

REVIEW

Optimization of Photovoltaic Systems via AI-Based Solar Tracking and MPPT: Trends, Challenges, and Bibliometric Insights

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ABSTRACT: The rapid expansion of photovoltaic (PV) technologies has necessitated the enhancement of energy conversion efficiency by developing more and more sophisticated control and optimization techniques. In particular, novel MPPT methods combined with solar tracking systems and AI approaches emerge as a promising solution to surmount the barriers of the conventional PV systems. This research presents a critical assessment of the recent developments in the research area of PV systems with MPPT algorithms, solar tracking mechanisms, and AI-based techniques. Therefore, papers with publication years from 2021 to 2025 were selected using Web of Science Core Collection. Then, a series of bibliometric metrics were used in this paper, including publication output, citation impact, collaboration patterns, and keyword co-occurrence, to highlight the evolution of this research area. The significant growth of scientific productivity is depicted in the paper, together with the strong contribution of both emerging and developed economies, in addition to rising interest in intelligent control strategies, machine learning, and hybrid optimization methodologies. As a result, these findings provide important insights regarding recent research developments and future challenges and offer a useful reference for researchers and practitioners interested in high-efficiency PV systems.

KEYWORDS: Maximum power point tracking; photovoltaic systems; intelligent control; artificial neural networks; metaheuristic optimization; power electronics; dc–dc converters; renewable energy integration; solar tracker

1 Introduction

Solar PV technologies rank among the most used RE technologies for the mitigation of the greenhouse gas emissions associated with the production of electricity, leading to large deviations in the generated power and resulting in significant power deviations and suboptimal energy harvesting. Notwithstanding advancements in cell technology and power electronics, solar PV systems are prone to issues caused by natural weather variability, including changes in irradiance, temperature, and shading, suboptimal conditions [1–3]. In practical solar PV applications, the solar PV array does not normally work at the optimal performance point because the operational conditions change from time to time. As such, there is a need for sophisticated control and optimization techniques to make solar PV systems work at or near their maximum potential and to enhance the reliability of solar PV generation [4–7].

One of the most effective means of increasing the energy potential of the PV system is the geometric alignment between the surface of the PV system and the sun [8,9]. In the traditional fixed orientation of the tilted PV system, the design is relatively cheaper; however, the system can potentially lose some amount of energy not reaped by the system, especially in regions with relatively high variation in the path of the sun throughout the year [10]. To address these limitations, solar tracking systems mechanically adjust the orientation of the PV module, which mechanically changes the orientation of the PV module to receive the maximum possible irradiance from the sun at any given time [11]. Depending upon the mechanical complexity of the system, there are two types of solar tracking systems: single-axis tracking systems or dual-axis tracking systems. Dual-axis tracking systems have the potential to increase the energy potential but add complexity to the system [12]. Contrarily, one-axis trackers usually comprise a trade-off between energy gain and system simplicity [13]. In both cases, the true value of tracking strongly depends on site conditions such as wind load, soiling, diffuse radiation fraction, and installation constraints [14]. Then, the maximization of PV yield is not only a matter of adding tracking hardware, but also robust tracking control needs to be developed, together with proper sensing/estimation and optimized operating strategies that are adjusted to the PV plant context.

Parallel to geometric optimization, (MPPT), an electrical optimization technique has gained prominence as an optimizing function in power converters for PV systems [15]. MPPT is a control action that focuses on continuously maintaining the maximum power point (MPP) of a PV array with the help of the DC-DC converter or inverter stage duty cycle or reference voltage/current [16]. Traditional MPPT techniques, like particle swarm optimization and the hill-climbing search with perturb-and-observe and the incremental conductance method, are still in use due to their simplicity and ease of computation [17,18]. However, their performance fails in rapidly varying conditions, partially shaded systems, and systems with complex power voltage profiles having local maxima [19,20]. Under these conditions, it is possible that the controller is entrapped in local optima, diverges with oscillations in the vicinity of the MPP, or exhibits sluggish response to dynamic changes, which will cause power loss and instabilities [21,22]. Therefore, there is a need to research more sophisticated MPPT algorithms with stronger adaptability to nonlinear, uncertain, and dynamic conditions with better tracking capability, with minimal limit cycles, and reduced oscillations [23,24].

It should be noted that in practical PV systems, solar tracking and MPPT algorithms cannot be viewed as separate processes [25], as there are several cross-effects that also impact optimization tasks. Tracking systems affect the irradiance distribution accessible to PV modules, which further affects the PV electrical parameters and thus points in the control process of the MPPT algorithm [26]. Also, high dynamics of MPPT algorithms might be required during tracker repositioning maneuvers and during transients due to cloud passage, while high actuator movement costs might be unacceptable if marginal power gains are compared to actuator losses and energy waste [27]. These considerations bring to light a new and substantial requirement: PV system optimization has to be addressed as a complex problem, taking into account simultaneous mechanical (tracking) and electrical control levels in MPPT algorithms, and cannot be separated along these lines in optimized practices [28]. In addition to the above, new requirements are constantly being presented in practical systems, like reaching efficiency maximization, increasing energy collection, speeding response times, and shortening converter stresses and costs, along with increasing reliability and cost-effectiveness [29].

Over the last decade, AI has emerged as a robust paradigm for managing nonlinear and uncertain systems in the context of energy applications [30,31]. The interest in applying AI algorithms in PV systems is driven by a number of reasons [32,33]. First, the PV cell dynamics are nonlinear, as they depend on certain environmental factors, which cannot be accurately represented using simple analytical models, especially in

the presence of complex phenomena such as partial shading, non-uniform temperatures, and dynamic solar irradiances [34]. Second, modern PV systems are expanded to incorporate sensors, monitoring systems, and Internet of Things (IoT) structures, which often generate ample amounts of field data to be harnessed through DL algorithms [35]. Third, the computational capabilities of modern embedded systems are sufficient to run computationally complex algorithms, which were considered unfeasible in real-time processing [36]. This has enabled the development of numerous AI algorithms, such as neural networks, fuzzy systems, DL, and reinforcement learning, which can be used in the PV community for tasks such as PV output prediction, fault detection, energy management, and optimal control [37,38].

In this regard, AI algorithms have been gainfully researched for MPPT and solar tracking applications [39–41]. In MPPT applications, AI algorithms can be applied to approximate the MPP based on measured values, classify system states, improve convergence speed, or escape from local optima in partial shading situations [42]. In this regard, ANN, fuzzy logic systems, and neuro-fuzzy approaches can offer certain learning capabilities depending on system modeling and design [43–46]. In solar tracking applications, AI can help estimate the location of the sun without using expensive sensors, improve noise robustness in sensors, or learn the relationship between the position command and maximum power gain through training [47]. Furthermore, metaheuristic optimization algorithms such as genetic algorithms and particle swarm optimization and stochastic algorithms have been applied in both offline and real-time optimization of critical system parameters as well as searching for the global optima of system operating points [48–51]. In this regard, metaheuristic optimization algorithms can offer an advantage in scenarios where the system has a large or multimodal search space and lacks gradient information or has a black-box objective function [52].

Although there is a growing body of work on AI-based enhancements of PV tracking and MPPT, it is apparent that this topic is currently split across several communities of scholars and researchers, namely power electronics [53], control systems [54], RE, and optimization and data sciences [55–58]. Typically, each individual paper will address a particular algorithmic innovation (such as a new neural network MPPT estimator, a fuzzy logic tracker controller, or metaheuristic optimizer hybrids) and analyze its performance on a shortlist of case studies [59]. Indeed, it is often challenging for scholars to gain a global perspective on the topic and related questions on how particular techniques have evolved and developed with time. Also, the sheer rate of publications in AI and RE ensures rapid obsolescence of particular developments what was cutting-edge only a few years ago may now be less relevant compared to newer advances in deep learning, hybrid models, and other related developments in AI and related frameworks [60].

In order to overcome these, bibliometric analysis offers a quantitative method to trace the structural and dynamic developments of a field of study. Based on the analyses of bibliographic data, citations, co-authorship patterns, and keywords, bibliometrics can identify publication patterns, highly cited works, top-tier journals, and international collaboration patterns. Furthermore, science mapping methods are also able to identify theme clusters and bursts of citations to specific subjects, providing information about how subject areas tend to emerge and change over time [61]. In comparison to review articles, which are potentially hampered by personal choices and restricted terms, bibliometric analysis offers systematic and verifiable information about scientific dynamics. Nevertheless, the interpretation of bibliometric findings must be facilitated through clarity and transparency about the applied database, search terms, filters, and time frame definitions, because these parameters significantly influence the findings and their outcomes [62].

In this work, the focus is placed on the convergence of four key elements: (i) solar PV systems, (ii) solar tracking (single-axis and dual-axis), (iii) MPPT, and (iv) AI. Concentrating on this intersection is important because many practical PV performance improvements rely on integrating mechanical and electrical optimization, while modern AI tools enable new control strategies that may surpass conventional

approaches under challenging conditions. The selected time window (2021–2025) corresponds to a period of intense growth in AI applications across engineering fields, driven by the maturation of deep learning and the increasing availability of data and computation. Restricting the scope to English-language journal articles also seeks to ensure peer-review consistency and comparability of bibliographic metadata, facilitating robust bibliometric indicators and network analyses [63].

The aim of the paper is to present a structured and all-encompassing bibliometric overview of research at the junction of PV systems, tracking solar, MPPT, and AI-based optimization during the 5-year period of 2021–2025. More specifically, this study aims at: (1) quantifying growth in publication output and identifying temporal trends; (2) determining the most productive and influential authors, institutions, countries, and journals; (3) characterizing collaboration networks and pathways of knowledge diffusion; (4) analyzing the citations of publications to determine their influence; and (5) discovering research hotspots and emerging themes through keyword co-occurrence and thematic clustering. Thus, the contributions will have an appealing global research map that will support researchers in identifying gaps for proposing promising future directions and positioning their work with regard to the broader field.

There are several applications and scientific challenges that make it necessary to create a map. First, there is a maturity of PV trackers and MPPT techniques, whereas incorporating AI makes it a fast-paced area of research that is still a frontier area, and there can be varying practices of evaluation that make it hard to make direct comparisons [64]. Secondly, there is an emerging area of hybrid methods that could potentially use physics-based simulation integrated along with data-driven methods, or even make use of classical MPPT logic integrated along with meta-heuristic-based or learning-based decisions, making it a complex landscape that is hard to fully explore [65]. Third, there is a challenge of whether simulation results are valid under certain conditions that are not necessarily easily transferable to varying sites and varying PV technologies because of potential difficulties of replicability and generalization of AI controllers trained specifically on certain datasets of climate conditions [66]. Fourth, to make use of advanced algorithms that run on hardware platforms, there is a challenge of performance optimization that necessarily balances hardware resource usage limitations [67]. A macro-level perspective to understand what is being done to address these is what makes it necessary to make use of bibliometrics.

Further, there has been a rising demand for the optimization of additional objectives other than the maximization of instantaneous power [68]. Additionally, the present state of research covers life-cycle issues and economic measurements like the consumption of trackers, the mechanical stress of converters, and the costs of maintenance [69]. This manner of extending the concept of “performance” and “efficiency” will allow for the applicability of multi-objective methods of optimization. However, the use of AI and meta-heuristics will provide challenges regarding the interpretability and control robustness of the methodology [70]. Determining the level of correspondence of such additional conditions within the literature may present valuable insights for the direction of future studies [71].

To provide a clear and verifiable perspective of this booming research field, the current study uses a design of bibliometric review guided through the use of the Web of Science Core Collection database. The search within the available literature has been carried out through the use of a Topic Search (TS), targeting the Title, Abstract, Author Keywords, and the field of Keywords Plus; the search is limited to the publication of English-language journals within the specified years of 2021–2025. The selection of documents, as well as cleaning the information, will use a PRISMA-inspired methodology designed specifically for a bibliography research study (identification-screening Elapsed Time Eligibility Inclusion), specifically emphasizing the aspects of eligibility consideration, information sources, and included studies [72]. The analyzed information is finally processed through the use of combined methods of performance measurement analysis and science mapping through the use of tools of Bibliometrix (Biblioshiny), VOSviewer, and CiteSpace software [73].

The rest of the paper is organized as follows: [Section 2](#) reviews relevant literature and situates this work with respect to existing surveys and bibliometric analyses in the field; [Section 3](#) describes the bibliographic database, search strategy, screening criteria, and data processing pipeline followed to build the final corpus and ensures the transparency and reproducibility of this study; [Section 4](#) presents the quantitative performance indicators and science-mapping results obtained from the dataset; and [Section 5](#) synthesizes key research hotspots, emerging directions, and persisting gaps, pointing out promising future research avenues regarding AI-driven PV tracking and MPPT optimization.

2 Related Work

To the best of our knowledge, this is the first bibliometric study that comprehensively evaluates the intersection of Solar Tracking and MPPT using AI. While the body of literature in this domain is extensive, previous scholars have primarily treated this subject through systematic literature reviews, comprehensive technical reviews, or narrative overviews.

As we shift our focus from the proposed work to the state-of-the-art in the present landscape, we see that there are several articles that either provide insight into technical classification systems in lieu of bibliographic information. For example, ref. [\[18,74\]](#) conducted an exhaustive review on MPPT algorithms that were divided on the lines of traditional and modern methods in their entirety, but their attention in that paper had been on their efficiency and hardware-oriented characteristics in lieu of studying the publication tendencies in their domain. Again, ref. [\[75\]](#) divided the entire set of MPPT algorithms on the lines of traditional methods, intelligent methods, optimal methods, and method combinations, with special attention to their acceleration and cost-feasibility in their review. Ref. [\[76,77\]](#) conducted their review with special attention to solar tracking systems based on one-axis and two-axis systems in their entirety, without providing any insight into the community that is researching it.

A major part of the literature is focused on the use of AI to address the non-linear issue associated with partial shading conditions (PSC). Ref. [\[78,79\]](#) carried out systematic reviews focused on the application of AI-based MPPT methods like Fuzzy Logic and Neural Network approaches in addressing the issue of tracking the Global Maximum Power Point (GMPP). There are other researchers who focused their research on the specific issue associated with the optimization methods, such as [\[80,81\]](#), who carried out systematic reviews of the algorithms developed especially for partial-shaded systems and the weaknesses associated with the methods like P&O.

Another vital region within this topic would be the development of Hybrid & Meta-Heuristic algorithms. Various authors have been attempting to improve a particular algorithm, for instance, authors like [\[82\]](#), who used an enhanced Grey Wolf Optimizer to optimize the process of tracking within the shade, or [\[83\]](#), who specifically investigated hybrid optimization algorithms designed to enhance both stability and convergence speed in MPPT applications under challenging conditions such as partial shading, for instance through the development of novel hybrid optimization strategies that combine the strengths of multiple techniques to improve tracking performance, rather than limiting the analysis to isolated simulation-based comparisons between individual algorithms or identifying the broader intellectual structure of the domain.

In addition, there have been recent efforts to integrate emerging technologies as part of these reviews. A critical review of the latest MPPT algorithm was offered by [\[84\]](#), touching on the benefits associated with soft computing compared with past techniques. Such reviews aim at providing technical perspectives through the synthesis of technical parameters such as efficiency, time, and complexity with the intention of assisting proof decisions by engineers.

Existing bibliometric studies on renewable energies have mainly concentrated on wide technological shifts or particularities that are not related to the studied area, creating a gap in the quantitative study of AI-assisted solar tracking and MPPT. In particular, works like [85,86] have performed broad bibliometric analyses on renewable energies and solar power generation in general, plotting worldwide scientific output without pinpointing algorithmic developments on MPPT per se. Likewise, work in [87] spread their bibliometric activities towards swarm engineering, which, although linked to optimization algorithms utilized in MPPT, for example, PSO or Ant Colony, does not deal with the PV system per se. Other works have investigated particular intersections, including machine learning techniques in energy economics or AI applications in intelligent buildings, and in particular, fail to detect the distinct scientific stream on intelligent tracking control. Even those reviews studying solar power, for example, ref. [88], explore the overall economic and political implications of the shift towards energies without identifying the technical developments in tracking controls under PSC. While several bibliometric studies have explored the broader landscape of renewable energy [86] or machine learning in general power systems [32], this is, to the authors' knowledge, the first study to specifically map the three-way convergence of solar tracking mechanisms, MPPT algorithms, and artificial intelligence. Previous scientometric works have often treated these as isolated topics; however, the current study distinguishes itself by analyzing the 'synergistic optimization' of mechanical and electrical systems through data-driven paradigms, providing a unique roadmap for the integration of physical hardware and intelligent software. Consequently, there is a distinct lack of a focused bibliometric study that specifically maps the intellectual structure of AI-integrated solar tracking and MPPT, necessitating this research to clarify the field's trajectory and key contributors.

Despite this wealth of technical knowledge, there is a striking lack of any study to date that examines scientific production in and of itself. Researchers, scientists, and graduates could greatly benefit from a bibliometric analysis through its application in decision-making within their fields concerning various properties, such as determining top authors, collaboration networks, and up-and-coming keyword trends, and in fostering further research for areas that need it. Although existing reviews explain how those algorithms work, they tell us nothing quantitative about where the research is going or who is leading the innovation. Thus, the goal of this paper is to perform such a macro-level assessment of the evolution of the field.

