networks has been addressed using renewable energy sources such as PV and wind systems [240]. The electrification of rural areas, particularly through off-grid PV systems, has emerged as a promising solution. Operational costs, such as spare parts and logistics, are crucial due to factors such as population sparsity, difficult access, and maintenance requirements in remote areas [6]. Several studies have focused on optimizing maintenance activities in off-grid systems, particularly in the context of rural electrification programs using solar home systems [155,157,225,226]. In Morocco, case studies were conducted to minimize maintenance costs [225,226], considering factors such as location, transportation conditions, and daily dispatch of teams and vehicles. These studies identified optimal agency locations, optimized maintenance structures, scheduled preventive maintenance and fee collection, and calculated the total service cost.

6.5. Optimizing the planning of transport and inspection routes

To ensure optimal performance, careful planning of transport routes and finding the most efficient maintenance path are crucial. Several studies have focused on determining the optimal maintenance path considering available resources [155,157,211,221,227]. The objective is to improve maintenance processes, reduce travel time and costs, and optimize resource utilization. In the field of PV maintenance, metaheuristic and computational intelligence algorithms have been used for route planning and scheduling. For example, Yin et al. [211] combined particle swarm optimization and genetic algorithm to find efficient routes to dispatch personnel and schedule intelligent devices for inspecting distributed PV systems. Hua et al. [227] applied a genetic algorithm to determine an optimal path for maintenance teams handling large-scale distributed PV plants. Their study considered factors such as cost, multiple technicians, multipoint departure and different dispatch conditions, providing flexibility in setting arrival times or minimizing transportation costs.

Other studies used the TSP as a modeling framework to optimize transportation routes in off-grid PV systems [155,157]. These studies considered factors such as distance, road conditions, environmental complexity, and availability of transportation resources. The objective is to optimize maintenance schedules and enhance effectiveness by coordinating task scheduling, transport route planning, team dispatch, inventory estimation, and vehicle estimation. In addition, TSP has been employed to plan PV cleaning routes in large-scale PV plants. Wang et al. [221] expanded the conventional TSP to a production-driven TSP with time-dependent cost. Their primary focus was optimizing the temporal scheduling and spatial routing for PV cleaning, with the aim of minimizing the overall economic loss associated with the cleaning process.

Since the long-term performance of PV plants is influenced by environmental factors and potential module faults, regular inspection is crucial. Given the large scale and distribution of current solar infrastructures, consisting of more than 10 000 modules, UAVs are well suited for efficient visual inspections. Consequently, efforts have been directed towards optimizing UAV path planning for monitoring and inspection of PV systems [228–236]. The main challenge lies in scheduling, which involves determining the most efficient path to visit all modules and collect maintenance data. The objective is to minimize the energy consumption of the UAVs during inspections and to significantly reduce the aerial inspection time. For example, An et al. [228] proposed a novel scheduling model and evolutionary algorithm to optimize remote sensing schedules for UAV swarms in urban distributed PV arrays. Their approach was to assign tasks to UAVs, minimizing total inspection time while maximizing maintenance efficiency. Furthermore, Di Placido et al. [234] introduced the close-enough TSP and proposed a novel genetic algorithm to minimize the length of UAV inspection routes to assess the operational condition of PV fields.

7. Research gaps and perspectives into the future

This study has identified three critical research domains that require further exploration and development. These domains include PV maintenance strategies, maintenance practices for large-scale and distributed PV installations, and optimization and scheduling of maintenance activities. The representation of these research gaps in Fig. 10 serves as a valuable roadmap, guiding future research efforts aimed at advancing the O&M landscape of PV systems.

The O&M of PV systems places greater emphasis on diagnosis than prognosis, as the latter is still in development. The wind energy sector has made progress in data-driven predictive maintenance [241–244], while the solar PV industry is still in its early stages, with limited research mainly on PV modules or inverters. The complexity of multiple components and interdependencies, especially in large-scale systems, poses challenges. As PV farms expand rapidly, the transition from

corrective maintenance to predictive maintenance is crucial to improve operational efficiency. Although corrective maintenance will remain a priority in addressing equipment damage, the PV energy sector anticipates significant advances in predictive maintenance. Artificial intelligence techniques, Internet of things devices, and digitization facilitated by digital twin technologies are driving this advancement, aiming to replicate expected system behavior and improving the management and operation of the PV plant [245].

Furthermore, when dealing with large PV portfolios, which involve installations such as farms, parks, and distributed fleets across multiple sites, the lack of well-established maintenance strategies becomes apparent. The expansion of PV installations introduces manufacturing and cost challenges, necessitating a reevaluation of O&M practices to adapt to the evolving dynamics of the solar industry. Scaling up maintenance practices while addressing resource limitations poses significant challenges. It is essential to consider interdependencies among PV systems, as they impact neighboring systems and fleet performance. Existing single-unit maintenance models serve as a foundation, but fail to address real-world complexities. In addition, component-level models often assume independence among components, neglecting stochastic dependencies within PV systems. This is reflected by the industry's predominant focus on individual component availability, often neglecting the broader system's availability perspective.

