RESEARCH AND REVIEWS IN SUSTAINABILITY

# Artificial Intelligence in Renewable Energy: A Systematic Review of Trends in Solar, Wind, and Smart Grid Applications

REVIEW

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## ABSTRACT

Artificial Intelligence (AI) revolutionizes the renewable energy sector by enabling advanced forecasting, real-time optimization, and autonomous system control. As global efforts toward decarbonization intensify, AI applications have rapidly expanded across various renewable energy domains. However, the literature remains fragmented, lacking a focused synthesis of evolving AI techniques and their domain-specific implementations. This study addresses this gap by systematically reviewing AI applications in three critical energy sectors: Solar Energy, Wind Energy, and Energy Storage & Smart Grids. Using the PRISMA methodology, peer-reviewed articles published between 2015 and 2025 were extracted from two authoritative databases—IEEE Xplore and ScienceDirect. The selected studies were classified based on AI methods, including machine learning, deep learning, reinforcement learning, fuzzy logic, and emerging paradigms such as explainable AI (XAI), generative AI, graph neural networks (GNNs), and physics-informed neural networks (PINNs). Key contributions of this review include a cross-source comparative analysis, domain-specific trend mapping over a decade, and the identification of gaps in methodological transparency. Findings reveal increasing use of hybrid models, growing interest in interpretable and physically grounded techniques, and persistent underreporting of AI methodologies in the literature. This review provides actionable insights and research directions toward developing intelligent, explainable, sustainable energy systems.

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## INTRODUCTION

The global push toward sustainable development and decarbonization has accelerated the adoption of renewable energy technologies, particularly in solar, wind, and energy storage systems. These technologies are central to reducing greenhouse gas emissions and ensuring long-term energy resilience and reliability. However, large-scale integration of renewable energy remains hindered by challenges such as intermittency, energy storage limitations, and grid complexity (Ipakchi and Albuyeh, 2009; Rugolo and Aziz, 2012). As these systems become increasingly decentralized and data-driven, there is a growing need for intelligent methods that can optimize operations in real-time.

Artificial Intelligence (AI) has emerged as a powerful tool for addressing these complexities in renewable energy systems. Through data-driven modeling and autonomous learning, AI enhances forecasting, optimizes system performance, and enables predictive and adaptive control. Techniques such as artificial neural networks (ANNs), support vector machines (SVMs), fuzzy logic systems, and reinforcement learning have been widely employed in these domains, including solar irradiance prediction (Sammar *et al.*, 2024), wind energy forecasting and fault detection (Liu *et al.*, 2025) and predictive maintenance in hybrid energy systems (Shao *et al.*, 2015).

Recent developments have expanded the AI landscape in renewable energy to include explainable AI (XAI), generative AI, graph neural networks (GNNs), and physics-informed neural networks (PINNs), which address the challenges of interpretability, data scarcity, and physical modeling (Huang and Wang, 2023; Latrach *et al.*, 2024). Additionally, integrating AI with Internet of Things (IoT) infrastructures facilitates real-time data acquisition and dynamic control in intelligent energy systems (Orumwense and Abo-Al-Ez, 2022).

Despite the growing body of research, existing studies are often fragmented by application type, energy domain, or AI technique. Most recent reviews focus on isolated sectors or single-use cases such as solar forecasting or wind turbine diagnostics. There remains a lack of comprehensive, cross-domain analysis of emerging AI paradigms and their integration across diverse renewable energy systems (Cacciamani *et al.*, 2023).

The main contributions of this review are as follows:

**i.** This review systematically examines AI applications across three critical renewable energy domains—Solar Energy, Wind Energy, and Energy Storage & Smart Grids—allowing for domain-specific insights and comparative understanding, which are often lacking in broader reviews.

**ii.** The study adopts a rigorous, PRISMA-based review framework using two trusted academic databases, IEEE Xplore and ScienceDirect, ensuring transparency, reproducibility, and comprehensive literature coverage from 2015 to 2025.

**iii.** A platform-level comparative analysis revealing discrepancies in AI technique reporting between IEEE Xplore and ScienceDirect, contributing new insights into publication behavior and methodological transparency.

**iv.** AI techniques were categorized and mapped thematically by domain, revealing significant trends in adopting methods such as machine learning, deep learning, fuzzy logic, and reinforcement learning, as well as their evolution over time.

**v.** The review highlights the growing, yet underutilized, application of Explainable AI (XAI), Generative AI, Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs), emphasizing their potential to address interpretability and physical modeling challenges in energy systems.

This review addresses the identified gaps by systematically mapping emerging trends and applications of AI in renewable energy using the PRISMA framework. Covering studies published between 2015 and 2025, this review categorizes AI approaches by technique and domain, highlights interdisciplinary integrations, and identifies research gaps. The goal is to provide researchers, practitioners, and policymakers with actionable insights into the future of AI-driven, sustainable energy systems.

## BACKGROUND

### OVERVIEW OF RENEWABLE ENERGY AND ITS CHALLENGES

The integration of renewable energy systems presents substantial challenges, largely attributed to the inherent intermittency of sources like wind and solar. This intermittency leads to fluctuations in power generation, creating significant hurdles for maintaining reliable power generation. As highlighted by Jiang et al., the inherent randomness associated with renewable sources poses challenges to power system stability, necessitating the development of energy storage systems to buffer these fluctuations (Jiang, Liu and Peng, 2024). Additionally, the limitations in energy storage technologies amplify these challenges; current systems, such as battery storage, are often constrained by issues of capacity and efficiency, which are pivotal to balancing supply with demand (Green *et al.*, 2023).

Moreover, integrating distributed intermittent energy sources introduces operational and maintenance complexities to the existing power infrastructure. This complexity is compounded by the need for advanced grid management strategies to maintain stability amid frequent fluctuations in generation. Garmabdari et al. highlight that the penetration of renewables in energy systems poses new challenges, including reliability and power quality issues arising from voltage variations and frequency instabilities related to renewable energy output (Garmabdari *et al*., 2019). The deployment of microgrids, as explored by (Albarakati *et al*., 2021), showcases the potential for localized energy systems that can better manage diverse energy inputs, yet they simultaneously require sophisticated management systems to coordinate the varying outputs. As renewable penetration increases, the resilience of the grid is tested, leading to potential instabilities that must be addressed through innovative grid integration strategies (Ragab et al., 2021).

Further complicating this scenario are the maintenance challenges of integrating intermittent energy sources into traditional power systems. The operational management becomes intricate due to reliability and quality issues, underscoring the increasing importance of engineering methodologies that effectively address these complexities (Kalair *et al*., 2021; Etukudoh *et al*., 2024).

In summary, ensuring reliable power generation from renewable sources such as solar and wind remains a critical challenge due to their inherent intermittency and variability. Current limitations in energy storage technologies and the complexities of grid integration further exacerbate these fluctuations. Moreover, the operational and maintenance demands of integrating decentralized and data-intensive renewable systems into traditional infrastructures pose additional hurdles. Addressing these challenges requires intelligent, adaptive solutions, making Artificial Intelligence (AI) an essential enabler for optimizing forecasting, control, and decision-making across modern energy systems. This review explores how AI is leveraged to overcome these issues in three pivotal domains: Solar Energy, Wind Energy, and Energy Storage & Smart Grids.

## THE RISE OF AI IN RENEWABLE ENERGY

The early applications of Artificial Intelligence (AI) have significantly impacted forecasting and control within renewable energy systems. This has enhanced operational reliability and increased the integration of renewable sources into the energy mix. In the context of renewable energy microgrids, various AI techniques, including Artificial Neural Networks (ANN), Fuzzy Logic, and Adaptive Neuro-Fuzzy Inference Systems (ANFIS), have demonstrated their effectiveness in capturing the complex relationships present in renewable energy data. These advancements have resulted in improved accuracy and reliability in power forecasting, thereby facilitating better microgrid operations and promoting a greater incorporation of renewable energy sources into existing grids (Islam and Othman, 2024; Wen *et al*., 2024).

AI technologies also play a crucial role in developing smart grids and autonomous energy systems. These technologies facilitate efficient grid management by enabling monitoring, diagnosing operational faults, and automatically responding to anomalies, thereby ensuring stability and resilience in energy delivery(Mysore, 2024; Rajitha and Raghu Ram, 2024). The advent of AI allows for dynamic energy demand forecasting and provides optimization solutions for renewable energy integration, which is essential for balancing the variability of energy resources (Fu *et al*., 2022; Yousef, Yousef and Rocha-Meneses, 2023). Moreover, the integration of reinforcement learning frameworks has enhanced real-time control mechanisms in microgrids, optimizing operations amid variable generation from renewable sources (Wang *et al*., 2023). Reinforcement learning (RL) is a type of machine learning where agents learn to make decisions by interacting with an environment to maximize a reward function over time.

Hence, Artificial Intelligence (AI) has emerged as a transformative force in renewable energy systems, particularly within solar energy, wind energy, and energy storage & smart grid infrastructures. Its strength is processing vast, complex datasets to improve forecasting accuracy, optimize energy flow, and enable adaptive control strategies. Techniques such as machine learning (ML), deep learning (DL), and fuzzy logic have been widely applied to address key operational challenges, ranging from solar irradiance prediction to wind speed forecasting and grid demand balancing. Additionally, AI-driven smart grid architectures facilitate the seamless integration of intermittent renewables into broader energy systems, enhancing real-time decision-making and resilience. This review critically examines the evolution and application of these AI techniques across the selected domains, mapping their growth and highlighting emerging paradigms reshaping the renewable energy landscape. networks.

## MOTIVATION FOR AI-DRIVEN REVIEW

Consolidating fragmented and domain-specific Artificial Intelligence (AI) studies in renewable energy into a unified review framework is crucial for several reasons. Firstly, integrating diverse insights from varying sub-disciplines can form a comprehensive understanding of AI's role in renewable energy systems. This synthesis helps in recognizing patterns, similarities, and inconsistencies across studies, thereby fostering a holistic perspective that can enhance decision-making and policy formulation related to renewable energy technologies (Adewumi *et al*., 2024; Mauro, 2024). Moreover, a unified framework can facilitate interdisciplinary collaboration, allowing researchers and practitioners from engineering, economics, environmental science, and computer science to contribute to and benefit from collective advancements (Necula, 2023; Ohalete *et al*., 2023).

Emerging AI techniques such as Explainable Artificial Intelligence (XAI), Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs) remain underexplored concerning their applications in renewable energy. XAI is critical for improving transparency in

AI systems, which is particularly important in energy applications where decision-making processes must be clear to stakeholders (Gawusu *et al.*, 2022). GNNs, which can effectively model complex relationships in data represented as graphs, hold great potential for optimizing energy distribution networks, but are still limited in their application within renewable energy domains (Ukoba *et al.*, 2024). PINNs, leveraging the principles of physics alongside data-driven approaches, can enhance the modeling of renewable energy systems; yet, their integration into practice has not been extensively realized (Soni, Dave and Paliwal, 2023).

Utilizing a structured and comparative review based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology can significantly advance the field of AI in renewable energy. The PRISMA framework provides a systematic literature review approach, identifying existing research gaps and generating informed insights into trends and future directions. By ensuring that studies can be rigorously compared, researchers can pinpoint not only common methodologies but also varying outcomes from the application of different AI techniques, leading to a deeper understanding of their effectiveness in real-world contexts (Camacho *et al.*, 2024; Onwusinkwue *et al.*, 2024). Furthermore, such a structured review could illuminate interdisciplinary research directions that address both technical and societal challenges in the renewable energy sector, guiding future initiatives and funding opportunities to support sustainable energy solutions (Hamdan *et al.*, 2024).

Given the rapid proliferation of AI research in renewable energy, existing studies remain largely fragmented, often focusing on isolated techniques or single domains without offering a unified perspective. This review is motivated by the need to consolidate and critically examine AI applications within three pivotal domains: Solar Energy, Wind Energy, and Energy Storage & Smart Grids. By adopting a PRISMA-guided methodology and leveraging trusted databases (IEEE Xplore and ScienceDirect), the review systematically maps research trends from 2015 to 2025, identifies underexplored intersections, and highlights the emergence of advanced AI paradigms such as Explainable AI (XAI), Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs). This structured approach enhances transparency and reproducibility and provides a foundation for interdisciplinary research and future innovation in intelligent, sustainable energy systems.

## METHODOLOGY

This review adopts a systematic approach guided by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to explore and synthesize the emerging applications of Artificial Intelligence (AI) in renewable energy systems. The methodology ensured transparency, reproducibility, and rigor in identifying, selecting, and analyzing relevant studies.