3 Data Collection

The bibliometric analysis is a widely known and scientific means of conducting and interpreting large-scale scientific data. The bibliometric analysis enables one to determine technological breakthroughs and the evolutionary path of a certain scientific area. Bibliometric analysis is aided by bibliometric software that simplifies the processing and statistical analysis of large amounts of scientific data acquired over a certain period. Compared to systematic reviews, bibliometric analysis puts great emphasis on scientific means and is less prone to subjective biases, considering that systematic reviews, when conducting analysis, place much reliance and interpretation on subjective scientific knowledge and experiences [89].

There are several databases that can be used to export bibliographic information, including Web of Science (WoS), Scopus, PubMed, Lens, and Google Scholar, each with its own features and scope. Although Google Scholar may include the widest scope of bibliography, Web of Science and Scopus return similarly high-quality results for bibliometric analyses [90]. WoS offers powerful tools to narrow a search result systematically, including General, Cited Reference, and Advanced searches. Both databases allow tracing, numbering, and data analysis for citation tracking and analysis [91]. While databases such as Scopus and IEEE Xplore offer extensive coverage of engineering and computer science publications, the Web of Science (WoS) Core Collection was selected as the primary data source due to its exceptionally rigorous indexing

standards and the high metadata quality required for complex bibliometric mapping (such as co-citation and factorial analysis). Merging multiple databases often introduces severe metadata heterogeneity, including duplicate records, inconsistent citation formatting, and mismatched institutional names, which can distort the reliability of science mapping software. WoS ensures that the analyzed records undergo strict peer review and contain clean, standardized metadata [92]. Nevertheless, the exclusion of Scopus and IEEE Xplore is acknowledged as a limitation, as it may omit certain highly technical studies or specialized conference papers that are not indexed in the WoS Core Collection.

The sources cited in this study are from respected publishers such as Elsevier, IEEE, Springer, and MDPI. These publishers have earned a reputation for their rigorous peer review practices, in addition to their immense contributions in the fields of engineering, computer science, and RE. The search conducted in this section is based on a database search done in December 2025. The search aimed at collecting bibliographic information at the nexus of solar tracking systems/MPPT and AI. The search strategy applied in this research is illustrated in Fig. 1.

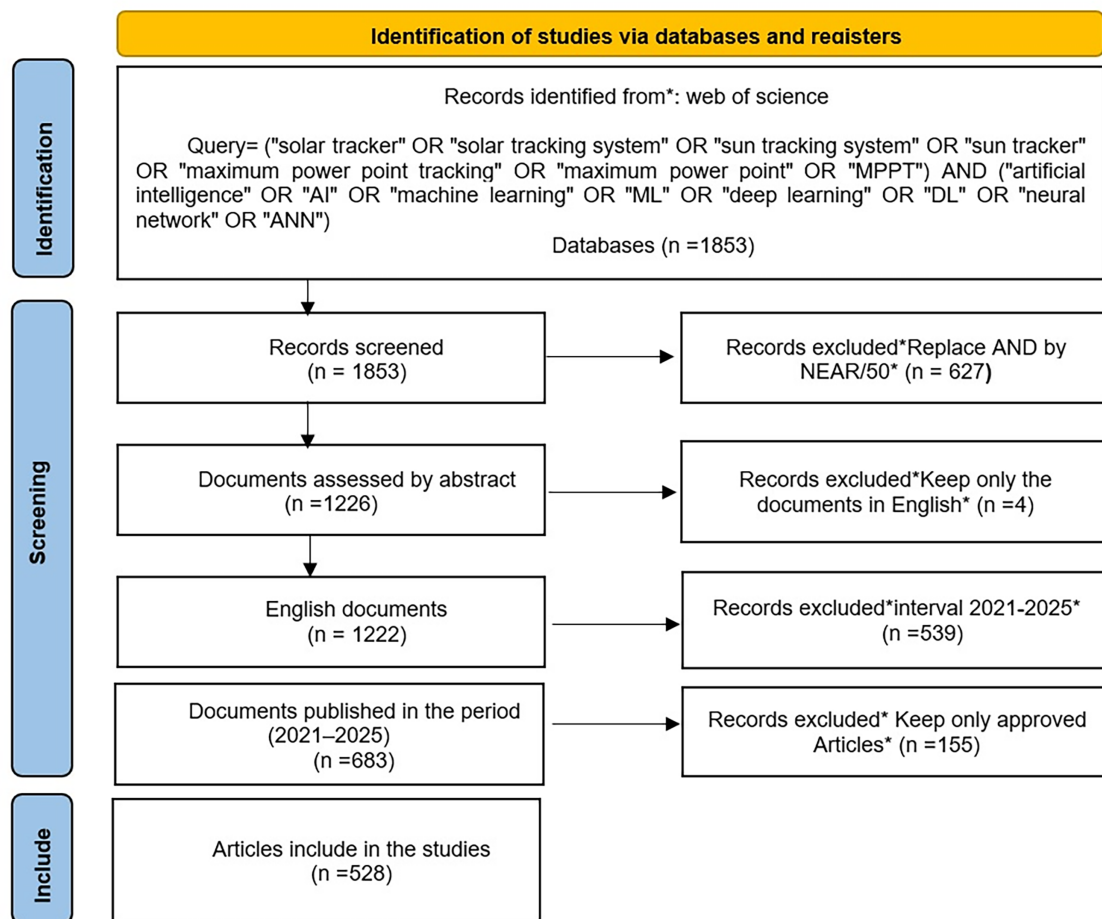


Figure 1: Flow chart of the search strategy. The asterisk (*) refers to the filtering criteria applied during the screening process, including (i) replacing the Boolean operator “AND” with the proximity operator “NEAR/50”; (ii) restricting the search to English-language publications; (iii) limiting the publication period to 2021–2025; and (iv) including only article-type publications.

The keywords are chosen from the broader terminology associated with PV optimization and AI. The keywords applied in this study for capturing the domain are related to the application as “solar tracker”, “solar tracking system”, “sun tracking system”, and “MPPT”. To capture the techniques in AI, keywords such as “AI”, “machine learning”, “ML”, “deep learning”, “DL”, “neural network”, and “ANN” are applied. In the beginning, the search for information was carried out by combining the keyword sets with the “AND” operator for all fields of the Web of Science Core Collection, and it generated a total of 1853 documents.

The search strategy was refined using specific filters and thresholds to ensure the high quality and relevance of the dataset. The ‘NEAR/50’ proximity operator was employed to ensure that keywords related to PV optimization and AI appeared within the same conceptual context (approximately one paragraph). This method increases the ‘precision’ of the retrieved corpus, filtering out papers that might mention both terms in unrelated sections (e.g., introduction and references) without actually integrating them. Furthermore, the search was restricted to English-language publications to maintain a standardized and universally accessible metadata set for bibliometric mapping. This is a critical methodological requirement for bibliometric mapping software (e.g., VOSviewer and Bibliometrix), as it ensures that citations, keyword structures, and affiliation data are universally compatible and comparable, thereby minimizing errors and noise in the resulting co-citation and collaboration networks. The 2021–2025 timeframe was specifically selected to capture the most recent ‘state-of-the-art’ advancements, as the intersection of AI and PV systems has entered a period of rapid maturation and exponential growth during this window. Finally, while the authors acknowledge that this research area frequently progresses through rapid IEEE conference publications, the exclusion of conference proceedings was a deliberate methodological choice. Original journal articles were prioritized because they typically undergo a more exhaustive peer-review process and provide more stable, comprehensive bibliographic metadata. For a scientometric study of this nature, journal articles offer the technical depth and citation longevity necessary to produce reliable co-citation networks and thematic clusters, whereas conference reports often represent preliminary findings that are later expanded in full-length journal publications.

In order to analyze recent developments, a filter has been applied to result in relevant documents from the specific period (2021–2025). Applying this filter meant that all records prior to this defined timeframe were eliminated, including 683 documents. The screening and data cleaning process followed a transparent pipeline to ensure the integrity of the analyzed dataset. First, although the search was restricted to journal articles, 5 records were cross-listed in WoS as ‘article; proceedings paper’. These were retained because they represent full-length, peer-reviewed articles published within regular journal volumes (such as Energy Reports or IEEE Access) rather than standalone conference booklets. Second, during the screening phase, 3 retracted publications were identified within the initial search results. To maintain scientific integrity and prevent retracted citations from skewing our bibliometric maps, these 3 records were systematically excluded from the dataset. Consequently, the final cleaned analytical corpus consisted of 528 active documents, which were used for all subsequent performance analyses and network mapping visualizations. The complete screening workflow is illustrated in [Fig. 1](#). It is essential to note that after this stage, a total of 528 documents were obtained that were analyzed in this study. The final query construction is structured in [Table 1](#). The use of keywords for this paper was strategically selected in an attempt to use high-level keywords to capture various special techniques in the domain. With the help of general keywords like ‘AI’ and ‘Machine Learning’, the keyword search strategy helps in capturing various special techniques that are sub-categorized within these high-level terms in the Web of Science categorization process. This strategy, which could be referred to as an umbrella strategy, is helpful in ensuring that there is no selection bias by listing all technical variations within the field, which would create a fragmented dataset.

Table 1: Search criteria for journal articles on solar trackers and AI (2021–2025).

Search Criteria	Search Terms/Filters
Keywords for Solar Tracker	“Solar tracker”, “solar tracking system”, “sun tracking system”, “sun tracker”, “MPPT”, “maximum power point”, MPPT
Keywords for Artificial Intelligence	“Artificial intelligence”, AI, “machine learning”, ML, “deep learning”, DL, “neural network”, ANN
Condition	NEAR/50 (Proximity search for related terms)
Content Type	Abstract
Language	English
Publication Year	2021–2025
Document Type	Article

4 Research Method

A bibliometric analysis is a research technique used in the field of science to obtain meaning from literature using statistical techniques in order to analyze the development, form, and influence of a particular field of science during a particular period of time. The relevance of the bibliometric analysis in the field of solar tracking and MPPT using AI can be understood by the fact that a bibliometric analysis is not only done to find the number of publications in the field but also to find how the work is distributed in terms of authors, organizations, countries, and publications in different journals based on the citation patterns from the most cited literature to the latest literature in the particular field of study.

In this work, after dataset retrieval from the Web of Science Core Collection data, processing was performed in a dedicated bibliometric environment based on the Bibliometrix R package (Biblioshiny v4.x) for most of the descriptive and inferential analyses, complemented by VOSviewer for network visualizations like co-authorship, co-citation, and keyword-co-occurrence maps [93]. This combined toolchain has broad diffusion in energy and energy-efficiency bibliometrics because it enables both performance analysis (e.g., productivity, citations) and science mapping (e.g., intellectual and social structures).

The analysis followed three main stages:

1. Descriptive performance analysis

In the first stage, an overview of the dataset was produced, including:

- Main information table: Basic characteristics of the corpus (number of documents, sources, authors, average citations, time span, etc.).
- Scientific production over time: Annual publication trends for AI-based solar tracking and MPPT to show how interest in the topic evolved.
- Citations per year: Temporal evolution of total and average citations per year to assess the impact dynamics of the field.
- Three-field plot (countries–authors–sources): A Sankey-style visualization linking the most productive countries, leading authors, and main journals to show how contributions are distributed geographically and by outlet.

2. Science mapping

The second stage focused on mapping the intellectual and collaborative structure of the domain through graphical and network-based indicators [92]. This stage parallels established bibliometric-SLR work in energy efficiency and related areas, and includes:

- Top journals: Identification of the ten most productive journals (by number of AI-solar tracking/MPPT articles) and the ten most cited journals (by total citations within the corpus).
- Top institutions: Ranking of institutions by number of documents to highlight the most active universities and research centers in AI-based solar tracking and MPPT.
- Most relevant authors: Identification of the most prolific authors based on their publication counts in the domain.
- Top countries (corresponding authors): Ranking of countries by single-country and multi-country publications to distinguish national productivity and international collaboration intensity.
- Globally cited authors and documents: Lists of the most cited authors and papers in the entire Web of Science (not only within the local corpus), showing which contributions have the highest global impact.
- Scientific productivity distribution (Lotka's law): Frequency distribution of authors' productivity to check whether publication patterns follow Lotka-like inverse-square behavior.
- Most frequent terms: Analysis and word cloud of the most recurrent words in titles, abstracts, and author keywords to identify dominant topics and terminology.
- Keyword co-occurrence network: Clustered network of author keywords, used to detect thematic groups (e.g., "solar tracker", "neural network MPPT", "metaheuristic optimization", "dual-axis tracking") and their relationships.

Collaboration world map and co-authorship networks:

- A world map displaying international collaboration links between countries.
- An institutional co-authorship network showing collaboration patterns between organizations.

Co-citation networks:

- Author co-citation network to reveal intellectual schools and seminal contributors.
- Journal co-citation network to show how AI-MPPT/solar tracking research is positioned within the broader journal ecosystem.

3. Advanced network and conceptual structure analysis

The third stage applied multivariate and network-analytic techniques to explore the conceptual structure of the field and to identify strategic themes:

- Thematic map: A keyword-based strategic diagram that positions clusters by centrality (relevance to the field) and density (internal development), classifying themes as motor themes, basic themes, emerging/declining themes, or highly specialized niches [94].
- Multiple Correspondence Analysis (MCA): Applied to categorical variables (e.g., high-level keyword groups or subject categories) to visualize the proximity between topics and to detect latent dimensions in the conceptual space [95].
- Correspondence Analysis (CA): Used on contingency tables (e.g., keywords $\times$ years, or keywords $\times$ journals) to display associations between themes and either time or outlets [96].
- Multidimensional Scaling (MDS): A dimensionality reduction approach used to project similarity matrices (e.g., keyword or reference co-occurrence) into a low-dimensional map, offering an alternative visualization of the thematic landscape [97].

All of these components together constitute the research method used to characterize the bibliometric profile of AI-integrated solar tracking and MPPT, as shown in Fig. 2, and the detailed results for each element are presented and interpreted in the subsequent Results section of the article.

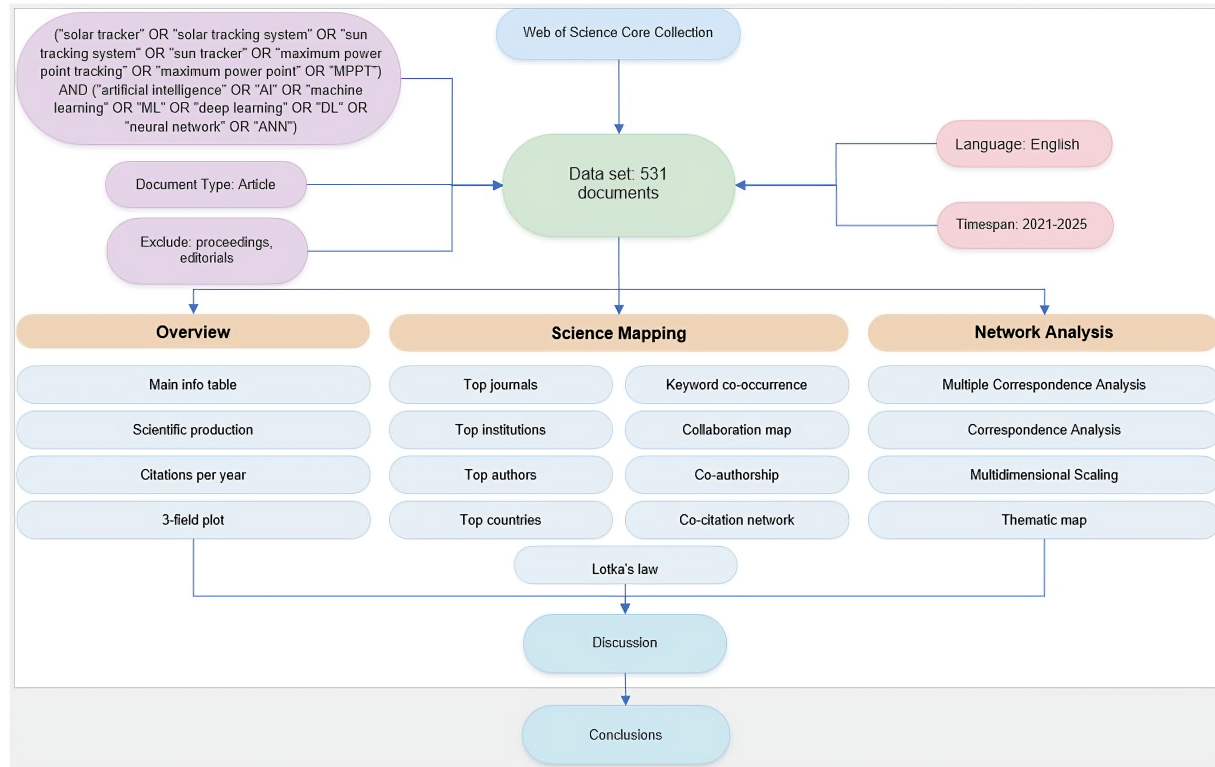


Figure 2: Flow chart of the bibliometric analysis.

