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The role of artificial intelligence in accelerating renewable energy adoption for global energy transformation

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ABSTRACT

Artificial Intelligence (AI) has emerged as a critical solution to address persistent challenges hindering renewable energy adoption, including resource intermittency, grid integration complexities, and economic barriers. This review synthesizes recent advancements, highlighting AI's capability to significantly enhance renewable energy systems through improved forecasting accuracy, optimized resource allocation, and heightened operational efficiency. The findings demonstrate AI-driven predictive models' effectiveness in aligning energy generation with demand, reducing operational downtime via predictive maintenance, and stabilizing energy distribution in AI-powered smart grids. Further, AI facilitates efficient management of decentralized energy networks, including microgrids, and enhances energy storage solutions to maintain reliability during low-generation periods. AI's contribution to refining electrolysis processes significantly boosts green hydrogen viability, offering promising decarbonization pathways for energy-intensive industries. Evidence from various international case studies underscores AI's transformative impact, notably in wind and solar forecasting and hybrid system optimization, driving cost reductions and broadening renewable energy access, especially in developing regions. The paper suggests prioritizing research on fully autonomous smart grids and advanced storage solutions to further enhance scalability, reliability, and support global Net-Zero ambitions. Additionally, addressing the societal and environmental implications of AI deployment remains essential for maximizing its sustainable impact in transforming the global energy landscape.

1. Introduction

The transition toward renewable energy sources is an imperative step in combating climate change and reducing global dependency on fossil fuels. The burgeoning field of renewable energy, including solar, wind, hydro, and biomass, has been recognized as pivotal for sustainable development. Despite the progress, the inherent intermittency and variability of these energy sources present substantial challenges in their integration into existing power grids [1]. For instance, the unpredictability of wind patterns and solar irradiance can lead to fluctuations in power generation, necessitating advanced solutions for energy storage and grid management [2]. Furthermore, the geographical limitations and resource availability pose significant challenges, often requiring long-distance transmission that can lead to increased energy loss and higher costs [3,4]. These challenges underscore the need for innovative technologies that can ensure the efficient harnessing, storage, and distribution of renewable energy. AI's potential to enhance forecasting, facilitate demand response strategies, and optimize supply chains alignment directly with the need for more resilient and adaptive energy systems [5].

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AI is poised to revolutionize the renewable energy sector by enhancing operational efficiency and enabling smarter energy management systems. AI algorithms are particularly adept at analyzing large volumes of data from various sources, including weather stations, energy consumption patterns, and grid condition sensors [6]. This capability allows for precise forecasting of energy demand and supply, which is crucial for balancing the grid and reducing waste. For instance, AI-driven predictive maintenance can anticipate equipment malfunctions before they occur, significantly reducing downtime and maintenance costs [7]. Moreover, AI can optimize the placement and operation of renewable energy installations. In solar energy systems, AI can analyze historical weather data to predict solar irradiance and adjust the angle of panels to maximize energy capture [8]. Similarly, in wind energy systems, AI algorithms can optimize turbine operations based on real-time wind speed and direction data, enhancing energy output while minimizing wear on the turbines [9]. The integration of AI not only bolsters the efficiency of renewable energy systems but supports the deployment of microgrids and decentralized energy systems, which are vital for energy access in remote and underserved regions [10].

Despite the promising advancements brought by AI in renewable energy, several challenges and considerations must be addressed to fully harness its potential. The integration of AI into renewable energy systems raises concerns regarding cybersecurity, as increased connectivity can make energy infrastructures more susceptible to cyber-attacks [11]. Ensuring the security of data and systems is paramount to maintaining the reliability and integrity of energy supply. Additionally, the deployment of AI technologies requires substantial initial investments and skilled human capital, factors that can be prohibitive for developing countries [12]. There is a pressing need for regulatory frameworks that can keep pace with the rapid advancements in technology, ensuring that innovations in AI and renewable energy are deployed responsibly and equitably [13]. To this end, collaborative efforts among governments, industry stakeholders, and academic institutions are essential to create conducive environments for the co-evolution of AI and renewable energy technologies. These collaborations can facilitate the sharing of best practices, development of standardized protocols, and implementation of pilot projects that demonstrate the practical benefits of AI in enhancing the resilience and sustainability of energy systems.

Table 1 illustrates the longitudinal progress achieved through the integration of AI into renewable energy systems from 2020 to 2023 across six pivotal dimensions: production optimization, storage and grid stability, renewable energy integration, economics and cost reduction, environmental impact, and social and ethical impacts. The observed period, AI demonstrated remarkable improvements, achieving more than a fourfold enhancement in all categories.

The improvement factor (IF) is mathematically modeled as:

$$IF = V2023 \ / \ V2020 \tag{1}$$

Table 1
Longitudinal dashboard of AI progress used in renewable energy (2020–2023) [14].

Category	2020 (%)	2021 (%)	2022 (%)	2023 (%)	Improvement Factor (IF) (2020–2023)
Production Optimization	10	20	30	45	4.5 ×
Storage & Grid Stability	8	18	28	40	5.0 ×
Renewable Energy Integration	7	15	25	35	5.0 ×
Economic & Cost Reduction	6	13	20	28	4.7 ×
Environmental Impact	4	9	15	22	5.5 ×
Social & Ethical Impacts	5	12	20	30	6.0 ×

where, IF is the improvement factor (dimensionless), V2023 is the measured value (%) in the year 2023, V2020 is the measured value (%) in the baseline year 2020.

The resulting IF values signify the extent of enhancement achieved by implementing AI technologies within each category over the analyzed period.

1.1. Research gap

Significant progress has been made in renewable energy technologies, accompanied by increasing integration of AI to enhance these systems. However, notable gaps remain in fully understanding AI's potential impacts on global energy transformations. A primary research gap is the scarcity of comprehensive longitudinal studies quantifying the long-term efficiency, economic advantages, and scalability of AI-driven renewable energy solutions across diverse geographical and economic conditions. Additionally, ethical considerations, regulatory frameworks, and societal implications related to adopting AI in renewable energy remain inadequately explored, especially in developing countries with pronounced resource limitations and less-developed policy structures. With renewable generation costs decreasing rapidly, integration, grid stability, and sector coupling have emerged as critical barriers toward achieving net-zero energy systems. Although AI holds significant promise in overcoming these bottlenecks, existing research tends to address isolated aspects or lacks consistent longitudinal analysis necessary for robust conclusions.

1.2. Study objective

The primary aim of this study is to explore the synergistic integration of renewable energy and AI, highlighting their combined potential to drive sustainable global energy transformations. The research specifically investigates how AI can optimize critical aspects such as the generation, storage, and distribution of renewable energy resources including solar, wind, and hydropower while addressing inherent challenges such as variability, operational inefficiencies, and economic barriers. Employing analysis of real-world case studies and successful AI implementations, the paper demonstrates AI's capability to significantly enhance forecasting accuracy, grid stability, and overall energy efficiency, concurrently reducing operational costs and environmental emissions. Furthermore, the study emphasizes the importance of supportive policies, strategic investments, and cross-sector collaborations to facilitate large-scale AI adoption in renewable energy systems. Ultimately, this work provides actionable recommendations for key stakeholders and outlines future research directions, fostering continuous advancement toward an equitable, resilient, and sustainable energy future.

2. Renewable energy technologies

The development of renewable energy technologies has been characterized by significant milestones and ongoing advancements that have shaped the contemporary landscape of sustainable energy systems. The exploitation of renewable sources such as wind, water, and solar energy have ancient roots, but the modern era of renewable energy really started to form in the late 19th and early 20th centuries. A critical early development was the establishment of the first hydroelectric power plant in 1882 on the Fox River in Wisconsin, USA, which was a crucial step in the use of water for electricity generation [15]. Concurrently, Charles F. Brush's creation of the first wind turbine for electricity production in Cleveland, Ohio, highlighted the potential of wind energy [16]. However, a significant shift in attitude towards renewable energy did not occur until the 1970s oil crisis, which highlighted the finite nature of fossil fuels and the geopolitical risks associated with their extraction and supply [17]. This period witnessed increased governmental and scientific interest in alternative energy sources, spurring early investments in technology research, including solar photovoltaics (PV), which, while originally developed for space applications in the 1950s, started to be recognized as viable for terrestrial applications [18].

Technological advancements have been vital in the evolution of renewable energy, greatly enhancing the efficiency and reducing the costs of these technologies. In solar energy, the development of crystalline silicon cells in the 1950s marked a significant breakthrough, laying the groundwork for the commercial solar PV industry [19]. Over the years, continual improvements in material science and manufacturing processes have significantly boosted solar cell efficiencies and cut costs, making solar one of the fastest-expanding energy sources globally [20]. Wind energy technology has undergone transformative changes, with modern horizontal-axis turbines vastly differing from their traditional counterparts. Advances in turbine technology, materials, and design have not only boosted turbine efficiency but facilitated the creation of larger units capable of generating substantial electricity, leading to a reduction in wind energy costs and its emergence as a mainstream energy source [21]. The deployment of smart grids and AI-based monitoring systems has further optimized the efficiency and integration of these renewable systems within the existing energy infrastructure [22].