Figure 1 presents the PRISMA flow diagram used in this review, which outlines the process of study identification,

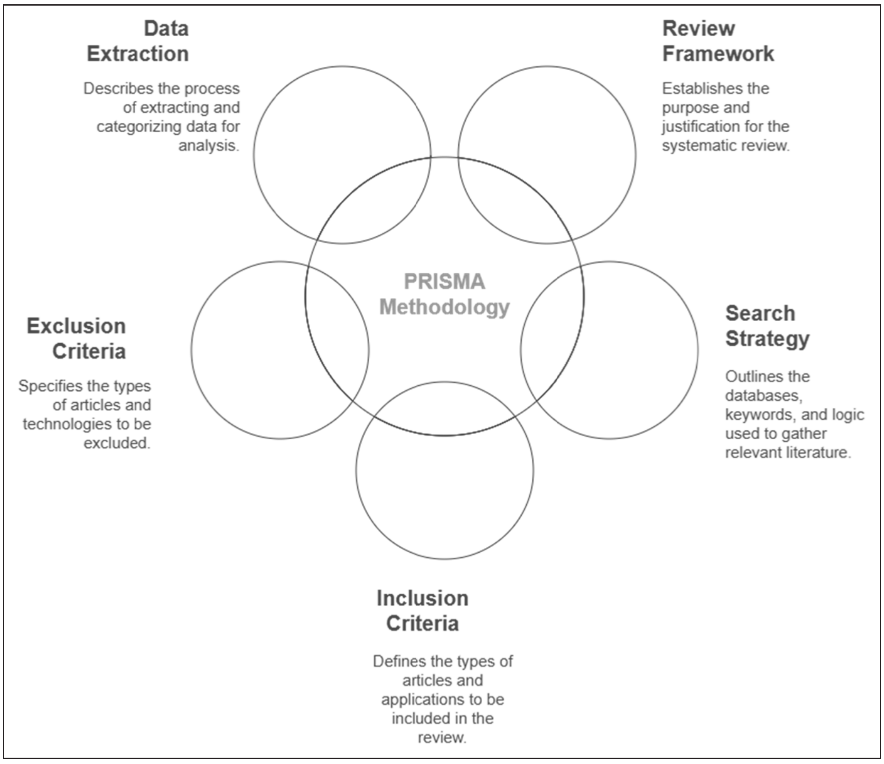


**Figure 1** PRISMA Flow Diagram depicting the study identification, screening, eligibility, and inclusion process used in this systematic review.

screening, eligibility assessment, and inclusion. This diagram ensures transparency and reproducibility in the selection of studies aligned with PRISMA guidelines.

## REVIEW FRAMEWORK

This review adopts the PRISMA framework to systematically identify, screen, and synthesize scholarly literature on the application of Artificial Intelligence (AI) in renewable energy systems. The review focuses on studies published between 2015 and 2025, encompassing eight key domains: solar energy, wind energy, hydropower, geothermal energy, energy storage, cooling systems, environmental monitoring, and smart grids. This timeframe was selected to capture both foundational developments in AI-driven energy research and recent innovations, including emerging techniques such as Explainable AI (XAI), Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs).

## SEARCH STRATEGY

A structured search was conducted to explore relevant literature on AI applications in renewable energy. Only two databases—IEEE Xplore and ScienceDirect—were used for the final review, as they provided the most relevant and accessible full-text peer-reviewed articles. IEEE Xplore and ScienceDirect were selected due to their strong relevance to engineering, artificial intelligence, and energy-related disciplines. These platforms also ensured access to peer-reviewed, full-text journal articles that met our methodological and domain-specific criteria. The search used a combination of keywords and Boolean operators, including:

- ("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "fuzzy logic" OR "XAI" OR "GNN" OR "PINN")
- AND ("renewable energy" OR "solar energy" OR "wind power" OR "hydropower" OR "geothermal energy" OR "energy storage" OR "smart grid" OR "cooling systems" OR "environmental monitoring")

The search was limited to peer-reviewed journal articles published in English between 2015 and 2025, as shown in Figures 2 and 3.

## INCLUSION AND EXCLUSION CRITERIA

To ensure the relevance and quality of the included studies, the following criteria were applied as in Table 1.

Table 1 outlines the specific conditions used to assess the eligibility of each publication. These criteria were applied consistently to all records retrieved from IEEE Xplore and ScienceDirect. Only peer-reviewed journal articles that employed AI techniques within renewable energy contexts and were published in English between 2015 and 2025 were considered. Non-journal contributions such as conference papers, editorials, or reviews lacking methodological depth were excluded. Duplicates across databases were identified and removed to maintain the integrity of the final dataset.

## SCREENING AND SELECTION PROCESS

All retrieved records underwent a structured multi-stage screening process to ensure consistency, transparency, and alignment with the defined eligibility criteria. The selection workflow comprised the following phases:

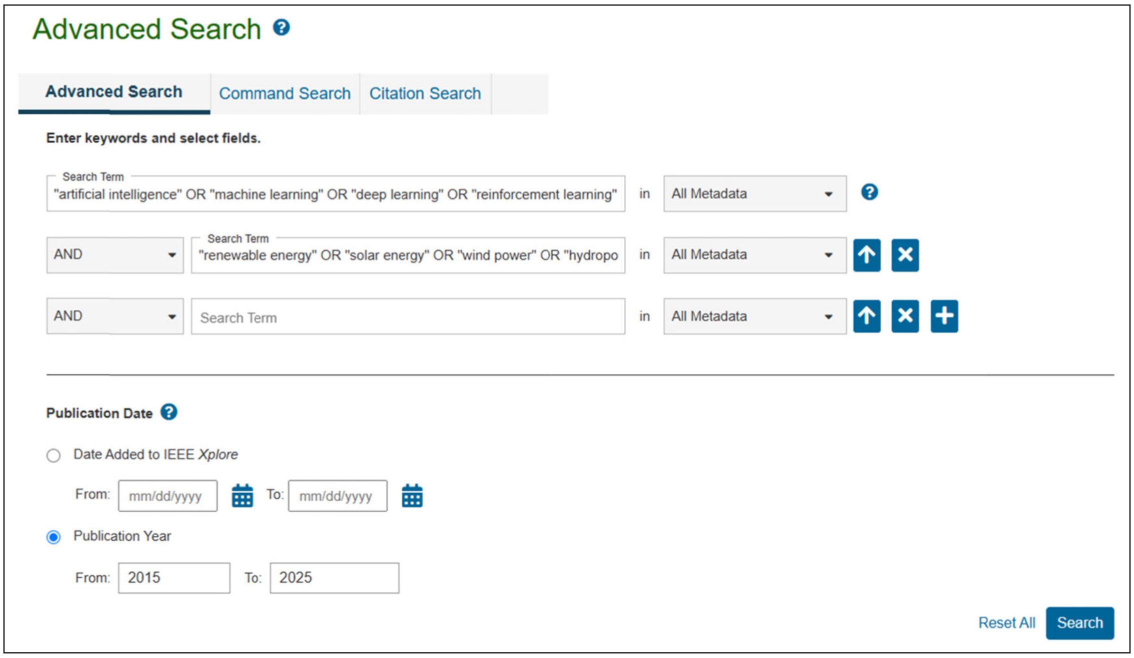


**Figure 2** IEEE Xplore Advanced Search interface showing the Boolean query used to retrieve literature related to Artificial Intelligence (AI) techniques and renewable energy domains. The search was restricted to publications from 2015 to 2025.

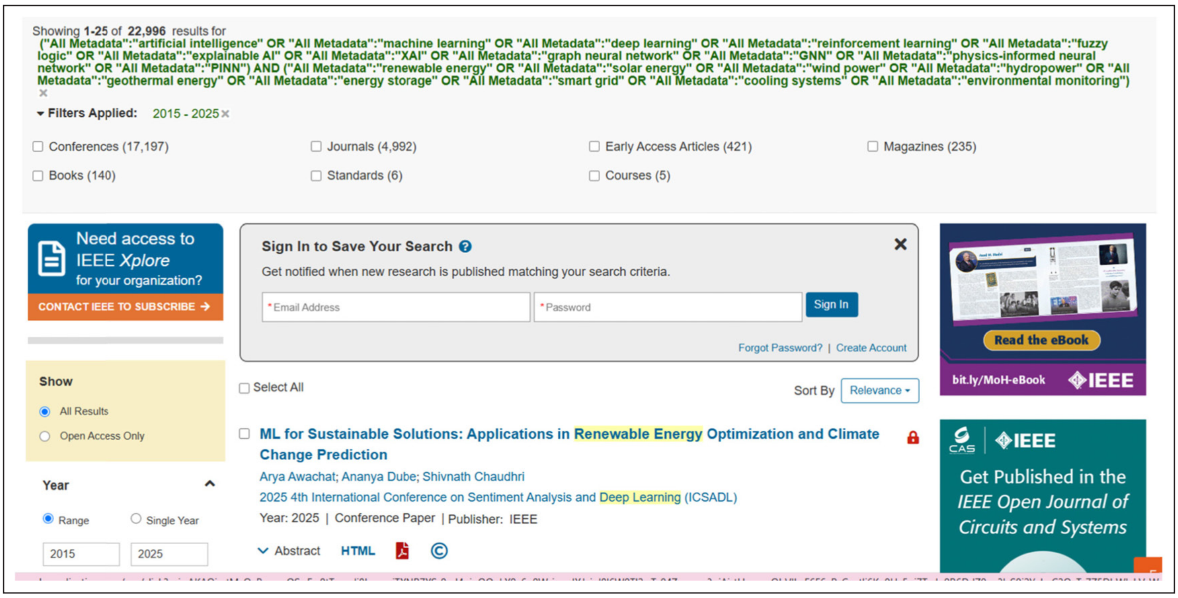


**Figure 3** Example of search results returned from IEEE Xplore using the specified Boolean string. 22,996 records were retrieved before screening, filtered by publication year and content type.

| CRITERIA TYPE | DESCRIPTION |
|---|---|
| Inclusion Criteria | – Studies applying AI methods to renewable energy domains |
| | – Peer-reviewed journal articles |
| | – Published between 2015 and 2025 |
| | – Full-text available in English |
| Exclusion Criteria | – Conference papers, editorials, and non-methodological reviews |
| | – Studies not applying AI or not focused on renewable energy |
| | – Articles published in languages other than English |
| | – Duplicate records across multiple databases (e.g., IEEE Xplore, ScienceDirect) |

**Table 1** Inclusion and Exclusion Criteria.

- *Title and Abstract Screening*: An initial assessment of titles and abstracts was conducted to evaluate thematic relevance, with studies unrelated to AI applications in renewable energy excluded at this stage.
- *Full-Text Eligibility Review*: Articles passing the initial screen were subjected to a comprehensive full-text evaluation to verify compliance with all inclusion criteria, including methodological rigor and domain-specific applicability.
- *Deduplication and Refinement*: Database duplicates (e.g., IEEE Xplore and ScienceDirect) were identified and removed. Additionally, studies lacking methodological contributions or misclassified by the search engines were excluded upon manual verification.

The selection process was documented and visualized using a PRISMA flow diagram, which reports the number of records identified, screened, excluded, and ultimately included in the final synthesis. This approach ensures methodological transparency and reproducibility in line with established guidelines for systematic reviews.

To illustrate the review's selection process, Table 2 presents real examples of articles retrieved during the initial search and screened based on their titles and abstracts. These samples demonstrate the application of the inclusion criteria during the first screening stage, specifically focusing on thematic relevance to AI methodologies and renewable energy domains. Each article's decision (inclusion or exclusion) is justified based on its abstract content and scope alignment with the review objectives. By presenting these examples, the review enhances methodological transparency and supports reproducibility in line with PRISMA guidelines. Following the screening process and removal of duplicates, a total of 1,314 studies were included in the final synthesis.

## DATA EXTRACTION AND THEMATIC CODING

For each study included in the final synthesis, a standardized data extraction process was employed to

| ARTICLE TITLE | ABSTRACT SUMMARY | SCREENING DECISION | JUSTIFICATION |
|---|---|---|---|
| ML for Sustainable Solutions: Applications in Renewable Energy Optimization and Climate Change Prediction (Awachat, Dube and Chaudhri, 2025). | Explores machine learning applications in environmental sustainability, emphasizing AI's role in smart energy and climate systems. | Included | Relevant AI techniques applied in sustainable and energy domains; falls within scope. |
| Machine Learning for Sustainable Energy Systems (Donti and Kolter 2021). | Reviews various machine learning models for predicting and optimizing solar, wind, hydropower, and bioenergy systems. | Included | Directly aligns with the paper's objective of surveying AI applications in renewable energy. |
| Solar Energy Forecasting Using Deep Learning Techniques (Machina, Koduru and Madichetty, 2022). | Investigates deep learning methods for solar irradiance forecasting using historical data and meteorological variables. | Included | A targeted study applying deep learning in solar forecasting—a key area in AI-driven energy research. |

**Table 2** Example Screening Table.

ensure consistency and analytical rigor. The following core attributes were systematically recorded:

- *Year of publication*, to identify temporal trends and research growth over time
- *Energy domain*, such as solar, wind, hydropower, geothermal, energy storage, or smart grid systems
- *AI technique applied*, including machine learning (ML), deep learning (DL), reinforcement learning (RL), fuzzy logic, explainable AI (XAI), graph neural networks (GNNs), and physics-informed neural networks (PINNs)
- *Application type*, such as forecasting, system optimization, fault detection, and predictive maintenance

After extraction, the studies were thematically categorized according to energy domain and AI methodology. This dual-layered classification enabled cross-domain comparisons and trend mapping across various techniques and applications. It also facilitated the identification of frequently adopted AI models, emerging paradigms, and underexplored intersections between AI and renewable energy technologies. The resulting categorization laid the foundation for the synthesis and visualization presented in the subsequent sections.