5 Research Findings

5.1 Overview of Retrieved Data

Table 2 presents the bibliometric statistics for the intersection of Solar Tracking, MPPT, and AI, as obtained with the Biblioshiny tool. A total of 528 documents from 202 sources (journals, books, etc.), from 2021 to 2025, were fetched. The corpus has a scientific vitality that is quite robust, with an annual growth rate of 21.43% and the average age of the document being 1.65 years.

A good majority of these were research papers, with a total of 495 articles and 24 articles that were accessible online. The average citation rate for these articles was 9.529 citations per document. The content analysis highlighted a wide range of keywords with a total of 499 Keywords Plus and 1.879 Author's Keywords. The data also showed a significant trend towards collaboration for academic purposes. A total of 1.951 authors were involved in creating the 528 documents analyzed in this study. Of those documents, nearly every author collaborated on multiple documents, while just 19 documents were single-authored. The collaboration statistics illustrate the level to which authors work together on documents, averaging 4.41 co-authors per document and an international co-author percentage of 33.4%.

Table 2: Descriptive statistics about the publications extracted between 2021 and 2025.

Description	Results
Main Information about Data	
Timespan	2021–2025
Sources (Journals, Books, etc.)	202
Documents	528 (3 Retracted Excluded)
Annual Growth Rate %	21.43
Document Average Age	1.65
Average citations per doc	9.529
Document Contents	
Keywords Plus (ID)	499
Author's Keywords (DE)	1879
Authors	
Authors	1951
Authors of single-authored docs	18
Authors Collaboration	
Single-authored docs	19
Co-Authors per Doc	4.41
International co-authorships %	33.4
Document Types	
Article	499
Article; early access	24
Article; proceedings paper	5
Article; retracted publication	3

5.2 Performance Analysis

In order to determine the effect of research elements on the research field, a descriptive analysis referred to as performance analysis is carried out. Performance analysis is where different publication sources and journal indices are scrutinized for the evaluation of the effectiveness of authors and sources.

5.2.1 Publication Trends

Fig. 3 reveals the number of papers published every year for the retrieved papers of 528 papers, ranging from the year 2021 to 2025, giving important details about the development of interest in the field of integration between Solar Tracking/MPPT and AI. The result made it clear that the number of papers started with about 69 papers in the year 2021, with an increase reaching a peak of 150 papers in the year 2025, with papers being published. This progression represents a compound annual growth rate of 21.43%, signaling a rapid industrial and academic shift toward intelligent automation in RE. Solar tracking and MPPT techniques are proven concepts, but the optimization of these concepts using the most advanced AI concepts in machine learning has witnessed increased development in recent years in the scientific world.

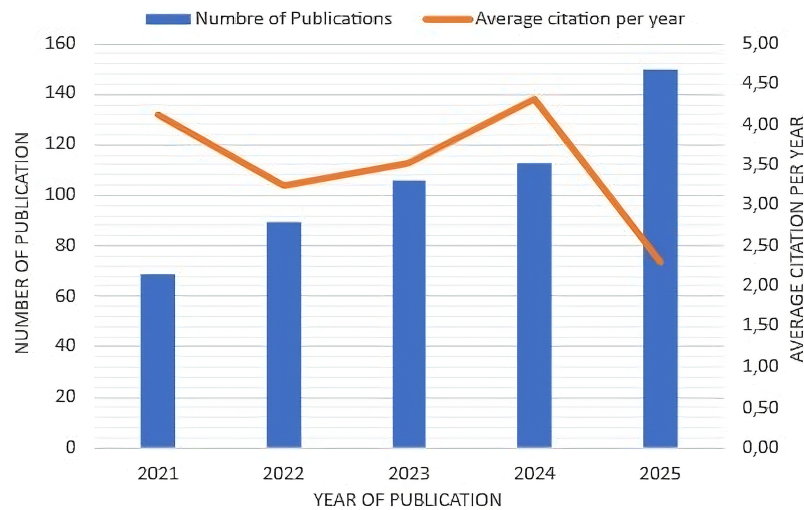


Figure 3: Year-wise publication growth trend of AI-based solar tracking and MPPT research.

As evident from Fig. 3, there has been a steady rise in the number of publications, especially since 2022 and 2024, when the number of publications increased from around 89 to 113 publications. Since 2021, the number of publications has shown a remarkable level of growth, which clearly illustrates that the use of AI technology within PV cells has become an increasingly trending area of scholarly interest around the globe. Although the average number of citations reached its peak in 2024 with around 4.3 citations, the decrement from 2024 to 2025 is, as a rule, associated with the relative newness of the publications, which have not yet garnered sufficient citations. This “citation lag” is a common bibliometric phenomenon where the most recent high-quality works are still in the process of being indexed and cited by the broader community.

The future outlook of the research field with respect to its trajectory is explored further using the models of cumulative growth and the life cycle of the field. Fig. 4 below highlights the Cumulative Growth Curve, which represents a logistic growth curve fitted to the 2021–2025 cumulative publication data using nonlinear least squares regression. The S-shaped profile of this curve confirms that the domain has transitioned from an exploratory niche into a mainstream engineering priority. Based on this trajectory, the field of AI in solar tracking and MPPT has not yet reached the 50% saturation point in terms of the cumulative number of publications, with this point tentatively projected to occur around the year 2040, thus underlining the enormous future potential of this field of research. Nevertheless, because this extrapolation extends well beyond the five-year observation window, the 2040 saturation point should be regarded as an indicative milestone derived from the current trajectory rather than a precise prediction. The maturity and future outlook are more precisely captured in Fig. 5, which presents the Life Cycle of Annual Publications. Unlike the cumulative growth curve in Fig. 4, the growth trend for this model was validated using a non-linear regression model (Life Cycle Analysis), yielding an R^2 value of 0.960. While this high coefficient of determination indicates a statistically robust fit for the observed 2021–2025 period, these long-term projections must be interpreted with caution. Given the relatively short 5-year observation window, these curves represent theoretical, model-driven scenarios rather than definitive predictions. Key observations from this model include:

- **Theoretical Peak Projection:** The mathematical model projects that the research interest could reach its theoretical peak around 2033, with a maximum of nearly 300 annual publications, assuming current growth drivers remain constant.

- **Current Position:** The data points from 2021 to 2025 align closely with the ascending slope of the curve, confirming a period of intense academic interest.
- **Model Sensitivity:** Following this projected peak, the model indicates a gradual stabilization. However, real-world factors such as sudden policy shifts, breakthroughs in alternative energy technologies, or changes in AI computational costs could significantly alter or disrupt this mathematical trajectory before the projected stabilization phase.

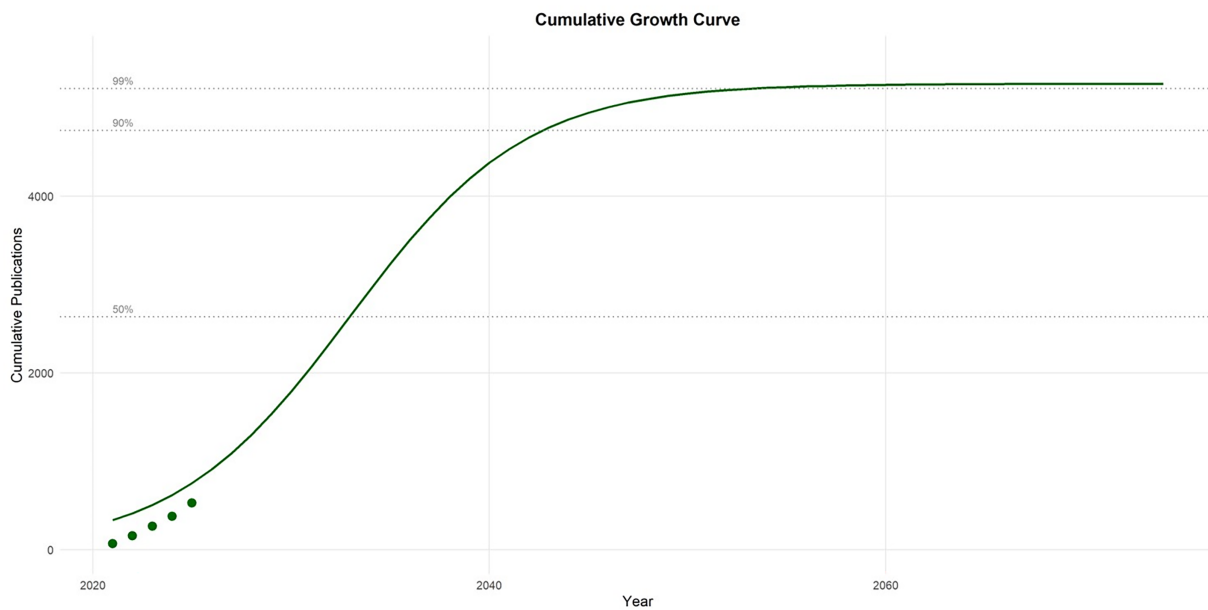


Figure 4: Cumulative growth curve of publications on AI-based solar tracking and MPPT.

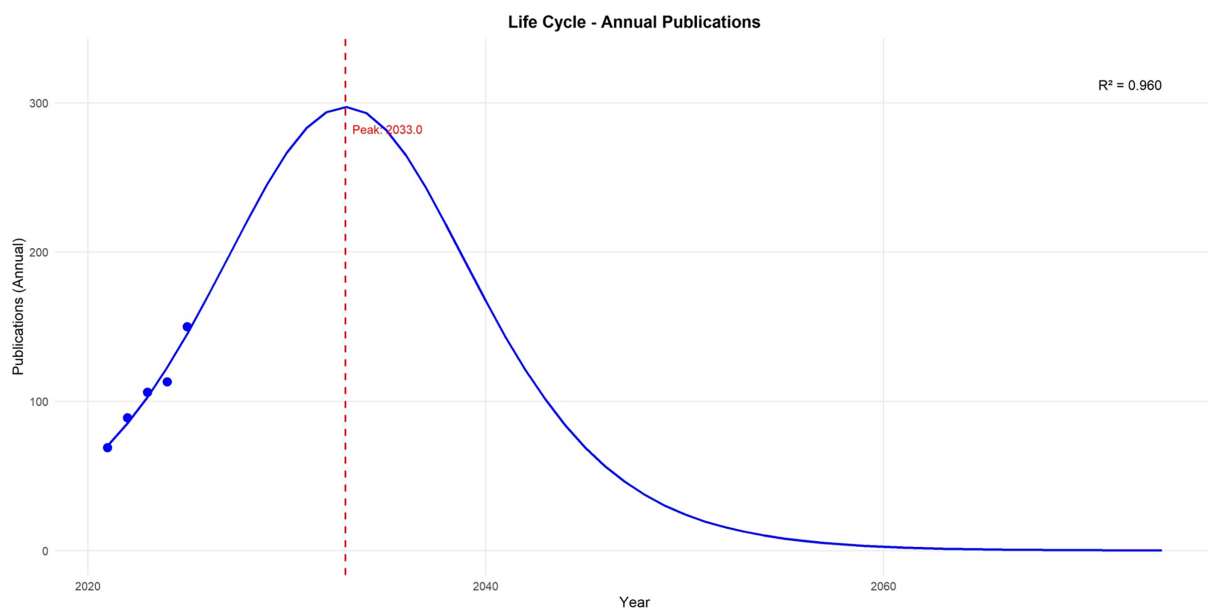


Figure 5: Life cycle analysis of annual publications.

These findings demonstrate that the convergence of AI and PV control technologies is not a fleeting trend but a sustainable research trajectory that is expected to dominate the RE discourse for at least the next ten to fifteen years.

5.2.2 Contribution of Dominant Research Areas

Table 3 and Fig. 6 present the distribution of literature on solar tracking and MPPT based on AI in combination with the top subject categories in the Web of Science indexing and citation platform. Table 2 above indicates that Energy Fuels and Engineering Electrical Electronic are the two top subject categories with an equal contribution of 162 papers, accounting for a joint distribution of 30.5% in each category. This goes to emphasize the entrenched background in the field of energy and electrical engineering, where the application of AI is focused on optimizing PV conversion efficiencies and solar tracking accuracies:

Table 3: Distribution of Web of Science categories for AI-based solar tracking and MPPT publications.

Web of Science Category	Records	Share (%)
Energy Fuels	162	30.508
Engineering Electrical Electronic	162	30.508
Engineering Multidisciplinary	62	11.676
Multidisciplinary Sciences	50	9.416
Green Sustainable Science Technology	48	9.04
Computer Science Information Systems	47	8.851
Telecommunications	38	7.156
Environmental Sciences	37	6.968
Automation Control Systems	34	6.403
Computer Science Artificial Intelligence	33	6.215



Figure 6: Treemap visualization of the Web of Science categories for AI-based solar tracking and MPPT publications.

Fig. 6, which is a treemap, is a good way of illustrating such a disciplinary organization, as it allows rectangles to vary in scale depending on record numbers. MC-sized blocks, such as: Engineering Multidisciplinary (62 records), Multidisciplinary Sciences (50), Green Sustainable Science Technology (48), mark the significance of cross-disciplinary, sustainability-related studies in this field. Other smaller, yet still important, areas of Computer Science Information Systems (47), Telecommunications (38), Environmental Sciences (37), Automation Control Systems (34), Computer Science AI (33), mark the computational, control, as well as environmental aspects that serve as a basis of intelligent solar energy systems. Notably, Table 2 & Fig. 6 combined therefore emphasize that solar tracking, MPPT through AI, represents a disciplinary area of integral interdisciplinary collaboration of energy, electrical engineering, computer science, and environmental sustainability.

5.2.3 Most Productive and Top Cited Journals

Knowing which journals publish the most on AI-based MPPT and solar tracking will help the researcher make informed decisions on where to send their manuscripts for publishing and which journal best fits the interdisciplinary nature of the topic. The top ten journals are listed in Table 4, together with their impact indicators (h-index, g-index, m-index, total citations, and total publications), Web of Science categories, JIF, quartile rank, and country of the publisher. These metrics have been extracted from the recent Journal Citation Reports and the corresponding Web of Science classifications, recognized as a common tool of journal scientific influence ranking in a specific subject category.

Table 4: Top 10 most productive journals in AI-based photovoltaic solar tracking and MPPT research.

Rank	Source	h_Index	g_Index	m_Index	TC	TP	WoS Category	JIF	Quartile	Country
1st	IEEE Access	12	24	2.4	589	29	Engineering, Electrical & Electronic	3.9	Q1	USA
2nd	Energies	10	17	2	313	29	Energy & Fuels	3.2	Q2	Switzerland
3rd	Energy Reports	9	15	1.8	316	15	Energy	6.8	Q1	Netherlands
4th	Scientific Reports	9	12	3	170	27	Multidisciplinary Sciences	4.6	Q1	UK
5th	Sustainability	9	14	1.8	204	17	Green & Sustainable Science	3.9	Q2	Switzerland
6th	Electrical Engineering	6	7	1.5	75	15	Engineering, Electrical	1.7	Q3	Germany
7th	International Journal of Hydrogen Energy	6	6	1.2	179	6	Energy & Fuels	7.2	Q1	UK
8th	International Journal of Re Research	6	8	1.2	75	12	RE	2.8	Q3	Turkey
9th	Clean Energy	4	5	1	39	5	Energy	3.1	Q2	China
10th	Electric Power Systems Research	4	4	0.8	112	4	Energy & Fuels	5.3	Q1	Netherlands

It is observed from Table 3 that IEEE Access tops the list with the highest value of h-index (12) and citation numbers (589), accompanied by a considerable number of published papers (29) in the Engineering, Electrical & Electronic field, portraying its nature of being a multidisciplinary but highly engineering-based journal. Energies and Sustainability, published from Switzerland, demonstrate high productivity (29

and 17 papers, respectively) in the Energy & Fuels and Green & Sustainable Science fields, reaffirming that a substantial amount of research on AI-based MPPT/solar tracking is being published through energy/sustainability journals rather than from strictly computer science-based ones. Energy Reports, Scientific Reports, International Journal of Hydrogen Energy, and Electric Power Systems Research have achieved a Q1 ranking with high impact factor values, suggesting that top-notch research contributions under this niche are published through top quartile energy/multidisciplinary citation-rated journals.

The presence of Electrical Engineering and International Journal of RE Research, being Q3 journals with medium JIF values, indicates that specialized journals like electrical engineering and RE research also serve as an equally valuable platform for the published research work, especially for papers with more technical or application-oriented approaches. Clean Energy, being a Q2 journal from China, exemplifies how new journals in the energy sector have started gaining submissions on AI-optimized MPPT and solar tracking, even with reduced numbers of published papers and citations. It is observed that the distribution of published papers for Q1 & Q2 journals with JIF values above 3 indicates that research on AI-optimized MPPT and solar tracking is being published on genuine, high-profile venues, marking the advancement and relevance of interdisciplinary research.