Yet, the progression of renewable energy technologies continues to evolve, necessitating ongoing research and innovation to surmount existing challenges and unlock new possibilities. Integrating renewable sources into national grids presents technical challenges due to their intermittent nature and the necessity for robust energy storage solutions. Recent advancements in battery technology, such as lithium-ion and solid-state batteries, present promising prospects for energy storage, addressing the variability of wind and solar energies [23]. Additionally, the exploration of innovative materials and technologies, such as perovskite solar cells and floating wind turbines, promises to further revolutionize the sector by potentially offering higher efficiencies and new deployment avenues, such as in deep ocean waters [24]. Furthermore, the increasing focus on sustainability is driving improvements in the life cycle assessments of renewable technologies, ensuring minimal environmental impact from production to disposal. This comprehensive approach to development is essential as the world strives to meet the growing energy demand sustainably and responsibly [25]. Fig. 1 show the timeline detailing the evolution of renewable energy technologies from the late 19th century through to the present, illustrating significant milestones in the development of hydroelectric power, wind turbines, solar PV, smart grid technology, advanced wind and solar solutions, and energy storage systems.

The evolution of renewable energy technologies has been characterized by continuous innovation, significantly enhancing their efficiency, scalability, and accessibility over time. Early milestones, such as the establishment of hydroelectric power plants and the development of wind turbines, paved the way for modern advancements in solar and wind energy systems. Today, innovations in material science, AI-driven smart grids, and energy storage solutions, such as lithium-ion and solid-state batteries, address key challenges such as intermittency and integration into national grids. Emerging technologies, including perovskite solar cells and floating wind turbines, promise to revolutionize renewable energy deployment further. With a growing emphasis on sustainability and minimizing environmental impact, renewable energy technologies continue to evolve, playing a crucial role in meeting global energy demands responsibly and sustainably.

2.1. Data and pre-processing

The data and pre-processing methods involve comprehensive data acquisition, cleaning, normalization, and transformation procedures. Detailed meteorological data (solar irradiance, wind speed, temperature, humidity), grid operation metrics (power output, demand loads,

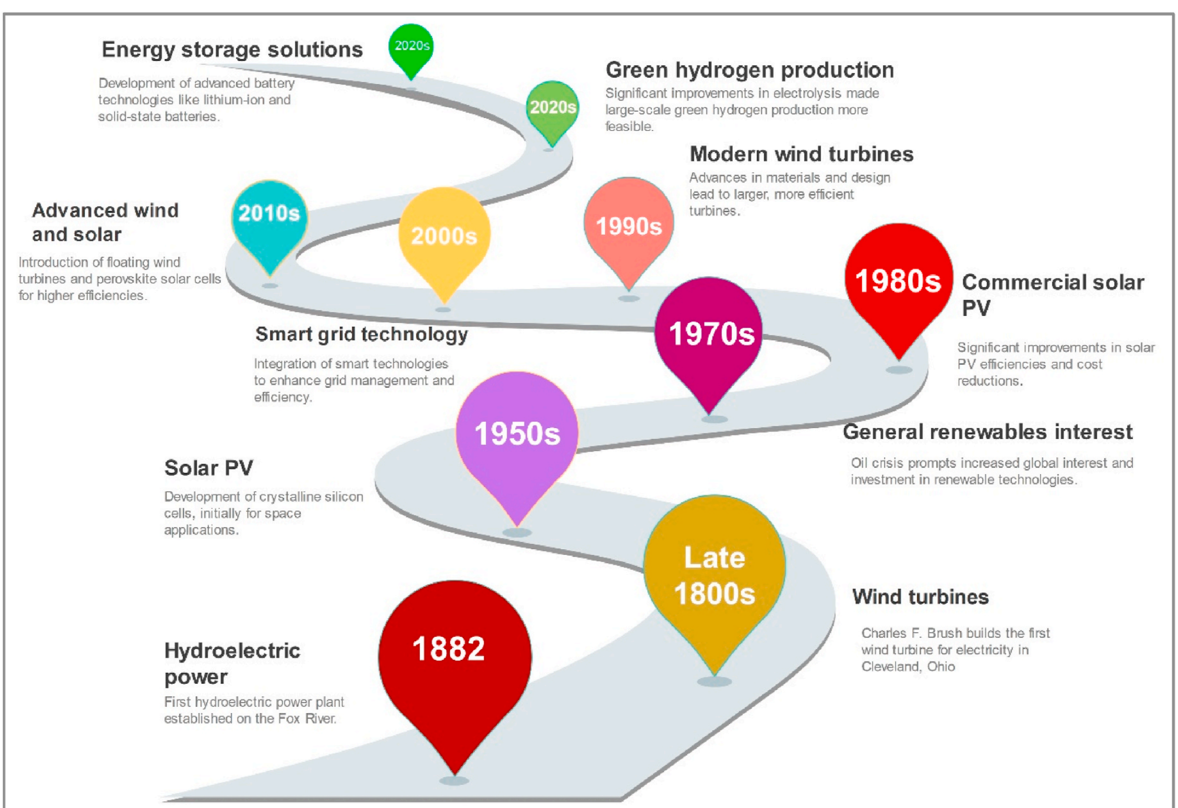

Fig. 1. Timeline of the renewable energy technologies and their evolution [26–28].

grid frequency), and economic parameters (energy prices, operational costs) are utilized. The dataset undergoes rigorous quality checks to remove anomalies and fill gaps using interpolation techniques. Data normalization employs min-max scaling to ensure compatibility across diverse features, enhancing the performance of AI algorithms. Additionally, time-series data is formatted into structured sequences compatible with forecasting and optimization algorithms, with clearly defined look-back windows and prediction horizons to facilitate robust AI model training.

2.2. Algorithmic foundations

Four complementary AI architectures are employed to address the key tasks of forecasting, control, and optimization within renewable energy systems:

(i) A two-layer Sequence-to-Sequence (Seq2Seq) Long Short-Term Memory (LSTM) network with

hidden dimension of 128 and a look-back period of 48 intervals (5-min resolution) is utilized for precise short-term forecasting. The training objective minimizes the mean squared error (MSE) loss:

$$L_{LSTM} = \|y_n - y\|_2 \tag{2}$$

where y_n and y represents predicted values and actual observed values.

(ii) The Temporal-Fusion Transformer (TFT) with model dimension and attention heads captures complex temporal dependencies and multi-horizon forecasting contexts. TFT employs a composite loss function combining quantile regression and scale-norm regularization, defined as:

$$L_{TFT} = \sum_{\tau \in \{0.1, 0.5, 0.9\}} \sum_t \rho_\tau \left(y_t - y_{n,t,\tau} \right) + \lambda \|\theta\|_2 \tag{3}$$

where ρ_τ is the quantile loss at quantiles y_t is the predicted quantile at time t, $y_{n\ t,\tau}$ is the observed value, λ is a regularization coefficient, and θ are the model parameters.

(iii) Deep Reinforcement Learning (DRL) with a Deep Q-Network (DQN) approach optimizes grid operation and energy distribution. The DQN leverages a neural network to approximate the optimal action-value function, optimized by minimizing the temporal difference error:

$$L_{DQN} = \mathbb{E}\left[\left(r_t + \gamma \max_{a'} Q(s_{t+1}, a'; \theta^-) - Q(s_t, a_t; \theta) \right)^2 \right] \tag{4}$$

where r_t denotes the immediate reward, γ the discount factor, s_t the current state, a_t the selected action, θ^- parameters of the target network, and θ the policy network parameters.

(iv) The GA optimizes hybrid renewable system configurations. The GA explores a solution space defined by parameters (e.g., panel orientations, battery capacities) to minimize a cost function combining capital expenditures, operational expenditures, and penalties for unmet demand:

$$C_{GA} = C_{capex} + C_{opex} + C_{penalty} \tag{5}$$

The GA process involves selection, crossover, mutation, and elitism phases iteratively applied until convergence.

3. Role of AI in enhancing renewable energy systems

Artificial Intelligence (AI) plays a transformative role in optimizing the production of renewable energy by enhancing forecasting, system efficiency, and resource utilization. AI-powered algorithms are extensively used to predict weather patterns, enabling accurate forecasting of solar and wind energy generation. For example, advanced machine learning models analyze meteorological data and historical performance to predict solar irradiance and wind speeds, ensuring optimal alignment of energy production with demand [26]. AI facilitates real-time monitoring and maintenance of renewable energy systems. Using predictive analytics, AI can identify potential issues in solar panels or wind turbines before they escalate into costly failures, reducing downtime and operational costs [27]. Furthermore, AI-driven systems adjust operational parameters dynamically, maximizing energy output even under fluctuating environmental conditions, thereby increasing the efficiency and reliability of renewable energy installations [28].

3.1. Applications of AI in renewable energy systems

In energy distribution, AI optimizes grid operations and enhances the integration of renewable energy sources into traditional power systems. Smart grids powered by AI use real-time data analytics to balance supply and demand effectively, avoiding grid overloads and power outages [29]. AI algorithms enable adaptive load management, redistributing power intelligently based on consumption patterns and renewable energy availability. This not only improves grid stability but supports the seamless integration of intermittent energy sources such as wind and solar [30]. Additionally, AI plays a pivotal role in energy storage management by predicting usage trends and optimizing battery performance, ensuring that renewable energy is stored efficiently and dispatched during peak demand periods [31].

