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Evolution of AI in Grid-Connected Renewable Energy Systems: A Systematic Literature Mapping

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ABSTRACT

The integration of artificial intelligence in grid-connected renewable energy systems is gaining increasing attention as a means to enhance efficiency, stability, and intelligent control. Yet, despite the growing interest, existing studies remain scattered across disciplines, lacking a structured overview of the research landscape. This paper presents a systematic literature mapping that investigates and synthesizes the current state of research through the lens of six key research questions. By applying a structured search strategy to the Scopus database, we identified 232 peer-reviewed articles published between 2014 and 2025 that met clearly defined inclusion and exclusion criteria. Each study was examined using both quantitative and qualitative analysis, covering key aspects such as dominant AI methods, renewable energy sources, main applications, simulation environments, collaboration networks, and the extent of real-world hardware implementations. Visualization tools like VOSviewer and Bibliometrix were used to map publication trends and co-authorship patterns. The findings reveal a sharp increase in research activity after 2020, with machine learning and neural networks leading the way, particularly in applications related to solar PV and hybrid systems. Most efforts are concentrated on simulation-based optimization and forecasting, while hardware integration is still underrepresented. This review not only maps out the current research landscape but also highlights research gaps and points toward promising directions for future interdisciplinary work and practical deployment.

1. INTRODUCTION

The global transition toward low-carbon and sustainable energy systems has brought about a fundamental transformation in the architecture and operation of power networks. Grid-connected renewable energy systems, particularly those based on solar and wind, are increasingly integrated into national and regional grids due to their environmental benefits and their potential to reduce dependence on fossil fuels [1, 2]. These systems play a central role in achieving carbon neutrality targets and supporting long-term energy security. However, their integration presents significant technical challenges. Solar and wind resources are inherently variable and weather-dependent, which can result in unpredictable power generation. This intermittency leads to imbalances between electricity supply and demand, causing voltage and frequency instability, and ultimately compromising grid reliability.

To address these challenges, the power systems community has increasingly turned to artificial intelligence (AI) as an enabling technology. AI encompasses a broad set of computational techniques, including machine learning, deep learning, neural networks, and fuzzy logic, that can process large volumes of real-time data and support intelligent decision-making. In the context of grid-connected renewable energy systems, AI enables a wide range of applications: from short-term forecasting of solar irradiance and wind speed to predictive maintenance [3, 4], real-time fault detection, grid control, optimization of power flows, and energy storage management. These capabilities are essential for improving the efficiency, resilience, and autonomy of modern power systems.

Over the past decade, research in this interdisciplinary area has grown rapidly. A wide array of studies has explored the use of AI in various configurations of renewable energy systems [5], employing diverse algorithms and focusing on different objectives, including forecasting accuracy, system stability, and economic optimization. Despite this growing body of work, the literature remains dispersed across multiple disciplines and application domains. No comprehensive effort has yet been made to systematically map the landscape of AI-based research in grid-connected renewable energy, leaving practitioners and researchers without a consolidated view of the field's evolution, trends, and key contributions.

This fragmentation underscores the need for a structured synthesis of existing knowledge. The fast development of AI tools and the increasing complexity of renewable power systems demand a clearer understanding of which AI methods are most prevalent, which application areas are most mature, and where knowledge gaps remain. A well-structured overview can guide future research, support interdisciplinary collaboration, and inform the development of robust and scalable solutions for smart grid integration.

To address this need, the present study conducts a systematic literature mapping (SLM) based on a review of 232 selected peer-reviewed articles indexed in the Scopus database [6]. Unlike traditional reviews or systematic literature reviews, which aim to answer specific research questions through detailed synthesis and quality assessment, the SLM provides a broader, high-level overview of the research landscape. It focuses on categorizing and classifying studies based on dimensions such as research focus, methodology, and application area, rather than deeply analyzing individual findings [7]. This makes it a more scalable and efficient method, particularly suited to large, diverse, and interdisciplinary fields like the integration of artificial intelligence into grid-connected renewable energy systems. In this study, the mapping process examines the types of renewable energy sources considered, AI techniques employed, simulation tools used, and the extent of hardware validation. It also identifies leading countries, institutions, and researchers, and explores collaborative research networks. By offering a structured synthesis of the literature, SLM helps researchers identify which areas are well-studied and which require deeper investigation. This approach is especially useful for funding agencies, policymakers, and PhD students in defining strategic research priorities and supporting evidence-based decisions. Ultimately, the mapping highlights both dominant themes and underexplored areas, providing valuable insights to guide future academic and industrial efforts [7].

The rest of the paper is organized as follows. Section 2 reviews the existing literature relevant to the study. Section 3 describes the research methodology, including the search strategy, selection criteria, and the framework used to classify and analyze the data. Section 4 presents the main results of the mapping process, followed by a discussion in Section 5 that highlights key findings, identifies research gaps, and suggests areas for future exploration. Finally, Section 6 concludes the paper with a summary of insights and recommendations for advancing research on AI-based management of grid-connected renewable energy systems. Figure 1 illustrates the overall outline of this paper.

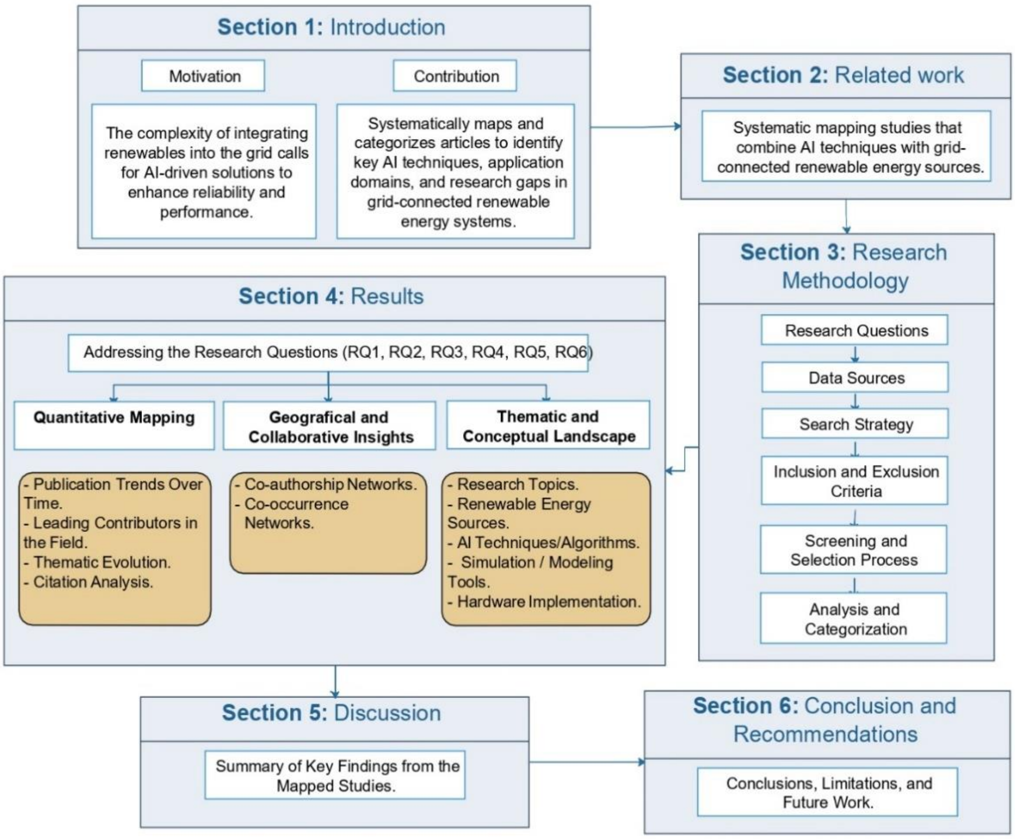

Figure 1. The overall outline of the paper

2. RELATED WORK

A search conducted in the Scopus database using the query ("grid-connected" OR "renewable energy") AND ("artificial intelligence" OR "machine learning" OR "neural networks" OR "fuzzy logic" OR "deep learning") AND ("systematic literature mapping" OR "systematic mapping study" OR "bibliometric") yielded 21 relevant articles after excluding articles and conference proceedings. Among these, only 10 present a structured mapping analysis of AI applications in renewable energy contexts. However, a closer examination reveals that these studies address diverse topics and rarely focus on grid-connected systems as a specific area of inquiry.

For instance, some works focus on narrow application domains. The study [8] investigates research trends in solar-powered membrane distillation, employing bibliometric and machine learning techniques to map the field. Similarly, Dzikevics et al. [9] explore AI-based control methods for solar thermal systems, identifying emerging trends in thermal energy applications. Meanwhile, Sepúlveda-Oviedo et al. [10] centers on fault detection in photovoltaic systems using AI, particularly emphasizing data-driven maintenance strategies.

Other studies adopt broader scopes. For example, Velasquez et al. [11] analyze AI applications in sustainable energy over the past decade, highlighting themes such as smart grids, hydrogen, and energy planning. Hernandez-Palma et al. [12] provide a regional review of machine learning use in Latin America's renewable energy systems, while Bracarense et al. [13] focus on AI for sustainability, covering smart grids and energy efficiency. Several articles [14-16] emphasize collaboration networks and major contributors, using bibliometric indicators to reveal research clusters in AI and energy.

Despite their contributions, none of the reviewed studies specifically map the intersection of AI and grid-connected renewable energy systems. Key topics such as grid integration, demand-side management, distributed energy resource (DER) control, and smart grid optimization, where AI could have a transformative impact, remain largely unexplored through a structured and comprehensive approach. Table 1 provides a comparative overview of these works, outlining their main focus areas and research limitations.

