

AI-driven forecasting for efficient integration of renewable energy systems

Olatunde Ibiyinka ^{1,*}, Tolu Omotoso ² and Ndubuisi Ekekwe ³

¹ Department of School of Engineering, Infrastructure and Sustainability, De Montfort University Leicester.

² Department of Civil Engineering, Purdue University, United States.

³ Department of Electrical and Computer Engineering, The Johns Hopkins University, United States.

Global Journal of Engineering and Technology Advances, 2026, 28(02), 047–055

Publication history: Received on 27 June 2026; revised on 03 August 2026; accepted on 05 August 2026

Article DOI: <https://doi.org/10.30574/gjeta.2026.28.2.0204>

Abstract

The global transition to renewable energy is critical for climate change mitigation, energy security, and the achievement of sustainable development goals. Nevertheless, the intermittent and unpredictable characteristics of renewable energy sources, particularly solar and wind, pose substantial challenges for reliable power grid operation and energy management. Artificial Intelligence (AI) has emerged as a transformative technology that enhances forecasting accuracy and enables intelligent decision-making for renewable energy integration. This paper reviews recent advances in AI-driven forecasting techniques that facilitate the efficient integration of renewable energy systems into power grids. Relevant studies were identified through a systematic search of peer-reviewed literature published in major scientific databases over the past decade, with an emphasis on works that applied AI methods to renewable energy forecasting and energy management. Studies were selected and synthesized based on criteria including methodological rigor, relevance to grid integration, and demonstrated impact on operational performance. The review examines the application of machine learning, deep learning, reinforcement learning, and hybrid AI models in forecasting renewable energy generation, electricity demand, energy storage management, and grid optimization. The review also discusses data acquisition and preprocessing methods, forecasting architectures, performance evaluation metrics, and real-world case studies that demonstrate the effectiveness of AI-enabled energy management systems. The findings indicate that AI-based forecasting substantially improves prediction accuracy, enhances grid stability, optimizes energy dispatch, reduces operational costs, and supports greater penetration of renewable energy resources. Despite these advancements, challenges related to data quality, computational complexity, cybersecurity, model interpretability, and regulatory frameworks continue to impede large-scale deployment. The paper concludes by identifying emerging research directions, such as explainable AI, federated learning, digital twins, edge intelligence, and physics-informed machine learning, as promising strategies for developing resilient, intelligent, and sustainable future power grids.

Keywords: Renewable Energy; Optimization; Artificial Intelligent; Solar; Wind

1. Introduction

The third decade of the 21st century marks a critical juncture in global energy development[1]. The increasing urgency of climate change, combined with the need for energy security and economic stability, has intensified international discourse regarding the future of energy sources. Central to this discourse is the transition to renewable energy, which is now regarded not only as an alternative to conventional power sources but also as a pivotal factor in reshaping interactions with the environment, the economy, and societal values[2]. Various forms of renewable energy, including solar, wind, hydro, geothermal, and biomass, play a crucial role in guiding this global energy transition[3]. These sources represent more than technical alternatives; they signify a fundamental transformation in energy production and consumption, reflecting a broader commitment to sustainability, resilience, and environmental balance. The AI-driven optimization of Hybrid Renewable Energy Systems (HRES) offers a transformative approach by utilizing artificial

* Corresponding author: Olatunde Ibiyinka.

intelligence (AI) to enhance the performance, reliability, and sustainability of integrated energy networks. HRES typically integrate multiple renewable energy sources, such as solar photovoltaics, wind turbines, biomass, hydropower, and energy storage systems[4], to establish a balanced, efficient, and resilient power generation infrastructure[5]. The main part of an HRES belongs to renewable energy technologies. The distribution of renewable energy sources in cited articles published from 2017 to 2024 as shown in Figure 1. Each bar represents the total number of articles per year, with individual contributions from six renewable energy categories: solar, wind, biomass, geothermal, hydropower, and tidal energy.

As global demand for clean energy increases and the need to decarbonize the energy sector becomes more pressing, interest in intelligent and adaptive energy systems has grown[6]. AI technologies, with advanced capabilities in data-driven modeling, prediction, and optimization, have become essential tools for addressing complex energy challenges. The integration of AI with renewable energy systems enables improved real-time decision-making, predictive analytics, and dynamic optimization across energy generation, distribution, and consumption. Techniques such as machine learning (ML), deep learning (DL), reinforcement learning (RL), and evolutionary computation are increasingly applied to anticipate energy production, forecast load demands, optimize power dispatch, and manage battery storage and grid integration[7].