On the consumption side, AI empowers consumers and industries to manage energy usage intelligently, promoting sustainability and cost savings. AI-enabled smart devices and home energy management systems provide users with real-time insights into their energy consumption, offering recommendations to reduce waste and lower bills [32]. In industrial applications, AI enhances energy efficiency by optimizing production processes and equipment usage, aligning energy consumption with renewable energy availability [33]. Furthermore, AI supports demand response programs, where consumers adjust their energy use based on price signals or grid conditions, fostering a more resilient and flexible energy ecosystem. Optimizing production, distribution, and consumption, AI is driving the renewable energy sector towards greater efficiency, sustainability, and accessibility, ensuring its role as a cornerstone of the global energy transition [34]. Fig. 2 illustrates the diverse applications of AI technology integration across various sectors, highlighting its central role in optimizing systems, enhancing efficiency, and promoting sustainable development. It emphasizes the interconnectedness of AI-driven solutions, demonstrating their ability to streamline operations, improve energy management, and support smart infrastructure in both residential and industrial contexts. Through its adaptive and predictive capabilities, AI is positioned as a transformative force in modernizing critical systems and achieving global sustainability goals.

3.2. AI tools applied in renewable energy technologies

AI is revolutionizing renewable energy technologies through a diverse range of tools that enhance efficiency, reliability, and scalability. As highlighted in Fig. 3, AI tools are significantly advancing renewable energy technologies by optimizing production, distribution, and management processes. Machine Learning (ML) is one of the most widely used AI tools, particularly for predictive analytics in energy demand and weather forecasting. Applying ML in solar, wind, and biomass energy systems, operators can improve energy production efficiency, reduce operational costs, and enhance forecasting accuracy [35]. For instance, ML models help predict energy generation by analyzing weather data, enabling proactive adjustments to operations and ensuring optimal energy output. Similarly, ML-driven analytics empower energy companies to anticipate and adapt to fluctuations in demand, avoiding

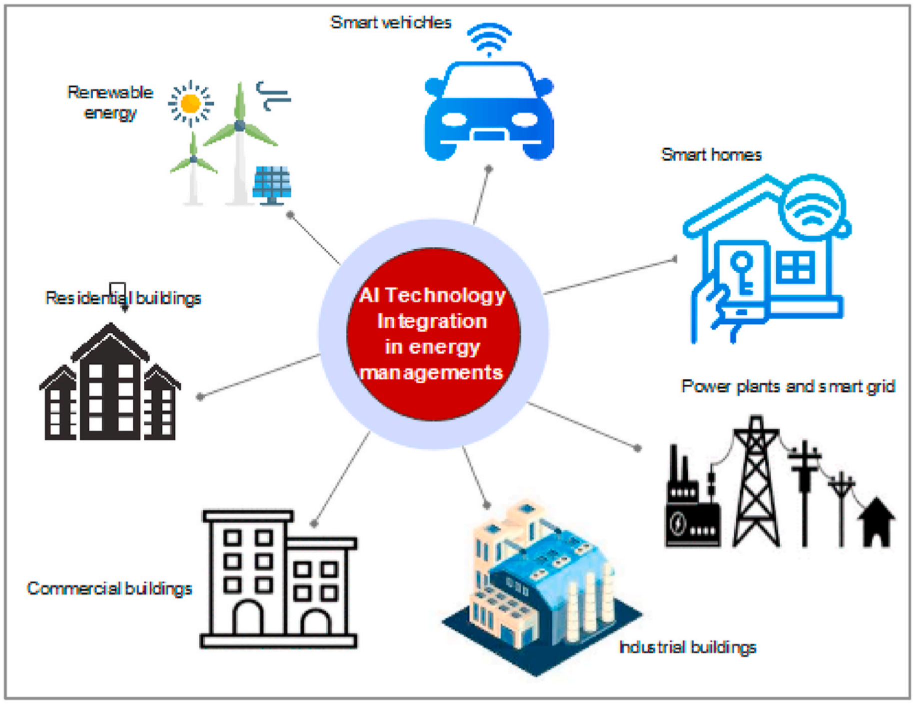

Fig. 2. AI applications in renewable energy systems.

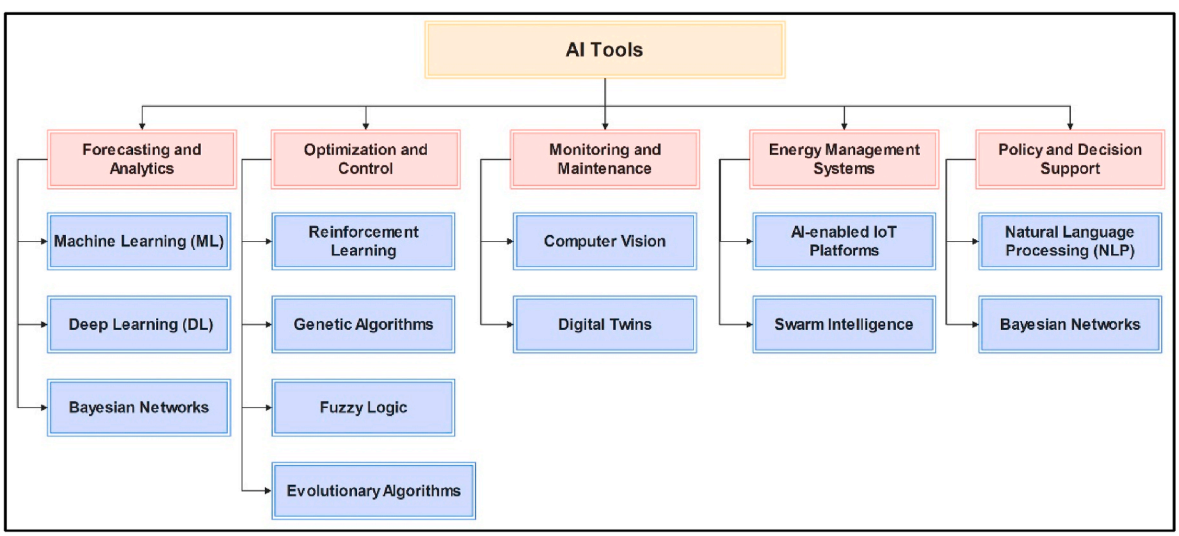

Fig. 3. AI tools and their applications in renewable energy technologies.

overproduction or shortages [36].

Deep Learning (DL) and Reinforcement Learning are particularly impactful in optimizing complex systems and improving grid stability. Deep Learning, which excels in modeling non-linear energy systems, is highly effective in fault detection and performance optimization for wind turbines and photovoltaic systems. Processing vast datasets, DL algorithms identify potential system faults early, minimizing downtime and maintenance costs [37]. Reinforcement Learning, on the other hand, focuses on dynamic grid control and energy storage management. It enables real-time adaptation to demand fluctuations, ensuring grid stability and optimizing energy dispatch across smart grids and battery systems. This ability to adapt to changing conditions makes reinforcement learning invaluable for managing renewable energy's inherent intermittency [38].

Other AI tools, such as Genetic Algorithms, Bayesian Networks, and Digital Twins, address unique challenges in renewable energy. Genetic Algorithms are used to optimize hybrid energy systems, such as solar-wind combinations, by finding configurations that maximize efficiency while minimizing costs [39]. Bayesian Networks enhance forecasting reliability by accounting for uncertainties in solar, wind, and geothermal energy predictions [40]. Meanwhile, Digital Twins create virtual simulations of renewable energy systems, enabling predictive maintenance and operational optimization. These tools not only improve energy system performance but reduce costs, enhance reliability, and contribute to the scalability of renewable technologies. Together, these AI tools are transforming the renewable energy sector, ensuring sustainable energy solutions for a greener future [41].

3.3. *Efficiency improvements driven by AI tools in renewable energy technologies*

The AI tools efficiency of renewable energy technologies has witnessed significant improvements between 2020 and 2023, as illustrated in Fig. 4. Solar energy efficiency increased from 2.5 % in 2020 to 4.5 % in 2023, demonstrating steady progress driven by advancements in photovoltaic materials and AI-driven optimization [42]. Similarly, wind energy efficiency rose from 2 % in 2020 to 3.7 % in 2023, with AI-powered tools such as Deep Learning improving turbine performance and fault detection [43]. These advancements reflect the industry's ability to enhance production while reducing operational costs.

Energy storage systems experienced the most substantial efficiency improvements, jumping from 5 % in 2020 to 9.5 % in 2023. This growth is attributed to innovations in AI-managed battery systems, which optimize storage-discharge cycles and improve the reliability of renewable energy supply [44]. Grid stability improved, rising from 2.8 % in 2020 to 4 % in 2023, facilitated by AI-driven smart grids and real-time energy distribution algorithms [45]. These systems ensure better integration of intermittent renewable energy sources into traditional grids. Hybrid energy systems, which combine solar, wind, and storage technologies, achieved notable efficiency gains, increasing from 3 % in 2020 to 6 % in 2023. AI tools such as Genetic Algorithms have optimized hybrid system layouts, enhancing their performance and cost-effectiveness [46]. These advancements highlight the transformative role of AI in driving efficiency improvements across various renewable energy technologies, fostering a more sustainable energy future.