This paper addresses this gap by conducting a systematic literature mapping that focuses on AI applications within grid-connected renewable energy systems. Unlike traditional bibliometric reviews, this study combines quantitative mapping with qualitative content analysis to identify the dominant themes, methodological approaches, and practical applications. It highlights key contributors, collaboration patterns, and emerging research areas related to AI-based forecasting, control, and optimization in grid-tied renewable systems. By doing so, the study offers a structured overview of how AI is currently being utilized to support the operation, stability, and integration of modern power grids, and suggests directions for future research.

Table 1. Summary of review articles based on systematic mapping analysis

Ref.	Contribution of the Study	Research Gap
[8]	Trends in solar-powered membrane distillation (MD) and machine learning techniques.	Does not address grid-connected systems or AI's role in integrating DER into grids.
[9]	Control methods for solar thermal systems using AI-based techniques.	Limited to solar thermal systems; does not explore grid-connected renewable energy.
[10]	AI-based fault detection in photovoltaic systems.	Focuses on fault detection in solar energy systems without addressing broader grid issues.
[11]	AI techniques in sustainable energy, including smart grids and hydrogen.	Broad focus; limited attention to specific challenges in grid-connected renewable systems.
[12]	Machine learning applications in renewable energy generation in Latin America.	Focuses on a regional context, lacking a global perspective on grid-connected systems.
[13]	AI's role in sustainability, including energy efficiency and smart grids.	Does not specifically address AI driven grid-connected renewable energy systems.
[14]	Collaboration patterns and contributors in AI and renewable energy.	Lacks focus on specific applications in grid-connected renewable energy systems.
[15]	Trends research of machine and deep learning applications in energy storage.	Does not specifically address AI driven grid-connected renewable energy systems.
[16]	Key players in renewable energy and artificial intelligence research.	Focuses on using artificial intelligence in renewable energy systems; Does not explore grid-connected systems.
Our article	The integration of AI into grid-connected renewable energy systems, with a focus on grid management, demand forecasting, power optimization, and the identification of key trends, contributors, and practical applications through a systematic literature mapping.	Addresses a critical gap in the literature by employing a mapping analysis approach to explore AI-driven solutions for grid-connected renewable energy systems.

3. RESEARCH METHODOLOGY

This section outlines the methodology used to conduct a systematic literature mapping on the application of AI in grid-connected renewable energy systems. The main objective is to identify, classify, and analyze relevant scientific contributions within this interdisciplinary field. To ensure transparency, replicability, and scientific rigor, the study adopts the Systematic Mapping Study methodology proposed by Petersen et al. [7], which is widely recognized in software engineering and technology-related research. This approach provides a structured and repeatable framework for organizing the literature and highlighting key research trends and knowledge gaps. The mapping process involves several phases, starting with the formulation of research questions and continuing through database selection, search strategy development, application of inclusion and exclusion criteria, article screening, data extraction, and finally, analysis and categorization.

3.1 Research questions

The systematic mapping study is guided by a set of research questions aimed at exploring the landscape of AI applications in grid-connected renewable energy systems. The main questions include:

- RQ1: What has been the growth trend of publications on AI and grid-connected renewable energy over time?
- RQ2: Who are the main contributors in this field, and how do their collaborations influence the development of key research themes?
- RQ3: What are the primary research topics in the application of AI to grid-connected renewable energy systems?
- RQ4: What renewable energy sources are most

commonly integrated with AI techniques in grid-connected systems?
- RQ5: Which AI techniques and algorithms are most commonly used in grid-connected renewable energy systems, and what tools are employed?
- RQ6: What types of hardware implementations are employed in AI-based grid-connected renewable energy systems, and how do they support real-time performance and system reliability?

3.2 Data sources

The Scopus database was chosen as the primary source for this literature review due to its comprehensive coverage of peer-reviewed scientific journals and conference proceedings, which are widely recognized for indexing high-quality, impactful research across various scientific and engineering disciplines.

3.3 Search strategy

A carefully constructed search strategy was applied to both databases to retrieve relevant documents. The search terms combined keywords related to AI, renewable energy, and grid connection. Boolean operators and truncation were used to capture variations of terms. The primary search string is presented in Table 2. The search was restricted to publications from 2014 to 2025, written in English, and limited to articles, conference papers, and reviews. A thesaurus file was applied during analysis (in VOSviewer) to group synonyms and eliminate ambiguities in keyword interpretation.

Table 2. Search string in Scopus database

Database	Query
Scopus	("grid-connected" OR "grid integration") AND ("renewable energy") AND ("artificial intelligence" OR "machine learning" OR "neural networks" OR "fuzzy logic" OR "deep learning")

3.4 Inclusion and exclusion criteria

To ensure that only relevant and high-quality studies were included, a set of predefined inclusion and exclusion criteria was applied:

Inclusion Criteria:
- Studies explicitly applying AI techniques to grid-connected renewable energy systems.
- Articles focusing on optimization, control, forecasting, or integration in the context of AI and renewable energy.
- Publications in peer-reviewed journals or international conferences.
- Documents published between 2014 and 2025.

Exclusion Criteria:
- Articles unrelated to AI or grid-connected systems.
- Studies focusing on off-grid renewable systems or conventional power systems.
- Non-English publications or those with inaccessible full texts.

3.5 Screening and selection process

To ensure a systematic, transparent, and reproducible mapping process, this study followed a structured multi-stage screening protocol adapted from the PRISMA 2020 guidelines [17]. The process was conducted in three stages: identification, screening, and eligibility. It began with the identification of documents from the Scopus database, followed by screening of titles and abstracts to assess relevance, and concluded with full-text reviews based on predefined inclusion and exclusion criteria. This rigorous filtering approach was designed to minimize selection bias and ensure the inclusion of studies directly relevant to the integration of AI in grid-connected renewable energy systems. The entire selection procedure is documented and visualized using the PRISMA 2020 flowchart presented in Figure 2. This flowchart provides a clear overview of each stage, starting from the initial number of retrieved records, through the removal of duplicates and irrelevant studies, to the final set of 232 peer-reviewed articles included in the analysis.

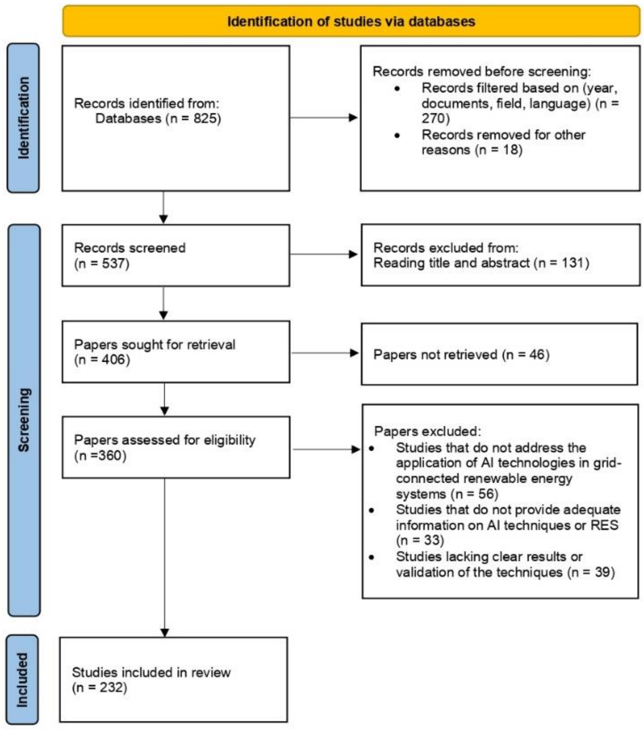

Figure 2. PRISMA flowchart illustrating the number of papers identified at each stage

4. RESULTS

The results section is structured into three main analytical dimensions aligned with the systematic mapping study. First, the quantitative analysis provides an overview of publication trends, including annual growth, publication types, and subject area distributions. Second, the structural and geographical analysis explores co-authorship networks, institutional collaborations, and country-level contributions to highlight key players and collaborative patterns. Finally, the thematic content analysis categorizes the selected studies based on research focus, applied AI techniques, types of renewable energy, and methodological tools. This multidimensional approach offers a comprehensive mapping of the research landscape, identifying gaps and emerging directions in the field.

4.1 Quantitative mapping

This section presents a comprehensive quantitative analysis that offers statistical insights into the growth patterns, publication trends, and the distribution of research across various subfields.

4.1.1 Publication trends over time

This subsection addresses RQ1, which provides an overview of the research growth and key subject areas that have contributed to the field of AI and grid-connected renewable energy systems over the period from 2014 to 2025.

a. Distribution of Publications over Time

The analysis of the 232 selected documents reveals a marked growth in research related to AI-driven grid-connected renewable energy systems over the period 2014–2025. A noticeable increase in publication activity begins around 2019, with a sharp surge after 2022, reflecting the escalating interest in leveraging artificial intelligence to address the complexities of renewable energy integration. This trend aligns with ongoing advancements in AI methodologies and growing global commitments to sustainability and decarbonization.

The years 2023 and 2024 stand out as the most productive, with 42 and 67 publications, respectively, underscoring the rapid expansion of this research area. This upward trajectory signals the increasing demand for intelligent solutions aimed at enhancing grid stability, energy management, and the integration of distributed energy resources (DERs). Figure 3 visualizes this growth, comparing the evolution of AI-based and non-AI-based research outputs in the domain.

While non-AI publications experienced a steady rise from 2015, peaking at over 913 studies in 2023, a decline in 2024 may indicate a saturation point or a strategic shift toward AI-driven investigations. In contrast, AI-based research, although modest in the earlier years, began gaining traction around 2022 and reached its peak in 2024. This trend highlights the increasing recognition of AI's potential to optimize grid-connected renewable energy systems, even as conventional approaches continue to dominate the broader research landscape.