5.2.4 Contribution of Leading Countries/Institutions

Analysis of [Table 5](#) makes it clear that a significant amount of literature on both AI-based MPPT techniques as well as solar trackers appears to be published by a few select nations, with India turning out to be a hotbed of publication activity. India alone has published 178 papers, which makes up 33.7% of the total literature published, with a significant portion of these being single-country published works (SCP) that strongly suggest that there exists a huge, internally closed community that has sufficient literature to publish prolifically with little need to collaborate heavily with international organizations. China comes second, publishing 63 papers, with a higher percentage of them being multiple-country published works (31.7%), implying that Chinese organizations are more internationally collaborative.

Table 5: Top 10 most productive countries in AI-based photovoltaic solar tracking and MPPT research.

Country	Articles	Articles %	SCP	MCP	MCP %
India	178	33.7	145	33	18.5
China	63	11.9	43	20	31.7
Morocco	34	6.4	27	7	20.6
Algeria	28	5.3	18	10	35.7
Egypt	27	5.1	15	12	44.4
Tunisia	19	3.6	14	5	26.3
Saudi Arabia	17	3.2	7	10	58.8
United Arab Emirates	10	1.9	3	7	70
United Kingdom	9	1.7	2	7	77.8
Korea	7	1.3	5	2	28.6

North African nations like Morocco (34 papers, 6.4%), Algeria (28, 5.3%), Egypt (27, 5.1%), and Tunisia (19, 3.6%) account for a large number of papers among the global production, ensuring that AI-based MPPT and solar tracking have been an area under intensive study in the whole MENA region. The countries illustrate different collaboration indexes, with Algeria and Egypt having large percentages like 35.7% and 44.4%, respectively, which explain their intensive global interaction, while Morocco and Tunisia largely depend on a global team, as evident by 20.6% and 26.3% MCP, respectively.

The geographical dominance of India and the MENA region (Morocco, Algeria, Egypt) can be attributed to a combination of high solar irradiance levels, specifically high Global Horizontal Irradiance (GHI) and Direct Normal Irradiance (DNI), and aggressive national renewable energy policies, such as India's National Solar Mission. These regions prioritize AI-based optimization as a low-cost means to maximize the efficiency of existing infrastructure in harsh, variable climates where partial shading and dust accumulation are frequent challenges. Consequently, research funding in these nations is heavily directed toward intelligent, self-adaptive solar technologies to ensure energy security.

The Gulf states and developed economies are more visible if collaboration intensity, not the quantity, is taken into account. Saudi Arabia (17 papers; 3.2%) and the United Arab Emirates (10 papers; 1.9%) both indicate more than half their publications as MCP, emphasizing that their level of notability in this area is largely contingent on international collaboration. Similarly, the United Kingdom, which has produced 9 papers (1.7%), has the highest level of collaboration among the listed countries (77.8% as MCP), emphasizing its position as a partner of choice for concerted action rather than a producer in large numbers. Korea rounds out the top ranks with 7 papers (1.3%), with an SCP and MCP proportion balanced evenly at 28.6% for SCP, emphasizing a developing but largely moderate level of global collaboration in this area.

The dominance of SCP, rather than MCP, for the large majority of countries listed suggests that, despite the broad global interest in AI-driven solar tracking and MPPT, global collaboration structures in this area remain modest and could use development in order to increase global knowledge transfer and convergence in methodology.

Fig. 7 presents the worldwide co-authorship network for research in AI-based MPPT and solar tracking. Each directed link corresponds to collaboration from one country to another, whose thickness is set with the collaboration strength measured by the frequency value. The full matrix underlying this graph shows that India, China, Saudi Arabia, and Algeria are among the main hubs, in close contact with several countries such as Australia, Vietnam, Qatar, Kuwait, Poland, and many European and African nations; instead, negative or low frequencies suggest weak or sporadic links between several pairs of countries.



Figure 7: International collaboration network in AI-based MPPT and solar tracking research.

5.2.5 Author's Influence

Authors play a central role in shaping the emerging field of AI-based MPPT and solar tracking, and Table 6 summarizes the contributions and influences of the most active researchers in this domain. The first block of the table lists the highly published authors according to their h-index, highlighting Sarwar Adil and (h_index = 6) Tariq Mohd (h_index = 5) as the leading researchers, followed by a group of authors such as Alsaif Faisal, Gaga Ahmed, and Khan Mohammad Junaid with h indices of 4, indicating consistent citation impact across multiple papers.

Table 6: Ranking of the most influential authors in AI-based MPPT and solar tracking.

Rank	h_Index		High-Published Authors		Most Local Cited Authors	
	Author	h_Index	Author	Articles	Author	Freq
1st	Sarwar Adil	6	Sarwar Adil	6	Khan Baseem	28
2nd	Tariq Mohd	5	Attia Hussain	5	Dhanamjayulu C.	23
3rd	Alsaif Faisal	4	el Akchioui Nabil	5	Hussaian Basha C.H.	23
4th	Gaga Ahmed	4	Gaga Ahmed	5	Kiran Shaik Rafi	23
5th	Khan Mohammad Junaid	4	Khan Mohammad Junaid	5	Prusty B. Rajanarayan	23
6th	Sain Chiranjit	4	Ncir Noamane	5	Singh Vishwa Pratap	23
7th	Senthilkumar S.	4	Sain Chiranjit	5	Mahmuda Khatun	18
8th	Agarwal Anshul	3	Tariq Mohd	5	Mithulananthan Nadarajah	18
9th	Ahessab Hajar	3	Ahessab Hajar	4	Alahakoon Sanath	18
10th	Ahmad Furkan	3	Alsaif Faisal	4	Amin Nowshad	18

The second block enumerates the most locally cited authors within the analyzed corpus. As shown in the rightmost panel of Table 6, Khan Baseem leads this list with 28 local citations, followed by Dhanamjayulu C., Hussaian Basha C.H., Kiran Shaik Rafi, Prusty B. Rajanarayan, and Singh Vishwa Pratap, each with 23 local citations. This distribution indicates that local influence is horizontally spread across a diverse core of researchers rather than vertically concentrated within a single scholar. It is noteworthy that the most prolific contributors in terms of publication output Sarwar Adil (6 articles) and Attia Hussain, Gaga Ahmed, Khan Mohammad Junaid, Ncir Noamane, Sain Chiranjit, and Tariq Mohd (5 articles each) do not appear among the most locally cited authors, underscoring that productivity and local citation impact represent distinct dimensions of scholarly influence within this field.

Finally, the most locally cited authors column ranks researchers by their local citation frequency within the analyzed corpus, with Khan Baseem leading (28 local citations), followed by a cluster of influential authors Dhanamjayulu C., Hussaian Basha C. H., Kiran Shaik Rafi, Prusty B. Rajanarayan, and Singh Vishwa Pratap each with 23 local citations, while several others, such as Mahmuda Khatun, Mithulananthan Nadarajah, Alahakoon Sanath, and Amin Nowshad, receive 18 local citations each. By contrast, the high-published authors column shows a more concentrated publication output: Sarwar Adil leads with 6 articles, followed by Attia Hussain, el Akchioui Nabil, Gaga Ahmed, Khan Mohammad Junaid, Ncir Noamane, Sain Chiranjit, and Tariq Mohd with 5 articles each, and Ahessab Hajar and Alsaif Faisal with 4 articles each. This pattern indicates that local citation impact is distributed across a broader set of researchers than publication volume, which is concentrated within a smaller core of prolific contributors, reflecting distinct dimensions of scholarly influence in AI-driven MPPT and solar tracking research.

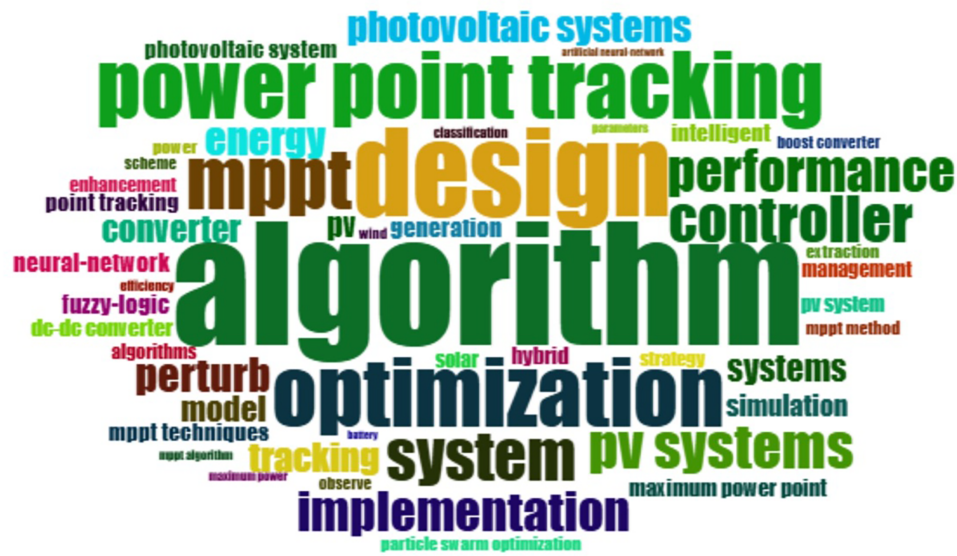


Figure 9: Word cloud of keyword plus.

5.3 Science Mapping

In research, science mapping is specifically interested in relations among different elements within a specific field and how they fit together into a larger intellectual structure. This is undertaken by scrutinizing relations based on citation, shared references, co-author relations, and co-keyword relations. By combining different bibliometric methods with other relations based on networks, it creates a strong methodology to graphically illustrate, on different levels, not only the intellectual structure of a specific field, but also the conceptual structure of an investigated area [98].

5.3.1 Collaborative Co-Authors Network Analysis

One other technique that can be applied in collaboration networks is the core author technique, which might enable the identification of the central authors and also reveal the structure of scientific collaborations within a particular field. With VOSviewer, authors can be depicted with different colors based on their co-authorship. Fig. 10 below depicts a co-authorship graph of authors involved in MPPT based on AI and solar tracking, with each node representing an author, and each line connecting two authors representing collaboration between authors. The size of each node displays author publication activity, with larger nodes denoting more active authors, and line thickness denoting higher levels of collaboration.

From Fig. 10, it is evident that there are a number of well-defined clusters within the network, which may be representative of several groups of researchers or schools of thought contributing moderately well within their clusters, and less so between clusters. Researchers who seem to be central to the network, such as those represented by authors such as Tariq Mohd, and their related collaborators, are likely to be bridge nodes, thereby enabling knowledge sharing among different groups of people within their defined networks. From this figure, it is evident that cooperation identified within this field of study is not equally disseminated; instead, it is dominated by a number of well-structured author groups, which are evident to comprise the backbone of cooperation for AI-based MPPT and solar tracking systems.

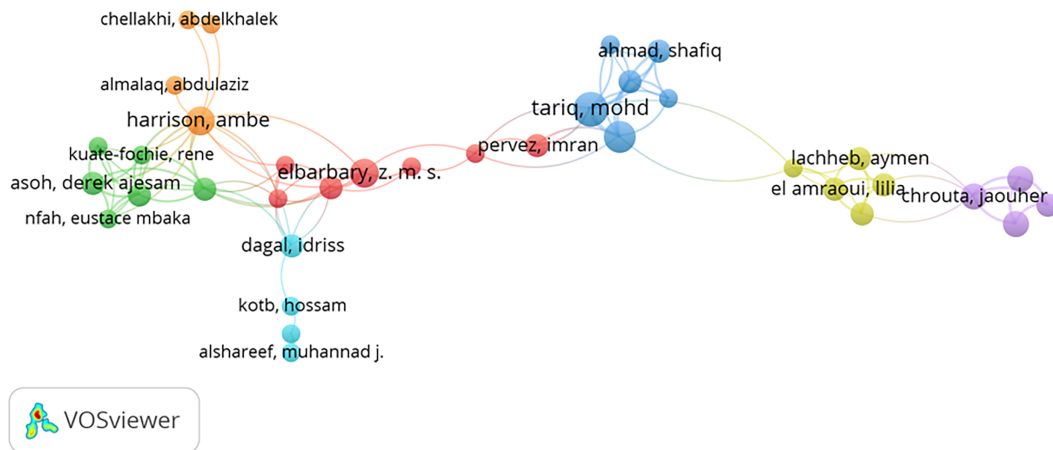


Figure 10: Co-authorship network of the most productive authors in AI-based MPPT and solar tracking research.

5.3.2 Collaborative Countries Network Analysis

Country co-authorship analysis is an important type of co-authorship analysis that reveals the degree of country interaction and the most important contributors, especially in a particular research area. In the current research, the VOSviewer tool is utilized to build the network of country co-authorship in the publications of AI-based MPPT and solar tracking, as shown in Fig. 11. In the figure, various colors are used to distinguish co-author clusters, while the scale of nodes corresponds to the number of publications from every country or region, and their thickness corresponds to their country connections.

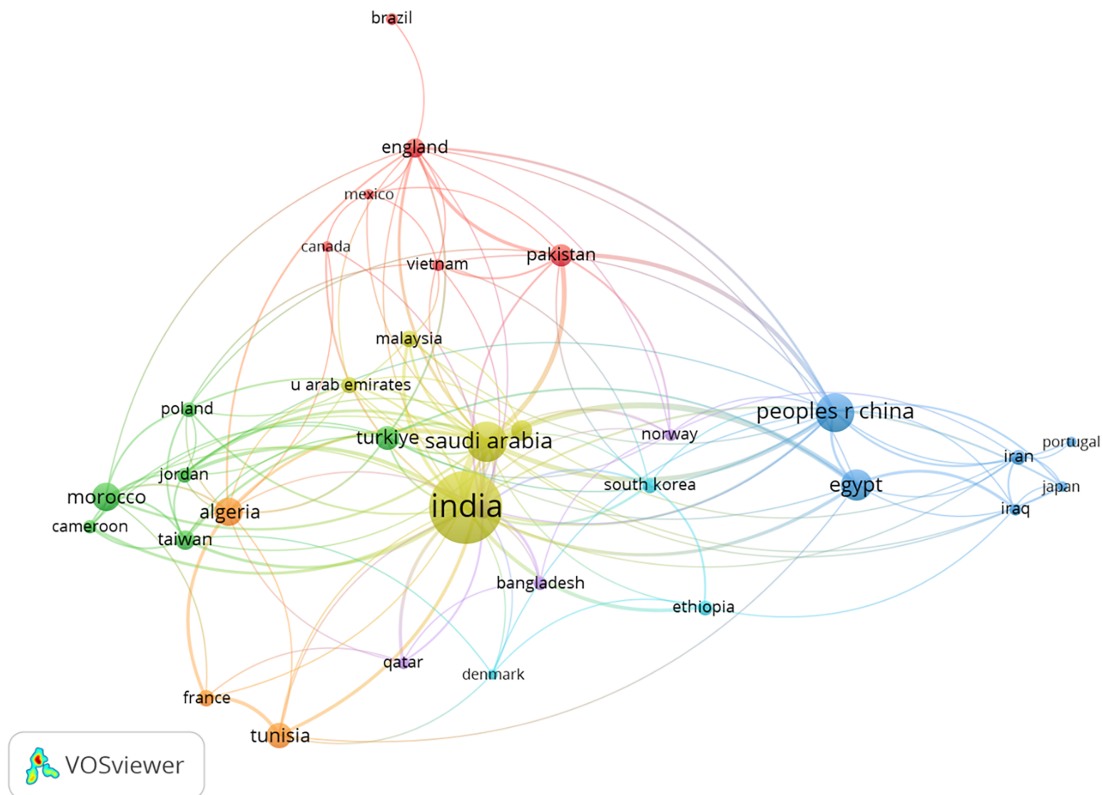


Figure 11: International co-authorship network in AI-based MPPT and solar-tracking research.

Table 8 presents the bibliographic coupling statistics for the 10 most productive countries in this field, ranked by total link strength derived from the VOSviewer analysis. Bibliographic coupling measures the extent to which countries share common references in their publications, reflecting intellectual proximity and thematic alignment rather than direct co-authorship ties. Saudi Arabia (TLS = 80) and India (TLS = 52) exhibit the strongest bibliographic coupling links, indicating a substantial overlap in their cited reference pools. These nations are followed by the People's Republic of China (64 documents, 545 citations, total link strength of 29). Egypt and Pakistan show comparable levels of bibliographic coupling, each with a total link strength of 25, while Australia, England, Jordan, the USA, and Algeria complete the top 10 list with progressively lower but still notable link strengths.

Table 8: Bibliographic coupling statistics for the most productive countries in AI-based MPPT and solar tracking research.