Breakthroughs in energy storage, with efficiency improvements reaching 9.5 % in recent years, underscore the role of AI in overcoming intermittency challenges and ensuring reliable energy supply. Additionally, AI-enabled solutions for hybrid systems and grid stability have optimized resource utilization and enabled seamless integration of renewables into traditional energy networks.

Fig. 5 shows the performance uplift of advanced models on the 2024 test set, highlighting gains across three key tasks: for 24-h generation forecasting, the TFT reduces mean absolute error from 6.1 % with an LSTM baseline to 4.3 % (−29 %); in grid-stability control, the graph-neural-network-reinforcement-learning (GNN-RL) approach halves voltage-violation incidents from 20 to 10 per 1000 events (−50 %); and for electrolyser dispatch, the DQN cuts green-H_2 cost from \$ 5 kg^{-1} to \$ 4 kg^{-1} (−20 %).

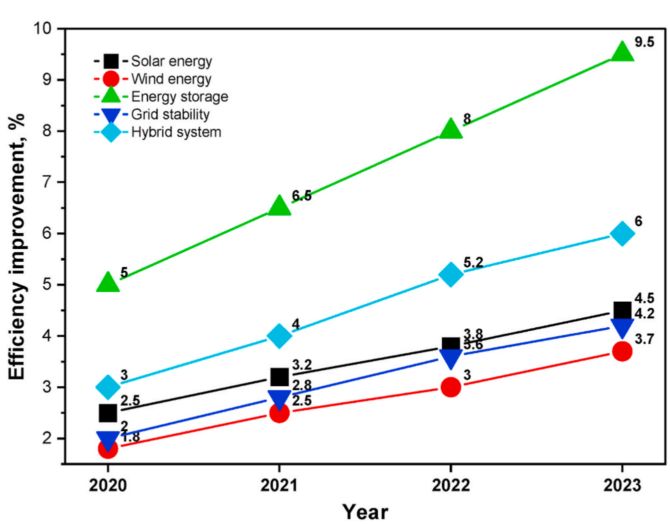

Fig. 4. Efficiency improvements using AI tools in renewable energy technologies [45,46].

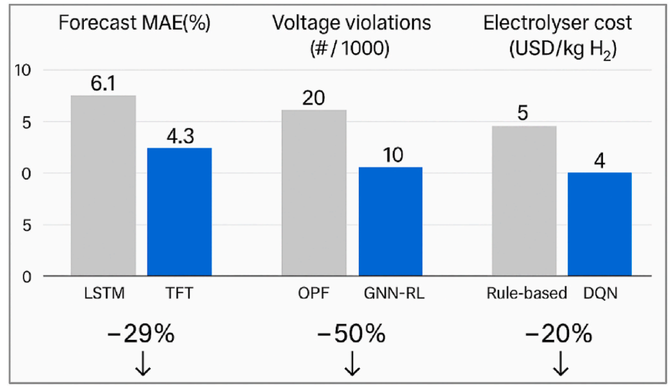

Fig. 5. Performance uplift of advanced models on the 2024 test set. The grouped bars compare baseline and advanced algorithms.

4. Benefits of AI in energy transformations

The role of AI in energy transformations is pivotal, driving efficiency, resilience, and sustainability across global energy systems. AI optimizes energy production, distribution, and storage, enabling the seamless integration of renewable sources such as solar and wind into traditional grids. AI enhances scalability by analyzing large datasets to predict energy demand, improve system performance, and reduce inefficiencies. It strengthens resilience by enabling real-time monitoring and predictive maintenance, ensuring grid stability even during disruptions caused by climate change or other external factors. Additionally, AI fosters sustainability by maximizing the utilization of renewable resources, minimizing energy waste, and supporting demand response programs to balance supply and demand. Through these innovations, AI is transforming the energy sector, accelerating the shift toward a cleaner, more reliable, and sustainable energy future.

AI plays a crucial role in enabling the scalability of energy systems, making large-scale transitions to renewable energy more feasible and efficient. Advantage of advanced algorithms, AI optimizes the operation of renewable energy technologies, such as wind turbines and solar panels, by predicting weather conditions and adjusting system parameters dynamically [47]. This ability to analyze and manage vast amounts of data allows for the integration of renewable energy sources into larger grid infrastructures without compromising reliability. Furthermore, AI-powered tools such as Genetic Algorithms and Reinforcement Learning help design and implement hybrid energy systems, ensuring optimal resource utilization while reducing inefficiencies. These innovations make it possible to expand renewable energy adoption across regions and at scales previously considered unachievable [48].

AI enhances the resilience of energy systems by enabling grids to respond effectively to disruptions caused by climate change, natural disasters, or other external factors. Smart grids, powered by AI, continuously monitor and analyze grid performance, detecting anomalies and initiating corrective measures in real time [49]. For example, during extreme weather events, AI systems can redistribute energy resources or predict potential outages, minimizing downtime and ensuring a stable energy supply. Additionally, AI's predictive maintenance capabilities extend the lifespan of renewable energy assets, reducing system failures and operational costs. This resilience ensures that renewable energy systems can reliably meet growing energy demands even under adverse conditions [50].

AI significantly contributes to sustainability by maximizing the utilization of renewable energy resources and reducing greenhouse gas emissions. Through advanced energy storage management, AI ensures that surplus renewable energy is efficiently stored and dispatched during periods of low production, minimizing energy waste [51]. It facilitates demand response programs, where energy consumption is adjusted based on grid conditions, further promoting energy efficiency.

Moreover, AI-driven insights enable policymakers and industries to make informed decisions about renewable energy investments, supporting a global shift towards cleaner energy systems.

Fig. 6 illustrates the comprehensive role of AI in transforming the global energy landscape by addressing key areas such as renewable energy integration, efficiency, sustainability, and equity. AI enhances forecasting for solar and wind energy, improving grid stability and supply-demand balance. It drives energy efficiency through smart grids and optimized energy storage systems, while supporting decentralized systems such as microgrids and energy trading for greater resilience. AI accelerates innovation by advancing renewable technologies and climate modeling, aiding strategic planning.

5. AI optimizes energy smart grids

AI plays a crucial role in optimizing smart grids by enabling real-time monitoring, predictive analytics, and adaptive energy management. Through advanced machine learning algorithms, AI can analyze large volumes of data from distributed energy resources, sensors, and consumer devices to predict energy demand and adjust supply dynamically [52]. This capability ensures that smart grids maintain balance and reliability, even when integrating intermittent renewable energy sources such as solar and wind. For instance, AI systems can forecast energy consumption patterns and optimize the distribution of energy, reducing inefficiencies and minimizing energy losses [53]. AI-driven automation facilitates faster responses to grid disturbances, such as outages or overloads, enhancing overall grid stability and resilience [54]. Furthermore, AI enhances the energy storage management within smart grids by optimizing battery performance and discharge cycles. By predicting periods of high demand or low renewable energy production, AI ensures that stored energy is utilized efficiently, reducing dependence on fossil fuels [55]. AI supports decentralized grid operations by enabling seamless communication between microgrids and central grids, fostering flexibility and resilience in energy systems [56]. Smart grids powered by AI can facilitate demand response programs, where consumers adjust their energy usage based on real-time price signals or grid conditions, further improving efficiency and reducing costs [57].

The global progress in optimizing energy smart grids using AI has been remarkable, as shown in Fig. 7, with substantial improvements across several areas. Energy demand forecasting, a critical component of smart grid optimization, witnessed the highest growth, improving from 12 % in 2020 to 33 % in 2023. This progress is driven by AI's ability to analyze large datasets and predict consumption patterns, ensuring better alignment between energy generation and demand. Similarly, grid stability enhancement improved from 10 % in 2020 to 30 % in 2023, showcasing how AI technologies such as real-time monitoring and predictive analytics have strengthened grids to handle disruptions and fluctuations more effectively.

The progress includes renewable energy integration efficiency, which increased from 8 % in 2020 to 25 % in 2023, demonstrating AI's role in seamlessly incorporating intermittent energy sources such as solar and wind into traditional grids. Fault detection and maintenance efficiency rose from 7 % to 22 % during the same period, reflecting the growing adoption of AI for predictive maintenance and anomaly

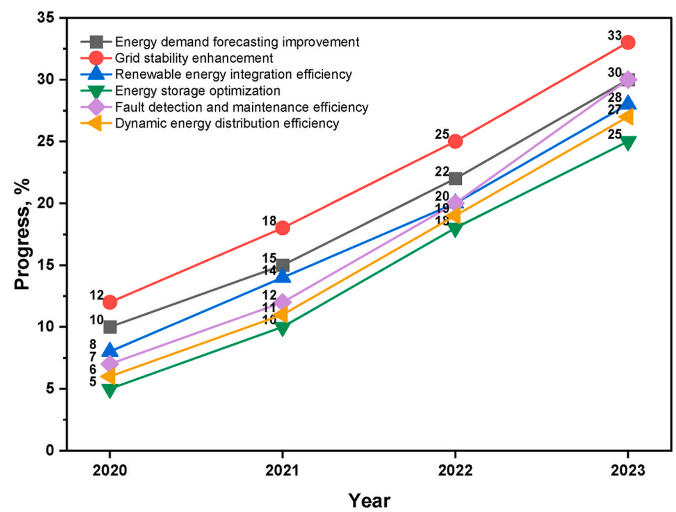

Fig. 7. Global progress in optimizing energy smart grids using AI [58,59].