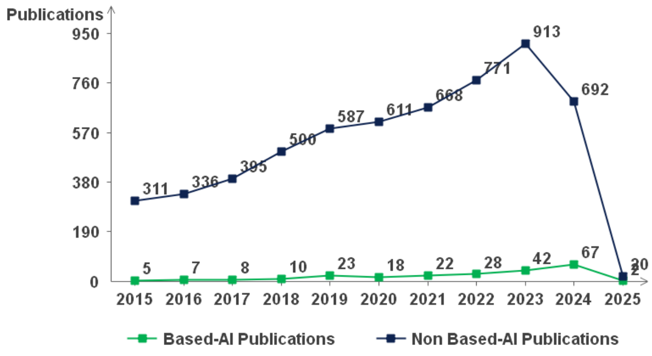

Figure 3. Growth trajectory of grid-connected renewable energy systems

b. Distribution of Publications by Journal

The distribution of the 232 selected documents across academic journals highlights the primary publication venues for research on AI-driven grid-connected renewable energy systems. This dispersion reflects the interdisciplinary scope of the field, which spans energy engineering, computer science, and applied artificial intelligence. Journals such as Energy Reports, Energies, and the Journal of Energy Storage consistently emerge as prominent outlets, providing platforms for disseminating innovative research on the integration of renewable energy and advanced computational methods.

Over the period 2014–2025, these journals demonstrated a steady increase in related publications, paralleling the overall growth in the domain. Figure 4 presents the top 10 journals with the highest number of publications. Energies and IEEE Access lead with 9 articles each, followed closely by Energy Reports with 8. Other key contributors include the Journal of Energy Storage and the International Journal of Hydrogen Energy, each contributing 4 to 5 articles.

This analysis underscores the vital role of multidisciplinary journals in driving forward the research agenda at the intersection of artificial intelligence and renewable energy integration. These journals not only shape the academic discourse but also serve as hubs for collaboration across diverse scientific communities.

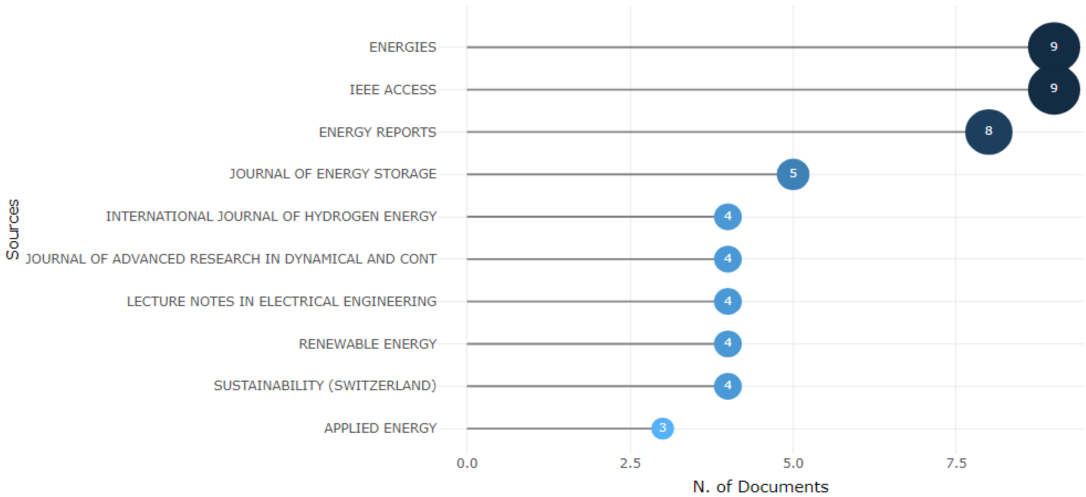

Figure 4. Distribution of publications by journal

c. Distribution of Publications by Subject Areas

The reviewed documents span a diverse range of subject areas, underscoring the interdisciplinary nature of research on AI applications in grid-connected renewable energy systems.

Dominant fields such as Energy and Engineering form the foundation for system design and implementation, while Computer Science and Mathematics contribute essential AI models and optimization techniques. Environmental Sciences and Material Sciences also play supportive roles, particularly in addressing sustainability and enhancing grid infrastructure and storage technologies. This convergence of disciplines reflects the complex and integrated approach required to advance intelligent renewable energy integration, as illustrated in Figure 5.

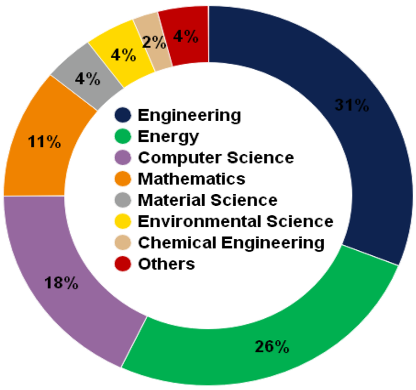

Figure 5. Proportional distribution of documents by subject area

4.1.2 Publication trends over time

In the rapidly evolving field of grid-connected renewable energy enhanced by artificial intelligence, identifying the key contributors is essential to understanding the development of innovative technologies and global research trends. The results presented here respond to RQ2, highlighting the most active authors, institutions, and countries contributing to this research area.

a. Distribution of Publications by Countries

The analysis of the 232 selected manuscripts revealed that research on AI-driven grid-connected renewable energy systems spans 55 countries, with notable disparities in publication output. While many countries contributed only a few documents, significant contributions came from India (101 publications), China (24), and Saudi Arabia (20), followed by Algeria, Malaysia, and Pakistan. Other active countries include Egypt, the United States, Tunisia, Bangladesh, Denmark, Iran, and Canada. This distribution, detailed in Table 3, reflects a strong global engagement, particularly from Asia, North Africa, and North America.

b. Distribution of Publications by Authors

This subsection highlights the most influential researchers in the field of AI and grid-connected renewable energy. By analyzing publication output, we can identify the individuals who have made significant contributions to advancing research and technology in this area. These key researchers shape the direction of future studies and play a vital role in driving innovation and collaboration across the global research community. Table 4 lists the top 10 researchers with the highest publication counts in AI and grid-connected renewable energy. Li et al. [18] lead with six publications on photovoltaic forecasting, hybrid systems, and neural networks. Sharma et al. [19] and Wang et al. [20] follow with four contributions each, focusing on AI techniques like neural networks and genetic algorithms. These researchers play a central role in advancing intelligent renewable energy integration.

Table 3. Most relevant countries in AI and grid-connected renewable energy systems

Country	Num. of Documents	Percentage of Total	Category
India	101	43.5%	Leading Contributor (≥ 50 docs)
China	24	10.3%	Leading Contributor (≥ 10 docs)
Saudi Arabia	20	8.6%	Leading Contributor (≥ 10 docs)
Algeria	18	7.8%	Leading Contributor (≥ 10 docs)
Malaysia	11	4.7%	Moderate Contributor (6 to 10 docs)
Egypt / Pakistan	8	3.4%	Moderate Contributor (6 to 10 docs)
United States / Tunisia / Bangladesh	7	3.0%	Moderate Contributor (6 to 10 docs)
Denmark / Iran / Canada	6	3.3%	Moderate Contributor (6 to 10 docs)
Denmark / Iran / Canada	96	15.5%	Minor Contributor (1 to 5 docs)

Table 4. Top 10 relevant authors with the highest number of publications

No.	Researcher Name	Research Areas	Num. of Publications in the Field
1	Li, J.	Photovoltaic power forecasting, Hybrid systems, Neural network.	6
2	Rizwan, M.	Artificial neural networks, Genetic algorithms, Hybrid systems, Distributed power generation.	4
3	Wang, Y.	Artificial neural networks, Genetic algorithms, Hybrid systems, Distributed power Generation.	4
4	Ahmad, I.	Artificial neural network, Hybrid systems, Microgrid.	3
5	Alam, M.M.	Artificial Neural Network, Energy storage, Photovoltaic systems.	3
6	Aly, H.H.	Hybrid systems, Power forecasting, Fuzzy logic.	3
7	Belkhier, Y.	Wind energy, Fuzzy logic.	3
8	Islam, M.S.	Energy management, Hybrid systems, Fuzzy logic.	3
9	Li, B.	Deep learning, Microgrids, Power quality.	3
10	Mansouri, M.	Deep learning, Grid-connected photovoltaic systems.	3

c. Thematic evolution of AI in grid-connected renewable energy systems

Figure 6 illustrates the temporal thematic evolution of research in AI-driven grid-connected renewable energy systems from 2014 to 2025, categorized into four distinct time periods: 2014–2020, 2021–2022, 2023–2023, and 2024–2025. Each block represents a specific thematic or keyword, with the connections between them showing the progression and linkage of topics across the years.

In the early phase (2014–2020), key themes included wind turbines, microgrids, fuzzy logic, and artificial neural networks. These foundational concepts laid the groundwork for subsequent research. Moving into 2021–2022, there was a shift towards more specialized applications such as renewable energy, maximum power point tracking (MPPT) [21], and fuzzy logic controllers (FLC), reflecting a deeper focus on optimization and control systems.