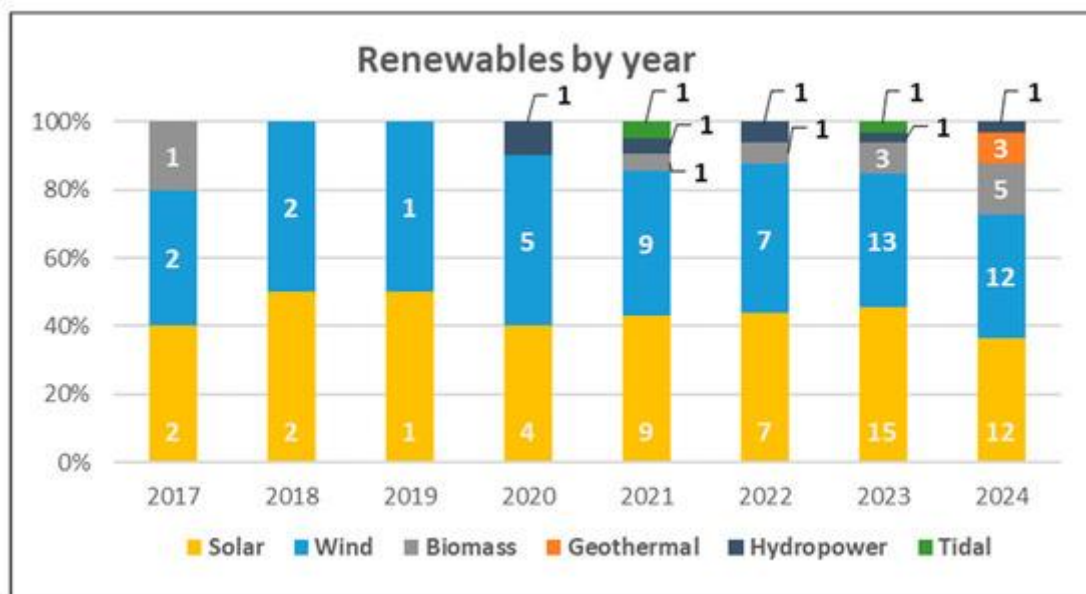


Figure 1 Distribution of renewable energy sources in cited references, each number represents the amount of the identified renewable energy sources in HRES in a given year

Renewable energy is central to global decarbonization and sustainable development initiatives. The electrification of transport, industry, and household sectors is projected to increase electricity demand by over 50% by 2040, according to the IEA [8]. Continued dependence on fossil fuels to meet this demand is incompatible with climate targets, as it would result in a 2.5–3 °C rise in global temperatures by the end of the century[9]. To avoid this outcome, renewables, particularly solar and wind, must supply nearly half of global electricity by 2030 and more than 70% by 2050 [10]. Renewable energy sources (RES) are therefore essential not only for emissions reduction but also for achieving the Paris Agreement and net-zero pathways. However, it is important to acknowledge that large-scale deployment of renewables can present challenges, including land use concerns, competition for resources such as water and critical minerals, and potential impacts on biodiversity or local communities. Addressing these challenges is key to ensuring that renewable energy contributes effectively and equitably to long-term sustainability goals.

A primary factor driving renewable energy adoption is the significant reduction in technology costs. Between 2010 and 2023, the levelized cost of electricity (LCOE) for solar photovoltaic (PV) decreased by nearly 89%, while onshore wind costs declined by approximately 70% [11]. In many regions, new solar and wind installations are now less expensive than operating existing coal plants. For example, *China* commissioned over 216 GW of renewable capacity in 2023, surpassing the combined capacity additions of the rest of the world in that year [12]. The United States and the European Union are also increasing deployment, supported by policy measures such as the Inflation Reduction Act and the REPowerEU Plan, which further enhance the economic competitiveness of clean energy [13]. These policies in

developed economies typically provide financial incentives, long-term planning certainty, and comprehensive grid integration efforts, rapidly accelerating renewable uptake. In contrast, in many developing countries, policy measures often focus on overcoming barriers such as limited access to finance, technical capacity, and institutional support. While feed-in tariffs or subsidy programs can spur growth, their effectiveness depends on broader infrastructure, governance, and market readiness. As a result, policy impacts on renewable energy adoption are influenced not just by the policies themselves but also by national contexts, highlighting the importance of tailored approaches for both developed and developing regions.