Rank	Country	Documents	Citations	Total Link Strength
1st	Saudi Arabia	68	952	80
2nd	India	213	1783	52
3rd	China	64	545	29
4th	Egypt	39	600	25
5th	Pakistan	22	427	25
6th	Australia	14	456	18
7th	England	17	302	17
8th	Jordan	10	36	13
9th	USA	18	255	12
10th	Algeria	33	331	7

5.3.3 Collaborative Institutions Network Analysis

To examine collaboration patterns at the institutional level, an institutional co-authorship network was generated using VOSviewer. In this analysis, all 849 contributing organizations were first considered, and a minimum threshold of two documents per organization was applied; 231 institutions met this criterion and were included in the map. The resulting network, shown in [Fig. 12](#), visualizes each institution as a color-coded node, with links between nodes representing co-authorship relationships whose thickness reflects collaboration strength.

5.3.4 Reference Citation Analysis

[Fig. 13](#) illustrates the citation network among the top citation papers using VOSviewer, which requires a minimum of 10 citations per item; among the dataset of 528 publications, there are 172 papers that satisfy this criterion to be positioned on the visualization. In this visualization, the size of the nodes represents the total number of citations, and colors represent clusters of authors whose work is closely related to specific research on intelligent renewable energy integration as well as advanced management systems.

As reported in [Table 9](#), the article by Ali (2021) in *Sensors* ranks first with 107 total citations, corresponding to 17.83 citations per year and a normalized citation count of 5.19, which confirms its central role as a methodological and conceptual reference. This paper is positioned near the center of the network in [Fig. 13](#), where it is connected to several other highly cited works, indicating that many subsequent studies build directly on its contributions.

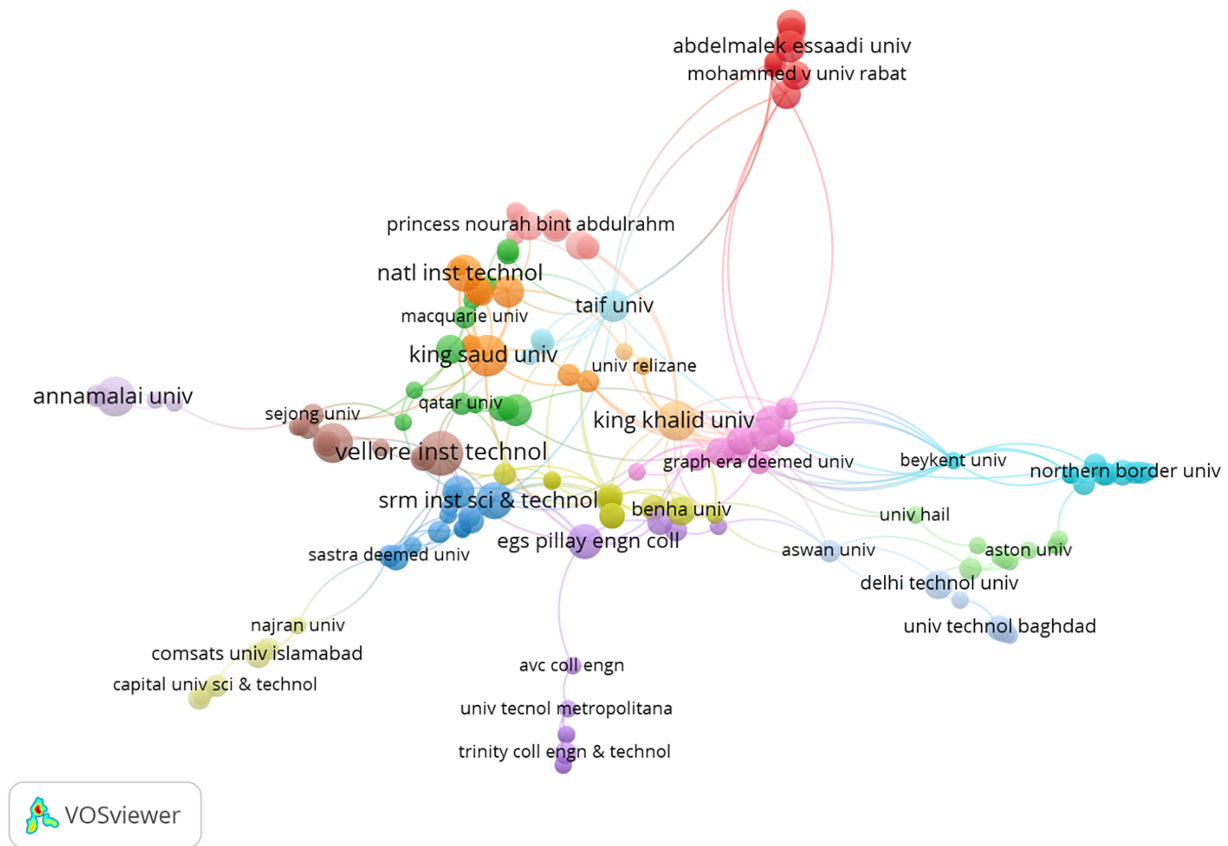


Figure 12: Institutional co-authorship network in AI-based MPPT and solar tracking research.

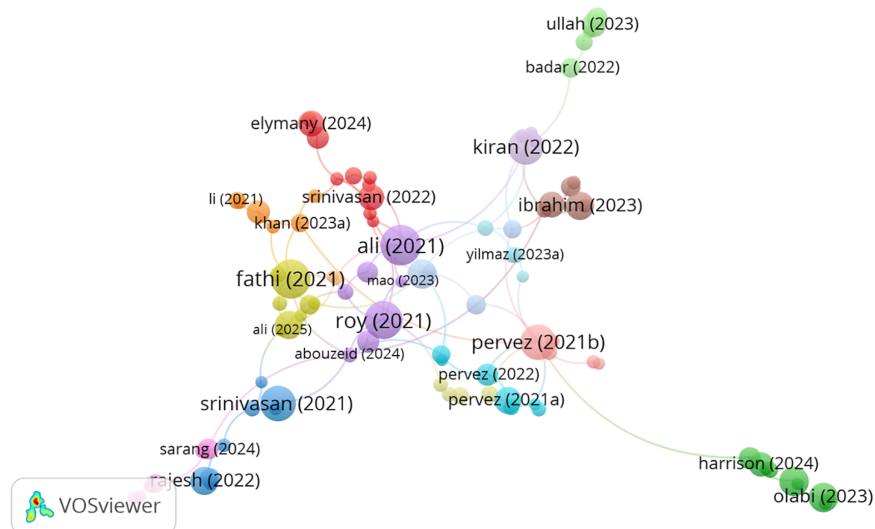


Figure 13: Co-citation network of the most influential references in AI-based MPPT and solar tracking research.

Table 9: Top cited papers in AI-based MPPT and solar tracking research and their citation metrics.

Rank	Paper	Doi	Total Citations	TC Per Year	Normalized TC
1	Ali, 2021, Sensors	[99]	107	17.83	5.19
2	Fathi, 2021, Energy Rep	[100]	101	16.83	4.90
3	Roy, 2021, IEEE Access	[101]	95	15.83	4.61
4	Chojaa, 2021, Energy Rep	[102]	95	15.83	4.61
5	Srinivasan, 2021, Int J Hydrog Energy	[103]	84	14.00	4.07
6	Kiran, 2022, IEEE Access	[104]	81	16.20	6.23
7	Pervez, 2021, IEEE Trans Sustain Energy	[105]	80	13.33	3.88
8	Allahabadi, 2022, IEEE Trans Ind Electron	[106]	59	11.80	4.54
9	Olabi, 2023, Therm Sci Eng Prog	[107]	58	14.50	5.47
10	Nouri, 2024, Electr Power Syst Res	[108]	55	18.33	6.34
11	Babes, 2022, Neural Comput Appl	[109]	54	10.80	4.15
12	Padmanaban, 2021, IEEE Access	[110]	54	9.00	2.62
13	Ibrahim, 2023, IEEE Access	[111]	53	13.25	5.00
14	Rajesh, 2022, Technol Econ Smart Grids Sustain Energy	[112]	53	10.60	4.08
15	Pervez, 2021, IEEE Access	[113]	49	8.17	2.38
16	Badr, 2021, IEEE Access	[114]	46	7.67	2.23
17	El Mezdi, 2023, J Energy Storage	[115]	45	11.25	4.24
18	Haq, 2022, Plos One	[116]	45	9.00	3.46
19	Srinivasan, 2022, Int J Electron	[117]	44	8.80	3.38
20	Elymany, 2024, Energy Conv Manag	[118]	44	14.67	5.07
21	Eskandari, 2023, Int J Electr Power Energy Syst	[119]	42	10.50	3.96
22	Harrison, 2024, Int J Dyn Control	[120]	42	14.00	4.84
23	Ullah, 2023, Ain Shams Eng J	[121]	40	10.00	3.77
24	Saleem, 2023, Energies	[122]	40	10.00	3.77

The second most cited article is Fathi (2021) in Energy Reports with 101 citations (16.83 citations per year, normalized TC 4.90), followed by Roy (2021) and Chojaa (2021), each with 95 citations and 15.83 citations per year. These studies belong to the same dense cluster as Ali (2021) in Fig. 13 and focus on optimization, planning, and control of hybrid and smart energy systems, forming a coherent core within the citation landscape.

Although more recent publications have fewer cumulative citations, their annual citation rates and normalized citation counts indicate rapidly growing influence. For instance, Kiran (2022) in IEEE Access and Nouri (2024) in Electric Power Systems Research have 81 and 55 citations, yet achieve 16.20 and 18.33 citations per year and the highest normalized citation scores in the set (6.23 and 6.34, respectively), showing fast uptake by the research community. Similarly, the works of Olabi (2023) and Elymany (2024) exhibit normalized citation values above 5, highlighting their emerging importance for topics such as energy storage, electric vehicles, and grid integration.

Fig. 13 reveals several dense clusters corresponding to well-defined sub-themes. One major cluster gathers mainly 2021 publications (Ali, Fathi, Roy, Srinivasan, Padmanaban, Badr, Rajesh, and others) that address modeling, control, and optimization of generation and storage systems, representing the methodological backbone of the field. A second cluster links authors such as Kiran, Pervez, Ibrahim, Ullah, and Olabi, emphasizing advanced smart grid architectures, power electronic interfaces, and multi-energy management, which mark a shift from foundational concepts to more integrated applications.

A third group of nodes, including Nouri, El Mezdi, Eskandari, Harrison, and Ul Haq, lies closer to the periphery of the network and is composed of the most recent studies on multi-objective optimization, AI-based dynamic management, and network stability assessment. Their peripheral but well-connected positions suggest that they extend the existing knowledge base while strongly relying on the seminal works located in the central clusters.

Combining the evidence from Fig. 13 and Table 8 shows that scientific impact depends not only on total citation counts but also on how quickly citations accumulate. Recent papers such as those by Kiran (2022), Nouri (2024), Olabi (2023), and Elymany (2024) display high annual citation rates and normalized TC values, indicating that they are shaping current research directions in intelligent energy systems more strongly than some older but moderately cited works. In contrast, earlier contributions such as Padmanaban (2021) and Badr (2021) maintain solid citation numbers but lower normalized TC, suggesting that they serve mainly as foundational references rather than drivers of the latest research fronts.

5.3.5 The Journals Co-Citation Analysis

Fig. 14: Journal co-citation network of the selected dataset. Each node corresponds to a journal, and links indicate how often two journals are cited together. The map is structured into four major clusters, each corresponding to a distinct thematic focus on RE systems, optimization methods, and intelligent control.

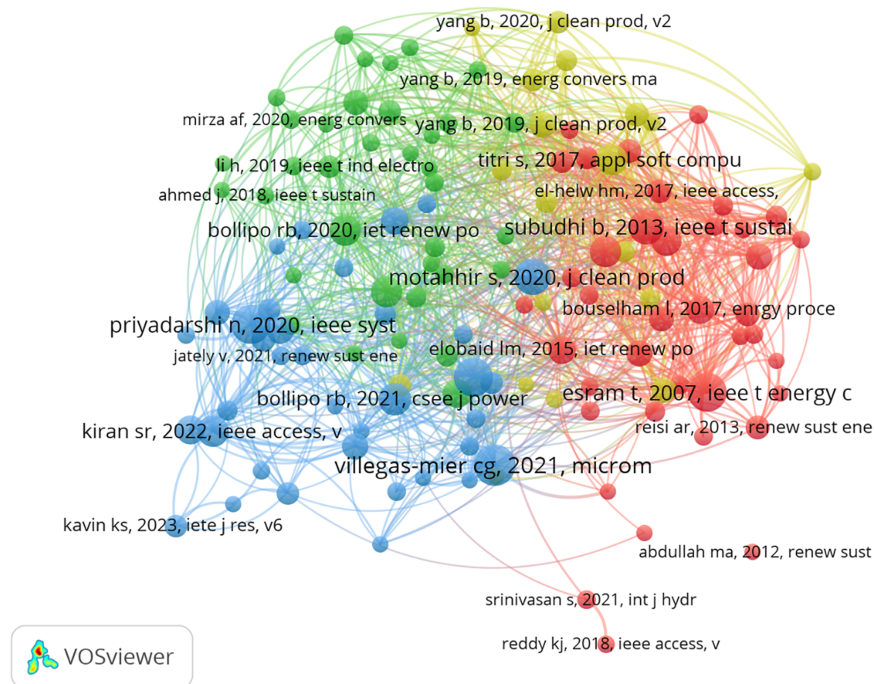


Figure 14: Reference co-citation network for AI-based MPPT and solar tracking publications.

The IEEE Transactions on Sustainable Energy and Renewable and Sustainable Energy Reviews dominated the red cluster, with a majority having foundational studies related to advanced power system operation and high-penetration renewable integration. The green cluster groups journals like Journal of Cleaner Production and Energy Conversion and Management on environmental performance, lifecycle assessment, and techno-economic evaluation of clean energy solutions.

The blue cluster focuses on engineering and power system application journals such as IEEE Access, IET Renewable Power Generation, and CSEE Journal of Power and Energy Systems that discuss case studies, control strategies, and implementations in the real world and bridge theory and practice. Finally, the yellow cluster is comprised of journals related to optimization, soft computing, and applied mathematics, such as Applied Soft Computing and companion titles emphasizing the methodological backbones of metaheuristic and AI-based approaches used throughout the other clusters.

5.3.6 Frequency Distribution of Scientific Productivity (Lotka's Law)

In this bibliometric analysis, Lotka's law was used to assess the output of authors who contributed to the AI-based MPPT and solar tracking study field. This was based on the relationship between the number of documents published by an author and the percentage of authors who published those documents [123]. In Lotka's law, a few authors with higher output published most of the documents, with a majority of authors having just one or two published works.

Fig. 15 below shows the productivity curve for the authors in the dataset, superimposed on the theoretical Lotka distribution, and indicates how well the actual data fits the predicted form, following the inverse square kind of fall-off with the number of papers. The steep fall in the percentage level of authors proceeding from one to multiple papers reinforces the idea that few people follow up on AI-based MPPT and solar tracking topics

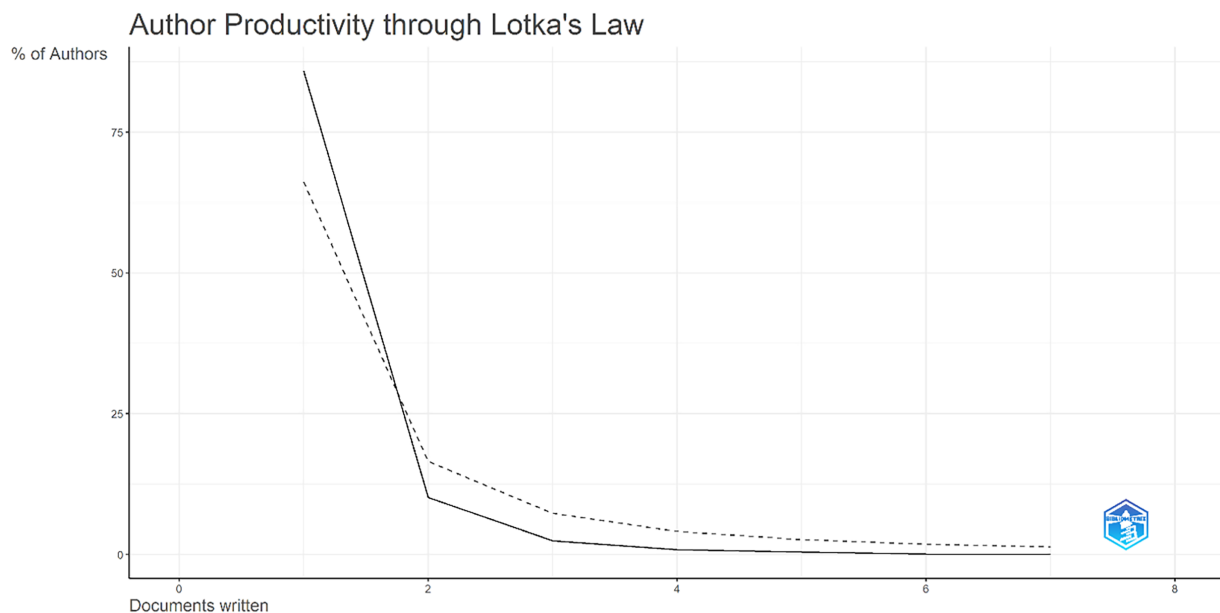


Figure 15: Author productivity distribution in the AI-based MPPT and solar tracking research field according to Lotka's law.