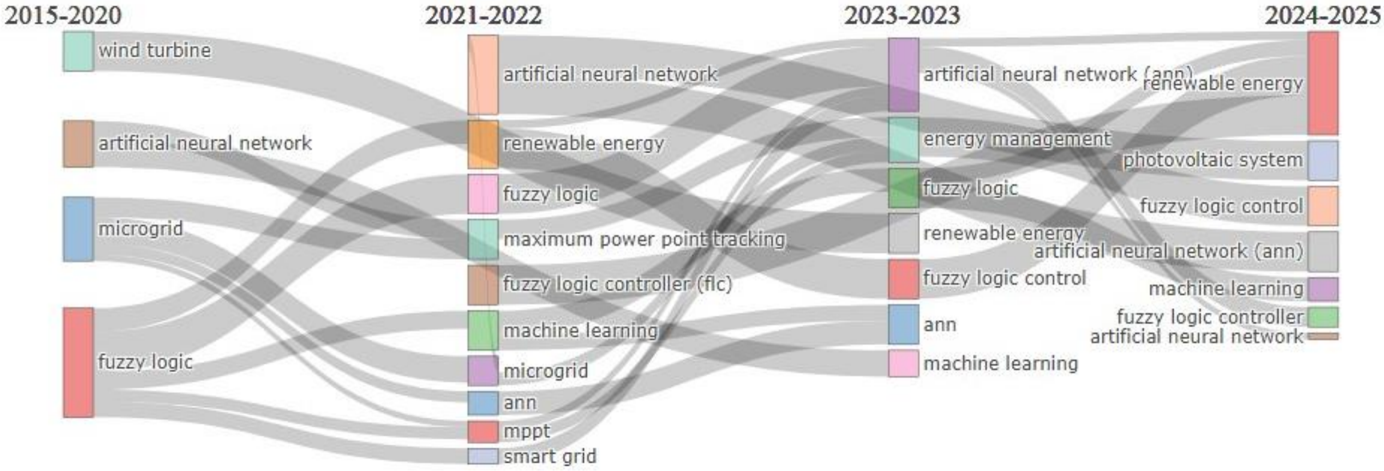

Figure 6. Thematic evolution of keywords for AI in grid-connected renewable systems

In 2023, themes like machine learning, artificial neural networks (ANNs), energy management, and fuzzy logic control continued to gain prominence, signifying ongoing interest in intelligent control strategies. By 2024–2025, research topics further consolidated around renewable energy, photovoltaic systems, and advanced methodologies like machine learning, artificial neural networks, and fuzzy logic controllers, showcasing a mature integration of AI techniques in renewable energy systems. This figure highlights the dynamic progression of research priorities over the decade, emphasizing the growing complexity and refinement of AI applications in grid-connected renewable energy systems.

d. Citations Analysis

Citation analysis reveals the most influential publications in AI-driven grid-connected renewable energy systems by identifying highly cited documents and sources. Table 5 highlights key papers that have significantly shaped research directions and methodologies in the field, serving as foundational references and demonstrating the impact of leading journals and authors.

The citation analysis of sources, as shown in Figure 7, highlights the journals most influential in AI and grid-connected renewable energy systems. Leading sources such as Renewable Energy and IEEE Access top the list with 259 and 257 citations respectively, underscoring their central role in advancing research. Other key contributors include Electronics (Switzerland), Energy Reports, and Energies, reflecting the interdisciplinary spread and depth of contributions in this field. This analysis confirms the foundational impact of specific journals in shaping academic progress and guiding future studies.

By analyzing the citation trends of the selected papers, it is clear that certain documents and sources have played a pivotal role in shaping the academic landscape. These highly cited works and outlets provide a strong foundation for future research and emphasize the interdisciplinary nature of this rapidly evolving field.

Table 5. Top 10 papers with the highest number of citations

No.	Article	Journal	Total Citations
1	[22]	Renewable Energy	229
2	[23]	IEEE Transactions on Sustainable Energy	134
3	[24]	IEEE Access	93
4	[25]	IEEE Journal of Emerging and Selected Topics in Power Electronics	87
5	[26]	Energy Conversion and Management	85
6	[27]	Electronics (Switzerland)	64
7	[28]	Frontiers in Energy	61
8	[29]	IEEE Transactions on Cybernetics	61
9	[30]	IEEE Access	56
10	[31]	IEEE Access	51

4.2 Geographical and collaborative insights

By responding to RQ2, this section provides a geographical analysis to explore the collaborative relationships among researchers, institutions, and countries in the field of AI and grid-connected renewable energy systems. By analyzing co-authorship and citation networks, the study highlights key contributors, influential clusters, and the interconnectedness of the global research community. This analysis sheds light on existing collaborations and reveals opportunities for fostering innovation and knowledge exchange within this dynamic field.

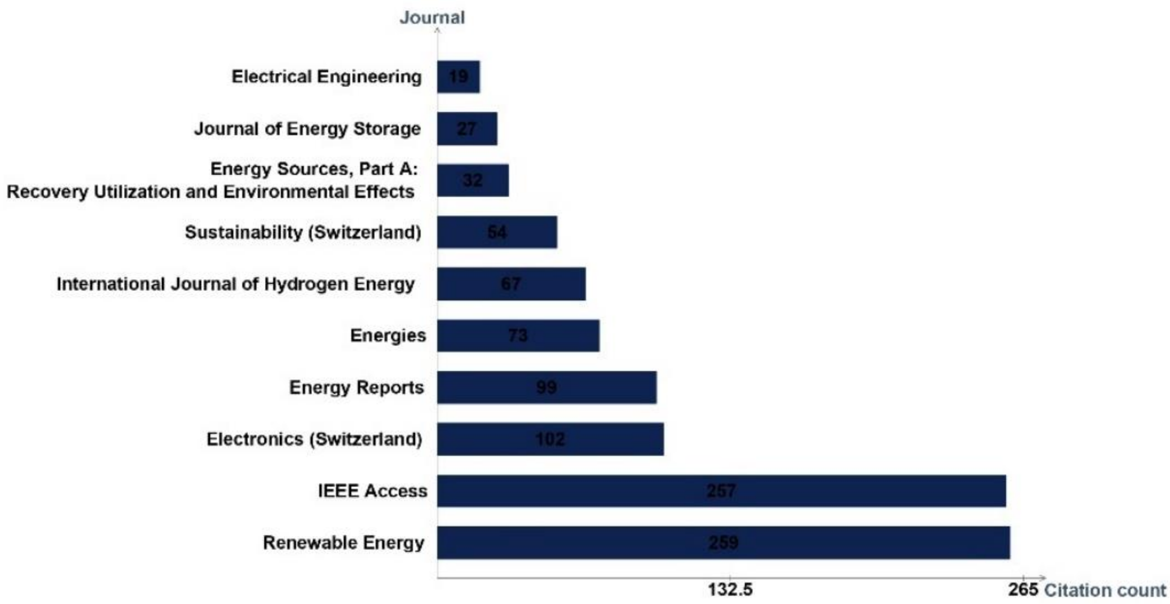

Figure 7. Most cited sources in AI and grid-connected renewable energy systems

4.2.1 Co-authorship networks

This section presents an analysis of research collaboration networks to explore how partnerships contribute to innovation in AI and grid-connected renewable energy systems. Using VOSviewer [32], a co-authorship network was generated (Figure 8), where each node represents a researcher and links denote co-authored publications. Node size reflects publication output, while link thickness indicates collaboration strength. The visualization reveals two prominent clusters: one led by Afzaal et al. [33] and Khan et al. [34], and by Nasim et al. [35], Alanazi et al. [36], and Ali et al. [37], illustrating strong intra-group collaborations alongside cross-cluster links, highlighting an active and interconnected global research community.

Figure 9 presents a VOSviewer visualization of global research collaborations in the field of AI and grid-connected renewable energy, focusing on key countries involved in this interdisciplinary area. Countries like the United States, China, Saudi Arabia, and India are represented with larger nodes, highlighting their prominent role in driving research in this domain. Collaborative links between countries like the United States and China, as well as India, underscore the global nature of this research, with significant cross-border partnerships facilitating knowledge exchange and innovation. Smaller nodes represent countries such as Turkey, Malaysia, and Pakistan, which, although contributing to the field, do so at a more modest scale compared to the larger research centers.