Beyond addressing climate change, renewable energy improves energy security by diversifying supply sources and reducing reliance on imported fossil fuels. However, the specific challenges and priorities associated with energy security and access can differ markedly between developed and developing regions. In developed economies, such as those in Europe, energy security concerns often center on safeguarding supply from geopolitical risks and stabilizing prices in the face of international supply disruptions. The 2022 energy crisis in Europe, associated with the conflict between Russia and Ukraine, highlighted the geopolitical risks of fossil fuel dependence. In response, several countries have accelerated renewable energy deployment to mitigate these vulnerabilities; for instance, Germany aims to generate 80% of its electricity from renewable sources by 2030 [14]. In contrast, many developing regions face fundamental challenges related to energy access, where large segments of the population still lack reliable or affordable electricity. Here, the focus is on overcoming infrastructural and financial barriers to provide basic energy services. Renewable energy plays a crucial role in expanding energy access in these contexts. Technologies such as solar mini-grids and wind-diesel hybrids are providing electricity to remote communities in Africa and South Asia, where grid extension is not economically feasible [15]. Thus, while renewables support energy security for industrialized countries by reducing import dependence and price volatility, they simultaneously promote social and economic development in less developed regions by enhancing energy access.

The socio-economic benefits of renewable energy are also significant. According to the International Renewable Energy Agency (IRENA), over 13.7 million people were employed globally in the renewable energy sector in 2022, with projections indicating an increase to 38 million jobs by 2030 if current growth trends persist [16]. These positions span manufacturing, installation, maintenance, and research, with the largest share of employment found in the solar photovoltaic sector, followed by wind energy. Regions such as Asia, particularly China and India, are expected to see the fastest job growth, reflecting the concentration of manufacturing and installation activities in these countries. In developed economies like the United States and the European Union, job creation is expected to expand primarily in installation, grid integration, and operation and maintenance. Such employment opportunities contribute to industrial development and poverty alleviation. Furthermore, renewable energy projects often facilitate local ownership and community participation, thereby advancing social equity during the energy transition.

Despite their advantages, renewable energy sources present challenges related to intermittency and unpredictability. Solar generation is constrained by daily cycles and weather variability, while wind output depends on seasonal and geographic factors. This variability complicates the balance between energy supply and demand, often straining grid stability at high levels of renewable integration [17]. Addressing these challenges requires advanced optimization and control strategies. Artificial intelligence (AI), machine learning (ML), and deep learning (DL) offer powerful tools for improved forecasting, real-time decision-making, and comprehensive system optimization [18]. However, the implementation of AI and ML technologies in renewable energy systems faces several barriers. Technical challenges include the need for high-quality, real-time data and robust cyber-physical infrastructure to ensure effective model training and operation. Economically, costs associated with developing, deploying, and maintaining AI/ML solutions can be significant, especially for resource-constrained utilities or developing regions. Additionally, regulatory and policy frameworks may lag behind technological progress, creating uncertainties about data privacy, security, and interoperability standards. Addressing these barriers will be crucial to fully realizing the potential of AI and ML to accelerate the renewable energy transition.

2. Literature Review

Prompted by the 1970 oil price crisis and widespread opposition to nuclear energy [19], the Institute for Applied Ecology in Germany introduced the concept of energy transition in 1980 [20], advocating for a shift toward clean energy sources [21]. The increasing urgency of climate change has further amplified this need [22]. The International Energy Agency (IEA) published the "Tracking Clean Energy Progress (TCEP)" report, which evaluates the latest developments in over 50 components of the energy system essential for the clean energy transition and benchmarks them against a net-zero scenario. With the exception of behavioral change and Carbon Capture and Storage (CCS) development, which are significantly lagging, most projects remain in the "needs more effort" category. The report provides a detailed assessment of sub-sectors within energy supply and usage. Specifically, low-carbon utilization of oil, natural gas, and

traditional biomass remains insufficient, while the development of smart electricity systems supported by renewable energy is progressing, with photovoltaic (PV) technology being the only area on track[23]. In contrast, aside from the electric vehicle sector, progress in transportation and industry is limited, with most sub-sectors experiencing significant developmental gaps. In summary, while the energy transition is inevitable, it currently encounters numerous challenges. This section offers a concise review of the areas undergoing substantial change during the transition and identifies major technological obstacles in key domains. Accordingly, the discussion is organized into four parts: clean energy supply, demand side management, energy transmission and distribution systems, and technology innovation support.

Currently, more than 80% of global carbon emissions originate from fossil fuels[24]. Replacing traditional high-carbon energy sources with clean energy is a central objective of the energy transition[25]. Achieving large-scale clean energy supply, involves two primary approaches: employing Carbon Capture and Storage (CCS) technology to decarbonize fossil fuels, and directly substituting fossil fuels with clean and renewable energy sources[26]. The first approach utilizes CCS technology as a transitional strategy, leveraging existing fossil fuel infrastructure while reducing carbon emissions[27]. In this process, carbon dioxide generated from fossil fuel use is captured at the emission source and securely stored underground or in other geological formations using advanced techniques[28]. This method allows existing power plants and industrial facilities to continue operating with only technical modifications required for emissions reduction[29]. CCS is particularly viable for regions and industries where a complete transition to renewable energy is not immediately feasible, such as steel and cement manufacturing. The second approach involves the direct replacement of fossil fuels with clean and renewable energy sources, including solar, wind, hydropower, and biomass. This strategy eliminates fossil fuel use at the source and necessitates the development of entirely new energy production and distribution systems. The primary advantage of renewable energy is its long-term sustainability and diminishing environmental impact. Furthermore, ongoing technological advancements and economies of scale are reducing the costs of renewable energy, enhancing its economic competitiveness.