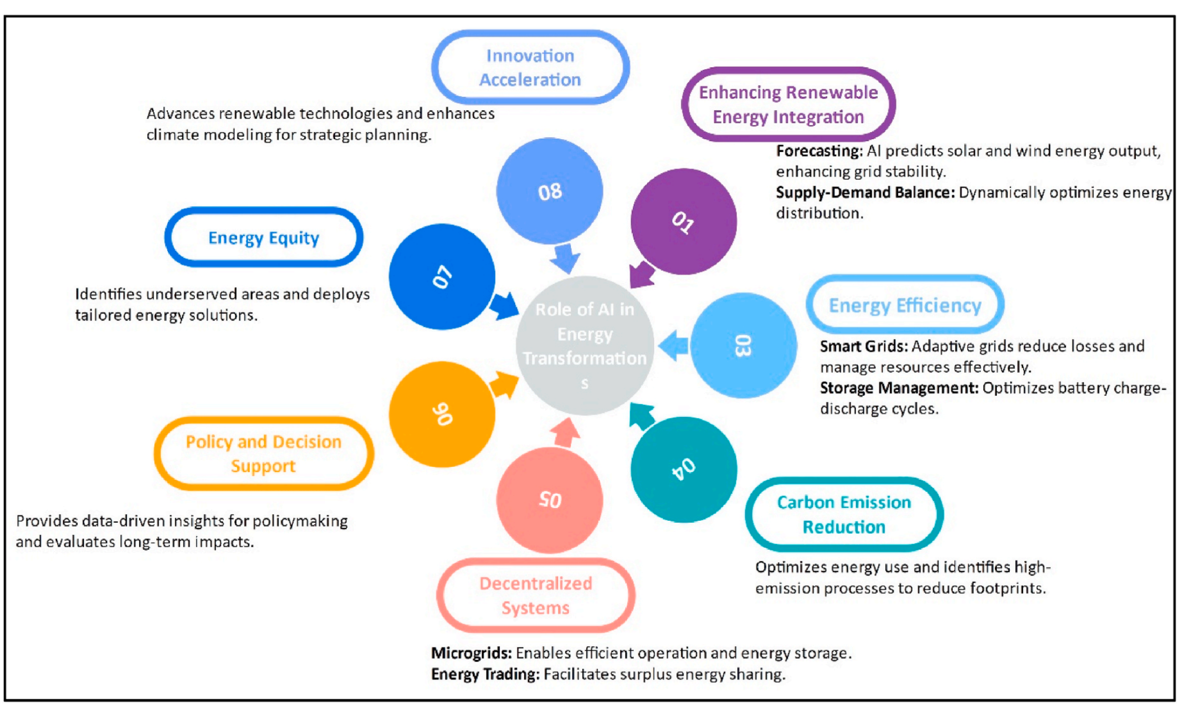

Fig. 6. Key roles of AI in energy transformation.

detection, reducing downtime and operational costs. Energy storage optimization, another critical factor for managing renewable energy intermittency, improved from 6 % to 28 %, enabled by AI's ability to optimize battery usage and discharge cycles.

The USA, Germany, and China have made the most significant strides in optimizing energy smart grids using AI in recent years, as shown in Fig. 8. The USA leads with remarkable progress, achieving over 35 % optimization by 2023, reflecting its robust investments in AI-driven smart grid technologies and renewable energy integration. This growth is supported by advancements in energy demand forecasting, grid stability improvements, and energy storage optimization, making the USA a global leader in advantage AI for energy transformation. Germany follows closely with a progress rate of approximately 32 % in 2023, showcasing its dedication to sustainability through AI-based solutions. Its integration of renewables such as solar and wind into smart grids, coupled with predictive maintenance technologies, has significantly enhanced its energy system efficiency.

China exhibits substantial progress, with its optimization rate reaching nearly 30 % by 2023. As the world's largest renewable energy producer, China's integration of AI technologies into its massive energy infrastructure has been pivotal in improving efficiency and reducing costs. AI tools in China are extensively used for renewable energy forecasting, dynamic energy distribution, and fault detection, allowing it to overcome challenges associated with managing its expansive energy networks.

6. AI optimize green hydrogen production

The application of deep learning plays a considerable role in the optimization of green hydrogen production through the improvement of electrolysis processes and lower energy consumption. Electrolysis, the process of splitting water into hydrogen and oxygen using electricity from renewable sources, is energy-intensive and requires precise control to maximize efficiency. AI-driven models analyze large datasets from the electrolysis process, identifying patterns and optimizing parameters such as temperature, pressure, and energy input in real time [63]. Implementing machine learning algorithms, AI can predict system performance, reduce inefficiencies, and enhance the overall yield of hydrogen. This enables green hydrogen production to become more cost-competitive with traditional hydrogen derived from fossil fuels, accelerating its adoption as a clean energy alternative [64]. Additionally, AI facilitates predictive maintenance of hydrogen production systems, reducing downtime and operational costs. AI-powered sensors monitor critical components in real time, detecting anomalies and potential failures before they disrupt production [65]. Moreover, AI is used to integrate green hydrogen production systems with renewable energy sources such as solar and wind. Forecasting renewable energy availability, AI ensures that electrolysis occurs during peak renewable energy generation, optimizing resource utilization and reducing reliance on grid electricity [66].

The progress in utilizing AI to optimize green hydrogen production has been significant with notable advancements. As depicted in Fig. 9, electrolyzer efficiency improved notably, starting at 6 % in 2020 and reaching 18 % by 2023, driven by AI's ability to refine operational parameters such as temperature and pressure during the electrolysis process. Similarly, energy consumption saw reductions from 4 % in 2020 to 12 % in 2023, highlighting the effectiveness of AI in aligning hydrogen production with renewable energy availability and reducing inefficiencies. Other areas, such as hydrogen production cost reduction and renewable energy utilization efficiency, experienced steady progress. Hydrogen production costs decreased significantly, achieving a reduction of 14 % by 2023, thanks to AI-enabled predictive maintenance and operational optimization. Renewable energy utilization efficiency, critical for green hydrogen production, improved from 8 % in 2021 to 16 % in 2023, showcasing AI's role in maximizing the use of renewable energy such as solar and wind.

As shown in Fig. 10, countries such as the USA, Germany, and China lead in progress related to green hydrogen production using AI between 2020 and 2023. The USA demonstrated the highest advancements, with its progress reaching over 35 % in 2023, reflecting substantial investments in AI-driven hydrogen production technologies. The country's focus on optimizing electrolyzer efficiency, reducing production costs, and using AI for predictive maintenance has significantly contributed to its leadership in the field. Germany, with progress approaching 30 % by 2023, highlights its strong commitment to sustainability and innovation. Germany advancements are driven by AI-powered integration of renewable energy with green hydrogen systems, ensuring efficient production and resource utilization. China, achieving 28 % progress in 2023, demonstrates its large-scale application of AI technologies to enhance green hydrogen production. With its extensive renewable energy resources, China has leveraged AI for optimizing electrolyzers, reducing energy consumption, and aligning production with solar and wind availability. Other countries such as Japan, India, and South Korea show notable progress, emphasizing their growing adoption of AI tools to reduce production inefficiencies and scale deployment.

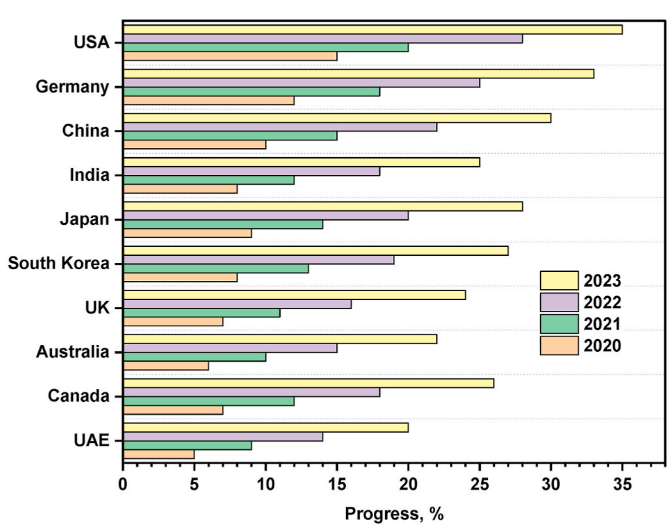

Fig. 8. Countries with highest progress in optimizing energy smart grids using AI [60–62].