## AI APPLICATIONS ACROSS RENEWABLE ENERGY DOMAINS

This section synthesizes the findings from selected studies across five key renewable energy domains, drawing on literature retrieved from IEEE Xplore and ScienceDirect (2015–2025). We highlight the primary AI techniques employed for each domain, common application areas, observed performance, and notable research trends or limitations.

This study utilizes two prominent academic databases—IEEE Xplore and ScienceDirect—as the primary sources for literature retrieval. A summary of the extracted data from each database is illustrated in Figures 4 and 5.

**1.** IEEE Xplore

Figure 4 illustrates the distribution of AI-related publications (n = 957) in renewable energy domains from 2015 to 2025, based on data extracted from IEEE Xplore. Most studies focus on Energy Storage and Smart Grids, followed by Wind Energy and Solar Energy. Many articles are marked as Uncategorized, which likely reflects general or cross-cutting AI applications that were not explicitly tied to a specific energy domain. In contrast, multi-domain studies and those addressing Thermal Energy and Cooling Systems appear less frequently, indicating opportunities for expanded interdisciplinary exploration in future research.

**2.** Science Direct

Figure 5 summarizes article frequency across renewable energy themes from ScienceDirect between 2015 and 2025, based on $n$ = 1,191 categorized publications (excluding uncategorized entries). The highest number of studies is concentrated in Energy Storage and Smart Grids, followed by Solar Energy, Wind Energy, Thermal Energy, and Cooling Systems. Comparatively fewer articles address integrated or multi-domain applications, indicating that cross-domain AI integration is an emerging research area with significant growth potential.

The following subsections present an in-depth discussion of AI applications within specific renewable energy domains, based on the thematic classification derived from the reviewed literature. In this paper, the analysis of AI applications specifically focuses on three key renewable energy domains—Solar Energy, Wind Energy, Energy Storage, and Smart Grids—for the subsequent sections. These domains were selected due to their prominence in current literature and critical importance in advancing intelligent and sustainable energy systems.

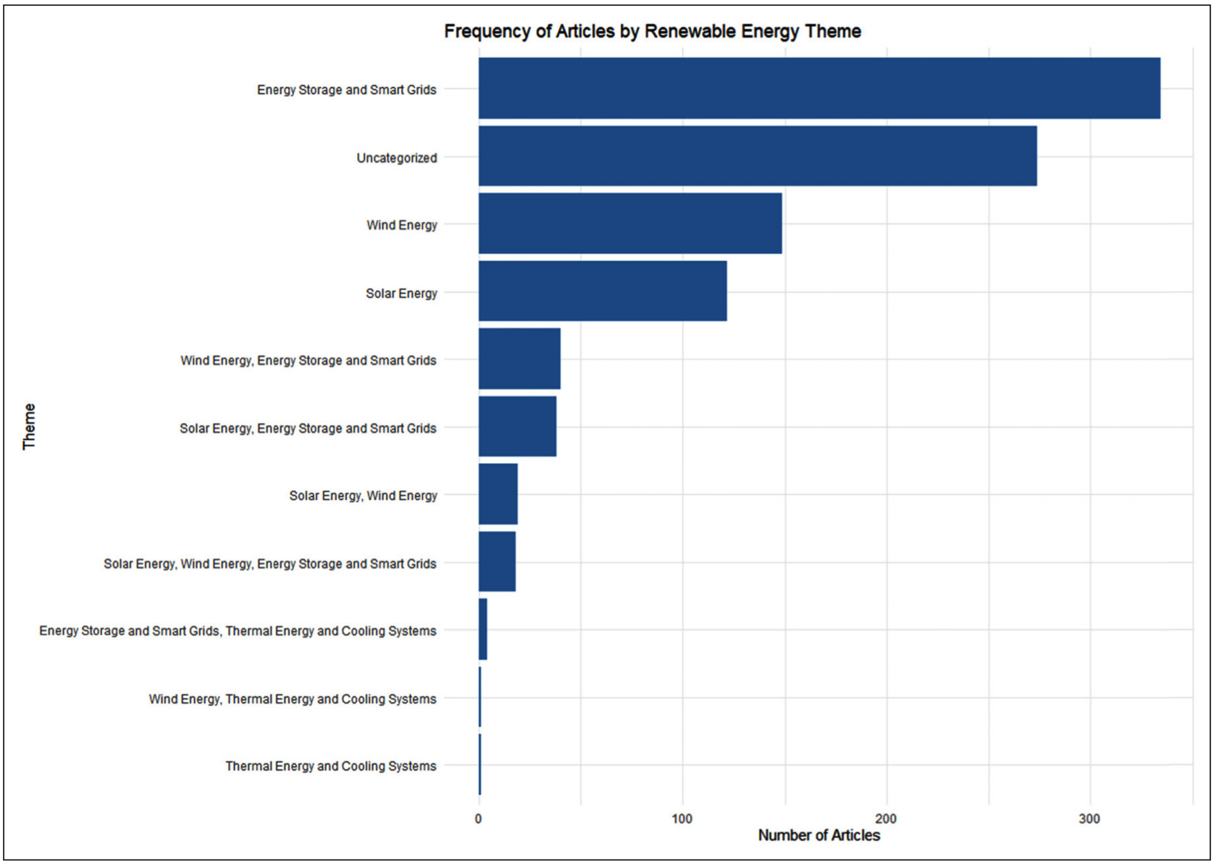


**Figure 4** Frequency of Articles by Renewable Energy Theme – IEEE Xplore.

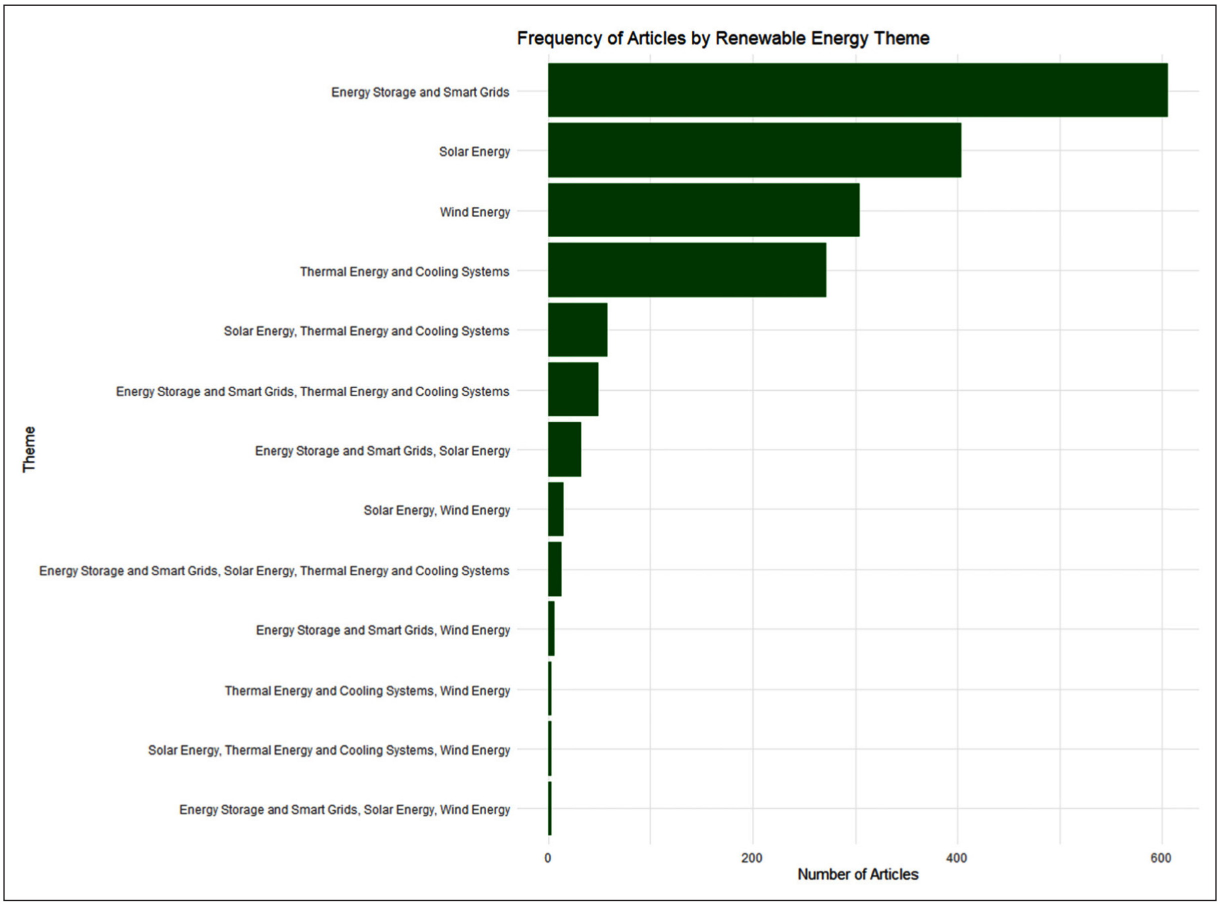


**Figure 5** Frequency of Articles by Renewable Energy Theme – Science Direct.

## SOLAR ENERGY

Solar energy is a cornerstone of the global shift toward sustainable energy due to its abundance, scalability, and decreasing cost. However, its effective utilization is hindered by inherent variability caused by weather conditions, diurnal cycles, and seasonal fluctuations. These uncertainties challenge accurate forecasting, efficient grid integration, and system reliability. As a result, Artificial Intelligence (AI) has emerged as a powerful tool to address these issues by enabling intelligent forecasting, real-time optimization, fault detection, and data-driven decision-making. AI techniques help enhance the performance and adaptability of solar energy systems, supporting their broader adoption in centralized and distributed energy infrastructures.

### Data Overview – Solar Energy

This section presents an overview of AI-related publications in the field of Solar Energy, based on data retrieved from IEEE Xplore and ScienceDirect.

Figure 6 illustrates the annual publication trend of AI-related Solar Energy articles from 2015 to 2025, based on IEEE Xplore and ScienceDirect. A strong upward trajectory is evident, particularly after 2020, highlighting the growing integration of AI in addressing solar energy challenges. ScienceDirect consistently shows higher publication counts, especially between 2021 and 2024. The peak in 2024 signals heightened interest in AI-powered solar solutions, likely driven by advancements in explainable AI, hybrid models, and international decarbonization efforts. This trend underscores the increasing role of AI as a transformative tool in the optimization and intelligent control of solar energy systems.

### AI Application in Solar Energy

This section examines the application of Artificial Intelligence (AI) in the domain of solar energy, based on data extracted from IEEE Xplore and ScienceDirect

The comparative heatmap in Figure 7 illustrates the frequency of various AI techniques used in solar energy research across IEEE Xplore and ScienceDirect from 2015 to 2025. Machine learning and deep learning emerge as the most frequently employed methods in both databases, highlighting their dominance in solar energy applications. Notably, fuzzy logic appears more prominently in IEEE Xplore, possibly reflecting its traditional strength in engineering-oriented research. In contrast, reinforcement learning and explainable AI (XAI) show moderate and balanced usage across both platforms, suggesting growing interdisciplinary interest. Many articles fall under the “Not Specified” category, indicating that many studies reference AI without explicitly identifying the technique used. The chi-square test ($\chi^2$ = 124.03, $p < 0.0001$) reveals a statistically significant difference in the distribution of AI techniques between the two sources, underscoring variations in methodological preferences and reporting practices across publication venues.