Table 10 quantifies this distribution, indicating that 1566 authors (85.9%) have written a single document, whereas only 185 authors (10.1%) have produced two documents and 45 authors (2.5%) have authored three documents. The tail of the distribution is very thin, with a few highly productive authors contributing four or more documents, which demonstrates that Lotka's law is well satisfied for this corpus and that scientific output in AI-based MPPT and solar tracking research is strongly concentrated among a small core of prolific researchers.

Table 10: Distribution of author productivity in the AI-based MPPT and solar-tracking research corpus.

Documents Written	Number of Authors	Proportion of Authors
1	1566	0.859
2	185	0.101
3	45	0.025
4	16	0.009
5	9	0.005
6	2	0.001
7	1	0.001

This high proportion of authors with only a single publication (85.9%) suggests that the field of AI-based PV optimization is highly multidisciplinary, attracting a large number of ‘transient’ researchers from computer science or general engineering who apply specific algorithms to PV datasets as one-time case studies. Scientifically, this indicates that while the field is ‘open’ and trending, the intellectual continuity is maintained by a very small, elite core of specialists (the 1.6% of authors with 4 or more papers). For new researchers, this implies that while the barrier to entry is low, achieving a high-impact standing requires long-term, sustained engagement with the technical complexities of hardware-software integration rather than simple algorithmic application.

5.3.7 Research Hotspots: Keyword Co-Occurrence Network Analysis

The keyword co-occurrence analysis can be seen to be an effective approach for analyzing the intellectual structure in the MPPT literature, since such an analysis helps to determine the prevalence of the specified author keywords and, therefore, serves to determine the major topics and their connections. The more frequently the specified author keywords occur in the same papers, the more closely they are associated.

For this paper, a co-occurrence analysis with author keywords was carried out using VOSviewer to produce a visual representation of the research area of MPPT, as shown in [Fig. 16](#) below. The different forms of the same word were merged before doing the analysis, taking into account the following parameters: type of analysis = co-occurrence, counting method = full counting, and unit of analysis = author keywords.

A minimum occurrence of 10 was used, which indicated that only those keywords that were found at least 10 times in the text were taken into consideration for representation in the graph; of the 2070 identified keywords, 70 were shortlisted and were used in the final graph (see [Fig. 16](#)) of the keyword co-occurrence map, and this map comprises 70 nodes and many relations between them, in which every node and relation illustrates the keyword and the link relation between the keywords respectively; every node in the graph has sizes proportional to its frequency of occurrence, while the thickness of the link shows the level of keyword co-occurrence.

The smart local movement algorithm was employed in the VOS viewer to identify several major clusters for the main research issues within MPPT and PV systems. The central blue color cluster contains the commonly occurring keywords such as ‘MPPT’, ‘mppt’ ‘PV systems and ‘algorithm’ signifying that the central theme revolves around these terms, while the remaining clusters contain keywords associated with intelligent control methods (artificial intelligence, machine learning, ANN, and fuzzy logic) and system level analysis (PV systems, converters, hybrid systems, and efficiency). Based on the analyzed corpus, the AI methodologies can be categorized into a distinct taxonomy: (i) Fuzzy Systems, primarily used for Linguistic control in MPPT; (ii) ANN, including Shallow and DL architectures for irradiance prediction; (iii)

Metaheuristic Optimization, such as Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO), used for global peak detection; and (iv) Hybrid Systems, which combine evolutionary algorithms with neural networks to balance convergence speed and tracking accuracy. The emergence of Reinforcement Learning (RL) represents the latest branch of this taxonomy, focusing on model-free adaptive control.

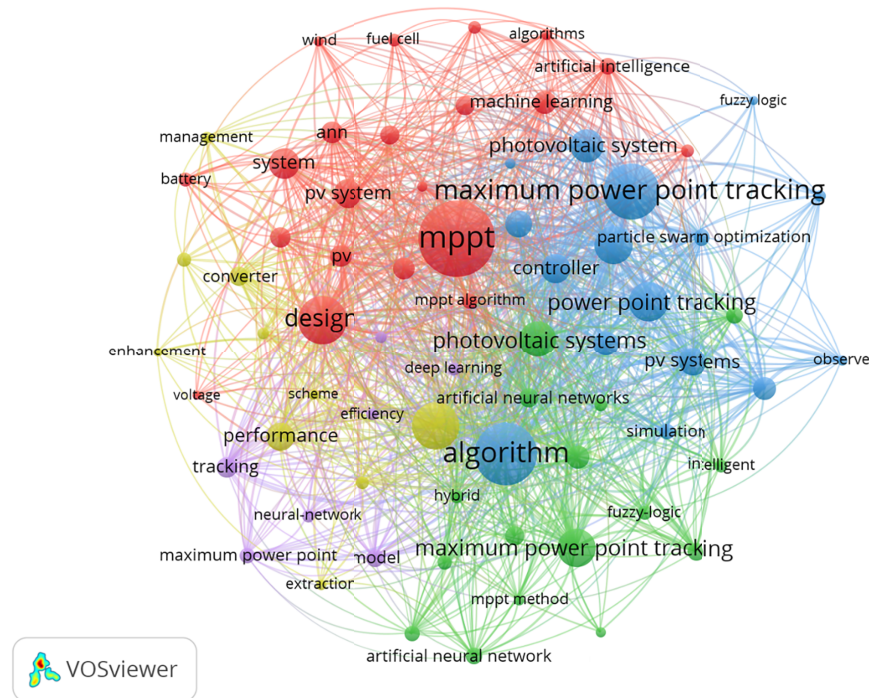


Figure 16: Keyword co-occurrence network of the AI-based MPPT and solar-tracking research field.

5.4 Network Analysis

5.4.1 Thematic Map

Fig. 17 shows the strategic diagram of themes for AI-based MPPT and solar tracking research, with each cluster located based on its centrality and density. The horizontal axis of this diagram indicates centrality, which expresses how well a theme is connected with other themes, and the vertical axis is density, which expresses how well a cluster is developed inside its domain of research.

Within the upper right quadrant, the well-developed and very central themes can be seen as motor topics for the AI-based MPPT and solar tracking literature and are usually described by keywords such as MPPT control, PV systems, and optimization algorithms. These themes are distinguished by having high links both internally and externally with other clusters and thereby demonstrate that they form the central areas of research and studies in the AI-based MPPT and solar tracking field.

The upper left corner includes specialized but isolated subjects that offer high density and low centrality, like niche AI-based MPPT and solar tracking methods or dedicated hardware solutions that offer methodological innovativeness but lower relatedness to the research agenda. The lower right corner includes emerging and transversal subjects that provide high centrality but low density, representing promising subjects related to intelligent control, AI-based approaches, or hybrid energy systems that are well related but not fully assimilated yet.

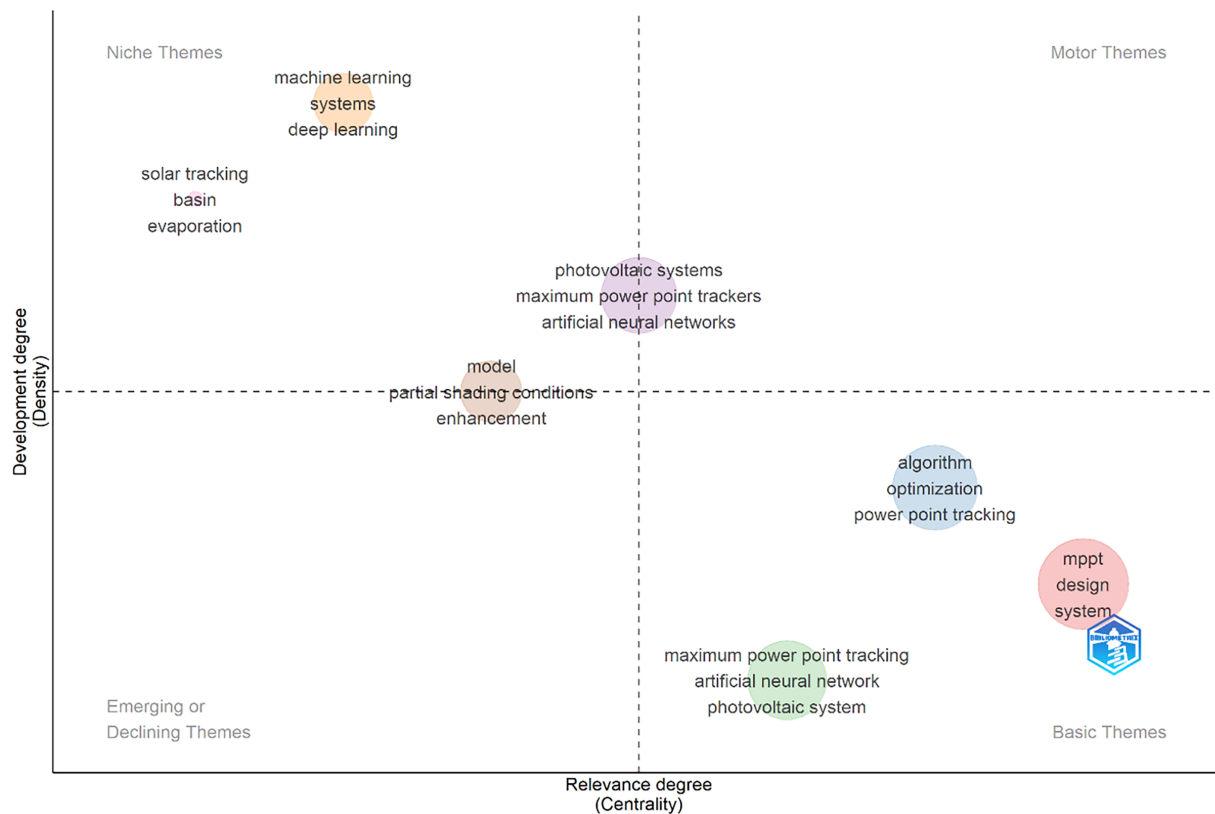


Figure 17: Evolution of the thematic structure of AI-based MPPT and solar tracking research.

Finally, there is the lower left quadrant that houses theme developments which have low density and low centrality, and which may include areas of an exploratory nature or those which have become less relevant within the field of AI-based MPPT and solar tracking. In summary, Fig. 17 above shows how the AI-based MPPT and solar tracking field has evolved from a traditional field of mostly AI-based MPPT and solar tracking control strategies into a more integrated and intelligent field of MPPT and solar tracking.

The strategic positioning of clusters in Fig. 17 provides a roadmap of the field's priorities. The presence of 'Maximum Power Point Tracking' and 'PV Systems' in the Motor Themes quadrant confirms that these topics are the established pillars of the current literature, possessing both high internal development and strong external relevance. Interpretation of the Emerging/Transversal quadrant reveals a critical shift: keywords such as 'Deep Learning' and 'Hybrid Optimization' are moving toward the center, suggesting that the field is pivoting away from 'reactive' traditional control toward 'predictive' intelligent architectures. This movement signifies a maturation of the research agenda, moving beyond the goal of simple power maximization toward the more complex challenges of grid-adaptive, intelligent energy management.

5.4.2 Multiple Correspondence Analysis

Multiple Correspondence Analysis (MCA) was used to investigate the relationship between the most occurring AI-based MPPT and solar tracking keywords to uncover implicit conceptual issues in this area, using multiple correspondence analysis to project data into a factorial space of low dimension, in which closeness to other points in this space corresponds to shared occurrences in documents, such that close points have more similar thematic material.

Fig. 18 shows the factorial map of the MCA for the keywords, representing how these words disperse along the first two axes, which account for the majority of the variability of the dataset. The keywords centered on PV systems and MPPT are positioned at the center of the graphic, reinforcing the notion that they represent key ideas, while other specialized ideas like ‘fuzzy logic’, ‘boost converter’, ‘DL’, or ‘battery’ tend towards being positioned at the periphery.

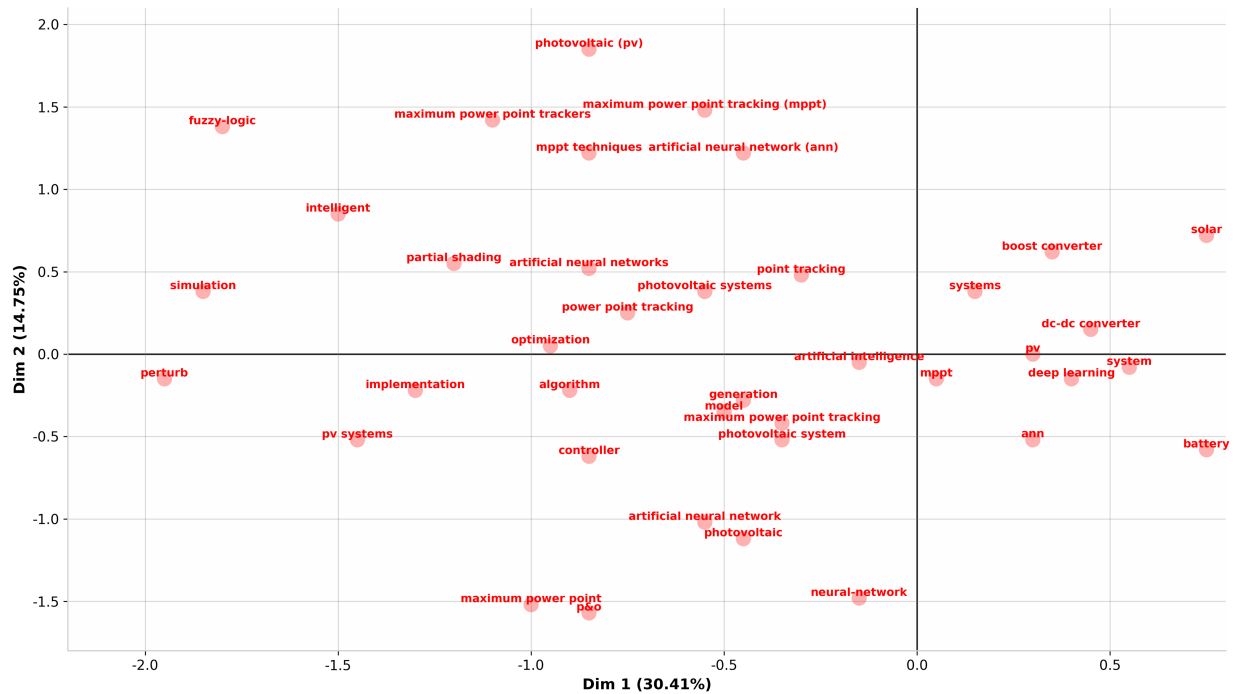


Figure 18: Multiple correspondence analysis (MCA) map of the main AI-based MPPT and solar tracking related keywords.

To demonstrate the topic structure that has been extracted by MCA, a hierarchical clustering algorithm was performed on the coordinates of the keywords in the factorial space, and the topic dendrogram is shown below in Fig. 19. The vertical axis shows the Aggregation Height (distance) between keywords, such that keywords that meet at shorter heights have similar occurrence profiles, implying thematic topics.

Fig. 20 illustrates how a map of the structural concepts shows how a given group of keywords is contained within a polygon defining the global structural territory of MPPT using AI and solar tracking. In this map, it is clear that a group of key phrases, such as “PV”, “MPPT”, “algorithms”, and “PV systems”, comprises a spine of this structural territory. Meanwhile, other phrases such as those involving intelligent control (AI, machine learning, and ANN) and power electronics (boost converter, Dc/Dc converter, and battery) define a territory circumscribing advanced algorithms and system-level integration

5.4.3 Correspondence Analysis

Correspondence analysis (CA) was applied to further explore the relationships between terms and documents in the AI-based MPPT and solar tracking literature, providing a two-dimensional graphical representation that summarizes the main association patterns in the data. This method reduces the complexity of the contingency tables built from textual information and allows for visually inspecting which terms tend to co-occur and how they jointly structure the research field.