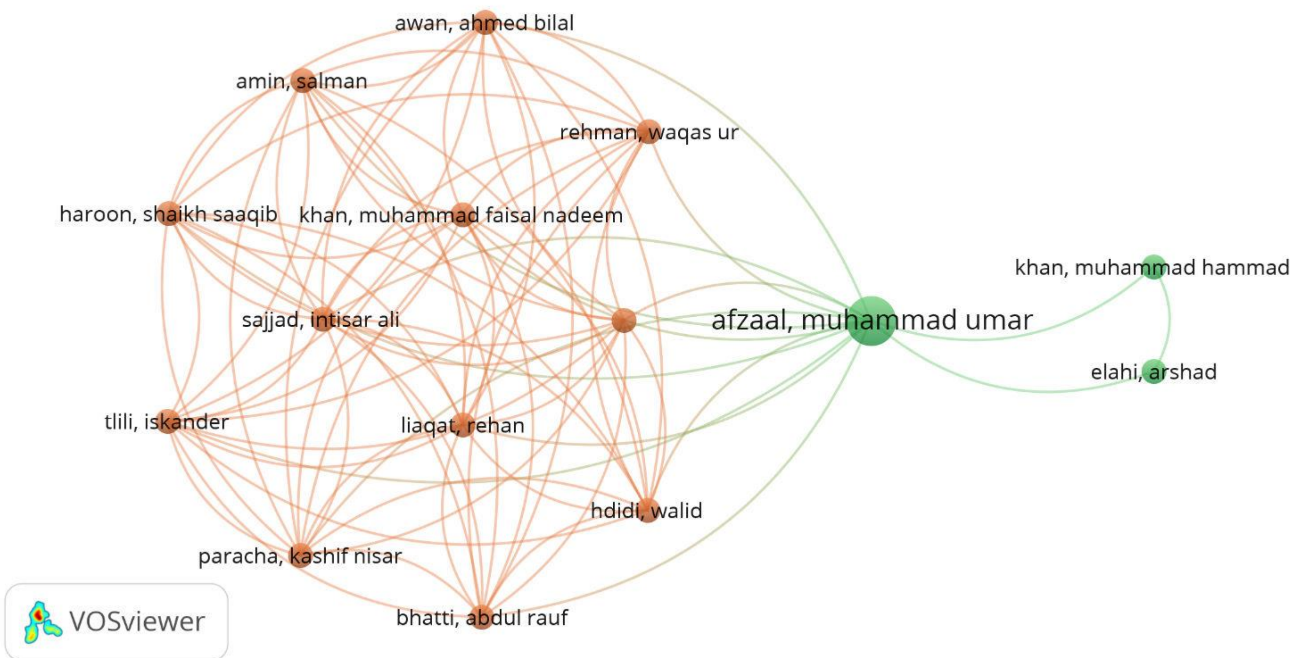

Figure 8. Co-authorship network among authors

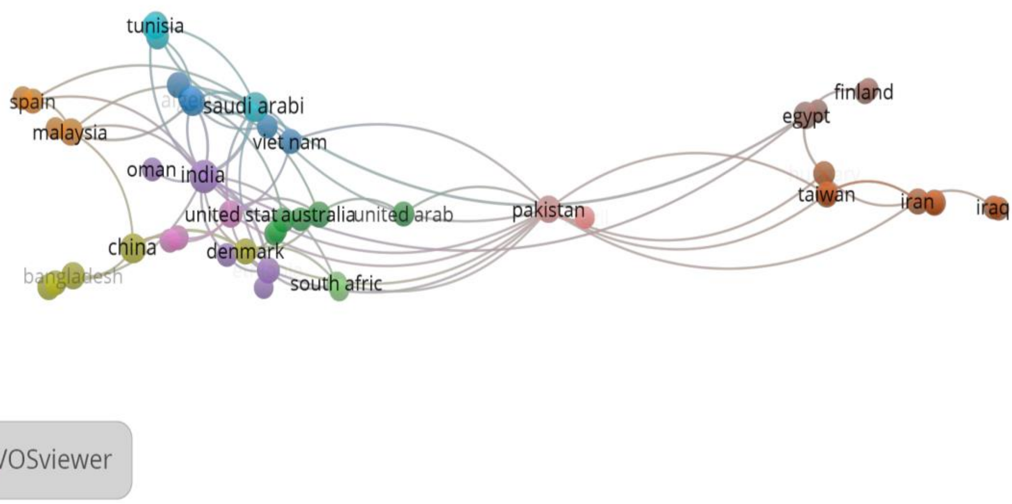

Figure 9. Co-authorship network among countries

4.2.2 Co-occurrence networks

Using the VOSviewer tool, keywords co-occurrence analysis was conducted to map the most commonly used terms in publications related to AI and grid-connected renewable energy. This analysis helps to identify the primary research themes driving the field forward. Figure 10 represents a keyword co-occurrence network, showcasing the most frequently used keywords in this field. Each node represents a keyword, and the size of the node corresponds to the frequency with which that keyword appears in the dataset. The lines between the nodes indicate co-occurrences, meaning that the two keywords are often mentioned together in the same publications. Thicker lines represent stronger connections between terms.

"Renewable energy" is the central term, closely linked to artificial intelligence, fuzzy logic, machine learning, and energy management. "Machine learning" is also a central concept, connected to terms like photovoltaic, deep learning, and microgrid. The network reveals clusters focused on AI applications in PV systems, energy optimization, forecasting, and power quality. Emerging topics such as fault detection, MPPT, and energy management highlight ongoing AI-based improvements in renewable energy systems.

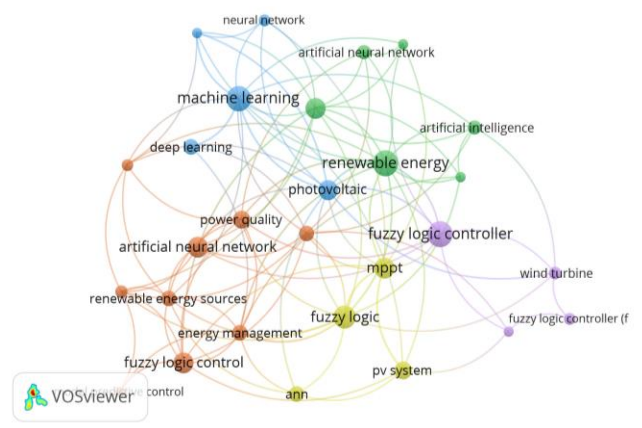

Figure 10. Author keywords co-occurrence map

Figure 11 presents a temporal overlay visualization of AI research trends in renewable energy systems. The color gradient indicates the evolution of research, with yellow representing recent topics (2023) and blue showing earlier areas of interest (2020). Older topics like "fuzzy logic control" and "MPPT" appear in blue, while newer areas such as "machine learning," "deep learning," "artificial neural network," and "forecasting" are highlighted in yellow, reflecting their growing importance. Strong connections between AI and "optimization," "energy management," and "deep learning" indicate a focus on improving system performance and prediction capabilities. The figure also highlights the integration of AI with renewable technologies like "photovoltaic" and "wind energy," which remain central to grid-connected systems, offering insights into both established and emerging research trends in AI applications for renewable energy.

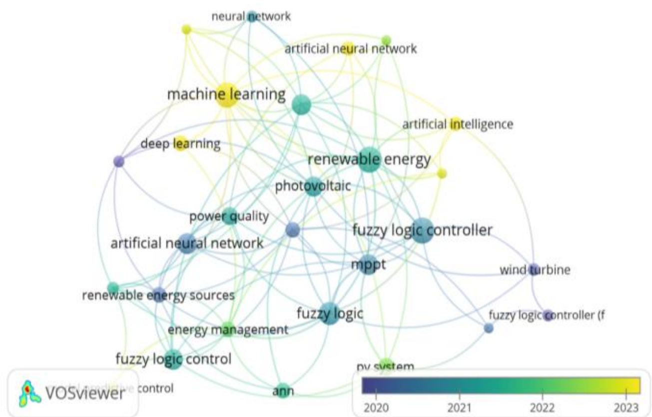

Figure 11. Temporal overlay visualization of author keywords co-occurrence

4.3 Geographical and collaborative insights

In this section, a detailed content analysis is presented, offering qualitative insights by examining the key areas of research, including the types of renewable energy sources utilized, the AI techniques and algorithms applied, the simulation and modeling tools used, and the extent of hardware implementation. By categorizing and synthesizing the findings from the selected papers, the content analysis provides a deeper understanding of the current trends in the integration of AI in grid-connected renewable energy systems.

4.3.1 Research topics

This section addresses RQ3 by examining the temporal evolution of key research topics concerning the application of AI in grid-connected renewable energy systems. The analysis focuses on four major areas: AI-based optimization in power systems, demand forecasting, grid management, and energy storage. These topics were chosen not only because they represent some of the most extensively researched areas in the intersection of AI and renewable energy, but also due to the critical challenges they address for the successful implementation of grid-connected renewable energy systems. These areas are closely interconnected, and progress in one often benefits the others. For instance, advancements in energy storage optimization enhance grid management, while improvements in demand forecasting increase the overall efficiency of power systems integration. To ensure a comprehensive analysis, we conducted an in-depth content analysis of the selected 232 papers to better understand their relevance and contribution. The results of this approach are presented in Figure 12, showcasing the growth of research in these critical areas over time. A notable increase across all areas begins in 2020, driven by advancements in AI and growing global focus on renewable energy solutions, highlighting the expanding role of AI in addressing energy challenges.

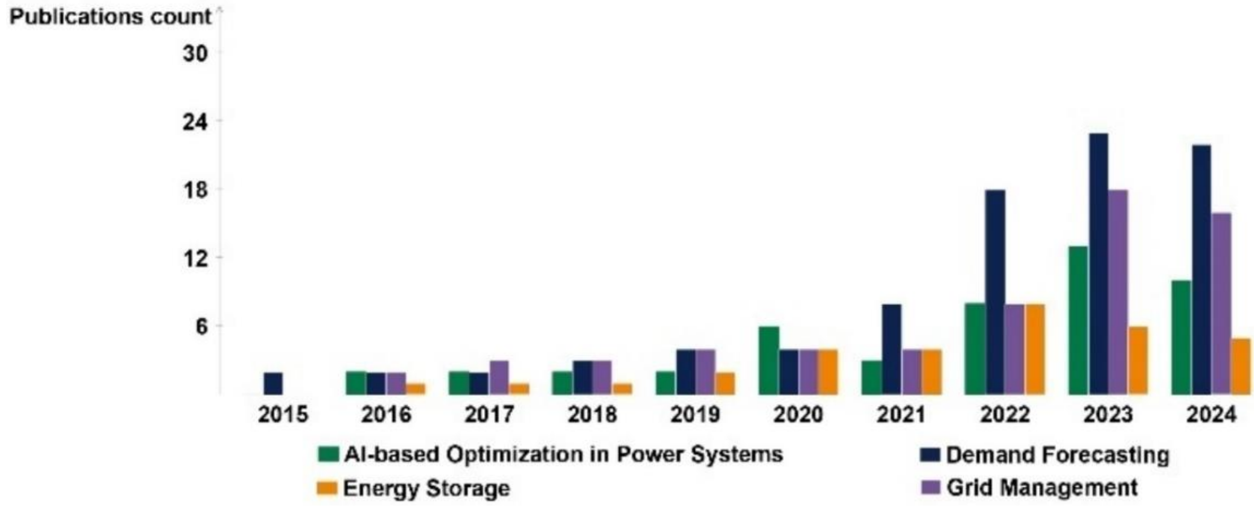

Figure 12. Temporal evolution of research topics (2014–2025)

4.3.2 Renewable energy sources

This section addresses RQ4 by exploring which renewable energy sources are most frequently combined with AI technologies in grid-connected systems. The integration of renewable energy sources into such systems has been a focal point of AI-driven research. The selected articles predominantly examine various RES, including solar energy, wind energy, and hybrid systems, highlighting the versatility of AI in addressing the unique challenges associated with each source.