Figure 8 displays the yearly publication trend of AI-related research in solar energy from 2015 to 2025, based on data from IEEE Xplore and ScienceDirect. The trend shows a consistent growth in publication volume across both sources, with ScienceDirect demonstrating a steeper rise starting around 2019. Peaks are observed in 2023 and 2024, particularly for ScienceDirect, which may reflect increasing research interest and funding in AI applications for renewable energy. IEEE Xplore also

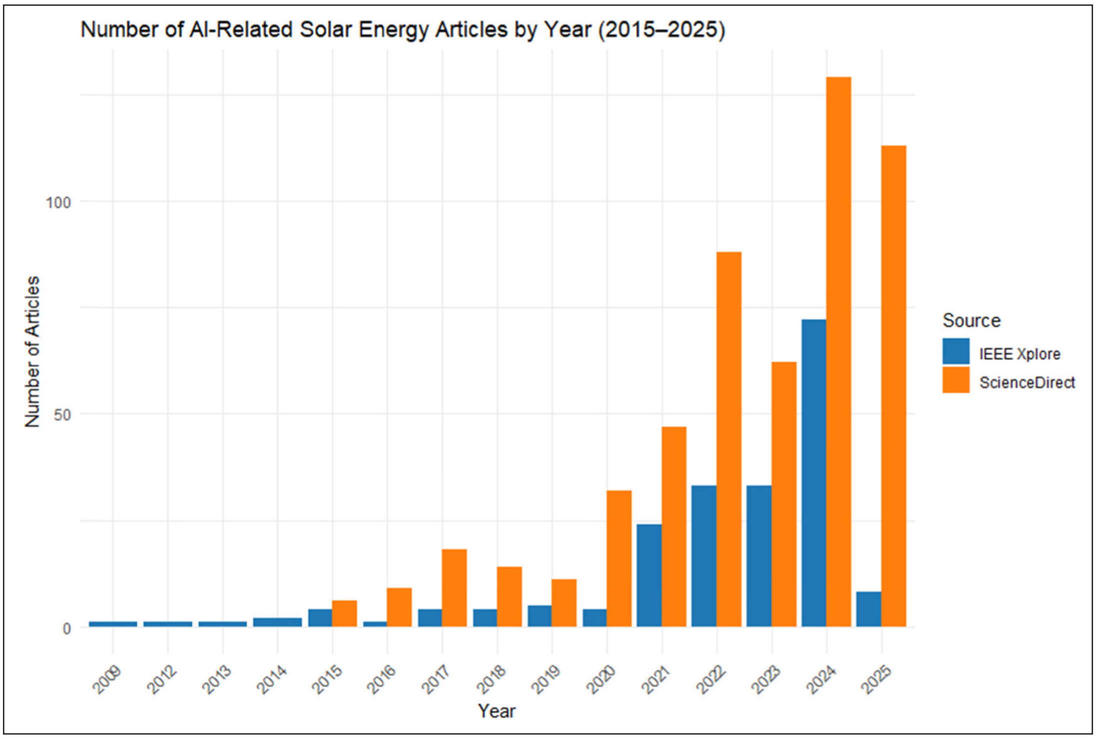


**Figure 6** Annual Trends of AI-Related Publications in Solar Energy (2015–2025) from IEEE Xplore and ScienceDirect.

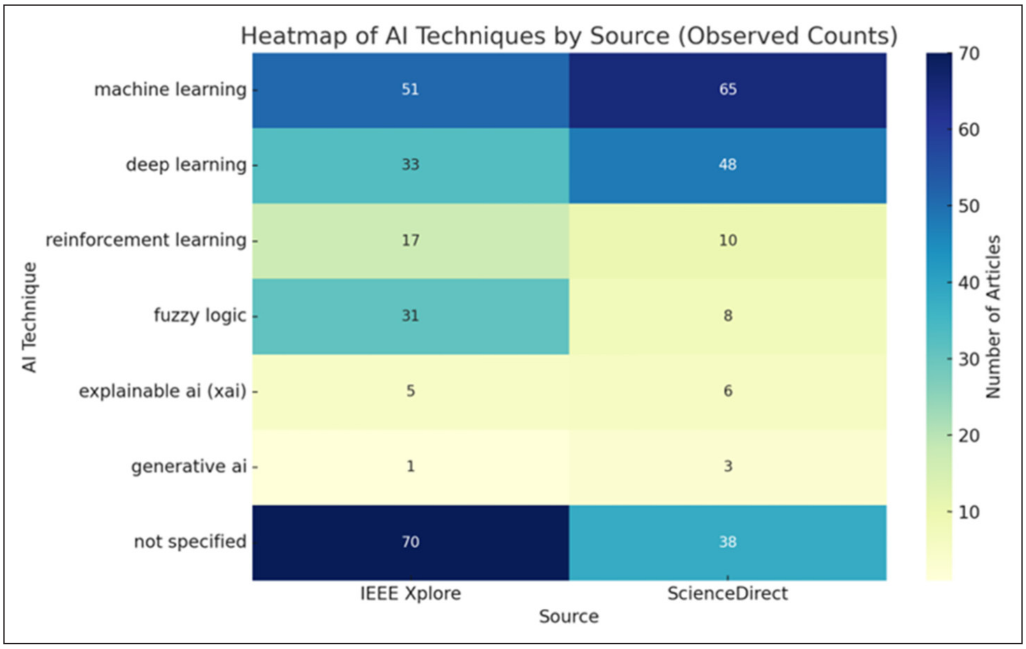


**Figure 7** Heatmap Showing the Frequency of AI Techniques Used in Solar Energy Research Across IEEE Xplore and ScienceDirect (2015–2025).

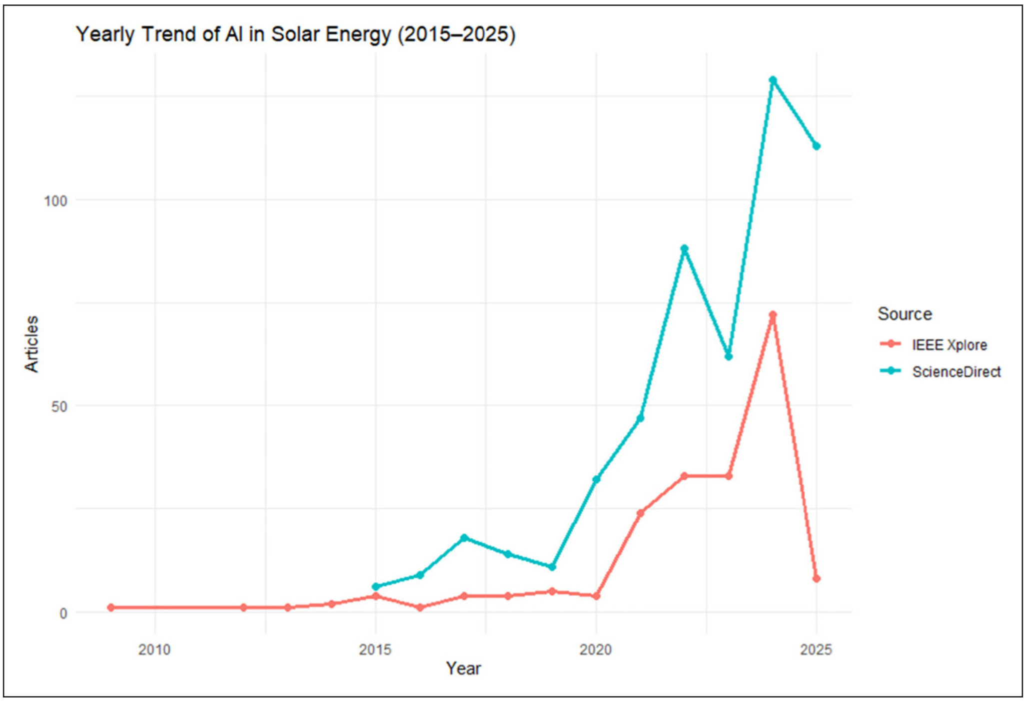


**Figure 8** Annual Publication Trends of AI Applications in Solar Energy (2015–2025) by Source.

shows a notable rise, though at a steadier pace. The drop in 2025 likely reflects partial-year data at the time of analysis. Overall, the figure suggests that AI in solar energy has gained substantial momentum recently, with ScienceDirect capturing more of this growth.

## Emerging Trends – Solar Energy

Emerging AI paradigms are increasingly adopted in solar energy research, reflecting a shift toward more advanced and interpretable analytical approaches. This section explores the utilization and growth of these emerging techniques, such as Explainable AI (XAI), Generative AI, Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs), within the context of solar energy applications.

Figure 9 illustrates the emerging trends in applying artificial intelligence (AI) techniques within solar energy research from 2015 to 2025, based on combined data from IEEE Xplore and ScienceDirect. The analysis reveals that machine learning has consistently been the most utilized approach, reflecting its foundational role in solar forecasting, control systems, and performance

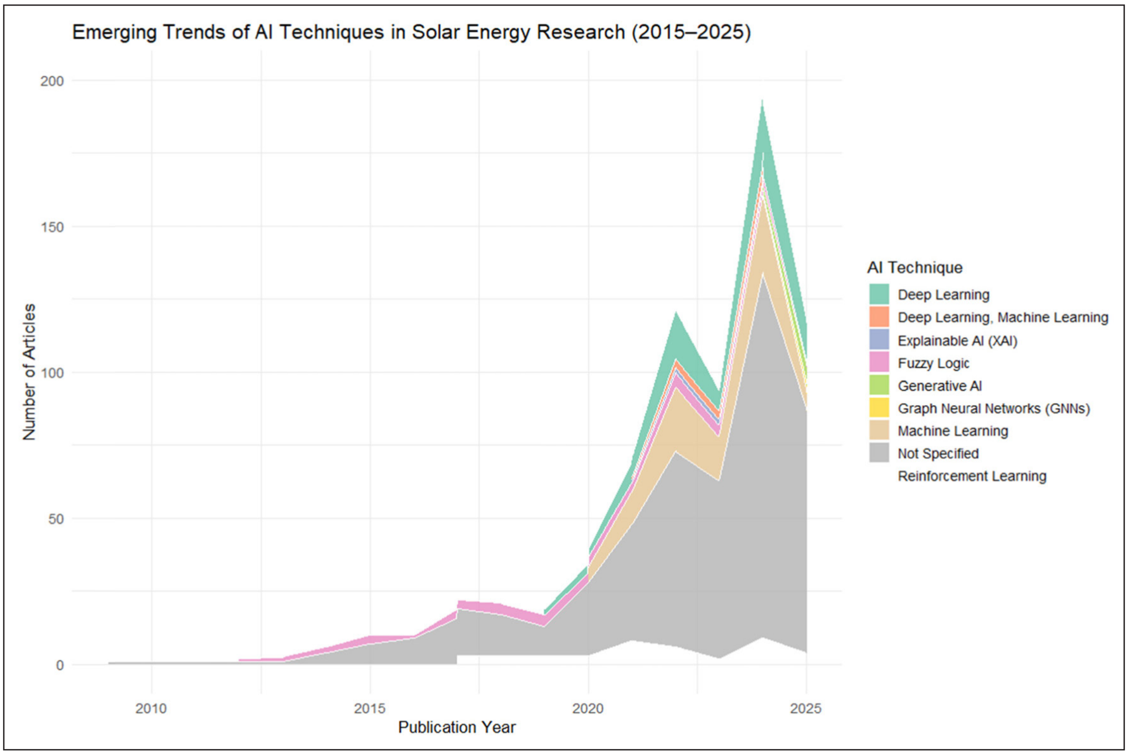


**Figure 9** Emerging Trends in AI Applications for Solar Energy (2015–2025).

optimization tasks. Deep learning techniques have experienced a noticeable surge in adoption, particularly after 2020, coinciding with the broader rise of data-intensive methods in renewable energy research. Earlier years (2015–2019) show relatively higher usage of fuzzy logic, especially in engineering-oriented literature, but this declines over time. New AI paradigms such as explainable AI (XAI), generative AI, and graph neural networks (GNNs) have emerged prominently in recent years, suggesting a shift toward interpretable and hybrid AI solutions. Despite this growth, many studies fall under the "Not Specified" category, indicating a lack of clarity in methodological reporting. Overall, the figure demonstrates an evolving and diversifying AI landscape in solar energy research, with a clear transition toward advanced and domain-adapted techniques in recent years.

## WIND ENERGY

Wind Energy is critical to the global transition toward sustainable and decarbonized energy systems. As one of the most mature and rapidly expanding forms of renewable energy, wind power is pivotal in reducing greenhouse gas emissions and enhancing energy security. However, its effective deployment is challenged by the inherent variability of wind patterns, intermittency, and the complex aerodynamics of turbine systems. These factors complicate accurate power forecasting, turbine performance optimization, and real-time fault detection. In this context, Artificial Intelligence (AI) has emerged as a powerful enabler for enhancing the efficiency and reliability of wind energy systems. Through advanced algorithms such as machine learning, deep learning, and reinforcement learning, AI facilitates data-driven forecasting, predictive maintenance, and intelligent control strategies, thereby supporting the robust integration of wind energy into modern power grids.

### Data Overview – Wind Energy

This section presents an overview of AI-related publications in Wind Energy, based on data retrieved from IEEE Xplore and ScienceDirect. The analysis highlights publication trends, source contributions, and the growing interest in AI-driven solutions to address the complex operational challenges of wind energy systems.

Figure 10 illustrates the annual publication trends of AI-focused research in the wind energy domain based on data from IEEE Xplore and ScienceDirect. The figure highlights a significant increase in research output over the past decade, particularly from 2020 onward, reflecting the growing integration of AI in addressing the challenges associated with wind energy systems. ScienceDirect consistently exhibits higher publication counts than IEEE Xplore, especially from 2021 to 2024, likely due to its broader coverage of multidisciplinary journals encompassing energy, environmental science, and applied AI. The peak observed in 2024 suggests heightened research interest and investment in intelligent wind energy solutions, while the drop in 2025 likely reflects partial-year data at the time of collection. Overall, the data reveal a clear trajectory of growth, underscoring the expanding role of AI in wind energy forecasting, turbine control, fault detection, and grid integration. This overview sets the stage for a deeper analysis of AI techniques and emerging trends in subsequent sections.

## AI Application in Wind Energy

This section examines the application of Artificial Intelligence (AI) in wind energy, based on data extracted from IEEE Xplore and ScienceDirect.