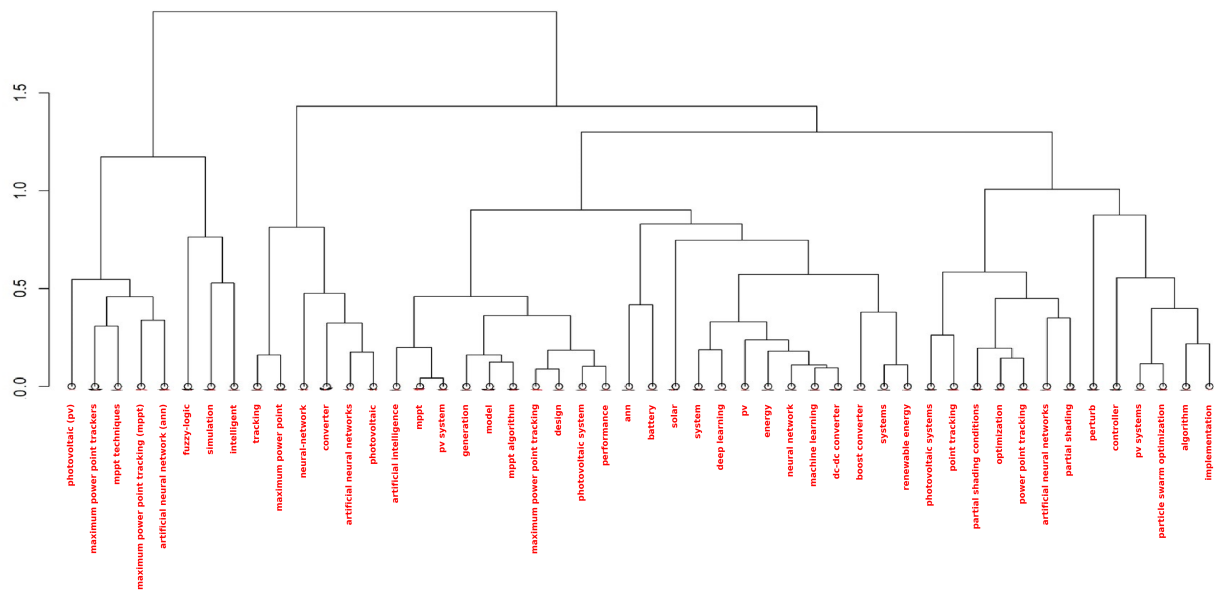


Figure 19: Hierarchical clustering dendrogram of AI-based MPPT and solar tracking-related keywords.

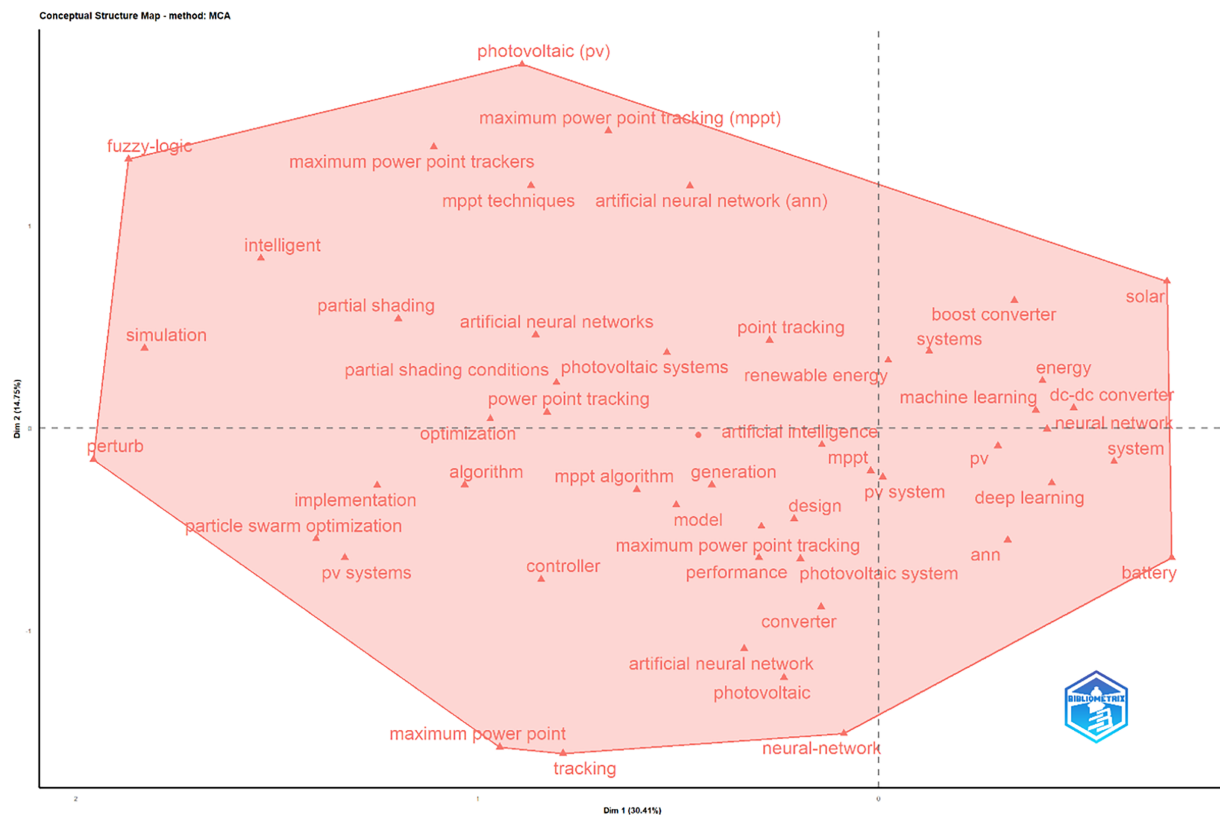


Figure 20: Conceptual structure map of AI-based MPPT and solar tracking research obtained by multiple correspondence analysis (MCA).

Fig. 21 shows the CA factorial map of the most frequent author keywords, projected onto the first two dimensions that together account for a substantial share of the total inertia. The spatial proximity of terms such as “MPPT”, “systems”, “ANN”, and “fuzzy logic” indicates that these concepts frequently appear together and form the conceptual core connecting AI-based MPPT and solar tracking control strategies with intelligent optimization techniques.

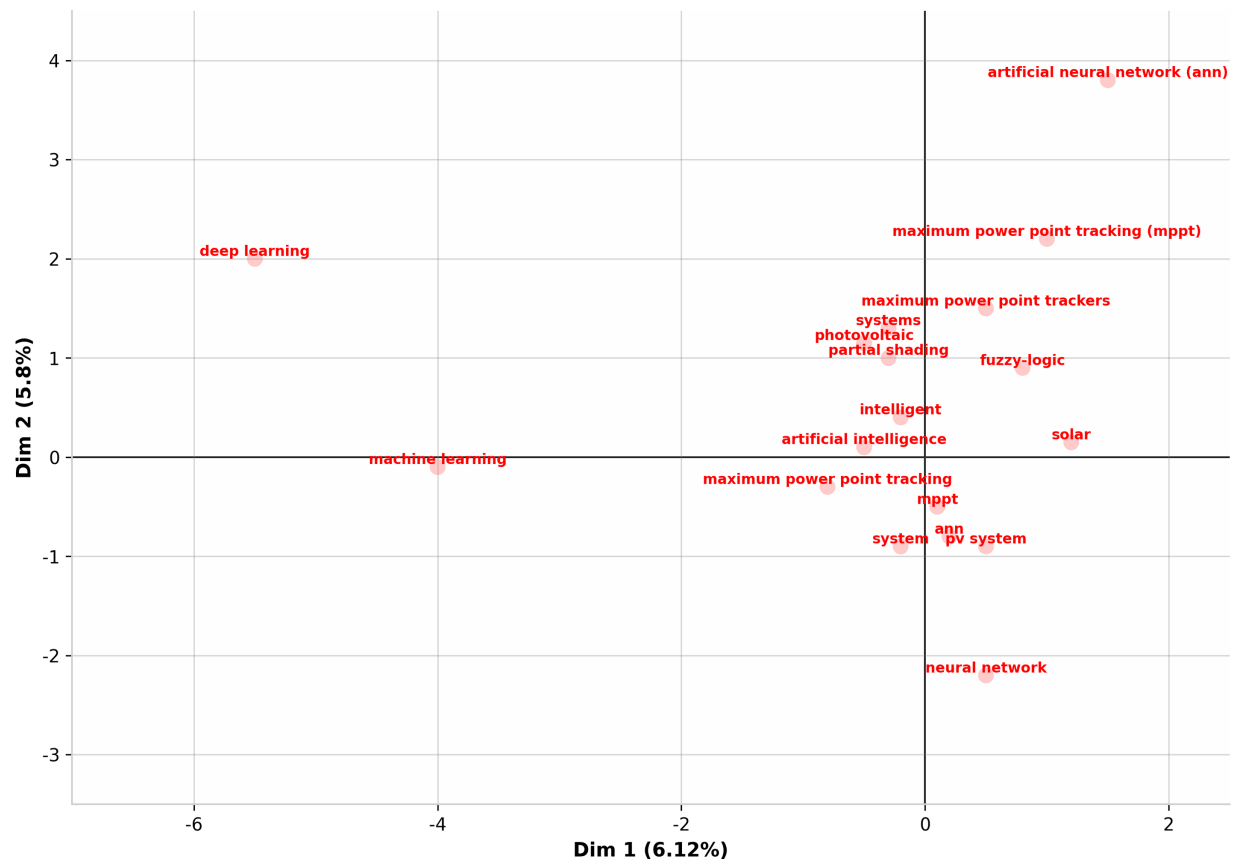


Figure 21: Factorial map using correspondence analysis of the most cited documents.

To complement this analysis, hierarchical clustering of the CA coordinates for the keywords was conducted, and the resulting topic dendrogram is shown in Fig. 22. In this figure, the y -axis shows the aggregation height, meaning the distance between the keywords, such that branches joining at lower heights connect keywords that have similar usage patterns and thus form topics in the AI-based MPPT and solar tracking area.

Fig. 23 finally reveals the conceptual structures map that has been produced through CA, where the same keywords are enclosed in a polygon that outlines the conceptual space defined by the particular topic or field. The conceptual structures map illustrates the area that has high density around the keywords related to traditional AI-based MPPT and solar tracking and PV concepts; in contrast, the keywords related to advanced concepts like “DL” and “machine learning” are placed at the edges of the conceptual space mapped onto the structures, which clearly indicates the expanding frontiers of AI-based approaches toward advanced intelligent control solutions.

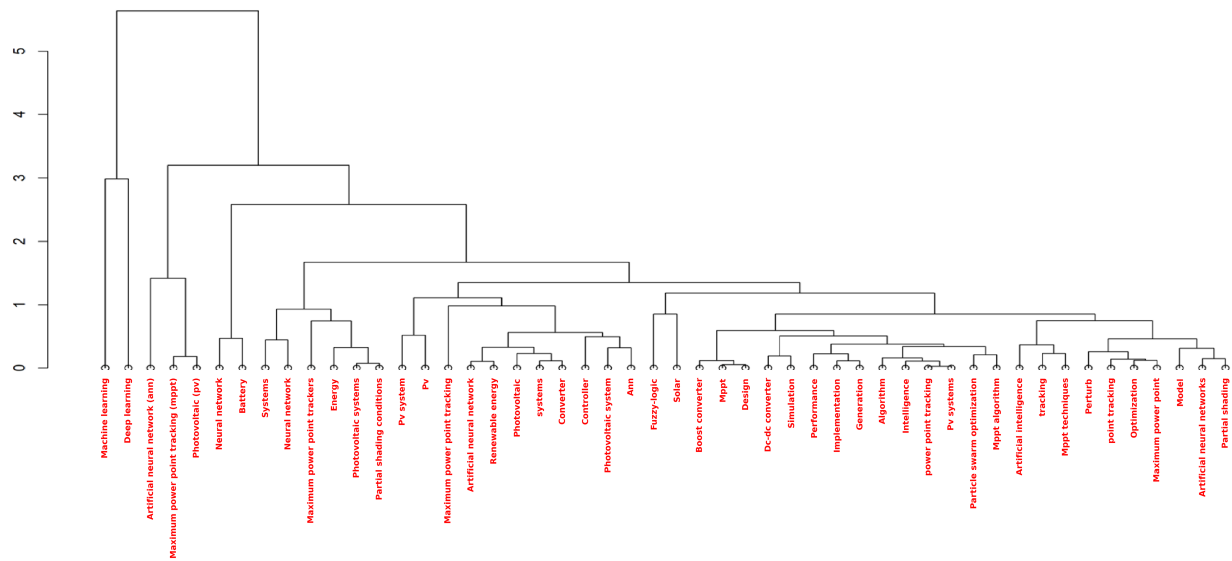


Figure 22: Topic dendrogram using correspondence analysis.

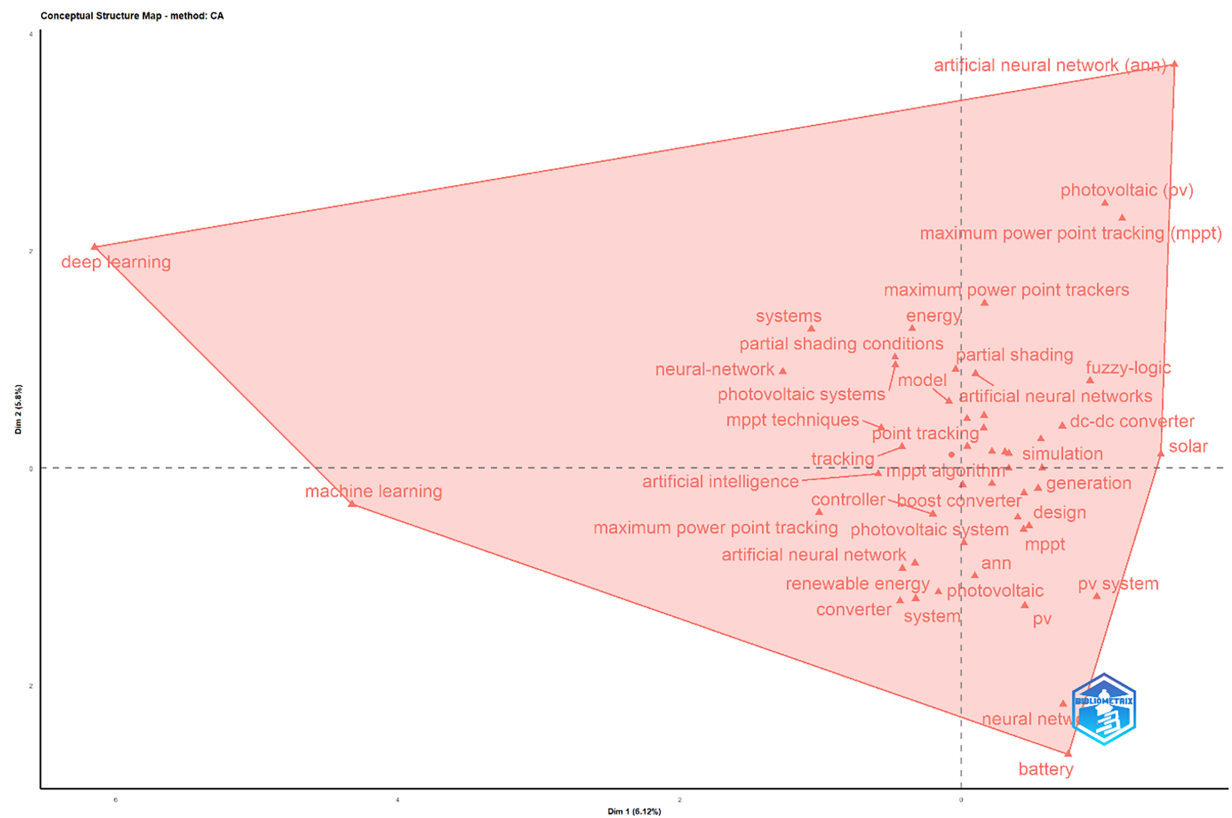


Figure 23: Conceptual structure map using correspondence analysis.

5.4.4 Multidimensional Scaling

Multidimensional scaling was used to further investigate the similarity relationships among the most frequent author keywords in the AI-based MPPT and solar tracking literature, by mapping them into a two-dimensional space where distances between points approximate their dissimilarities. The input to the MDS algorithm is a dissimilarity matrix derived from keyword co-occurrence patterns, so that closely positioned terms are used in similar contexts, whereas distant points correspond to conceptually distinct topics.

Fig. 24 presents the conceptual structure map obtained by MDS, in which core concepts like “MPPT”, “PV”, “artificial neural network (ANN)”, and “fuzzy logic” are grouped toward the center of the map, while more detailed methods and applications, like “particle swarm optimization”, “RE”, “boost converter”, and “battery”, radiate outward. This reflects that MPPT control and PV systems provide the backbone of the specialty to which a variety of intelligent control and power electronics techniques are arranged around.