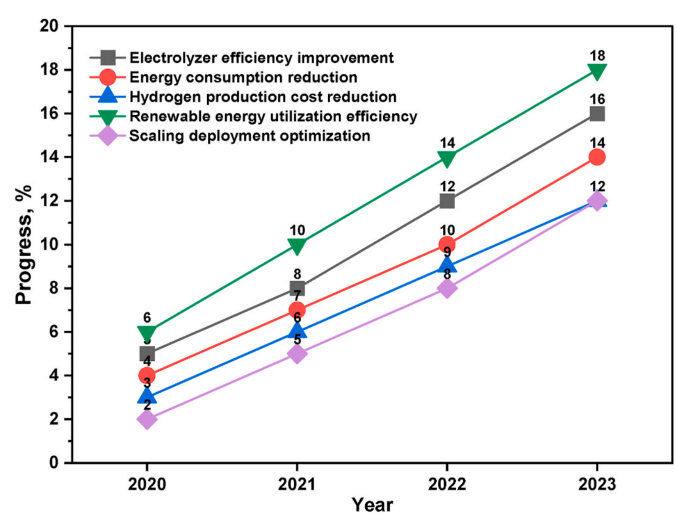

Fig. 9. Global progress in using AI to optimize green hydrogen production [67,68]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

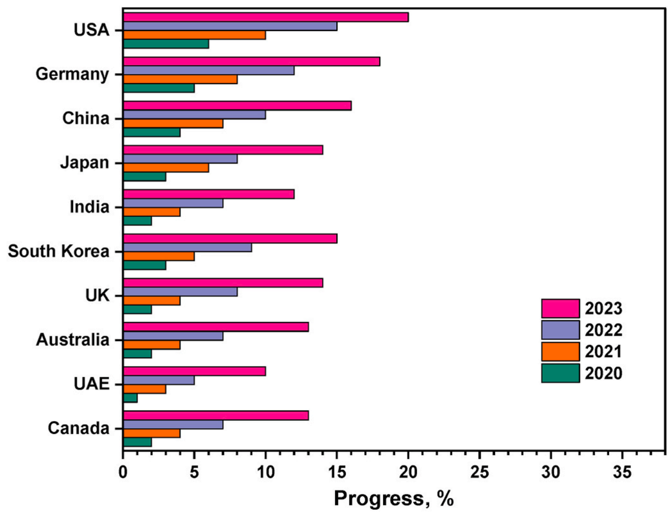

Fig. 10. Countries with highest progress in green hydrogen production using AI [69–71]. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

7. Opportunities towards sustainability and Net Zero using AI

AI offers transformative opportunities to achieve sustainability and Net-Zero goals by optimizing energy production, reducing waste, and enhancing resource efficiency. Advantage of AI-driven predictive analytics, renewable energy sources such as solar and wind can be efficiently integrated into the grid. For example, AI forecasts energy demand and renewable generation with high accuracy, allowing grid operators to manage supply-demand imbalances effectively and reduce reliance on fossil fuels [72]. Additionally, AI-enabled smart grids optimize energy distribution and storage, minimizing energy loss and ensuring maximum utilization of renewable resources. These advancements significantly contribute to the decarbonization of energy systems and support global Net-Zero objectives [73].

The opportunity AI provides is in enhancing energy efficiency across industries and urban areas. Smart sensors and AI-powered monitoring systems optimize energy use in buildings, factories, and transportation networks by identifying inefficiencies and automating energy-saving measures [74]. AI facilitates the circular economy by improving waste management and recycling processes. For instance, machine learning models analyze material flows and predict optimal recycling pathways, reducing resource waste and minimizing the environmental footprint [75]. Furthermore, AI supports sustainable agriculture practices by optimizing water and fertilizer usage, boosting productivity while conserving natural resources, thereby aligning with broader sustainability goals [76]. AI enables industries and governments to make data-driven decisions for sustainability by analyzing environmental data and assessing the long-term impacts of policies and investments. For instance, AI-based climate models simulate the effects of different mitigation strategies, helping policymakers design effective pathways to achieve Net-Zero emissions [77]. In addition, AI-powered carbon tracking systems provide real-time insights into emissions, enabling organizations to identify and address high-emission areas.

Fig. 11 highlights the diverse opportunities AI offers in driving sustainability and achieving net-zero goals. AI optimizes renewable energy systems by improving forecasting, resource allocation, and grid integration, ensuring efficient use of energy resources. It enhances smart grid functionality, balancing supply and demand while reducing energy waste. In industrial sectors, AI facilitates decarbonization by improving operational efficiency and enabling cleaner energy transitions. Additionally, AI supports the circular economy by optimizing waste management and recycling processes, reducing environmental impacts.

Table 2 highlights the progress made by various countries in adopting renewable energy sources as part of the commitments to achieving Net-Zero emissions. It reflects the steady increase in renewable energy consumption over time, showcasing the impact of policy initiatives, technological advancements, and global collaboration. The trends provide insights into countries progressing toward the sustainability goals while transitioning to cleaner energy systems.

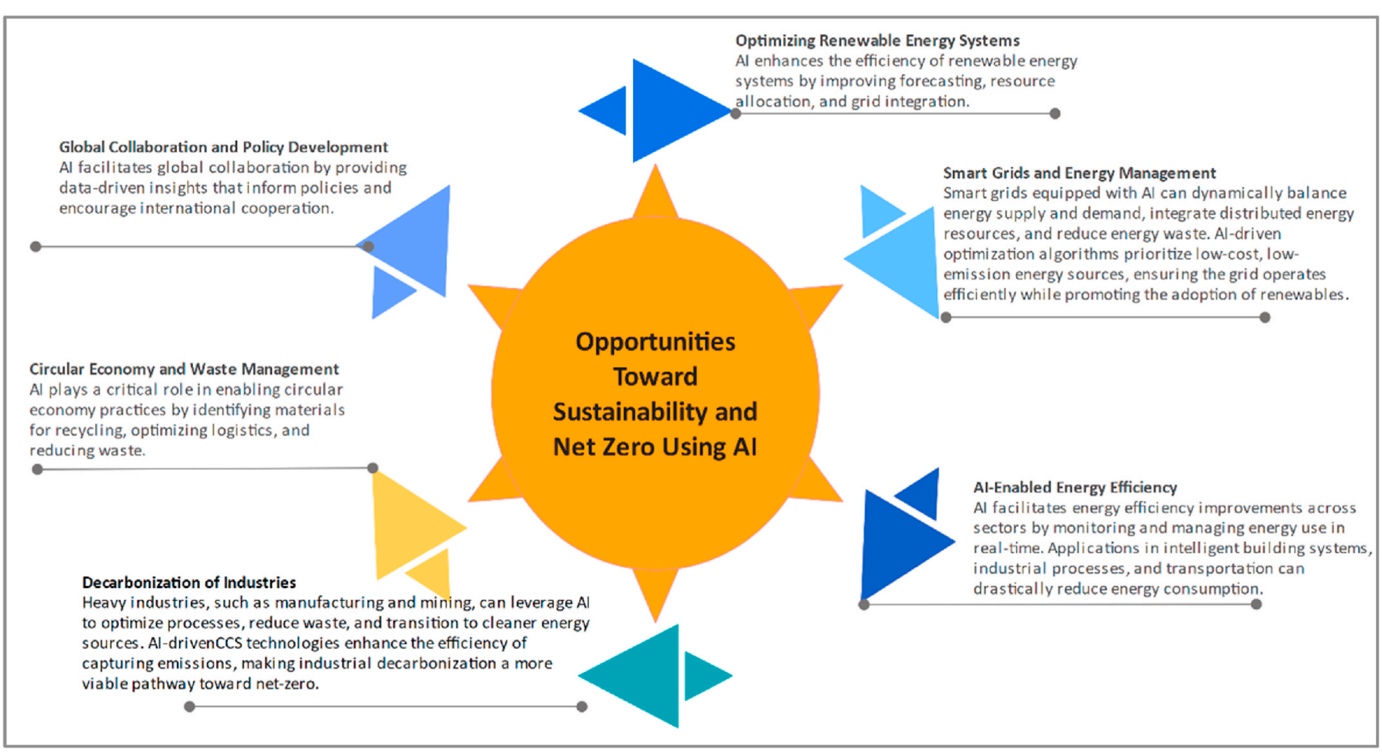

Fig. 11. Opportunities toward sustainability and Net Zero using AI.

Table 2
Net-Zero targets and renewable energy consumption trends by country [78,79].

Country	Net-Zero target year	Renewable energy consumption (%)			
		2020	2021	2022	2023
USA	2050	20	22	25	28
Germany	2045	40	42	45	48
China	2060	15	18	20	22
India	2070	22	24	26	28
Japan	2050	18	20	22	25
UK	2050	35	37	40	42
France	2050	33	35	37	40
Australia	2050	25	27	30	32
Canada	2050	30	32	35	38
UAE	2050	12	14	16	18

Fig. 12 outlines a roadmap detailing the stages required to leverage AI for achieving environmental sustainability and net-zero goals. The process begins with the Foundation Phase, which emphasizes building infrastructure and raising awareness. Developing robust data infrastructure and fostering global collaboration are essential components of this phase, as they provide the necessary groundwork for AI-driven solutions. Raising awareness among policymakers, industries, and the public ensures a collective understanding of AI's potential in sustainability efforts. The phases focus on research, implementation, and optimization. The Research and Development Phase drives innovation by advancing AI algorithms, targeting key applications, and encouraging interdisciplinary collaboration. This leads to the Implementation Phase, where AI is integrated into renewable energy systems, smart cities, and carbon management processes. Deploying AI at this stage enables industries and governments to transition to efficient and low-emission systems. Following implementation, the Monitoring and Optimization Phase ensures effectiveness through real-time monitoring and resilience-building strategies, addressing potential bottlenecks in achieving sustainability targets. The Social and Economic Phase emphasizes skill development, ethical AI practices, and support for green financing, ensuring equitable access to AI-driven solutions. The Scaling Phase focuses on achieving global impact by harmonizing regulations and expanding deployment across regions.