The heatmap illustrates (as in Figure 11) the distribution of various AI techniques used in wind energy research across IEEE Xplore and ScienceDirect from 2015 to 2025. A notable observation is the dominance of the "Not Specified" category, particularly within ScienceDirect, where 206 articles reference AI without explicitly identifying the specific technique employed. This trend underscores a broader issue in the literature regarding insufficient methodological transparency. Among the explicitly stated techniques, deep learning and machine learning are the most prevalent, reflecting their extensive use in key applications such as wind speed prediction, turbine performance modeling, and fault detection.

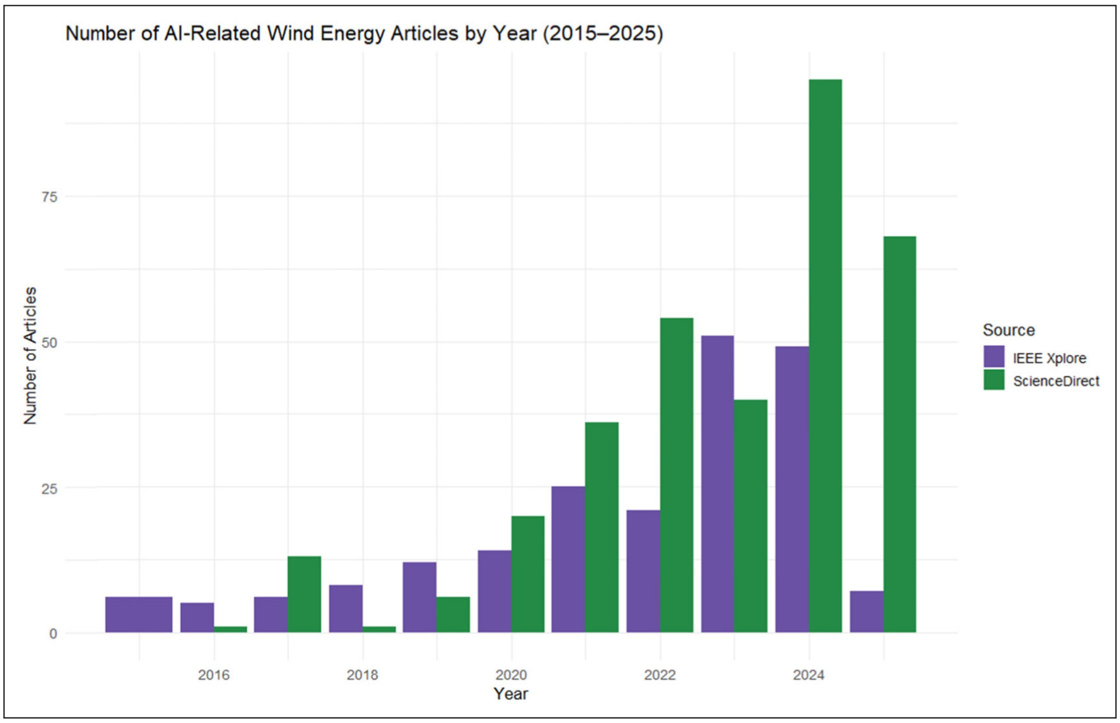


**Figure 10** Number of AI-Related Wind Energy Articles by Year (2015–2025) from IEEE Xplore and ScienceDirect.

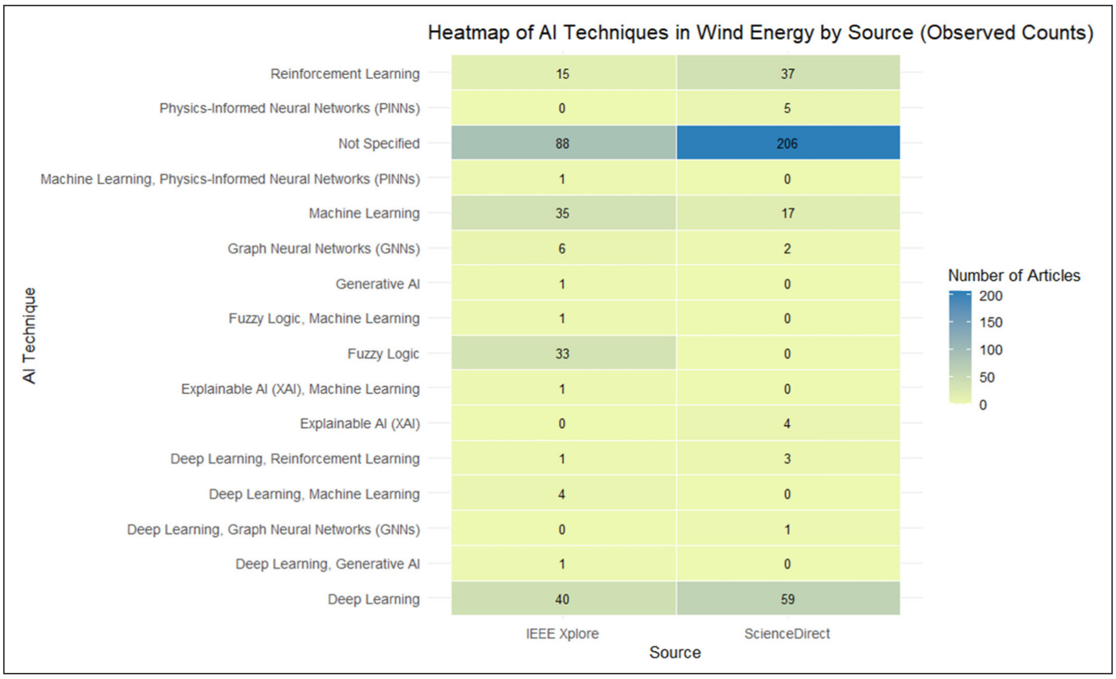


**Figure 11** Distribution of AI Techniques Used in Wind Energy Research Across IEEE Xplore and ScienceDirect (2015–2025).

Reinforcement learning appears more frequently in ScienceDirect, indicating a growing interest in adaptive control and decision-making algorithms tailored for dynamic wind environments. Fuzzy logic maintains a strong presence in IEEE Xplore, likely due to its historical application in engineering-oriented and control-based solutions. Although less frequent, the emergence of newer techniques—including Explainable AI (XAI), Generative AI, Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs)—signals an evolving research focus on interpretability and domain-specific modeling. Additionally, hybrid approaches (e.g., deep learning combined with reinforcement learning or XAI) reflect a shift toward integrating multiple AI paradigms to enhance robustness and explanatory power. The findings highlight a mature and diversifying AI landscape in wind energy, balancing traditional methods with emerging innovations.

Figure 12 illustrates the yearly trend of AI-related publications in wind energy research from 2015 to 2025, comparing two major academic sources: IEEE Xplore and ScienceDirect. The overall trajectory indicates a clear increase in publication volume for both sources, particularly after 2020. ScienceDirect shows a more rapid growth curve, peaking in 2024 with the highest number of publications (~90 articles), indicating a surge of interest likely due to enhanced funding and advancements in adaptive AI models for wind energy. Meanwhile, IEEE Xplore demonstrates a steadier growth, with a peak in 2023, followed by a decline in 2025, which may be attributed to incomplete data for the final year. The visible growth reflects increasing reliance on AI technologies—especially machine learning and deep learning—to address challenges in wind energy, such as forecasting wind patterns, optimizing turbine operations, and predictive maintenance. The rise across both sources underscores AI's expanding role in supporting reliable and intelligent wind energy systems.

## Emerging Trends – Wind Energy

Emerging AI paradigms are increasingly adopted in wind energy research, signaling a transition toward more advanced, adaptive, and interpretable analytical approaches. This section explores the utilization and growth of cutting-edge techniques, such as Explainable AI (XAI), Generative AI, Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs), within the context of wind energy applications. These methods are gaining traction for enhancing transparency, integrating physical laws into modeling, and improving the robustness of predictive and control systems in complex, variable wind environments.

The stacked area in Figure 13 provides a comprehensive view of the evolving landscape of artificial intelligence applications within wind energy research. The visualization shows that machine learning has consistently played a central role, as a foundational method for predictive modeling, wind speed forecasting, and turbine performance optimization. Starting around 2020, there is a marked rise in deep learning, reflecting a broader shift toward data-intensive approaches

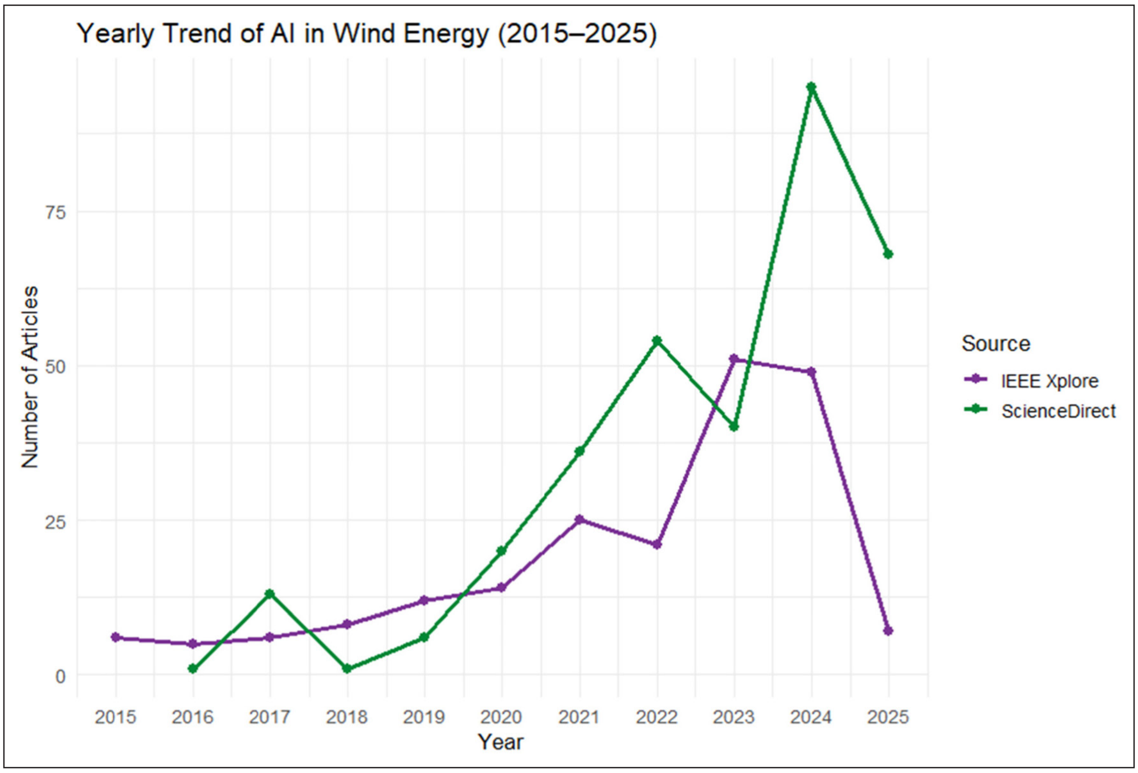


**Figure 12** Annual Trend of AI-Related Publications in Wind Energy Research (2015–2025) by Source.

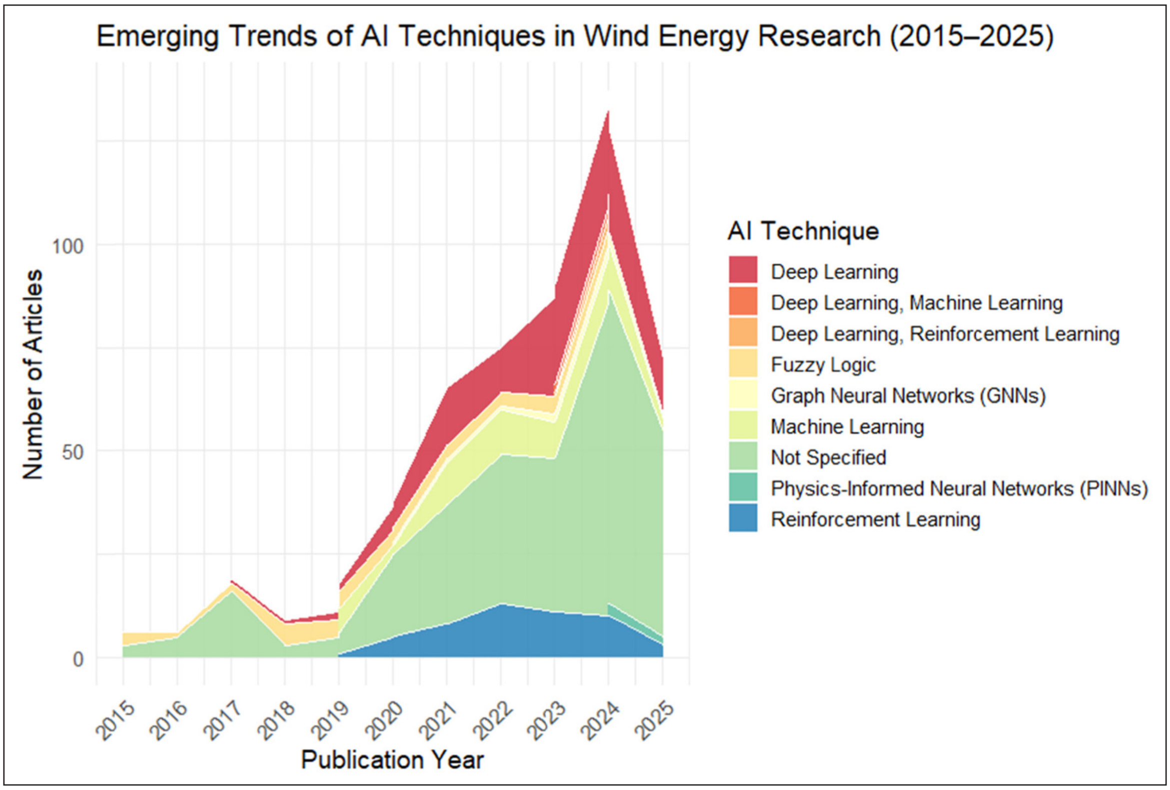


**Figure 13** Temporal Trends of Emerging AI Techniques in Wind Energy Research (2015–2025).

capable of capturing complex, nonlinear patterns in wind datasets. Reinforcement learning and physics-informed neural networks (PINNs) also show an upward trend, particularly in the later years, suggesting a growing interest in adaptive and physics-aware models for real-time control and fault diagnosis in wind systems. Meanwhile, fuzzy logic retains a steady, albeit smaller, presence, highlighting its enduring value in interpretability and rule-based decision systems. Emerging techniques such as graph neural networks (GNNs) and hybrid combinations (e.g., deep learning with machine learning or reinforcement learning) have begun to surface, indicating experimental efforts to enhance model robustness and scalability.