Although advances are being achieved in developing KPIs for large-scale PV installations, these indicators may not comprehensively capture individual system performance and the complex interdependencies within multi-system fleets. Traditional KPIs often focus on factors such as energy generation and efficiency for individual PV systems, overlooking how the performance of one system affects others in the same fleet. Factors such as mutual panel shading, load distribution, and resource sharing can significantly impact overall fleet performance. Standardized metrics are essential for a comprehensive evaluation of system performance and maintenance effectiveness. Specialized indicator models should be developed to monitor and predict O&M outcomes, especially for difficult-to-access large installations. The expansion of PV projects requires a well-coordinated approach that involves multiple stakeholders and the establishment of clear channels and collaborative tools.

A notable gap in the existing literature revolves around the limited attention given to PV system maintenance optimization, which has primarily focused on individual components, especially in the context of optimizing PV module cleaning schedules. This approach tends to overlook the comprehensive perspective of the entire plant. In contrast, the field of wind farms O&M optimization has seen substantial development, but the same level of emphasis has not been placed on the maintenance of PV systems. This disparity arises from the fundamental differences between the two fields, which complicates the direct application of the findings from the wind industry to the PV sector. Wind farms involve a diverse range of complex configurations, including onshore and offshore installations, each posing unique operational challenges. Conversely, PV systems tend to exhibit a more standardized structure with fewer moving parts, simplifying maintenance procedures compared to the intricate nature of wind turbines. Hence, insights and methodologies from wind farms O&M optimization may not be directly applied to PV systems due to their distinct characteristics and inherent differences as renewable energy technologies.

It is crucial to recognize that current PV optimization models predominantly revolve around fixed maintenance schedules, which prove inadequate for modern large-scale PV systems. These expansive installations span vast areas, leading to varying levels of soiling across different zones within the solar field. Implementing fixed cleaning schedules for the entire installation can prove impractical and expensive. The complexity increases when managing multi-system fleets, as different systems exhibit unique cleaning requirements, with some necessitating more frequent cleaning than others. To maximize efficiency, it is

Identified Gaps		
PV Maintenance Strategies	Large-Scale PV Systems Maintenance	PV System Maintenance Scheduling and Optimization
<ul style="list-style-type: none"> Emphasis on Diagnosis Instead of Prognosis: Current PV O&M practices prioritize diagnosing issues as they arise rather than proactively predicting and preventing them. Limited Integration of Prognostic Predictions: Ineffective integration of prognostic predictions into PV maintenance decisions hampers the accuracy of cost estimates and risk evaluations. Narrow Research Focus: PV predictive maintenance research predominantly centers on modules and inverters, overlooking crucial system components and broader system-level considerations. 	<ul style="list-style-type: none"> Insufficient Focus on Large-Scale Maintenance: Current research primarily focuses on smaller PV systems, overlooking the specific maintenance requirements of extensive PV portfolios. Component Repair Over System Repair: Current models prioritize individual PV component repair, neglecting holistic system considerations and interdependencies, particularly within PV fleets. The emphasis on "component availability" rather than "system availability" is notable. Limited KPIs for Large PV Portfolios: Existing KPIs may not adequately account for the intricate interconnections among PV systems in fleets, potentially hindering a comprehensive assessment of extensive portfolio performance. 	<ul style="list-style-type: none"> Component-Centric Focus: Current research primarily optimizes individual components, especially PV module cleaning, ignoring the holistic system view. Single-Objective Optimization: Existing maintenance models often prioritize system reliability or cost reduction separately, lacking exploration of multi-objective approaches. Static Scheduling: Many PV maintenance approaches rely on fixed schedules based on time intervals or degradation thresholds. Neglecting Long-Term Maintenance Impact: Current research often ignores long-term maintenance effects, focusing on short-term optimization and immediate needs.

Fig. 10. Identified research gaps in PV system maintenance literature.

crucial to consider the unique characteristics and operational requirements of each system when developing maintenance plans. Tailoring maintenance strategies to site-specific challenges, such as location and climate, requires customized approaches, regular site assessments, and the adoption of adaptive maintenance protocols.

Furthermore, within the PV industry, the prevailing research focus often centers on short-term optimization and immediate maintenance, often failing to consider the potential enduring effects on system performance. Despite progress in dynamic maintenance strategies, the literature in the PV field generally tends to neglect the persistent consequences of maintenance actions, their interconnected nature, and their susceptibility to changing factors. An emerging and adaptable approach that is gaining interest is prescriptive maintenance, as discussed by Fox et al. [242], employing reinforcement learning (RL) to directly identify optimal actions, eliminating the need for predefined strategies. The use of RL techniques in the PV industry has been limited, with recent research focusing primarily on fault detection in specific components such as inverters [117] and arrays [246,247].