3. Artificial Intelligence Techniques for Renewable Energy Optimization

The success of AI in optimizing energy use largely depends on the quality and availability of the data it relies on. Renewable energy systems gather a wealth of information from various sources like sensors, weather stations, smart meters, and grid components. However, this data often comes with challenges such as gaps, inconsistencies, noise, and a lack of standardization. These problems can seriously impact the performance of machine learning and deep learning models, leading to less accurate predictions and unreliable control decisions[30]. Additionally, extreme weather conditions or equipment malfunctions can result in significant data loss, with some records missing over 15% of their data[31]. These gaps can complicate the training of models and make it harder to maintain operational resilience in real-time. In many developing areas, the infrastructure for collecting and transmitting data in real-time is often lacking, which only makes the situation worse. For these reasons, it is crucial to implement strong data preprocessing techniques, calibrate sensors effectively, and adopt standardized data acquisition methods to create reliable AI-powered systems.

3.1. Case Studies: Establishment of Artificial Intelligence in Hybrid Renewable Energy Systems

Artificial Intelligence (AI) applications in Hybrid Renewable Energy Systems (HRES) have progressed from theoretical concepts to practical implementations, demonstrating substantial advancements across diverse regions and operational contexts [32]. Recent case studies demonstrate that artificial intelligence (AI) is increasingly applied to enhance energy production, maintain grid stability, and optimize resource management in systems integrating solar, wind, and battery storage. These cases highlight AI's adaptability and scalability in addressing the complex challenges of contemporary energy systems.

3.2. Case Study 1: AI-Based Dynamic Modeling in Solar-Wind-Battery Hybrid Systems

Artificial intelligence integration in renewable energy is a hybrid system combines solar, wind, and battery technologies. In this project, Python was employed for system modeling, and AI algorithms were implemented to optimize energy utilization. By analyzing both real-time and historical data on solar and wind patterns, the system generated more accurate forecasts and scheduled operations efficiently. This configuration enabled informed decisions about deploying stored energy, particularly during periods of peak demand, thereby minimizing waste and enhancing resource utilization. The application of AI-driven strategies improved energy efficiency, balanced the load, and maximized both economic and environmental benefits associated with renewable energy sources[33].

3.3. Case Study 2: AI-Enhanced Solar Tracking and Photovoltaic Management

A state-of-the-art solar power system integrated artificial intelligence to enhance performance and efficiency. Utilizing computer vision and advanced algorithms, the system automatically adjusted the angle of solar panels to optimize sunlight capture under varying weather conditions. This intelligent configuration maximized energy collection and continuously monitored system health. By incorporating predictive maintenance and early fault detection, the system significantly reduced downtime and ensured reliable long-term operation[34]. This approach improved the efficiency and robustness of the solar energy system, demonstrating the substantial benefits of AI in optimizing hybrid energy operations.

3.4. Case Study 3: Policy Simulation and Strategic Planning through Artificial Intelligence Optimization

Recent research has leveraged artificial intelligence (AI) to simulate and optimize complex policy and economic scenarios, particularly within Hybrid Renewable Energy Systems (HRES). By utilizing advanced optimization techniques such as Genetic Algorithms, Particle Swarm Optimization, and Deep Q-Networks, researchers have examined the impact of regulatory incentives, carbon pricing, and renewable energy subsidies on the performance of these hybrid systems[35]. AI-driven analyses have clarified the trade-offs among energy cost management, emission reduction, and power grid reliability under varying policy conditions[36]. The findings from these studies inform strategies to expand renewable energy adoption while maintaining grid stability and controlling overall costs. These simulations serve as critical tools for policymakers and energy planners seeking to facilitate a transition toward more sustainable energy solutions.

3.5. Case Study 4: Artificial Intelligence for Grid Stability and Load Forecasting

Grid stability remains a critical challenge in the operation of Hybrid Renewable Energy Systems (HRES) due to the inherent variability of solar and wind resources. In a case study involving a grid-connected hybrid power plant, researchers utilized artificial intelligence methods, specifically Long Short-Term Memory (LSTM) networks and fuzzy logic systems, to predict fluctuations in energy demand and generation with high accuracy[37]. These models incorporated diverse data inputs, including weather conditions, historical energy production, and real-time grid status. Through comprehensive analysis, the AI systems forecasted short-term imbalances and recommended timely corrective actions. This strategy enabled grid operators to dynamically adjust energy distribution and optimize storage utilization. Consequently, the stability and reliability of the local power grid were enhanced, and reliance on fossil fuel-based backup systems was reduced.