## ENERGY STORAGE AND SMART GRIDS

Energy storage and smart grids are pivotal in modernizing electricity systems to accommodate renewable sources and improve grid reliability. These systems address the intermittent nature of solar and wind energy by enabling efficient energy storage, load balancing, and real-time energy distribution. However, their complexity and dynamic behavior pose significant challenges in prediction, optimization, and control. Artificial Intelligence (AI) has emerged as a transformative enabler, facilitating intelligent energy management through predictive analytics, autonomous control, fault detection, and demand forecasting. By leveraging AI, energy storage and smart grid systems are becoming more adaptive, resilient, and user-centric—key traits for future-ready energy infrastructure.

### Data Overview – Energy Storage and Smart Grids

This section presents an overview of AI-related publications focusing on Energy Storage and Smart Grids, based on datasets compiled from IEEE Xplore and ScienceDirect from 2015 to 2025. By analyzing publication trends over time, we aim to identify patterns in research intensity, highlight periods of rapid development, and compare scholarly contributions across the two major databases. This quantitative snapshot serves as a foundation for understanding the evolution of AI applications in this domain. It sets the stage for deeper exploration into the techniques employed and emerging research directions.

Figure 14 illustrates the yearly publication trends of AI-related research in Energy Storage and Smart Grids from 2015 to 2025, based on IEEE Xplore and ScienceDirect data. The figure highlights a significant and sustained growth in research activity over the past decade, with a pronounced surge beginning in 2020. ScienceDirect consistently leads in publication volume, particularly in 2023 and 2024, where it exhibits a sharp rise, reaching a peak of over 200 publications in 2024. IEEE Xplore follows a similar growth pattern but at a slightly lower magnitude, indicating active contributions from engineering-focused communities. The sharp drop observed in 2025 likely reflects the partial nature of the dataset for that year. These findings underscore the rapidly increasing academic and industrial interest in leveraging AI to enhance the performance, reliability, and integration of energy storage systems and smart grids, especially amid global efforts to modernize power infrastructure and accommodate renewable energy sources.

## AI Application in Energy Storage and Smart Grids

This section examines the application of Artificial Intelligence (AI) in Energy Storage and Smart Grids, based on data extracted from IEEE Xplore and ScienceDirect. AI is pivotal in this field by enabling predictive analytics for energy demand, intelligent load balancing, real-time grid monitoring, and optimizing distributed resources. These capabilities are essential for managing the increasing complexity of modern energy systems, ensuring reliability, efficiency, and resilience in smart grid infrastructure.

Figure 15 illustrates the observed counts of various Artificial Intelligence (AI) techniques applied in Energy Storage and Smart Grids research, categorized by source (IEEE Xplore and ScienceDirect) from 2015 to 2025. The "Not Specified" category dominates across both sources—457 articles in ScienceDirect and 187 articles in IEEE Xplore—highlighting a recurring limitation in the literature where AI is applied but the specific technique is not reported. This trend underscores the need for improved methodological transparency in scholarly

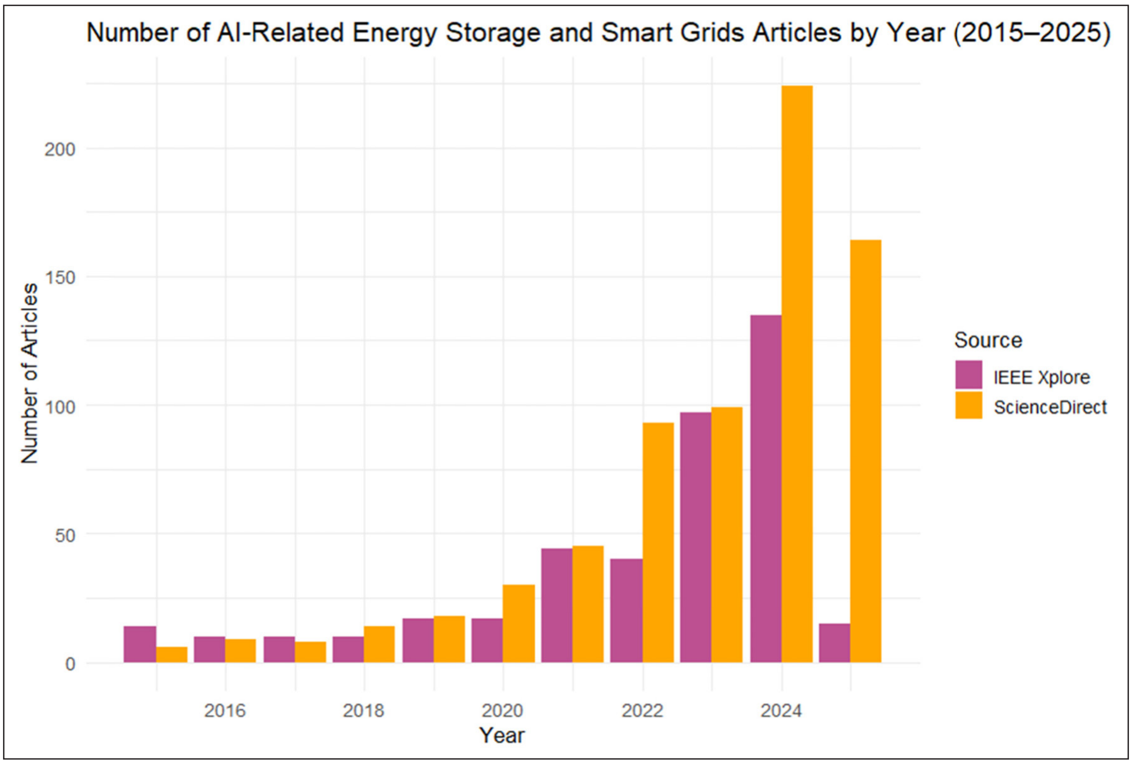


**Figure 14** Annual Trends of AI-Related Publications in Energy Storage and Smart Grids (2015–2025) from IEEE Xplore and ScienceDirect.

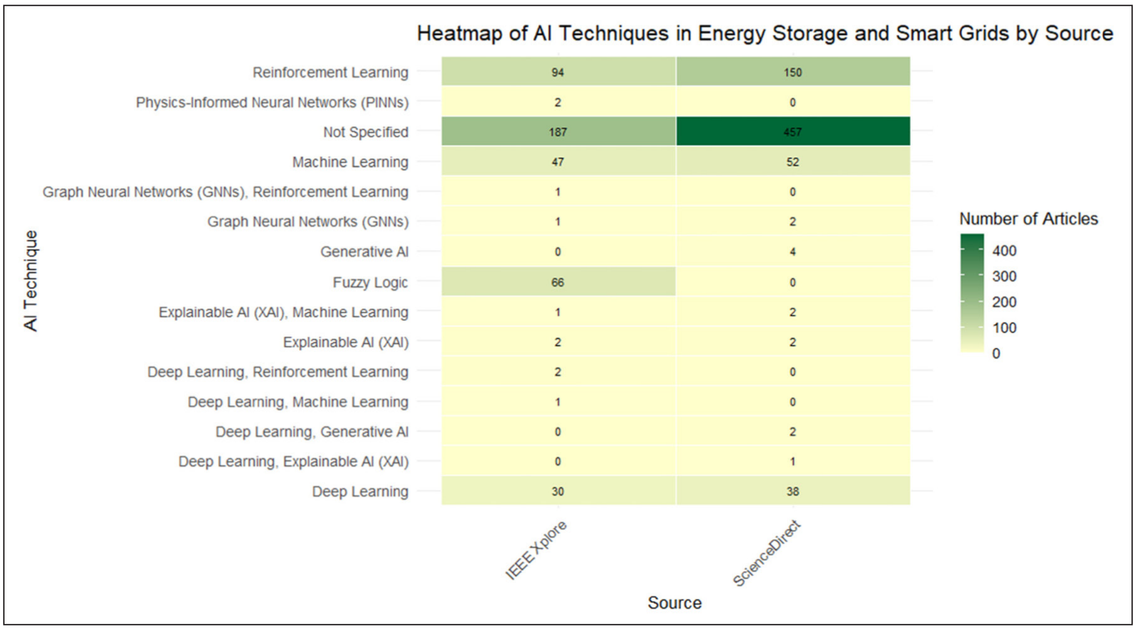


**Figure 15** Heatmap of AI Techniques in Energy Storage and Smart Grids by Source (Observed Counts).

publications. Reinforcement Learning stands out with a substantial presence among the specified techniques, particularly in ScienceDirect (150 articles) and IEEE Xplore (94 articles), indicating its growing role in adaptive decision-making and control strategies for smart grids and storage systems.

Machine Learning is also widely reported, with similar counts across both sources (ScienceDirect: 52, IEEE Xplore: 47), reflecting its extensive use in tasks such as load forecasting, anomaly detection, and battery management. Fuzzy Logic is more prominent in IEEE Xplore (66 articles) than ScienceDirect (none reported), consistent with its historical strength in control systems and engineering-centric domains. Deep Learning and its hybrid forms (e.g., with XAI, Generative AI, or Reinforcement Learning) are present but with lower counts, suggesting their emerging but not yet mainstream role in this specific domain. Emerging techniques such as Physics-Informed Neural Networks (PINNs), Graph Neural Networks (GNNs), and Explainable AI (XAI) appear sporadically, signaling early adoption trends and potential for future expansion. Overall, this heatmap highlights a strong presence of both traditional and emerging AI techniques in energy storage and smart grids, while emphasizing the need for clearer reporting on methodologies to enhance the replicability and impact of future research.

Figure 16 presents the annual trend of AI-related research publications in Energy Storage and Smart Grids from 2015 to 2025, sourced from IEEE Xplore and ScienceDirect. The figure reveals a clear upward trajectory in publication volume, particularly after 2020. ScienceDirect shows a steeper growth rate, with a significant peak in 2024, reflecting increased academic and industrial interest in leveraging AI for smart grid optimization, demand forecasting, and energy storage management. IEEE Xplore follows a steadier incline with notable growth until 2024, before showing a dip in 2025—likely due to partial-year data. The sharp rise in both datasets aligns with global momentum toward intelligent energy systems, where AI plays a pivotal role in enhancing operational efficiency, real-time control, and grid resilience. The findings highlight the accelerating integration of AI techniques in modernizing energy infrastructure, making this a prominent research area within the renewable energy transition.

## Emerging Trends – Energy Storage and Smart Grids

Emerging AI paradigms are increasingly embraced in energy storage and smart grid research, marking a shift toward more intelligent, scalable, and interpretable system design. This section explores the growing adoption of advanced techniques such as Explainable AI (XAI), Generative AI, Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs) within the context of energy storage and grid optimization. These methods are gaining attention for improving decision-making transparency, incorporating domain-specific physical constraints, and enhancing the resilience and adaptability of complex grid operations and storage systems, especially in managing decentralized resources, forecasting energy demand, and enabling real-time control across dynamic energy networks.