8. Real-world effects of AI on renewable energy

AI has had profound real-world effects on renewable energy, revolutionizing its production, integration, and management. One key impact is the enhancement of energy forecasting accuracy, which enables renewable systems such as wind and solar to predict weather patterns and energy output with greater precision. Analyzing vast amounts of meteorological and historical data, AI algorithms ensure that energy supply aligns with demand, reducing waste and improving efficiency. This has helped grid operators integrate intermittent renewable sources into the energy mix without compromising stability. Additionally, AI-powered predictive maintenance systems monitor equipment such as wind turbines and solar panels, identifying potential failures before they occur. This reduces downtime and operational costs while extending the lifespan of renewable energy assets, ensuring more consistent energy production. A significant real-world effect of AI is its role in optimizing energy storage and distribution. AI-driven energy storage systems predict energy demand trends and manage battery charge-discharge cycles efficiently, addressing the intermittency of renewables such as solar and wind. This ensures a reliable power supply during periods of low energy generation. Moreover, smart grids powered by AI dynamically balance supply and demand by redistributing energy in real-time, reducing grid stress and preventing outages. AI facilitates the integration of decentralized systems such as microgrids, enabling localized energy production and consumption.

Table 3 highlights the steady advancements in AI applications within the renewable energy sector over time, showcasing improvements across various critical categories. AI has been instrumental in optimizing energy production, enhancing energy storage and grid stability, and facilitating the integration of renewable energy sources into existing systems. It underscores the growing economic and environmental benefits driven by AI, as well as its contributions to addressing social and ethical impacts.

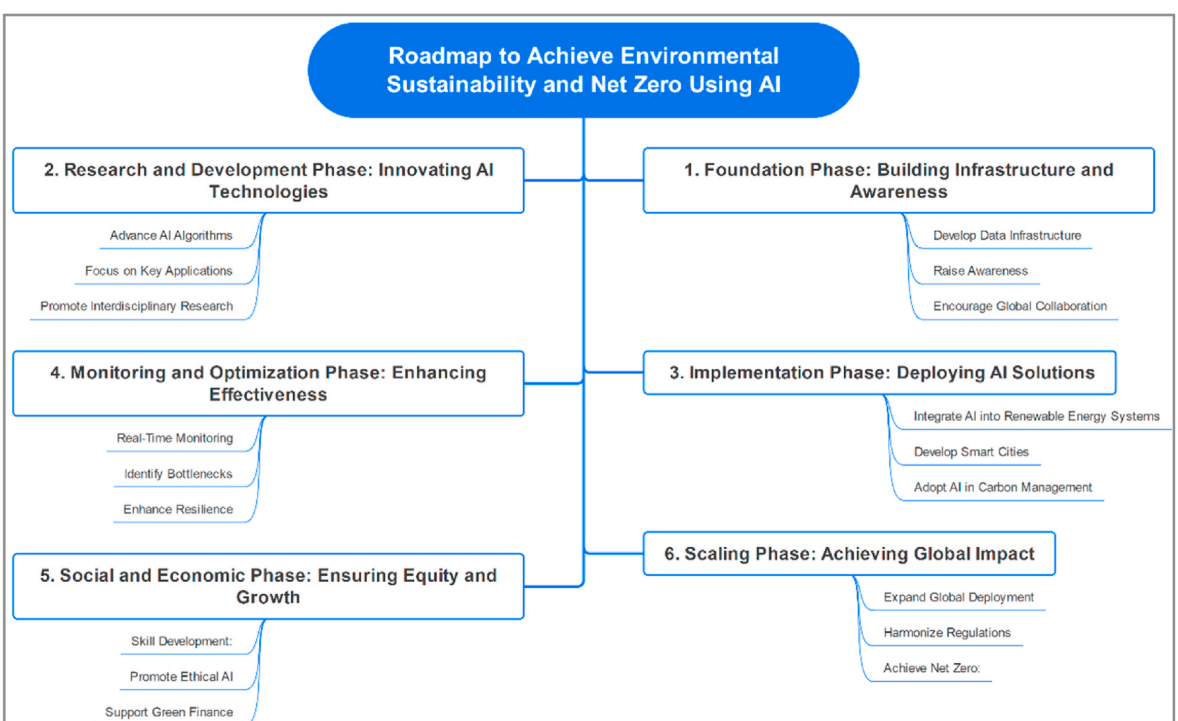

Fig. 12. Roadmap for the role of renewable energy and AI to achieve environmental sustainability and Net Zero.

Table 3
AI progress in renewable energy across key categories [80–82].

Category	AI progress in renewable energy (%)			
	2020	2021	2022	2023
Social and ethical impacts	5	12	20	30
Environmental Impact	4	9	15	22
Cost reduction and economic benefits	6	13	20	28
Integration of renewable energy sources	7	15	25	35
Energy storage and grid stability	8	18	28	40
Optimization of energy production	10	20	30	45

9. Success stories and case studies

The success projects summarized in this section highlight the transformative impact of AI on renewable energy systems, showcasing its ability to drive efficiency, reliability, and sustainability on a global scale. Across various regions, AI has proven to be a critical enabler in overcoming traditional challenges associated with renewable energy, such as intermittency, high costs, and integration into existing grids.

- **Google's data centre energy optimization (USA)**

Google utilized machine learning to optimize energy consumption in its data centers, achieving a remarkable 40 % reduction in cooling system energy usage [83]. AI-driven models monitored energy usage patterns and made real-time adjustments to improve efficiency. This case study highlights the importance of continuous data collection and analysis to optimize energy-intensive operations in large-scale infrastructure. Moreover, it underscores how AI can reduce operational costs while supporting environmental sustainability.

- **DeepMind's wind power forecasting (USA)**

The project implemented advanced AI techniques to forecast wind power generation more accurately, improving predictability by 20 % [84]. The AI model analyzed historical weather data and wind patterns, enabling better alignment of energy generation with demand. This improvement reduced the unpredictability of wind energy, making it a more reliable source for grid operators. The case highlights the importance of forecasting tools in mitigating the intermittency of renewables. It demonstrates the potential of AI to support renewable energy scheduling, ensuring that wind power can be seamlessly integrated into the grid while reducing reliance on fossil fuels.

- **TenneT's smart grid management (Germany/Netherlands)**

The project employed AI for managing grid stability, successfully preventing overloads by optimizing energy flow across interconnected systems [85]. The AI-based system monitored grid conditions in real-time, dynamically redistributing energy to avoid imbalances and disruptions. This case underscores the importance of real-time coordination between grid operators and AI systems to ensure stable and reliable power distribution. It demonstrates AI's potential to enhance grid resilience, particularly as the share of intermittent renewable energy sources increases.

- **Iberdrola's renewable energy optimization (Spain)**

Iberdrola used AI to optimize wind turbine maintenance and performance, increasing operational efficiency by 25 % [86]. The AI system identified early signs of wear and tear, enabling predictive maintenance and reducing downtime. This proactive approach not only improved energy production but reduced costs associated with unplanned repairs. The case highlights how AI can enhance asset reliability and maximize renewable energy output. It serves as a model for other energy producers looking to optimize operations and reduce inefficiencies through advanced monitoring and data-driven decision-making, reinforcing the value of AI in renewable energy systems.

- **Pinggao Group's smart energy dispatch (China)**

The Pinggao Group applied reinforcement learning to optimize energy dispatch, effectively balancing variable renewable sources and enhancing grid efficiency [87]. AI systems analyzed energy demand and generation patterns, making adjustments in real-time to stabilize the grid. This application demonstrated AI's ability to integrate diverse renewable sources, such as solar and wind, into existing energy infrastructures. Leveraging AI for smart energy dispatch, the Pinggao Group reduced energy losses and improved overall system reliability. This case emphasizes how AI can support the seamless incorporation of renewables into grids, accelerating the global shift toward sustainable energy solutions.

- **Australian energy market operator (Australia)**

Project used AI to predict solar energy demand and supply, achieving a reduction in energy waste by aligning production with demand [88]. The AI model provided accurate forecasts of energy generation, ensuring that surplus energy was efficiently stored or redirected. This reduced the risks associated with solar energy intermittency, improving overall system reliability. The case highlights the value of AI in optimizing renewable energy operations, particularly in regions with high solar penetration.

- **Engie's AI-Powered solar farms (France)**

Project implemented AI systems to monitor and detect faults in solar farm equipment, achieving 98 % accuracy in anomaly detection [89]. Identifying equipment failures early, the system reduced maintenance costs and downtime, ensuring continuous energy production. This case demonstrates the transformative potential of AI in improving the reliability and efficiency of solar energy assets. AI-driven asset monitoring enhances decision-making, allowing operators to allocate resources more effectively. Engie's success serves as a model for solar energy operators seeking to optimize operations and maximize returns on their renewable energy investments through AI integration.

- **RENAI project by SoftBank (India)**

Project employed AI to forecast solar and wind energy generation, improving prediction accuracy by 30 % [90]. The AI model leveraged data from multiple renewable sources to provide real-time insights into energy availability, enabling better resource planning and grid integration. This case highlights the importance of accurate forecasting in hybrid renewable systems, ensuring that energy supply meets demand efficiently. Demonstrating the benefits of AI-driven energy prediction, the RENAI Project provides a blueprint for effectively managing hybrid systems and optimizing renewable energy deployment in regions with diverse energy sources.