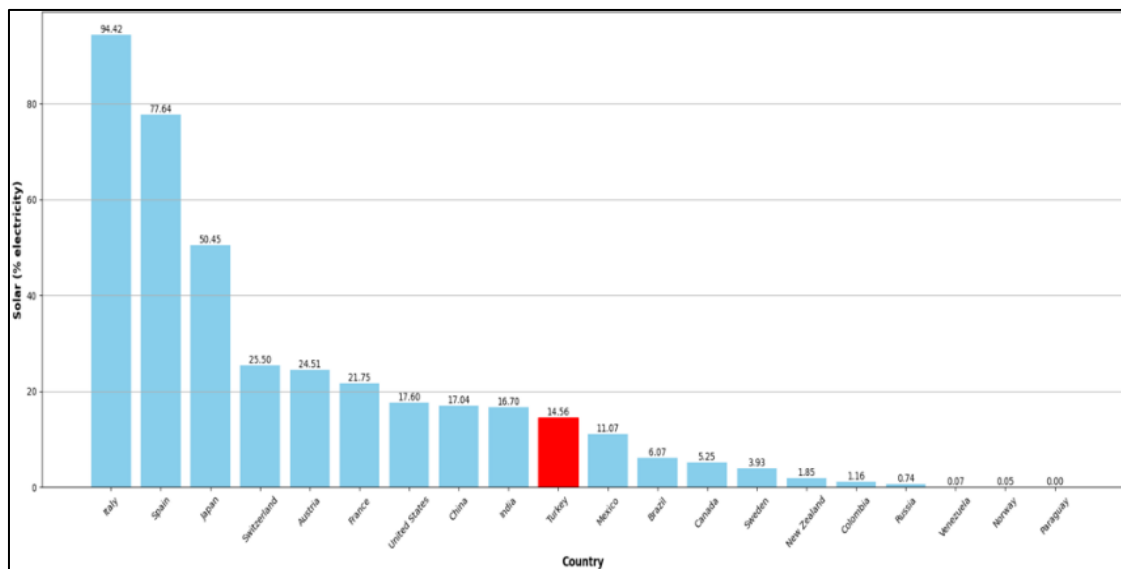
3.6. Hybrid Renewable Energy Systems (HRES)

Advancements in artificial intelligence (AI) underscore its significance as a critical tool for driving substantive change within the renewable energy sector. As energy systems grow more complex, deploying AI technologies is becoming indispensable for achieving sustainable, resilient energy infrastructure. Numerous case studies demonstrate the transformative potential of AI in optimizing hybrid renewable energy systems. A primary advantage is enhanced operational efficiency; AI enables improved forecasting, innovative scheduling, and adaptive controls, resulting in more effective resource utilization and reduced energy waste[38]. Furthermore, the adaptability of AI allows for its application across diverse contexts, ranging from small rural microgrids to extensive urban intelligent grid networks. This versatility supports a broad spectrum of applications and system configurations (Table 1). In addition to technical improvements, AI integration yields significant economic and environmental benefits by improving system performance, reducing operational costs, and lowering carbon emissions, thereby advancing both profitability and sustainability. Intelligent AI-driven systems also support policymakers and planners by simulating various regulatory and market scenarios, thereby informing the development of effective energy strategies and regulations. Moreover, AI contributes to grid resilience and security by predicting fluctuations in energy generation and demand, managing variability, and ensuring reliable power delivery. AI has evolved beyond a theoretical concept to become a powerful catalyst for change in the transition to renewable energy. As energy systems continue to develop, the strategic implementation of AI technologies will be essential for constructing a more intelligent and sustainable energy landscape.

Table 1 Summary of AI Applications in Hybrid Renewable Energy Systems (HRES)

AI Techniques	Applications	Challenges	Future Opportunities
ML, DL, RL, Evolutionary Algorithms	Energy forecasting, load optimization, smart EMS	Data scarcity, computational demand, policy gaps	Collaboration, local community inclusion, adaptive systems
- ML (SVM, Decision Trees, PCA, Clustering)- RL- DL (CNN, RNN, LSTM)- Hybrid AI (GA + NN, PSO)- Blockchain Integration	Forecasting energy output, P2P trading, microgrid control, anomaly detection	Complexity of models, high data requirements	Federated learning, edge computing, hybrid modeling
Supervised (SVM, RF), Unsupervised (PCA, Clustering)	Forecasting solar/wind power, demand-side clustering	Limited data standardization	Smarter resource allocation
Q-learning, Deep RL	Battery storage, off-grid energy control	Dynamic system adaptation	Resilient and self-optimizing systems
CNNs, RNNs, LSTM	Forecasting, predictive maintenance, fault detection	Model interpretability	Advanced anomaly detection
GA + NN, Fuzzy logic + RL, PSO	Smart grid optimization, scheduling, voltage regulation	Algorithmic complexity	Real-time energy routing
ML + Blockchain, RL	Peer-to-peer trading, shared storage, load balancing	Coordination and prediction accuracy	Enhanced community energy resilience