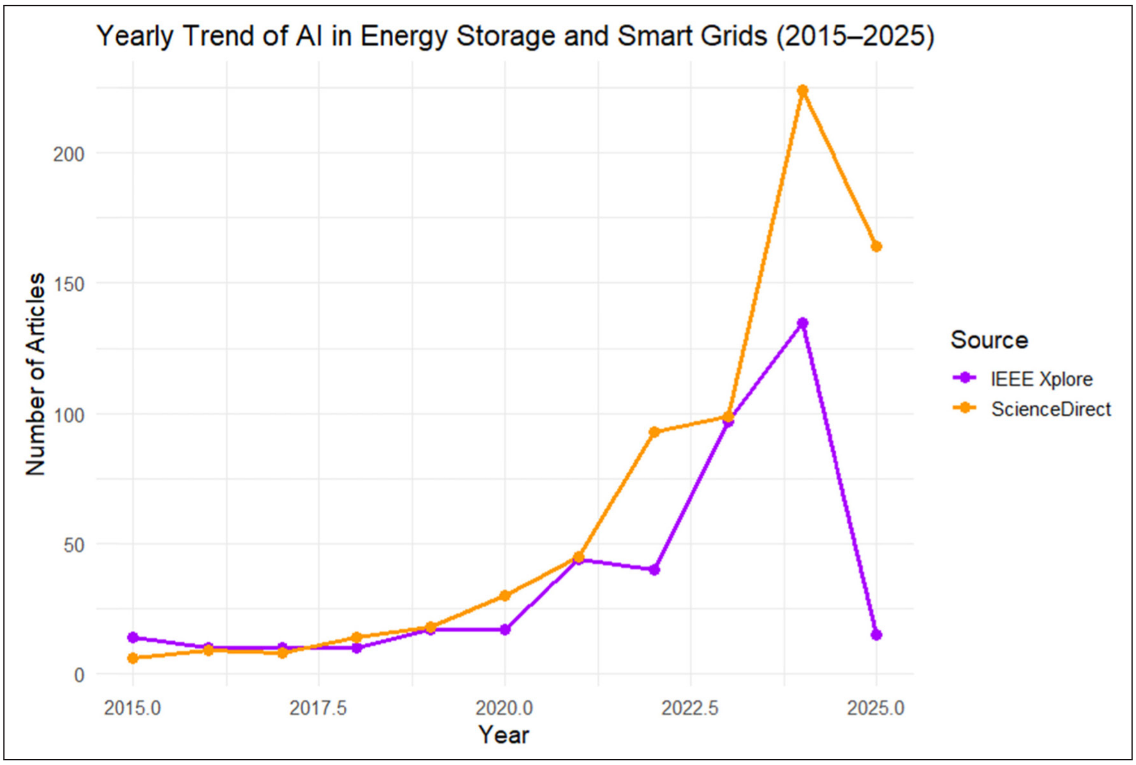


**Figure 16** Yearly Trend of AI-Related Publications in Energy Storage and Smart Grids (2015–2025) Based on IEEE Xplore and ScienceDirect.

This stacked area chart (in Figure 17) illustrates the growth and evolution of AI techniques in Energy Storage and Smart Grids research from 2015 to 2025, using data from IEEE Xplore and ScienceDirect. A clear upward trend is observed, especially after 2020, indicating increasing interest in AI-driven solutions for managing energy systems and optimizing grid performance. Machine Learning remains the most widely applied technique, reflecting its effectiveness in tasks such as forecasting and control. Deep Learning also shows notable growth, aligning with the demand for processing complex sensor data in smart environments. Emerging techniques like Reinforcement Learning, Explainable AI (XAI), Generative AI, and Physics-Informed Neural Networks (PINNs) began to appear after 2022, suggesting a shift toward more advanced and interpretable models. However, many articles still fall under the "Not Specified" category, indicating a need for better reporting of AI methodologies. Overall, the trend highlights a diversifying and maturing research landscape, with increasing emphasis on intelligent, adaptive, and transparent AI systems for energy applications.

## DISCUSSION AND FINDINGS: CROSS-DOMAIN INSIGHTS ON AI IN RENEWABLE ENERGY

In this paper, we reviewed the integration of Artificial Intelligence (AI) across three critical domains of renewable energy: Solar Energy, Wind Energy, and Energy Storage & Smart Grids. The findings reveal a consistent and accelerating trajectory of AI adoption, particularly from 2020 onward. By analyzing publication trends from two major academic databases—IEEE Xplore and ScienceDirect—this study uncovers key patterns, prevalent AI techniques, and emerging paradigms shaping intelligent energy systems' evolution. The review also identifies methodological gaps and reporting inconsistencies that must be addressed to support the continued advancement of AI-driven solutions for a sustainable energy future.

### AI APPLICATION TRENDS

This review highlights the pivotal role of Artificial Intelligence (AI) in driving innovation across three critical renewable energy domains: *Solar Energy, Wind Energy, and Energy Storage & Smart Grids*. Across all domains, a marked increase in publication volume is observed after 2020, underscoring the growing momentum of AI integration in energy systems. The analysis reveals several important trends, dominant techniques, and notable gaps.

**(i)** *Dominance of Machine Learning (ML)*
Machine Learning (ML) consistently emerges as the most widely applied AI technique across all three domains examined—Solar Energy, Wind Energy, and Energy Storage & Smart Grids. Its dominance is particularly evident in Solar Energy and Energy Storage, where it is frequently used for forecasting key variables such as solar irradiance, wind speed, and energy demand. Additionally, ML plays a crucial role in fault detection and diagnostics, helping to identify and address system anomalies in real-time. Its application in optimization further supports

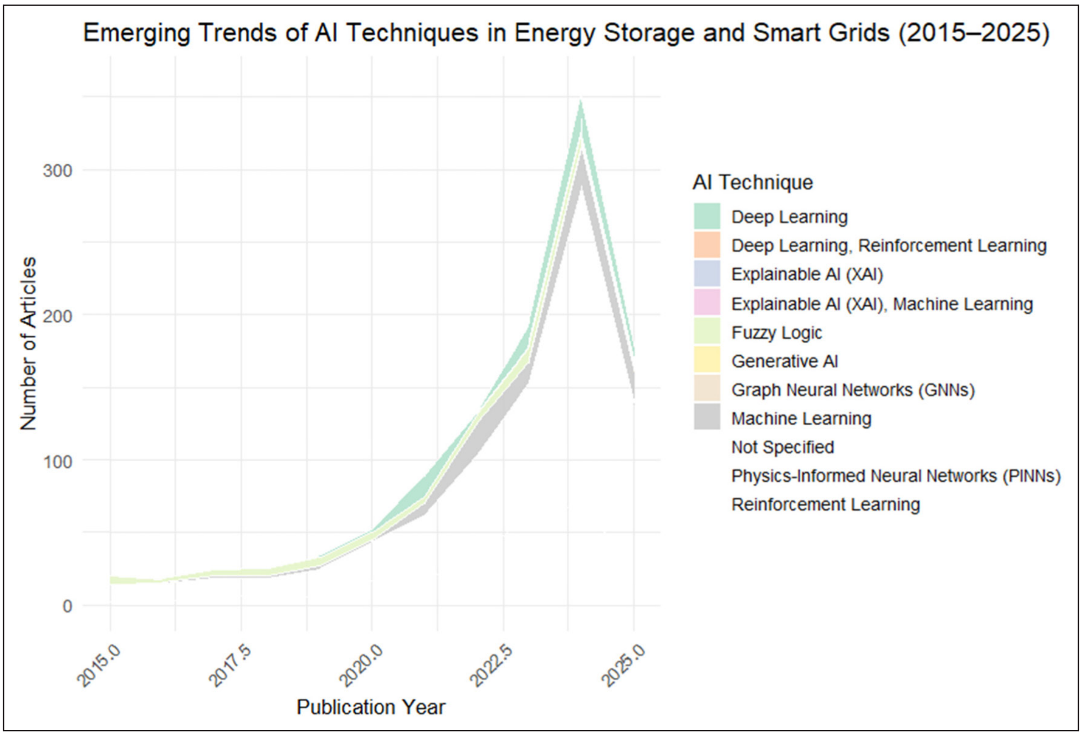


**Figure 17** Emerging Trends of AI Techniques in Energy Storage and Smart Grids Research (2015–2025).

intelligent energy management by fine-tuning energy flow and enhancing system efficiency. The widespread use of ML can be attributed to its methodological flexibility, relatively low computational demands, and ability to perform well even with moderate-sized datasets. Compared to more complex models like deep neural networks, ML offers a balanced trade-off between performance and interpretability, making it a go-to approach for many researchers and practitioners in the renewable energy field.

**(ii)** *Rise of Deep Learning (DL)*
Deep Learning (DL) demonstrates a growing presence in renewable energy, particularly within Wind Energy and Smart Grid research. This rise is closely tied to the increasing availability of high-dimensional and complex datasets, such as satellite imagery, weather models, and IoT sensor streams. DL's ability to capture non-linear relationships and extract intricate spatial-temporal patterns makes it especially valuable for applications where traditional models may fall short. In practice, DL is widely employed for wind power forecasting, energy load prediction, and smart meter data analytics—tasks that benefit from its deep representational power. Furthermore, DL excels in fault detection through advanced pattern recognition, allowing systems to pre-emptively identify anomalies and improve resilience. Its rapid adoption reflects the ongoing shift toward data-intensive approaches in managing the complexities of modern energy systems.

**(iii)** *Fuzzy Logic in Engineering-Oriented Platforms*
Fuzzy Logic remains a prominent technique in engineering-oriented research, as evidenced by its higher occurrence in IEEE Xplore than ScienceDirect. Its rule-based structure and high interpretability make it especially suitable for applications where transparency and expert knowledge integration are critical. Fuzzy Logic is frequently applied in control systems, load balancing strategies, and decision support systems, particularly within grid stability contexts. Its ability to model uncertainty and imprecise inputs without requiring large datasets makes it appealing in complex, real-world energy environments. Moreover, it plays a crucial role in hybrid AI systems, where combining data-driven learning with human reasoning enhances reliability and explainability.

**(iv)** *Emerging Role of Reinforcement Learning (RL)*
Since 2020, Reinforcement Learning (RL) has seen a noticeable rise in adoption across Solar Energy, Wind Energy, and Energy Storage & Smart Grids. This trend reflects a growing interest in dynamic and real-time decision-making capabilities within energy systems. RL's strength lies in its ability to learn optimal control policies through interaction with complex, uncertain environments, making it particularly well-suited for applications such as optimizing energy dispatch in microgrids, fine-tuning turbine operations under fluctuating wind conditions, and enabling adaptive strategies in demand-response programs for smart grids. Its capacity for autonomous learning and continuous improvement positions RL as a promising approach for developing self-optimizing, intelligent energy infrastructures.

## EMERGING TRENDS IN AI

Table 3 provides a comparative overview of emerging AI trends across three major renewable energy domains—Solar Energy, Wind Energy, and Energy Storage & Smart Grids—from 2015 to 2025. It consolidates patterns in technique adoption, temporal growth, and domain-specific applications. Several key insights have been identified through this comparative analysis.

- Emerging AI paradigms—such as Explainable AI (XAI), Generative AI, Graph Neural Networks (GNNs), and Physics-Informed Neural Networks (PINNs)—are gaining attention but remain in early stages of adoption across renewable energy domains. XAI shows noticeable growth between 2022 and 2025, driven by the increasing demand for transparency and regulatory accountability in critical systems like Smart Grids, where black-box models are less acceptable.
- The rise of XAI also coincides with broader industry movements emphasizing trustworthy AI and stakeholder interpretability. Generative AI, though still rare, begins to surface post-2023 in response to data scarcity challenges—its potential for simulation, scenario generation, and synthetic data augmentation aligns well with the needs of complex energy modeling tasks.
- Similarly, GNNs and PINNs reflect a growing interest in incorporating structural and physical domain knowledge into AI models. Their emerging usage, especially in grid-related applications, suggests a shift toward physics-informed and topology-aware learning to represent real-world system constraints better.
- The persistent dominance of the "Not Specified" category, particularly in Energy Storage & Smart Grids and ScienceDirect publications, signals a methodological reporting gap. This may stem from interdisciplinary submissions where AI methods are used as tools rather than research contributions, resulting in vague or incomplete descriptions. This trend highlights a critical need for standardized reporting practices, clearer taxonomy of AI techniques, and stronger collaboration between AI experts and domain scientists to ensure technical rigor and reproducibility.

| AI TECHNIQUE | SOLAR ENERGY | WIND ENERGY | ENERGY STORAGE & SMART GRIDS |
|---|---|---|---|
| Machine Learning (ML) | Most dominant; used for forecasting, PV performance optimization | Widespread for wind speed prediction, control, and anomaly detection | Key technique in grid optimization, energy demand prediction |
| Deep Learning (DL) | Emerging post-2020; spike seen in 2023–2024 | Strong uptake post-2020; widely used for spatial-temporal modeling | Rapid growth post-2021 due to IoT & smart meter data |
| Reinforcement Learning | Still emerging, but visible after 2021 | More active than Solar; used in adaptive turbine control | Growing rapidly for real-time control in dynamic grid environments |
| Fuzzy Logic | Present but less dominant; popular in early years | Strong in IEEE Xplore; used in rule-based turbine control | Frequently used in decision-making and load balancing systems |
| Explainable AI (XAI) | Gaining attention 2022–2025; tied to hybrid systems | Emerging post-2022, limited but increasing focus on transparency | Present in recent years, key for interpretability in smart systems |
| Generative AI | Very limited use | Rare, but a few exploratory studies | Rare, emerging mostly post-2023 in hybrid modeling frameworks |
| Graph Neural Networks | Sparse usage, some hybrid works emerging | Slight increase post-2021 for turbine networks | Slight growth post-2022 for grid topology analysis |
| PINNs (Physics-Informed Neural Networks) | Rare application | Emerging use in hybrid models post-2023 | Notable application in physics-based grid modeling, mostly in IEEE Xplore |
| Not Specified | Still large proportion, especially 2020–2023 | Very high in ScienceDirect, suggesting poor methodological reporting | The highest volume of "unspecified" label, indicating the urgent need for clearer documentation |

**Table 3** Summary of Emerging AI Trends (2015–2025).

Overall, this review offers novel contributions by cross-analyzing trends across publication platforms, revealing inconsistencies in AI methodology reporting, and mapping emerging techniques like XAI, PINNs, and GNNs across domains. These findings expose underexplored intersections and offer a foundation for improving methodological transparency and interdisciplinary research integration in future AI-energy studies.