- Solar Energy: Many studies focus on solar photovoltaic (PV) systems, leveraging AI for tasks such as maximum power point tracking, fault detection, and performance optimization under varying weather conditions. The intermittent nature of solar energy necessitates robust AI techniques for real-time management and forecasting.
- Wind Energy: AI techniques are applied to wind energy systems for turbine control, fault diagnosis, and power generation forecasting. The complexity of wind dynamics, such as turbulence and wind shear, makes AI an essential tool for enhancing system reliability.
- Hybrid Systems: A notable portion of the literature examines hybrid systems, combining solar, wind, and sometimes other sources like biomass or hydropower. AI plays a critical role in optimizing energy dispatch, balancing generation, and managing storage to ensure system stability and efficiency.
- Other Sources: While less common, some articles address other renewables like hydropower and biomass. These studies often focus on integrating these sources into existing grids using AI for optimization and fault detection.

The distribution of articles across these renewable energy sources is illustrated in Figure 13, which provides an overview of their respective focus areas.

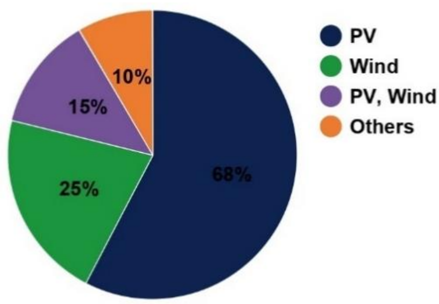

Figure 13. Distribution of renewable energy sources

4.3.3 AI techniques/algorithms

This subsection answers RQ5. The selected articles employ a variety of AI techniques and algorithms to address challenges in grid-connected renewable energy systems. These methods are tailored to specific tasks such as forecasting, optimization, fault detection, and energy management. Below is a breakdown of the most commonly used AI techniques.

- Machine Learning: Widely utilized for tasks such as energy production forecasting and load prediction. Algorithms like decision trees, support vector machines (SVM), and ensemble methods are frequently applied for their accuracy and adaptability.

- Deep Learning: Advanced methods like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used for complex tasks, including fault detection and time-series analysis of energy data.
- Fuzzy Logic: Popular for its ability to handle uncertainties in renewable energy systems, especially in control applications like MPPT and demand-response management.
- Neural Networks: Applied across a range of tasks, including energy storage optimization and grid stability analysis. Feedforward and backpropagation neural networks are the most commonly mentioned types.
- Reinforcement Learning (RL): Emerging as a robust tool for real-time decision-making and grid management, with applications in energy dispatch and microgrid control.

The distribution of AI techniques in the selected articles is illustrated in Figure 14, providing a clear overview of their usage. To complement this overview, a cross-tabulated summary is presented in Table 6, detailing the usage of each AI technique across key application areas. This classification provides a clearer understanding of how specific techniques are tailored to different tasks within grid-connected renewable energy systems, highlighting the practical alignment between algorithmic capabilities and system requirements.

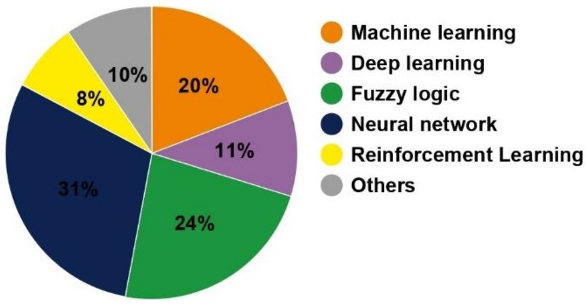

Figure 14. Distribution of the most used AI techniques

Table 6. Distribution of AI techniques by application area in arid-connected renewable energy systems

AI Technique	Forecasting	Optimization	Control	Fault Detection	Energy Management	Others
Machine learning	15	7	8	6	5	5
Deep learning	7	3	4	6	3	2
Fuzzy logic	4	5	24	3	13	6
Neural network	13	11	22	8	10	7
Reinforcement learning	3	3	4	3	3	2
Others	4	3	6	5	3	4

4.3.4 Simulation/modeling tools

This section addresses RQ5. Simulation and modeling tools play a critical role in the research and development of AI-driven grid-connected renewable energy systems. These tools enable researchers to design, test, and validate AI algorithms in a controlled environment before real-world implementation. The selected articles demonstrate the use of a variety of software platforms for tasks such as energy system modeling, optimization, and grid stability analysis. Below are the most commonly used tools\item MATLAB/Simulink: The most frequently used tool for simulating power systems and validating AI algorithms. It is particularly favored for its flexibility in integrating control strategies and conducting dynamic simulations.

- HOMER Energy: Widely employed for techno-economic analyses of hybrid energy systems, providing insights into system design and financial feasibility.
- Python-based Tools: Tools such as TensorFlow and PyTorch are increasingly being adopted for AI-specific tasks like deep learning model training and optimization.
- OpenDSS (Open Distribution System Simulator): An open-source tool for simulating distributed energy resources integration and grid optimization.
- PVsyst: Used for the design, simulation, and analysis of photovoltaic systems, including grid-connected, off-grid, and hybrid configurations.

The frequency of simulation tools used across the analyzed articles is depicted in Figure 15, highlighting their relative popularity.

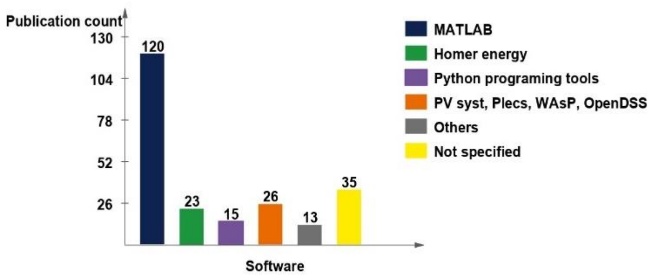

Figure 15. Type of software used

4.3.5 Hardware implementation

In this section, we address RQ6. Hardware implementation is a crucial aspect of research on AI-driven grid-connected renewable energy systems, as it bridges the gap between theoretical simulations and practical applications. The selected articles highlight various approaches for incorporating hardware components to prototype, test, and validate AI algorithms in real-world settings. Below are the key areas of focus for hardware implementations:

- Prototyping with Inverters: Some studies utilize three-phase inverters to demonstrate the integration of AI algorithms for grid synchronization, power quality improvement, and control of renewable energy sources.
- Energy Storage Systems: Hardware implementations often involve batteries or other storage technologies, testing AI-based energy management systems to optimize charging and discharging cycles.
- Microgrid Testbeds: Some research leverages microgrid setups to validate AI-driven control

strategies, such as demand-response optimization and fault-tolerant grid management.

- Sensors and Data Acquisition Systems: To enable real-time monitoring and control, researchers implement hardware setups with voltage, current, and temperature sensors integrated with AI models.
- Embedded Systems: AI algorithms are deployed on microcontrollers or field-programmable gate arrays (FPGAs) for efficient execution and control of grid-connected renewable energy systems.

To showcase trends in hardware-related research, Figure 16 provides an overall distribution of studies featuring hardware implementations over the years. The distribution of hardware implementation types in the selected articles is presented in Table 7, highlighting the most common components and systems.

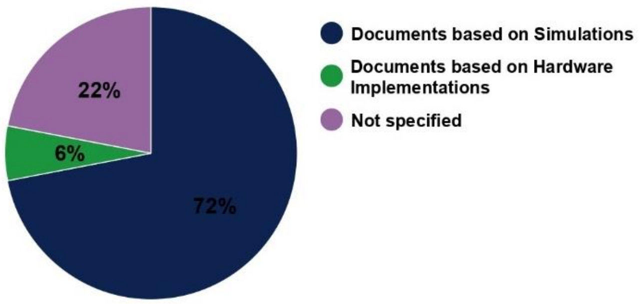

Figure 16. Distribution of research type

Table 7. Distribution of hardware implementation types in the selected articles

Year	Article	Hardware Implementation	AI Technique
2024	[38]	DSP-based controller	Neuro-Fuzzy-SVPWM
2024	[39]	C2000 Delfino microcontroller	ANN for MPPT
2024	[40]	Raspberry PI controller	Hybrid DWT-SVM
2024	[41]	Imperix B-Board and Typhoon HIL	Reinforcement learning
2023	[42]	DSP-based controller	ANN
2023	[43]	TMS320ds lunch xl DSP (Switzerland)	NN
2023	[44]	MS320F28379D Dual-Core Delfino Micro-controller	ANN
2022	[45]	OPAL RT HIL simulator	Adaptive Neuro-Fuzzy Inference
2022	[46]	PIC microcontroller	Fuzzy logic based MPPT
2022	[47]	Hardware-in the-Loop	ML
2019	[48]	Hardware setup-based DC-DC fused CUK-SEPIC converter	Fuzzy logic
2019	[49]	Arduino ATMEGA-328P	Fuzzy logic
2017	[23]	Hardware validation- PV system	ANN

Despite its importance, hardware validation remains relatively underrepresented in the literature. This can be attributed to several factors, including the high cost of equipment, limited access to advanced testing facilities, and the complexity involved in integrating AI algorithms with real-time control hardware. Moreover, safety concerns and regulatory barriers can restrict experimental deployment in real grid-connected environments. Consequently, many researchers opt to perform their studies in simulation environments, which offer greater flexibility and lower resource requirements, especially during early-stage development.