The bar chart presents the aggregate share of solar power production for twenty countries shown in figure 2, illustrating the cumulative impact of solar energy adoption. A uniform sky-blue color represents each country's contribution, while Turkey is highlighted in red to emphasize its specific performance. The chart clearly conveys the relative standings of these nations regarding solar energy output, offering a comparative perspective on the global distribution of solar power. Data annotations on each bar provide precise information on solar power percentages, thereby enhancing the chart's informational value.

**Figure 2** Total Solar Power Production Share of Specified Countries[39]

The polar area chart depicts average solar power production percentages across multiple years in a circular format that emphasizes temporal progression as shown in figure 3. The use of sky-blue fill and a solid blue outline visually convey fluctuations in solar energy production, with each radial segment representing a specific year. This visualization facilitates direct comparison of annual averages and enables identification of temporal trends. The chart highlights the cyclical nature of solar power growth, emphasizing periods of notable increase or stability in production.

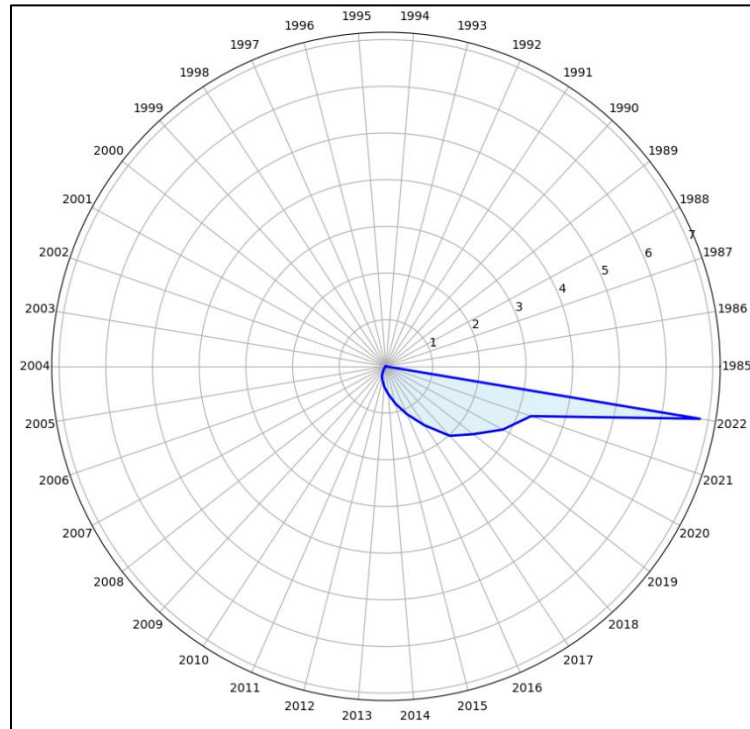


Figure 3 Polar Chart of Solar Power Production percentages over different years[40]

4. Conclusion

Artificial intelligence is increasingly recognized as a foundational technology for addressing operational challenges in the integration of renewable energy into modern power systems. This review demonstrates that AI-driven forecasting techniques, such as machine learning, deep learning, reinforcement learning, and hybrid optimization methods, significantly enhance the prediction of renewable energy generation, electricity demand, and grid conditions. These advancements enable more informed operational decisions and contribute to improved grid stability, efficient energy dispatch, optimized storage utilization, reduced reliance on fossil-fuel-based reserve generation, and enhanced economic performance of renewable energy systems. The case studies reviewed confirm that AI applications have advanced from theoretical models to practical implementations that improve the reliability, flexibility, and resilience of hybrid renewable energy systems. However, widespread adoption continues to encounter challenges related to data availability and quality, computational demands, model transparency, cybersecurity, interoperability, and evolving regulatory frameworks. Overcoming these barriers will require interdisciplinary collaboration among researchers, utilities, policymakers, and technology developers. Future research should focus on explainable and trustworthy AI, federated learning, digital twin technologies, edge computing, and physics-informed machine learning to develop scalable and robust forecasting solutions. As renewable energy penetration increases globally, AI-driven forecasting is expected to play a critical role in enabling smarter, cleaner, and more resilient power grids that support global decarbonization and long-term energy sustainability.