- **KEPCO's AI for grid optimization (South Korea)**

KEPCO utilized AI for dynamic energy distribution, improving grid reliability by 35 % [91]. The AI system adjusted energy flow in real-time, ensuring that power supply met fluctuating demands in densely populated areas. This case underscores the importance of AI in enhancing grid flexibility and reliability, particularly in urban regions with high energy consumption. KEPCO's approach illustrates how AI-driven solutions can address the challenges of managing complex energy grids, supporting the integration of renewables while maintaining stable operations. It serves as an example for other countries looking to modernize their energy distribution systems.

- **Masdar City renewable system (UAE)**

Masdar City employed AI to manage energy consumption in its smart city infrastructure, achieving a 50 % reduction in energy usage [92]. AI systems optimized energy distribution across residential, commercial, and industrial sectors, ensuring maximum efficiency. This case demonstrates the role of AI in creating sustainable urban environments by minimizing energy waste and promoting renewable energy adoption.

10. Pathways and future outlook

10.1. Future projections for ai in renewable energy

AI is poised to revolutionize renewable energy systems even further in the coming years, with enhanced energy forecasting being one of the most transformative advancements. Current AI models already demonstrate significant accuracy in predicting energy output from renewable sources, but future projections estimate forecasting accuracies exceeding 95 % by 2030 [93]. This level of precision enables grid operators to predict solar and wind energy output with near-perfect accuracy, ensuring better alignment of energy supply with demand. For instance, in countries such as Germany, where renewable energy penetration exceeds 40 %, such accuracy minimizes energy waste and reduce grid instability. Enhanced forecasting plays a pivotal role in regions such as India and China, where variable renewable energy sources are rapidly scaling up. These improvements drastically reduce curtailment rates and enhance the reliability of renewable energy systems globally [94]. Another significant projection involves the development of fully automated AI-driven grids by 2030. These grids utilize AI to manage energy flow dynamically, making real-time adjustments without human intervention [95]. In countries such as the USA and Australia, where smart grid adoption is accelerating, AI is expected to enable seamless integration of distributed energy resources, such as rooftop solar and community wind farms. By autonomously balancing supply and demand, these grids optimize energy flow, prevent overloads, and reduce operational inefficiencies. For example, it is projected that fully autonomous grids reduce transmission losses by up to 20 % globally. This advancement particularly benefits countries with large, complex energy networks, such as China, ensuring efficient energy distribution even as renewable energy capacity expands [96].

The integration of AI into renewable energy systems drive significant cost reductions, making renewable energy highly competitive with fossil fuels. By 2030, AI is projected to reduce the cost of renewable energy production by 15–20 %, depending on the energy source and region [97]. This cost reduction be achieved through optimized resource allocation, predictive maintenance, and enhanced system efficiencies. For example, in South Korea, where AI is already used for grid optimization, future advancements reduce operational costs, further accelerating the adoption of renewables. Similarly, in Africa, where renewable energy infrastructure is still developing, AI can help lower initial deployment costs, enabling access to affordable clean energy for underserved communities. These cost reductions drive global investments in renewables, potentially increasing the share of renewable energy in the global energy mix from the current 30 % to over 50 % by 2030 [98]. AI's role in renewable energy extends beyond technological advancements to foster global energy equity and sustainability. Enhanced energy forecasting and autonomous grids enable developing countries, such as those in Southeast Asia and Africa, to deploy renewable energy systems more efficiently, bridging the energy access gap. AI-powered solutions ensure optimal resource utilization, minimizing the carbon footprint of renewable energy projects. Countries such as the UAE, which have already achieved notable milestones in AI-driven smart city initiatives, such as serve as models for integrating AI into urban energy systems [99].

10.2. Renewable energy role in energy transition

Renewable energy plays a pivotal role in global energy transition efforts, particularly in meeting ambitious carbon neutrality goals. By 2050, renewables are projected to account for over 70 % of global energy production, with solar and wind energy driving this transformation [100]. Countries such as Germany and Spain, which already have renewable shares of over 40 % in their energy mix, serve as prime examples of how renewables can rapidly scale up. In the USA, renewable energy consumption increased to 28 % in 2023, reflecting a steady shift from fossil fuels. Solar energy, in particular, is expected to dominate future growth due to its cost competitiveness and scalability, while wind energy remains a key contributor, especially in regions with abundant wind resources such as China and the UK. The widespread adoption of renewables not only reduce global greenhouse gas emissions but enhance energy security by diversifying energy supply sources [101]. The rise of the hydrogen economy represents another transformative development, with green hydrogen production becoming a cornerstone of energy transition strategies. Green hydrogen, produced through electrolysis powered by renewable energy, offers a sustainable solution for hard-to-decarbonize sectors such as heavy industry, shipping, and aviation [102]. Countries such as Australia and Saudi Arabia are investing heavily in green hydrogen projects, aiming to become global leaders in its production and export. For example, Australia's Hydrogen Energy Supply Chain project is expected to produce thousands of tons of green hydrogen annually, leveraging the country's vast solar and wind resources. By 2050, green hydrogen could account for up to 20 % of global energy demand, reducing emissions in sectors that contribute significantly to global warming [103].

Energy storage technologies play a critical role in enabling stable, round-the-clock energy availability, a necessity for achieving energy transition targets. Batteries paired with renewable energy systems, such as lithium-ion and solid-state batteries, have already made significant progress in addressing the intermittency of solar and wind energy. By 2030, energy storage capacity is projected to increase by over 300 %, ensuring reliable power supply even during periods of low renewable energy generation [104]. Countries such as the USA and South Korea are at the forefront of energy storage innovation, with large-scale battery installations supporting grid stability. Meanwhile, emerging economies, such as India, are adopting energy storage solutions to complement their rapidly expanding renewable energy infrastructure. These advancements ensure that renewable energy systems can meet the growing energy demands of a decarbonized global economy. In addition to technological advancements, renewable energy's role in the energy transition extends to fostering global collaboration and equitable access. Regions such as Africa and Southeast Asia are leveraging international partnerships to deploy renewable energy systems, addressing energy access disparities while reducing dependence on fossil fuels. Countries such as Kenya, which has achieved over 90 % renewable energy generation, highlight the potential for renewables to transform energy systems in developing regions [105]. Moreover, initiatives such as the European Green Deal demonstrate how renewables can drive comprehensive policy frameworks that align environmental, economic, and social goals.

11. Conclusions

The transition from fossil fuels to renewable energy is crucial for addressing global environmental challenges, including climate change, resource depletion, and energy inequity. Renewable energy sources, characterized by their natural replenishment and minimal greenhouse gas emissions, offer viable alternatives to fossil fuels. Despite their potential, several obstacles such as intermittency, high initial costs, and integration challenges with existing infrastructure hinder widespread adoption. The AI technologies provide transformative solutions by optimizing energy systems and enhancing their efficiency. This study investigated the synergies between renewable energy and AI, exploring their combined potential to foster a sustainable, resilient, and secure global energy future.

The key inferences from this study are summarized below:

1. Renewable energy sources (solar, wind, geothermal, hydropower) face significant challenges due to inherent variability, impacting grid stability and continuous power supply.
2. AI technologies effectively address renewable energy intermittency by providing accurate predictive analytics based on historical and real-time environmental data, thus ensuring balanced energy supply and demand.
3. AI significantly enhances energy storage systems by optimizing battery performance and extending lifecycle efficiency, ensuring consistent renewable energy availability.
4. The adoption of AI-driven smart grids promotes decentralized energy distribution, empowering consumers as "prosumers," capable of generating, storing, and sharing energy efficiently.
5. Economically and technologically, AI integration in renewable energy leads to substantial cost savings, reduced operational expenses, and maximized renewable resource utilization.
6. AI fosters innovation in energy technology, facilitating advances in photovoltaic materials, high-capacity energy storage, and efficient maintenance processes through predictive analytics.
7. Innovative business models enabled by AI, including demand-response programs and peer-to-peer energy trading, create more equitable and sustainable energy markets.
8. The successful deployment of AI-powered renewable energy systems requires robust policy frameworks, interdisciplinary collaboration, and effective public-private partnerships.
9. Governments should prioritize research and development investments, incentivize renewable energy adoption, and establish clear regulations guiding AI applications in energy systems.
10. Private sector engagement is vital in driving innovation, technology transfer, and ensuring the affordability and accessibility of AI-driven renewable energy solutions.
11. Comprehensive education and workforce development initiatives are essential to cultivate skilled human capital capable of supporting and advancing the integration of AI in renewable energy systems.

CRediT authorship contribution statement

Sameer Algburi: Conceptualization, Methodology, Supervision, Project administration. **Salah Sabeeh Abed Al Kareem:** Methodology, Validation, Writing – review & editing. **I.B. Sapaev:** Investigation, Resources, Data Curation, Writing – review & editing. **Otabek Mukhitdinov:** Software, Visualization, Formal analysis. **Qusay Hassan:** Conceptualization, Supervision, Writing – review & editing. **Doaa H. Khalaf:** Investigation, Formal analysis, Conceptualization. **Feryal Ibrahim Jabbar:** Validation, Visualization, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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