5. DISCUSSION

This systematic mapping study offers a comprehensive overview of how AI is being used in grid-connected renewable energy systems, addressing each of the six research questions posed at the start of the analysis.

Growth trend of research and the contributing subject areas (RQ1): The analysis reveals a notable increase in publications after 2015, with significant momentum gained post-2019. This growth reflects the global push for intelligent energy solutions and the urgency to manage high renewable penetration. Dominant research themes include AI-based forecasting, optimization, energy management, and grid control.

Major contributors (RQ2): Countries such as India, China, the United States, and Saudi Arabia lead in research contributions. Influential researchers from these nations focus on areas such as solar energy integration and neural network-based control. Strong international collaboration networks, especially co-authorship between leading countries, play a critical role in accelerating innovation and promoting knowledge sharing.

Emerging research trends and hot topics (RQ3): Emerging topics include the increasing use of machine learning, deep learning, and hybrid AI methods, tailored for real-time control, energy forecasting, and fault detection. Solar and wind systems dominate the application domain, with solar being the most frequently studied. Simulation tools such as MATLAB/Simulink are commonly used for algorithm development and validation.

Types of renewable energy systems most studied (RQ4): Solar energy emerges as the most extensively studied source, followed by wind and hybrid systems. This reflects their technological maturity and widespread deployment across various regions.

Applied AI techniques (RQ5): The review reveals that a range of AI techniques, including artificial neural networks, fuzzy logic, support vector machines, and reinforcement learning, are being applied to optimize different aspects of grid-connected systems. These methods are customized to tasks such as power quality monitoring, renewable energy forecasting, and operational optimization. Researchers often use software platforms to fine-tune their models before considering real-world deployment.

Hardware implementations (RQ6): The results indicate that this area is less explored compared to simulation-based studies, yet it plays a critical role in translating theoretical advances into practical applications. Several articles highlight the development of hardware prototypes involving microgrids, power converters, and embedded controllers. These implementations serve to validate AI algorithms under realistic operating conditions, effectively bridging the gap between laboratory simulations and real-world deployment.

The findings indicate that AI will remain central to optimizing renewable energy integration, emphasizing the need for future research to focus on bridging gaps in energy storage, grid management, and real-world applications of AI technologies. Advancing this field will require enhanced international collaboration and interdisciplinary research efforts.

6. CONCLUSION AND RECOMMENDATIONS

In conclusion, this systematic literature mapping has highlighted the rapid evolution of AI applications in grid-connected renewable energy systems, revealing key trends, active contributors, dominant technologies, and persistent research gaps. While solar and wind remain the most studied sources, and tools like MATLAB/Simulink dominate simulations, there is a clear need for more hardware-based validations and real-world implementations.

Geographically, countries such as China, India, and the United States lead in publications and collaboration networks. However, a more inclusive global research effort is needed, particularly involving underrepresented regions. Additionally, while traditional AI techniques such as neural networks and fuzzy logic are widely used, the field has yet to fully explore the potential of newer paradigms like transformer-based models and generative AI.

To provide a concise synthesis of this study’s insights, Table 8 summarizes the main findings and corresponding recommendations based on the six research questions.

In light of these findings, future research should:

- Bridge theoretical research and real-world deployment through applied validation;
- Foster interdisciplinary collaboration across AI, energy, and engineering fields;
- Explore advanced AI models like transformers and generative AI, especially for time-series forecasting, adaptive control, and synthetic data generation;
- Promote inclusive international cooperation to ensure balanced progress across regions.

By addressing these priorities, researchers can contribute to smarter, more resilient, and sustainable power systems that leverage the full potential of artificial intelligence.

Table 8. Main findings and recommendations based on the research questions

RQs	Main Finding	Recommendations
RQ1	Significant rise in publications after 2015, with a peak after 2019. Forecasting and optimization dominate.	Encourage deeper exploration of emerging topics and interdisciplinary approaches.
RQ2	China, India, USA are the top contributors. Strong international collaboration patterns.	Strengthen collaboration with underrepresented regions to promote global equity.
RQ3	Forecasting, optimization, and control are the most common themes.	Focus future work on underexplored areas like fault detection and grid coordination.
RQ4	Solar is the most studied, followed by wind and hybrid systems.	Increase studies on hybrid systems and integration with storage.
RQ5	Neural networks and fuzzy logic are the most popular. MATLAB/Simulink is widely used.	Explore the use of advanced AI (e.g., transformers) and validate models on hardware.
RQ6	Still limited; most studies remain simulation-based.	Prioritize real-world testing and implementation to validate practical feasibility.

REFERENCES

[1] Alves, D., Mendonça, F., Mostafa, S.S., Morgado-Dias, F. (2024). A comprehensive IoT cloud-based wind station ready for real-time measurements and artificial intelligence integration. e-Prime-Advances in Electrical Engineering, Electronics and Energy, 10: 100862. https://doi.org/10.1016/j.prime.2024.100862

[2] Unsal, D.B., Aksoz, A., Oyucu, S., Guerrero, J.M., Guler, M. (2024). A comparative study of AI methods on renewable energy prediction for smart grids: Case of Turkey. Sustainability, 16(7): 2894. https://doi.org/10.3390/su16072894

[3] Al-Dahidi, S., Alrbai, M., Alahmer, H., Rinchi, B., Alahmer, A. (2024). Enhancing solar photovoltaic energy production prediction using diverse machine learning models tuned with the chimp optimization algorithm. Scientific Reports, 14(1): 18583. https://doi.org/10.1038/s41598-024-69544-8

[4] Ramadevi, B., Kasi, V.R., Bingi, K. (2024). Enhancement of Texas wind turbine power predictions using fractional order neural network by incorporating machine learning models to impute missing data. Knowledge-Based Systems, 300: 112176. https://doi.org/10.1016/j.knosys.2024.112176

[5] Bin Abu Sofian, A.D.A., Lim, H.R., Siti Halimatul Munawaroh, H., Ma, Z., Chew, K.W., Show, P.L. (2024). Machine learning and the renewable energy revolution: Exploring solar and wind energy solutions for a sustainable future including innovations in energy storage. Sustainable Development, 32(4): 3953-3978. https://doi.org/10.1002/sd.2885

[6] Pranckutė, R. (2021). Web of Science (WoS) and Scopus: The titans of bibliographic information in today’s academic world. Publications,9(1): 12.

[7] Petersen, K., Feldt, R., Mujtaba, S., Mattsson, M. (2008). Systematic mapping studies in software engineering. In 12th International Conference on Evaluation and Assessment in Software Engineering (EASE), University of Bari, Italy, pp. 1-10. https://doi.org/10.14236/ewic/EASE2008.8

[8] AlMallahi, M.N., Mustafa, J., Al-Marzouqi, A.H., Elgendi, M. (2024). Research progress and state-of-the-art on solar membrane desalination. Case Studies in Chemical and Environmental Engineering, 10: 100825. https://doi.org/10.1016/j.cscee.2024.100825

[9] Dzikevics, M., Jaunzems, D., Terauds, M. (2021). Bibliometric analysis of the solar thermal system control methods. Rigas Tehniskas Universitates Zinatniskie Raksti, 25(1): 1114-1127. https://doi.org/10.2478/rtuect-2021-0084

[10] Sepúlveda-Oviedo, E.H., Travé-Massuyès, L., Subias,

A., Pavlov, M., Alonso, C. (2023). Fault diagnosis of photovoltaic systems using artificial intelligence: A bibliometric approach. Heliyon, 9(11): e21491. https://doi.org/10.1016/j.heliyon.2023.e21491

[11] Velasquez, J.D., Cadavid, L., Franco, C.J. (2023). Intelligence techniques in sustainable energy: Analysis of a decade of advances. Energies, 16(19): 6974. https://doi.org/10.3390/en16196974

[12] Hernandez-Palma, H.G., Alvarado, J.R.P., Guiliany, J.E.G., Dotto, G.L., Ramos, C.G. (2024). Implications of machine learning in the generation of renewable energies in Latin America from a globalized vision: A systematic review. International Journal of Energy Economics and Policy, 14(2): 1-10. https://doi.org/10.32479/ijeep.15301

[13] Bracarense, N., Bawack, R.E., Fosso Wamba, S., Carillo, K.D.A. (2022). Artificial intelligence and sustainability: A bibliometric analysis and future research directions. Pacific Asia Journal of the Association for Information Systems, 14(2): 9. https://doi.org/10.17705/1pais.14209

[14] Lampropoulos, G. (2023). Artificial intelligence in smart grids: A bibliometric analysis and scientific mapping study. Journal of Mechatronics, Electrical Power, and Vehicular Technology, 14(1): 11-34. https://doi.org/10.14203/j.mev.2023.v14.11-34

[15] Ajibade, S.S., Zaidi, A., Al Luhayb, A.S.M., Adediran, A.O., Voumik, L.C., Rabbi, F. (2023). New insights into the emerging trends research of machine and deep learning applications in energy storage: A bibliometric analysis and publication trends. International Journal of Energy Economics and Policy, 13(5): 303-314. https://doi.org/10.32479/ijeep.14832

[16] Eslava-Zapata, R., Sánchez-Castillo, V., Juaneda-Ayensa, E. (2024). Key players in renewable energy and artificial intelligence research. EAI Endorsed Transactions on the Energy Web, 11(1): 1. https://doi.org/10.4108/ew.5182.