## CONCLUSION

In conclusion, this review provides a comprehensive synthesis of Artificial Intelligence (AI) applications in Solar Energy, Wind Energy, and Energy Storage & Smart Grids, based on data from IEEE Xplore and ScienceDirect spanning 2015 to 2025. The analysis reveals a sharp rise in AI-related research activity after 2020, reflecting global momentum toward intelligent and sustainable energy systems. Machine Learning (ML) and Deep Learning (DL) emerged as the most dominant techniques, widely used for forecasting, optimization, and fault detection. ML remains especially prevalent due to its adaptability and lower data demands, while DL thrives in domains rich with high-dimensional data, such as sensor networks and smart grids. Fuzzy Logic is consistently represented in engineering-focused studies, while Reinforcement Learning is gaining traction for real-time control and adaptive energy management.

Despite these advancements, emerging AI paradigms—such as Explainable AI (XAI), Generative AI, and Physics-Informed Neural Networks (PINNs)—remain underutilized, signaling important opportunities for future research. A critical limitation identified across both sources is the lack of methodological transparency, with many studies omitting specific AI techniques. This gap hinders reproducibility and cross-study synthesis, underscoring the need for standardized reporting practices. Moving forward, embracing interpretable and hybrid AI models, enhancing data documentation, and fostering interdisciplinary collaboration will be key to building trustworthy, scalable, and resilient renewable energy systems.

To translate these findings into actionable outcomes, we recommend that future research prioritize the use of clearly defined AI methodologies and reporting standards to improve transparency and reproducibility. Researchers should explore hybrid models that integrate conventional techniques with emerging paradigms such as XAI and PINNs to address domain-specific challenges. It is also crucial to encourage interdisciplinary collaborations among AI developers, energy system engineers, and policy stakeholders to co-create adaptive, explainable, and scalable AI-driven solutions that align with real-world energy needs and sustainability goals.

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## COMPETING INTERESTS

The authors have no competing interests to declare.

## AUTHOR CONTRIBUTIONS

Dr. Tajul Rosli Razak conceptualized the study, led the data collection and analysis, and drafted the manuscript. He also conducted the PRISMA-based systematic review and visualization of results. All authors have read and approved the final version of the manuscript.

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## REFERENCES

**Adewumi, A.** *et al.* (2024) 'Reviewing the impact of AI on renewable energy efficiency and management', *International Journal of Science and Research Archive*, 11(1), pp. 1518–1527. Available at: https://doi.org/10.30574/IJSRA.2024.11.1.0245

**Albarakati, A.J.** *et al.* (2021) 'Real-Time Energy Management for DC Microgrids Using Artificial Intelligence', *Energies*, 14(17). Available at: https://doi.org/10.3390/EN14175307

**Awachat, A., Dube, A.** and **Chaudhri, S.** (2025) 'ML for Sustainable Solutions: Applications in Renewable Energy Optimization and Climate Change Prediction', *4th International Conference on Sentiment Analysis and Deep Learning, ICSADL 2025 – Proceedings*, pp. 1689–1694. Available at: https://doi.org/10.1109/ICSADL65848.2025.10933273

**Cacciamani, G.E.** *et al.* (2023) 'PRISMA AI reporting guidelines for systematic reviews and meta-analyses on AI in healthcare', *Nature medicine*, 29(1), pp. 14–15. Available at: https://doi.org/10.1038/S41591-022-02139-W

**Camacho, J. de J.** *et al.* (2024) 'Leveraging Artificial Intelligence to Bolster the Energy Sector in Smart Cities: A Literature Review', *Energies*, 17(2). Available at: https://doi.org/10.3390/EN17020353

**Donti, P.L.** and **Kolter, J.Z.** (2021) 'Machine Learning for Sustainable Energy Systems', *Annual Review of Environment and Resources*, 46(Volume 46, 2021), pp. 719–747. Available at: https://doi.org/10.1146/ANNUREV-ENVIRON-020220-061831

**Etukudoh, E.A.** *et al.* (2024) 'Electrical Engineering in Renewable Energy Systems: A Review of Design and Integration Challenges', *Engineering Science &Amp; Technology Journal*, 5(1), pp. 231–244. Available at: https://doi.org/10.51594/ESTJ.V5I1.746

**Fu, X.** *et al.* (2022) 'Planning of distributed renewable energy systems under uncertainty based on statistical machine learning', *Protection and Control of Modern Power Systems*, 7(1). Available at: https://doi.org/10.1186/S41601-022-00262-X

**Garmabdari, R.** *et al.* (2019) 'Optimal Power Flow Scheduling of Distributed Microgrid Systems Considering Backup Generators', *2019 9th International Conference on Power and Energy Systems (ICPES)* [Preprint]. Available at: https://doi.org/10.1109/ICPES47639.2019.9105372

**Gawusu, S.** *et al.* (2022) 'The dynamics of green supply chain management within the framework of renewable energy', *International Journal of Energy Research*, 46(2), pp. 684–711. Available at: https://doi.org/10.1002/ER.7278

**Green, I.A.** *et al.* (2023) 'Technological advances of ammonia as energy storage solution', *Global Journal of Engineering and Technology Advances*, 16(3), pp. 151–155. Available at: https://doi.org/10.30574/GJETA.2023.16.3.0185

**Hamdan, A.** *et al.* (2024) 'AI in renewable energy: A review of predictive maintenance and energy optimization', *International Journal of Science and Research Archive*, 11(1), pp. 718–729. Available at: https://doi.org/10.30574/IJSRA.2024.11.1.0112

**Huang, B.** and **Wang, J.** (2023) 'Applications of Physics-Informed Neural Networks in Power Systems – A Review', *IEEE Transactions on Power Systems*, 38(1), pp. 572–588. Available at: https://doi.org/10.1109/TPWRS.2022.3162473

**Ipakchi, A.** and **Albuyeh, F.** (2009) 'Grid of the future', *IEEE Power and Energy Magazine*, 7(2), pp. 52–62. Available at: https://doi.org/10.1109/MPE.2008.931384

**Islam, A.** and **Othman, F.** (2024) 'Renewable Energy MicroGrid Power Forecasting: AI Techniques with Environmental Perspective', *Research Square Platform LLC* [Preprint]. Available at: https://doi.org/10.21203/RS.3.RS-4260337/V1

**Jiang, R., Liu, H.** and **Peng, H.** (2024) 'An optimal configuration method of energy storage system considering source-load matching', *Journal of Physics: Conference Series*, 2788(1). Available at: https://doi.org/10.1088/1742-6596/2788/1/012018

**Kalair, A.** *et al.* (2021) 'Role of energy storage systems in energy transition from fossil fuels to renewables', *Energy Storage*, 3(1). Available at: https://doi.org/10.1002/EST2.135

**Latrach, A.** *et al.* (2024) 'A critical review of physics-informed machine learning applications in subsurface energy systems', *Geoenergy Science and Engineering*, 239, p. 212938. Available at: https://doi.org/10.1016/J.GEOEN.2024.212938

**Liu, Z.** *et al.* (2025) 'A Comprehensive Review of Wind Power Prediction Based on Machine Learning: Models, Applications, and Challenges', *Energies 2025, Vol. 18, Page 350*, 18(2), p. 350. Available at: https://doi.org/10.3390/EN18020350.

**Machina, S.P.C., Koduru, S.S.** and **Madichetty, S.** (2022) 'Solar Energy Forecasting Using Deep Learning Techniques', *2022 2nd International Conference on Power Electronics and IoT Applications in Renewable Energy and its Control, PARC 2022* [Preprint]. Available at: https://doi.org/10.1109/PARC52418.2022.9726605

**Mauro, G.** (2024) 'The New Power Couple: Artificial Intelligence and Renewable Energy', *Journal of Strategic Innovation and Sustainability*, 19(3). Available at: https://doi.org/10.33423/JSIS.V19I3.7374

**Mysore, S.** (2024) 'Role of Artificial Intelligence in Grid Modernization: Loring How Ai Can Enhance Grid Management, Predict Energy Demand, and Optimize Renewable Energy Usage', *International Research Journal of Modernization in Engineering Technology and Science* [Preprint]. Available at: https://doi.org/10.56726/IRJMETS48452

**Necula, S.C.** (2023) 'Assessing the Potential of Artificial Intelligence in Advancing Clean Energy Technologies in Europe: A Systematic Review', *Energies*, 16(22). Available at: https://doi.org/10.3390/EN16227633

**Ohalete, N.C.** *et al.* (2023) 'AI-driven solutions in renewable energy: A review of data science applications in solar and wind energy optimization', *World Journal of Advanced Research and Reviews*, 20(3), pp. 401–417. Available at: https://doi.org/10.30574/WJARR.2023.20.3.2433

**Onwusinkwue, S.** *et al.* (2024) 'Artificial intelligence (AI) in renewable energy: A review of predictive maintenance and energy optimization', *World Journal of Advanced Research and Reviews*, 21(1), pp. 2487–2499. Available at: https://doi.org/10.30574/WJARR.2024.21.1.0347

**Orumwense, E.F.** and **Abo-Al-Ez, K.** (2022) 'Internet of Things for smart energy systems: A review on its applications, challenges and future trends', *AIMS Electronics and Electrical Engineering*. American Institute of Mathematical Sciences, pp. 50–74. Available at: https://doi.org/10.3934/electreng.2023004

**Ragab, R.** *et al.* (2021) 'Optimized Hybrid Renewable Energy System for a Baseload Plant', *Energy Proceedings*, 17. Available at: https://doi.org/10.46855/ENERGY-PROCEEDINGS-8674

**Rajitha, M.** and **Raghu Ram, A.** (2024) 'An overview of Artificial Intelligence applications to electrical power systems and DC microgrids', *E3S Web of Conferences*, 547. Available at: https://doi.org/10.1051/E3SCONF/202454701002

**Rugolo, J.** and **Aziz, M.J.** (2012) 'Electricity storage for intermittent renewable sources', *Energy &Amp; Environmental Science*, 5(5), pp. 7151–7160. Available at: https://doi.org/10.1039/C2EE02542F

**Sammar, M.J.** *et al.* (2024) 'Illuminating the Future: A Comprehensive Review of AI-Based Solar Irradiance Prediction Models', *IEEE Access*, 12, pp. 114394–114415. Available at: https://doi.org/10.1109/ACCESS.2024.3402096

**Shao, H.** *et al.* (2015) 'Rolling bearing fault diagnosis using an optimization deep belief network', *Measurement Science and Technology*, 26(11), p. 115002. Available at: https://doi.org/10.1088/0957-0233/26/11/115002

**Soni, P., Dave, V.** and **Paliwal, H.** (2023) 'Artificial Intelligence-Enabled Techno-Economic Analysis and Optimization of Grid-Tied Solar PV-Fuel Cell Hybrid Power Systems for Enhanced Performance', *Data Science and Intelligent Computing Techniques*, pp. 781–794. Available at: https://doi.org/10.56155/978-81-955020-2-8-67

**Ukoba, K.** *et al.* (2024) 'Optimizing renewable energy systems through artificial intelligence: Review and future prospects', *Energy & Environment*, 35(7), pp. 3833–3879. Available at: https://doi.org/10.1177/0958305X241256293

**Wang, W.** *et al.* (2023) 'Fast frequency response for centralized renewable energy source stations based on deep reinforcement learning', *Second International Conference on Energy, Power, and Electrical Technology (ICEPET 2023)*, p. 126. Available at: https://doi.org/10.1117/12.3004411

**Wen, X.** *et al.* (2024) 'Leveraging AI and Machine Learning Models for Enhanced Efficiency in Renewable Energy Systems', *Applied and Computational Engineering*, 96(1), pp. 107–112. Available at: https://doi.org/10.54254/2755-2721/96/20241416

**Yousef, L.A., Yousef, H.** and **Rocha-Meneses, L.** (2023) 'Artificial Intelligence for Management of Variable Renewable Energy Systems: A Review of Current Status and Future Directions', *Energies*, 16(24). Available at: https://doi.org/10.3390/EN16248057

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