References

- [1] Q. Hassan et al., "The renewable energy role in the global energy Transformations," *Renewable Energy Focus*, vol. 48, p. 100545, Mar. 2024, doi: 10.1016/j.ref.2024.100545.
- [2] M. Aklin and J. Urpelainen, *Renewables*. The MIT Press, 2018. doi: 10.7551/mitpress/11112.001.0001.

- [3] D. Gielen, F. Boshell, D. Saygin, M. D. Bazilian, N. Wagner, and R. Gorini, "The role of renewable energy in the global energy transformation," *Energy Strategy Reviews*, vol. 24, pp. 38–50, Apr. 2019, doi: 10.1016/j.esr.2019.01.006.
- [4] A. Giedraityte, S. Rimkevicius, M. Marciukaitis, V. Radziukynas, and R. Bakas, "Hybrid Renewable Energy Systems—A Review of Optimization Approaches and Future Challenges," *Applied Sciences*, vol. 15, no. 4, p. 1744, Feb. 2025, doi: 10.3390/app15041744.
- [5] A. Giedraityte, S. Rimkevicius, M. Marciukaitis, V. Radziukynas, and R. Bakas, "Hybrid Renewable Energy Systems—A Review of Optimization Approaches and Future Challenges," *Applied Sciences*, vol. 15, no. 4, p. 1744, Feb. 2025, doi: 10.3390/app15041744.
- [6] C. J. Ejiyi et al., "Comprehensive review of artificial intelligence applications in renewable energy systems: current implementations and emerging trends," *J. Big Data*, vol. 12, no. 1, p. 169, Jul. 2025, doi: 10.1186/s40537-025-01178-7.
- [7] K. Wang et al., "Evolutionary Game Theory in Energy Storage Systems: A Systematic Review of Collaborative Decision-Making, Operational Strategies, and Coordination Mechanisms for Renewable Energy Integration," *Sustainability*, vol. 17, no. 16, p. 7400, Aug. 2025, doi: 10.3390/su17167400.
- [8] B. Bergougui, S. M. Murshed, M. Shahbaz, M. A. Zambrano-Monserrate, A. Samour, and M. I. Aldawsari, "Towards secure energy systems: Examining asymmetric impact of energy transition, environmental technology and digitalization on Chinese city-level energy security," *Renew. Energy*, vol. 238, p. 121883, Jan. 2025, doi: 10.1016/j.renene.2024.121883.
- [9] C. Kuzemko, M. Blondeel, M. Bradshaw, G. Bridge, E. Faigen, and L. Fletcher, "Rethinking Energy Geopolitics: Towards a Geopolitical Economy of Global Energy Transformation," *Geopolitics*, vol. 30, no. 2, pp. 531–565, Mar. 2025, doi: 10.1080/14650045.2024.2351075.
- [10] Q. Teng, X. Wang, N. Hussain, and S. Hussain, "Maximizing economic and sustainable energy transition: An integrated framework for renewable energy communities," *Energy*, vol. 317, p. 134544, Feb. 2025, doi: 10.1016/j.energy.2025.134544.
- [11] H. Vatankhah Ghadim et al., "Are we too pessimistic? Cost projections for solar photovoltaics, wind power, and batteries are over-estimating actual costs globally," *Appl. Energy*, vol. 390, p. 125856, Jul. 2025, doi: 10.1016/j.apenergy.2025.125856.
- [12] H. Vatankhah Ghadim et al., "Are we too pessimistic? Cost projections for solar photovoltaics, wind power, and batteries are over-estimating actual costs globally," *Appl. Energy*, vol. 390, p. 125856, Jul. 2025, doi: 10.1016/j.apenergy.2025.125856.
- [13] B. Nastasi, N. Markovska, T. Puksec, N. Duić, and S. A. Kalogirou, "Practical solutions for a sustainable future - advancing renewable and sustainable energy systems," *Renewable and Sustainable Energy Reviews*, vol. 225, p. 116136, Jan. 2026, doi: 10.1016/j.rser.2025.116136.
- [14] Q. Hassan et al., "RETRACTED: A comprehensive review of international renewable energy growth," *Energy and Built Environment*, Jan. 2024, doi: 10.1016/j.enbenv.2023.12.002.
- [15] O. O. Babayomi et al., "A review of renewable off-grid mini-grids in Sub-Saharan Africa," *Front. Energy Res.*, vol. 10, Jan. 2023, doi: 10.3389/fenrg.2022.1089025.
- [16] M. Ram, A. Aghahosseini, and C. Breyer, "Job creation during the global energy transition towards 100% renewable power system by 2050," *Technol. Forecast. Soc. Change*, vol. 151, p. 119682, Feb. 2020, doi: 10.1016/j.techfore.2019.06.008.
- [17] M. Shoaie, Y. Noorollahi, A. Hajinezhad, and S. F. Moosavian, "A review of the applications of artificial intelligence in renewable energy systems: An approach-based study," *Energy Convers. Manag.*, vol. 306, p. 118207, Apr. 2024, doi: 10.1016/j.enconman.2024.118207.
- [18] T. Alazemi, M. Darwish, and M. Radi, "Renewable energy sources integration via machine learning modelling: A systematic literature review," *Heliyon*, vol. 10, no. 4, p. e26088, Feb. 2024, doi: 10.1016/j.heliyon.2024.e26088.
- [19] R. E. Kaspersen, G. Berk, D. Pijawka, A. B. Sharaf, and J. Wood, "Public Opposition to Nuclear Energy: Retrospect and Prospect," *Sci. Technol. Human Values*, vol. 5, no. 31, pp. 11–23, Apr. 1980, doi: 10.1177/016224398000500203.