[17] Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ, 372: n71. https://doi.org/10.1136/bmj.n71

[18] Li, B., Han, M., Li, J. (2023). Sizing grid-connected microgrids based on deep reinforcement learning. In International Conference on Wireless Power Transfer, pp. 515-523. https://doi.org/10.1007/978-981-97-0869-7_56

[19] Sharma, B., Rizwan, M., Anand, P. (2023). Optimal design of renewable energy-based hybrid system considering weather forecasting using machine learning techniques. Electrical Engineering, 105(6): 4229-4249. https://doi.org/10.1007/s00202-023-01945-w

[20] Wang, C., Wang, Y., Liang, W., Ren, M., et al. (2024). Integrated modelling approach for CCES grid connection and fuzzy logic frequency regulation. In 2024 4th Power System and Green Energy Conference (PSGEC), Shanghai, China, pp. 743-748. https://doi.org/10.1109/PSGEC62376.2024.10721165

[21] Satif, A., Hlou, L., Mekhfioui, M., Elgouri, R. (2024). Enhancing grid stability and efficiency: Cost-effective hardware implementation for advanced control of grid-connected PV systems. Journal Européen des Systèmes Automatisés, 57(5): 1305-1320. https://doi.org/10.18280/jesa.570506

[22] Doucoure, B., Agbossou, K., Cardenas, A. (2016). Time series prediction using artificial wavelet neural network and multi-resolution analysis: Application to wind speed data. Renewable Energy, 92: 202-211.

[23] Sun, Y., Li, S., Lin, B., Fu, X., Ramezani, M., Jaithwa, I. (2017). Artificial neural network for control and grid integration of residential solar photovoltaic systems. IEEE Transactions on Sustainable Energy, 8(4): 1484-1495. https://doi.org/10.1109/TSTE.2017.2691669

[24] Sarita, K., Kumar, S., Vardhan, A.S.S., Elavarasan, R.M., Saket, R.K., Shafiullah, G.M., Hossain, E. (2020). Power enhancement with grid stabilization of renewable energy-based generation system using UPQC-FLC-EVA technique. IEEE Access, 8: 207443-207464. https://doi.org/10.1109/ACCESS.2020.3038313

[25] Jafari, M., Malekjamshidi, Z., Zhu, J., Khooban, M.H. (2018). A novel predictive fuzzy logic-based energy management system for grid-connected and off-grid operation of residential smart microgrids. IEEE Journal of Emerging and Selected Topics in Power Electronics, 8(2): 1391-1404. https://doi.org/10.1109/JESTPE.2018.2882509

[26] Shivam, K., Tzou, J.C., Wu, S.C. (2021). A multi-objective predictive energy management strategy for residential grid-connected PV-battery hybrid systems based on machine learning technique. Energy Conversion and Management, 237: 114103. https://doi.org/10.1016/j.enconman.2021.114103

[27] Zeb, K., Islam, S.U., Din, W.U., Khan, I., et al. (2019). Design of fuzzy-PI and fuzzy-sliding mode controllers for single-phase two-stages grid-connected transformerless photovoltaic inverter. Electronics, 8(5): 520. https://doi.org/10.3390/electronics8050520

[28] Rezvani, A., Esmaeily, A., Etaati, H., Mohammadinodoushan, M. (2019). Intelligent hybrid power generation system using new hybrid fuzzy-neural for photovoltaic system and RBFNSM for wind turbine in the grid connected mode. Frontiers in Energy, 13(1): 131-148. https://doi.org/10.1007/s11708-017-0446-x

[29] Teo, T.T., Logenthiran, T., Woo, W.L., Abidi, K., et al. (2020). Optimization of fuzzy energy-management system for grid-connected microgrid using NSGA-II. IEEE Transactions on Cybernetics, 51(11): 5375-5386. https://doi.org/10.1109/TCYB.2020.3031109

[30] Alrifaey, M., Lim, W.H., Ang, C.K., Natarajan, E., et al. (2022). Hybrid deep learning model for fault detection and classification of grid-connected photovoltaic system. IEEE Access, 10: 13852-13869. https://doi.org/10.1109/ACCESS.2022.3140287

[31] Yap, K.Y., Sarimuthu, C.R., Lim, J.M.Y. (2020). Grid integration of solar photovoltaic system using machine learning-based virtual inertia synthetization in synchronverter. IEEE Access, 8: 49961-49976. https://doi.org/10.1109/ACCESS.2020.2980187

[32] Van Eck, N., Waltman, L. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping. Scientometrics, 84(2): 523-538.

[33] Afzaal, M.U., Khan, M.H., Elahi, A. (2022). Water flow patterns generation model for grid connected run-of-river hydro power plant. In 2022 IEEE International Conference on Environment and Electrical Engineering and 2022 IEEE Industrial and Commercial Power Systems Europe (EEEIC/I&CPS Europe), Prague, Czech Republic, pp. 1-6. https://doi.org/10.1109/EEEIC/ICPSEurope54979.2022.9854662

[34] Khan, M.T., Shoaib, M., Hammad, M., Salahudin, H., Ahmad, F., Ahmad, S. (2021). Application of machine learning techniques in rainfall–runoff modelling of the soan river basin, Pakistan. Water, 13(24): 3528. https://doi.org/10.3390/w13243528

[35] Nasim, U., Bhatti, A.R., Farhan, M., Zeb, O., Butt, A.D., Paracha, K.N. (2024). An improved barrier function double integral sliding mode control of SynRM for hybrid energy storage system-based electric vehicle. Journal of Energy Storage, 104: 114401. https://doi.org/10.1016/j.est.2024.114401

[36] Alanazi, M., Alanazi, A., Memon, Z.A., Awan, A.B., Deriche, M. (2024). Multi-objective energy management in microgrids: Improved honey badger algorithm with fuzzy decision-making and battery aging considerations. Energies, 17(17): 4373. https://doi.org/10.3390/en17174373

[37] Ali, M.A., Bhatti, A.R., Farhan, M., Rasool, A., Ali, A. (2024). AI-optimization operation of biomass-based distributed generator for efficient radial distribution system. International Journal of Renewable Energy Development, 13(6): 1044-1057. https://doi.org/10.61435/ijred.2024.60224

[38] Ertekin, D., Özden, M., Deniz, A., Toprak, M.Z. (2024). Neuro-fuzzy-SVPWM switched-inductor-capacitor-based boost inverter for grid-tied fuel cell power generators, design and implementation. Renewable Energy, 227: 120469. https://doi.org/10.1016/j.renene.2024.120469

[39] Ghias, R., Hasan, A., Ahmad, I. (2024). Artificial neural network based conditional controllers with saturated action for multi-renewable hybrid alternating or direct current microgrids in islanded and grid-connected modes. Journal of Energy Storage, 94: 112139. https://doi.org/10.1016/j.est.2024.112139

[40] Nair, D.S., Rajeev, T.N., Miraj, S. (2024). Enhanced fault identification in grid-connected microgridwith SVM-based control algorithm. Indonesian Journal of Electrical Engineering and Computer Science, 36: 115–126. https://ijeecs.iaescore.com/index.php/IJEECS/article/view/36995.

[41] Khan, D., Qais, M., Hu, P. (2024). A reinforcement learning-based control system for higher resonance frequency conditions of grid-integrated LCL-filtered BESS. Journal of Energy Storage, 93: 112373. https://doi.org/10.1016/j.est.2024.112373

[42] Baltacı, K., Ertekin, D., Bayrak, G. (2024). Design and experimental validation of an artificial neural network-SVPWM controller for a novel micro grid-tied fuel cell-based 3-phase boost inverter. International Journal of Hydrogen Energy, 52: 1247-1265. https://doi.org/10.1016/j.ijhydene.2023.10.291

[43] Acharya, D.P., Hannon, N., Choudhury, S., Nayak, N., Satpathy, A. (2023). Design and hardware in loop testing of an intelligent controller for power quality improvement in a complex micro grid. Energy Reports, 9: 4135-4156. https://doi.org/10.1016/j.egyr.2023.03.032

[44] Mehdi, H.M., Azeem, M.K., Ahmad, I. (2023). Artificial intelligence based nonlinear control of hybrid DC microgrid for dynamic stability and bidirectional power flow. Journal of Energy Storage, 58: 106333. https://doi.org/10.1016/j.est.2022.106333

[45] Prasad, D., Dhanamjayulu, C. (2022). Solar PV integrated dynamic voltage restorer for enhancing the power quality under distorted grid conditions. Electric Power Systems Research, 213: 108746. https://doi.org/10.1016/j.epsr.2022.108746

[46] Nirmala, R., Venkatesan, S. (2022). Inverter current control for reactive power compensation in solar grid system using self-tuned fuzzy logic controller. Automatika: časopis za automatiku, mjerenje, elektroniku, računarstvo i komunikacije, 63(1): 102-121. https://doi.org/10.1080/00051144.2021.2009653

[47] Behrends, H., Millinger, D., Weihs-Sedivy, W., Javornik, A., Roolfs, G., Geißendörfer, S. (2022). Analysis of residual current flows in inverter based energy systems using machine learning approaches. Energies, 15(2): 582. https://doi.org/10.3390/en15020582

[48] Dayalan, S., Rathinam, R., Pandey, P., Adap, M. (2019). A fuzzy logic based energy management of grid connected hybrid energy system. SAE Technical Paper 2019-28-0076. https://doi.org/10.4271/2019-28-0076

[49] Bihari, S.P., Sadhu, P.K., Das, S., Arvind, P., Gupta, A. (2019). Design and implementation of a photovoltaic wind hybrid system with the assessment of fuzzy logic maximum power point technique. Revue Roumaine des Sciences Techniques-Série Électrotechnique et Énergétique, 64(3): 235-240.