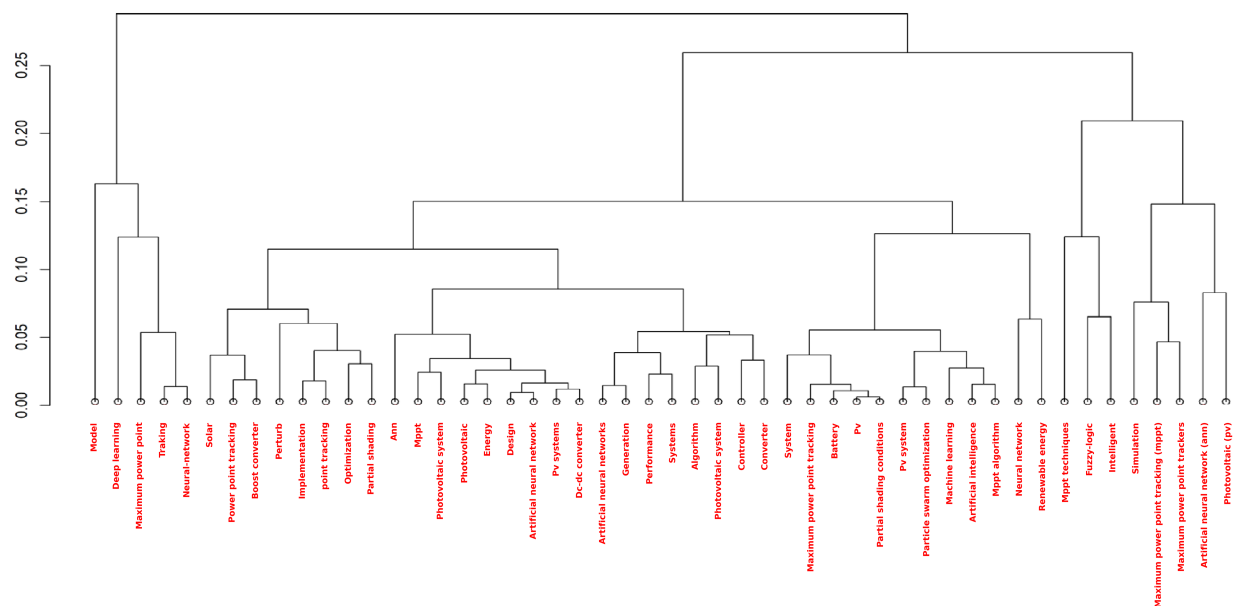


Figure 24: Topic dendrogram using multidimensional scaling.

Complementing this geometric perspective, hierarchical clustering was carried out on the MDS coordinates, and the resulting topic dendrogram is presented in Fig. 25. The height of each merge along the vertical axis represents the distance between clusters; thus, branches joining at low height represent strongly related keywords that merge and form a coherent thematic area, while merges at higher levels represent broader aggregations of topics. Figs. 24 and 25 present a structured landscape wherein one cluster of terms focuses on core MPPT and PV concepts, and another on advanced AI-based methodologies and system-level components, capturing well the dual focus of MPPT research on both fundamental control principles and emerging intelligent optimization techniques.

Table 11 (continued)

Author (Year)	AI/Optimization Approach	Application Domain	Main Technical Contribution	Limitations	Implementation Challenges
[100]	Evolutionary Fuzzy Logic and ANN	Global maximum power point tracking (GMPPT)	Enhanced robustness under PSC; effectively avoided local optima.	Accuracy is heavily dependent on the “Expert Knowledge” used to define fuzzy membership functions.	Evolutionary search algorithms require iterative loops that can be difficult to run in real-time on low-cost chips.
[101]	Artificial Neural Network Algorithms	PV energy harvesting optimization	Demonstrated faster convergence than conventional P&O techniques.	The model is strictly data-dependent; it may not generalize if moved to a different type of PV panel.	High initial effort required for offline data collection and labeling across thousands of environmental scenarios.
[102]	ANN-based Sliding Mode Control	DFIG-based wind energy conversion system (WECS)	Improved system stability and dynamic performance under variable weather.	Sliding Mode Control is prone to the “chattering” phenomenon, which can increase mechanical stress or ripples.	High mathematical complexity in defining the “switching surface” for two different energy sources simultaneously.
[103]	Neural Network with Quadratic Boost Converter	Fuel cell application rather	Achieved high voltage gain while reducing output power fluctuations.	The quadratic converter has a high component count, leading to lower reliability and higher hardware costs.	Managing the thermal stress and electromagnetic interference (EMI) of the high-gain converter while maintaining ANN precision.
[104]	Variable-Step ANN Technique	Partial shading mitigation	Reduced computational burden while maintaining tracking accuracy.	The variable step logic can lead to steady-state oscillations if the irradiance changes faster than the sampling rate.	Difficult to optimize the “step-size” boundaries for embedded systems with limited RAM/Memory.
[105]	Most Valuable Player Algorithm (MVPA)	Multimodal P–V characteristic analysis	Improved global peak detection capability under complex shading.	Stochastic nature means convergence time is not guaranteed to be consistent across every trial.	Complex coding required to manage “teams” and “leagues” within the algorithm on standard industrial controllers.
[106]	Fast ANN-Based Estimation Method	Real-time GMPPT	Enabled rapid estimation of GMPP without exhaustive search.	Performance degrades as PV modules age (increasing series resistance R_s), which is not always accounted for in training.	Highly sensitive to sensor noise; requires high-precision voltage and current sampling circuits to feed the ANN.

(Continued)

Table 11 (continued)

Author (Year)	AI/Optimization Approach	Application Domain	Main Technical Contribution	Limitations	Implementation Challenges
[107]	Deep Neural Networks (Review Study)	Performance analysis of shaded PV systems	Identified suitable ANN architectures for varying temperature and shading.	Deep Learning models require significantly more computational resources than “shallow” ANN models.	Transferring large pre-trained deep models into existing low-power PV inverters without specialized AI accelerators.
[108]	Hybrid ANN-Particle Swarm Optimization (PSO)	Smart grid and vehicle-to-grid (V2G) integration	Optimized the trade-off between efficiency, grid stability, and performance.	PSO can still occasionally get trapped in local optima in extremely high-dimensional grid search spaces.	Communication latency between the EV battery and the grid-side optimization controller can disrupt real-time performance.

The literature reveals a decisive transition from conventional algorithms, such as P&O and Incremental Conductance (IC), toward AI-driven methods. As demonstrated by [101,106], traditional methods are fundamentally limited under PSC because they are designed to find the nearest peak, often getting “trapped” in local maxima. Intelligent approaches, particularly ANN, allow the system to treat MPPT as a function approximation problem, leaping directly to the GMPP and significantly reducing energy wastage.

A critical trend observed in the most recent studies [98–100] is the adoption of Hybrid Architectures. Researchers are increasingly combining distinct paradigms such as Metaheuristics for global search, Fuzzy Logic for handling environmental uncertainty, and ANNs for high-speed mapping. While this hybridization yields superior accuracy and stability, it introduces a “complexity tax”. The integration of multiple AI layers requires high-performance Digital Signal Processors (DSPs) and complex software synchronization, which may be prohibitive for low-cost commercial applications.

A recurring limitation is the high dependency on training data. Algorithms proposed by [101] and the review by [107] require massive datasets to ensure accuracy. Furthermore, ref. [106] highlights a critical real-world gap: the Aging Problem. As PV modules age, their internal series resistance (R_s) increases, a variable often missing from static training sets. Without online learning or adaptive weight updates, the accuracy of these models will inevitably degrade over the 20-year lifespan of a typical PV installation.

Technical contributions from [102,103] emphasize that optimization algorithms cannot be decoupled from power electronics hardware. The use of specialized hardware, like the Quadratic Boost Converter, facilitates high voltage gains but introduces new challenges in managing thermal stress and Electro-magnetic Interference (EMI). Similarly, the use of Sliding Mode Control (SMC) helps stabilize hybrid systems (Wind/PV) but must be carefully tuned to prevent high-frequency “chattering”, which can damage electrical components.

The study by [108] represents the “Next Frontier” in the field: the transition from component-level tracking to system-level management. In Vehicle-to-Grid (V2G) applications, the AI must balance energy harvesting with grid stability and battery health. Here, the implementation challenge shifts from local processing power to communication latency and data security between the mobile EV unit and the stationary grid controller.

While AI and metaheuristic optimization have effectively solved the mathematical challenges of tracking global peaks in simulated environments, the path to universal commercial adoption remains blocked

by three hurdles: computational cost, sensor noise sensitivity, and long-term robustness against panel aging. Future research should focus on “lightweight” hybrid models that maintain 99% efficiency while operating on low-cost, 32-bit microcontrollers.

To contextualize these benchmarks within the broader academic landscape, a focused comparison of the major AI-based MPPT and solar tracking families identified in our bibliometric mapping reveals distinct operational trade-offs. First, Fuzzy Logic Control (FLC) serves as a robust linguistic paradigm that does not require an exact mathematical model of the PV system [100]. While FLC excels in smooth mechanical tracking control and handles non-linear solar variations gracefully, its design is heavily dependent on human ‘expert rules’ and lacks intrinsic self-learning mechanisms. Second, Artificial Neural Networks (ANN) and Deep Learning (DL) models offer exceptionally fast, millisecond-scale execution speeds [101,106,107]. However, their performance relies heavily on the availability of highly comprehensive training datasets, and they struggle to generalize when deployed on panels with varying electrical configurations or when physical degradation and aging occur over time. Third, Metaheuristic Optimization techniques, such as Particle Swarm Optimization (PSO) and Grey Wolf Optimizer (GWO) [105,123], are highly robust at locating the global maximum power point under complex partial shading conditions. Nevertheless, their iterative exploration cycle introduces steady-state power oscillations and exhibits stochastic execution times, which can increase electrical wear. Fourth, emerging Reinforcement Learning (RL) approaches [39,66] represent a model-free, highly adaptive alternative. RL agents continuously interact with the PV environment, allowing the control loop to optimize both converter duty cycles and mechanical tracking angles online as panels degrade. However, the extreme computational overhead and the risk of early-stage control instability during the training or exploration phase remain major hurdles for low-power embedded controllers. Finally, Hybrid Architectures seek to balance these trade-offs [99,108]. By utilizing a metaheuristic global search to identify the global peak zone, and subsequently handing control over to a fast, local ANN or FLC for rapid fine-tuning, researchers can minimize power oscillations while ensuring the tracker escapes local maxima. This progressive optimization paradigm underscores the scientific community’s transition from isolated, component-level tracking toward highly integrated, self-adaptive, and multi-variable solar optimization frameworks.

The AI-based MPPT and solar tracking-related research in PV systems, according to this bibliometric and conceptual study, is an ever-growing and highly collaborative research community. This includes a heavy number of publications produced by an extensive community of research authors, where most publications are jointly authored, signifying highly collaborative work and collective approaches and frameworks. On the other hand, however, the citations evidenced that a relatively small group of highly productive authors and highly cited papers play a highly influential role in this community, influencing its foundations and its development.

The keyword mapping and clustering results emphasize how the intellectual focus of this body of literature is strongly centered around MPPT, PV systems, and related control algorithms in which various additional themes are embedded. These are: intelligent control techniques and AI-related approaches (ANNs, FL, ML, DL), power electronics interfaces (boost converters and dc-to-dc converters), as well as system-level issues like MCDM-related issues in PV systems. The above pattern illustrates how current literature does not focus on MPPT as merely a control issue but is increasingly positioned in the larger context of intelligent data-driven PV system design.

The conceptual structure, correspondence analysis, and multidimensional scaling plots show collectively that AI-based approaches occupy a mediating role between conventional MPPT algorithms and new applications and that future developments would most probably emerge through a synergistic integration of classical control and optimization approaches informed by data analysis. The peripheral but easily traceable

clusters of ideas surrounding energy storage solutions, batteries, and hybrid/multi-source systems indicate new applications-directed avenues that might emerge as new focus themes for motors as the role of solar energy and, therefore, grid integration needs expand. The dendrograms also confirm this view as AI-directed keywords are aligned with keywords for MPPT and solar energy applications.

The synthesis of these conceptual maps reveals the future trajectory of the field. Specifically, the transition from basic MPPT to intelligent ‘Motor Themes’ (as shown in the upper-right quadrant of Fig. 17) suggests that future research will move toward DL based prediction. This is quantitatively supported by the emergence of the ‘Machine Learning’ cluster in the MDS analysis (Fig. 24), which demonstrates a shift from single-objective power maximization toward multi-objective optimization, including grid stability and battery health as identified in the high-centrality nodes of the collaboration network.

From a methodological perspective, the application of a variety of complementary mapping approaches (co-occurrence networks, MCA, CA, MDS, and hierarchical clustering) has been successful for identifying not only the structural but also the dynamic parts of the MPPT knowledge base. The above tools not only allow one to analyze the actual topic structure but also assist with the detection of new fronts, as well as possibly declining topics, providing a strategic perspective on the development of this area for researchers, practitioners, and funding authorities alike, helping new entries identify key papers for each of the identified clusters, create systematic reviews on specific subtopics, or detect promising research directions with high conceptual links.

Beyond the dominant trends identified in the mapping analysis, the field is currently witnessing a transition toward several high-impact emerging frontiers that address the practical limitations of traditional AI. Reinforcement Learning (RL) is increasingly recognized as a superior paradigm for MPPT, as it allows agents to learn optimal tracking policies through direct interaction with stochastic environments, effectively bypassing the need for precise mathematical modeling under complex partial shading. Simultaneously, the rise of Edge AI and TinyML is bridging the gap between high-level simulation and real-world deployment by enabling the execution of quantized neural networks directly on low-power microcontrollers. This localized ‘on-device’ intelligence is critical for minimizing control latency and energy consumption in solar tracking actuators. Furthermore, the integration of Digital Twins is transforming PV management from reactive control to proactive optimization, allowing for high-fidelity virtual replication and predictive maintenance of the entire system lifecycle. However, the successful adoption of these technologies hinges on overcoming the challenges of real-time embedded implementation. Future research must focus on the hardware-efficient execution of hybrid algorithms on platforms such as FPGAs and DSPs, balancing the computational complexity of advanced AI with the high-speed sampling requirements of modern power electronic converters.

This study, however, is not without limitations. The analysis is restricted to publications indexed in the Web of Science Core Collection and to works written in English. While these database filters were necessary to ensure high peer-review quality and metadata standardization a crucial requirement for accurate scientometric mapping the reliance on a single database means that the absolute publication and citation metrics presented here should be interpreted as representative rather than exhaustive. Specifically, the exclusion of databases such as IEEE Xplore and Scopus may lead to an underrepresentation of rapid-turnaround conference papers or highly specific engineering case studies that are central to the early stages of hardware prototyping in solar tracking and MPPT applications. Furthermore, restricting the scope to English-language publications may introduce a geographic or language bias, potentially under-representing significant regional research published in other languages or indexed elsewhere. These factors should be taken into account when interpreting the identified dominance of certain regions. In

addition, the use of mathematical growth curves (such as logistic and lifecycle models) on a relatively short five-year dataset (2021–2025) introduces forecasting uncertainties. While these models successfully illustrate the current momentum of the field, their long-term predictions (extending to 2033 and beyond) are highly sensitive to initial conditions and assume that current trends will continue without external disruption. Consequently, these forecasts should be viewed as tentative baseline projections rather than deterministic outlooks. Moreover, the results depend on the search strategy, keyword normalization, and proximity threshold choices (e.g., NEAR/50) used in constructing the networks; alternative parameter settings could slightly modify cluster boundaries or the prominence of certain topics. Future research could explore multi-database and multi-lingual datasets to provide an even broader perspective on global AI-PV optimization trends. Despite these constraints, the overall patterns observed are robust and point to an increasingly mature and interdisciplinary research area in which control engineering, power electronics, AI, and RE systems converge around the common goal of PV energy extraction under diverse and challenging operating conditions.

7 Conclusions

This study provides a comprehensive bibliometric and conceptual evaluation of the AI-based solar tracking and MPPT research landscape from 2021 to 2025. Unlike previous qualitative reviews, this research provides quantitative evidence of the field's rapid maturation, characterized by an annual growth rate of 21.43% and a statistically validated growth model with a coefficient of determination of 0.960. The analysis reveals that the intellectual core of the domain is no longer confined to traditional control logic; rather, it has evolved into a sophisticated intersection of metaheuristics and DL.

The thematic mapping and conceptual scaling results reveal that optimization algorithms, MPPT control, and PV systems represent the primary motor themes driving innovation, as evidenced by their position in the upper-right quadrant of high centrality and high density (Fig. 17). In contrast, 'Machine Learning' resides in the niche themes quadrant, reflecting its specialized yet concentrated development, while 'Intelligent Control' and related AI-based approaches occupy the basic themes space, underscoring their foundational but less dynamically evolving role within the current structure. This structural distribution is further supported by the technical synthesis of the most influential works in the field, which highlights a clear transition from simple power tracking toward robust, multi-objective optimization designed to handle complex environmental constraints such as partial shading. These findings suggest that the research community is moving toward a 'Smart Grid' integration phase, where AI-based trackers and MPPT controllers act as predictive units rather than merely reactive actuators.

Furthermore, the analysis of international collaboration networks identifies key nations in Asia and the MENA region as central hubs with the highest total link strength, serving as critical bridges for knowledge diffusion between emerging and developed economies. However, as the field transitions from theoretical simulations toward real-world deployment, significant challenges remain regarding the interpretability of AI-based decisions and the optimization of computational resource usage on resource-constrained embedded hardware platforms.

While this analysis is restricted to the Web of Science Core Collection and English-language journal articles to ensure high metadata quality and rigorous peer-review standards, the findings offer a robust benchmark for researchers and practitioners. Future research should prioritize the standardization of climatic datasets to improve the generalization of AI models and explore the integration of 'Edge AI' to minimize the control latency of MPPT systems. In conclusion, AI-driven solar tracking and MPPT optimization represent a flourishing research frontier that is successfully bridging the gap between control engineering and data science to maximize the efficiency of global PV systems.

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Availability of Data and Materials: The data that support the findings of this study are available from the Corresponding Author, [Daniel Tudor Cotfas], upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

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