- [20] K. Kappner, P. Letmathe, and P. Weidinger, “Causes and effects of the German energy transition in the context of environmental, societal, political, technological, and economic developments,” *Energy Sustain. Soc.*, vol. 13, no. 1, p. 28, Aug. 2023, doi: 10.1186/s13705-023-00407-2.
- [21] Olubunmi Bashiru, Chidi Ochem, Lawrence Anebi Enyejo, Helena Nbéu Nkula Manuel, and Tola Ojemai Adeoye, “The crucial role of renewable energy in achieving the sustainable development goals for cleaner energy,” *Global Journal of Engineering and Technology Advances*, vol. 19, no. 3, pp. 011–036, Jun. 2024, doi: 10.30574/gjeta.2024.19.3.0099.
- [22] C. Fletcher et al., “Earth at risk: An urgent call to end the age of destruction and forge a just and sustainable future,” *PNAS Nexus*, vol. 3, no. 4, Mar. 2024, doi: 10.1093/pnasnexus/pgae106.
- [23] R. Li, Y. Wu, Z. He, and S. Wang, “Clean Energy Technology Development and Integration Pathways toward Carbon Neutrality: A Comprehensive Review,” *Environmental Reviews*, Jul. 2026, doi: 10.1139/er-2026-0078.
- [24] N. Armaroli and V. Balzani, “The Legacy of Fossil Fuels,” *Chem. Asian J.*, vol. 6, no. 3, pp. 768–784, Mar. 2011, doi: 10.1002/asia.201000797.
- [25] A. Ștefania Chenic et al., “Logical Analysis on the Strategy for a Sustainable Transition of the World to Green Energy—2050. Smart Cities and Villages Coupled to Renewable Energy Sources with Low Carbon Footprint,” *Sustainability*, vol. 14, no. 14, p. 8622, Jul. 2022, doi: 10.3390/su14148622.
- [26] J. L. Holechek, H. M. E. Geli, M. N. Sawalhah, and R. Valdez, “A Global Assessment: Can Renewable Energy Replace Fossil Fuels by 2050?,” *Sustainability*, vol. 14, no. 8, p. 4792, Apr. 2022, doi: 10.3390/su14084792.
- [27] E. D. Solomon-Eseh and M. O. Olubajo, “Carbon Capture and Storage: An Optimal Solution to Nigeria’s Energy Transition,” in *SPE Nigeria Annual International Conference and Exhibition*, SPE, Aug. 2025. doi: 10.2118/228723-MS.
- [28] Z. Zhang and D. Huisingh, “Carbon dioxide storage schemes: Technology, assessment and deployment,” *J. Clean. Prod.*, vol. 142, pp. 1055–1064, Jan. 2017, doi: 10.1016/j.jclepro.2016.06.199.
- [29] J. M. Beér, “High efficiency electric power generation: The environmental role,” *Prog. Energy Combust. Sci.*, vol. 33, no. 2, pp. 107–134, Apr. 2007, doi: 10.1016/j.pecs.2006.08.002.
- [30] X. Zhao, Y. Sun, Y. Li, N. Jia, and J. Xu, “Applications of machine learning in real-time control systems: a review,” *Meas. Sci. Technol.*, vol. 36, no. 1, p. 012003, Jan. 2025, doi: 10.1088/1361-6501/ad8947.
- [31] A. S. AlSalehy and M. Bailey, “Improving Time Series Data Quality: Identifying Outliers and Handling Missing Values in a Multilocation Gas and Weather Dataset,” *Smart Cities*, vol. 8, no. 3, p. 82, May 2025, doi: 10.3390/smartcities8030082.
- [32] M. Halimuzzaman, “AI-driven optimization of hybrid renewable energy systems: A review of techniques, challenges, and future direction,” *Pacific Journal of Advanced Engineering Innovations*, vol. 2, no. 1, pp. 22–32, Jun. 2025, doi: 10.70818/pjaei.v02i01.093.