RL has also been applied to optimize operational scheduling in solar thermal energy-driven hot water systems [248] and wind farm O&M [249]. These studies highlight the potential of using RL techniques to efficiently optimize long-term PV system maintenance. This approach ensures that maintenance decisions are aligned with the core goals of enhancing system reliability, maximizing efficiency, and promoting sustainability. Additionally, RL offers the opportunity to introduce customized KPIs for large PV installations, addressing a previously identified research gap within this study. The integration of RL offers the capability to fine-tune the performance evaluation criteria within particular environmental and operational contexts, whether at the system or fleet level. Therefore, expanding the application of RL techniques in PV O&M creates an opportunity to ensure the continued relevance and effectiveness of KPIs, thereby continuously enhancing the performance and maintenance action of PV systems.

8. Conclusion

This systematic review explores the current literature on O&M management for PV systems. With the growing capacity of PV systems, there is growing recognition of the critical necessity for systematic O&M practices to guarantee sustained performance and longevity. The advancements in maintenance practices and operational enhancements implemented by other renewable energy sectors, particularly the wind industry, have set a standard for the PV sector. As a result, this review goes beyond the usual technical focus in PV energy, incorporating planning and organizational factors into the broader maintenance discussion. Through the application of the PRISMA framework

and bibliometric analysis, the examination of 186 articles revealed four interconnected research domains: maintenance strategies, KPIs, degradation modeling, and maintenance optimization and planning.

Analysis of thematic evolution reveals that maintenance receives relatively less emphasis in PV research compared to other operational aspects of energy management. Various maintenance strategies have been investigated for PV systems, each with its own importance. However, relying solely on a single maintenance strategy may be ineffective, especially for large-scale installations. Strategic selection and synergistic integration of maintenance strategies significantly improve system reliability. The management of O&M for PV systems is also closely related to a range of operational, economic, and maintenance-related KPIs. The integrated consideration of these KPIs guides decision-making processes by helping managers prioritize efficient maintenance actions. Modeling PV system degradation is also crucial to identify critical components and implement effective maintenance measures. Integrating the reliability assessment with the criticality analysis, economic considerations, and quantification of technical risks supports informed decision making on maintenance strategies and component selection. The literature on PV maintenance optimization places a primary emphasis on scheduling PV panel cleaning to mitigate the impact of soiling, considering economic factors. A structured maintenance optimization approach, utilizing various modeling and optimization techniques, is essential to achieve key objectives such as maximizing availability, minimizing costs and travel time, and efficiently allocating resources.

Furthermore, this review highlights gaps in the current literature, emphasizing areas that require further research. Maintenance strategies for PV systems prioritize diagnostic activities over prognostic measures and lack the integration of predictive maintenance. Additionally, there is insufficient attention to large-scale maintenance, with a tendency to prioritize component repair over holistic system considerations. Challenges in PV system maintenance scheduling and optimization include a component-centric focus, a single-objective approach, and reliance on static schedules that neglect the long-term maintenance impact. The growing PV sector requires strategic planning that involves multiple stakeholders in a well-coordinated maintenance approach. Intelligent technologies, such as Internet of things and digital twins, are vital for coordinated maintenance and resource sharing, enabling virtual testing. Improved communication, collaboration, and standardized metrics are essential for assessing system performance and interconnections between PV sites. Customizing maintenance plans to site-specific needs is equally crucial, demanding a shift from fixed to adaptive protocols. Despite advances in dynamic maintenance, the PV industry tends to favor short-term gains, neglecting long-term consequences. Addressing this presents an opportunity for prescriptive maintenance, using RL techniques to provide actionable insights based on real-time data and

predictive models. Finally, this review underscores the need for a comprehensive approach in PV O&M to enhance the competitiveness of PV systems in delivering clean energy. Maintenance is vital for sustainable production, aligning with the Sustainable Development Goals of the United Nations for affordable, reliable, and sustainable energy. The study provides key insights into effective PV system integration, emphasizing maintenance strategies for improved reliability, seamless integration, and grid security.

Some limitations are recognized in the methodology and scope of this review, such as the reliance on selected search terms and the focus on publications from the past decade. These constraints may have affected the results by potentially excluding relevant articles and overlooking valuable contributions from earlier work. Additionally, while the PRISMA framework is robust, it might have excluded valuable articles that did not meet its specific criteria. To overcome these limitations, future studies are encouraged to use alternative keywords and employ a broader methodology with a more extensive temporal scope. In addition, the sustainability impact of maintenance practices, including waste minimization and resource management, is not addressed in this work. Striking a balance between profitability and environmental sustainability is crucial in developing suitable maintenance strategies. Future research should explore sustainable technologies, conducting a comprehensive life-cycle sustainability assessment with a focus on eco-friendly materials, energy-efficient procedures, and responsible maintenance protocols.

CRediT authorship contribution statement

Hind Abdulla: Conceptualization, Methodology, Visualization, Writing – original draft. **Andrei Sleptchenko:** Supervision, Conceptualization, Validation, Writing – review & editing. **Ammar Nayfeh:** Conceptualization, Writing – review & editing.

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.

Data availability

Data will be made available on request.

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