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Review Article

AI Applications in Renewable Energy: A Comprehensive Review

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Abstract - *In renewable energy systems, including wind, solar, Bio-Electrochemical, and Artificial Intelligence (AI), are increasingly being applied. In this paper, the most evident issues of producing, regulating, and manufacturing renewable energy by AI are explored. We examine the different AI techniques, including machine learning, deep learning, reinforcement learning, and hybrid techniques, and their applications to forecasting, optimization, predictive maintenance, and grid management. The review paper discusses the applications of solar, wind, and hydropower in different areas and identifies major concerns of data quality, cybersecurity, and scalability. AI not only makes things work better technologically but also promotes green innovation and assists us in achieving the Sustainable Development Goals. We summarize strategic suggestions and possible future research directions in this rapidly developing field.*

Keywords - *Artificial Intelligence, Renewable Energy, Solar Energy, Wind Energy, Energy Forecasting*.

1. Introduction

The number of renewable energy systems that incorporate AI technologies is increasing, such as wind, solar, and bio-electrochemical systems. AI can be extremely helpful in determining the extent of renewable energy to be generated since it can examine a large amount of information and identify trends that are nearly impossible to observe. Renewable energy is always affected by changes in nature (G. Li et al., 2023). The field of engineering is the most dynamic one, and the network of collaboration is strong, which means that there is a dynamic, interdisciplinary research community (Hou, 2022). On a macro level, bibliometric studies have shown that AI and big data have now become central to energy studies, engineering, and computer science knowledge disciplines, being the most prevalent. The field is rapidly expanding, collaborating in the global arena, and trending towards cross-disciplinary approaches (Mamodiya, Kishor, Garine, Ganguly, & Naik, 2025). At the macro-level, AI assists green innovation and sustainable development by promoting green productivity, attracting trained labor, and simplifying access to renewable energy technology. The studies indicate that AI and emerging green technologies can contribute to long-term green growth to a significant extent. They also relate to Sustainable Development Goals (SDGs), which are comprised of fair work, economic globalization, and innovation in the industry (Behera, Pata, Sethi, & Sethi, 2025). The effects of AI are not limited to technical optimization, but also green productivity, promoting the use of renewable energy, recruiting talented workers, and creating channels of communication with economic development.

However, the environmental impacts of AI and the necessity for holistic policy frameworks remain underexplored, marking an essential area for future research (Tao, 2024). Figure 1 shows the growth of renewable electricity capacity by technology segment, main case, 2013–2030. The existing studies explain how AI contributes to optimizing renewable energy systems. However, a clear research gap exists as these studies do not sufficiently examine the environmental side effects, ethical concerns, or policy frameworks required to ensure the sustainable use of AI in renewable energy. Addressing this gap is essential for developing a more holistic understanding of AI's role in advancing green innovation and long-term sustainability.

The objective of this review paper is to systematically analyze the integration of Machine learning (ML), Deep Learning (DL), and AI technologies and their applications into renewable energy systems such as wind, solar, and hydro power, along with challenges and limitations.

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2. Background

2.1. Renewable Energy Systems Overview

The uses of natural resources in renewable energy systems are several. Solar photovoltaic converts solar energy to electrical power, and wind turbines convert the power of wind into electricity as it blows.

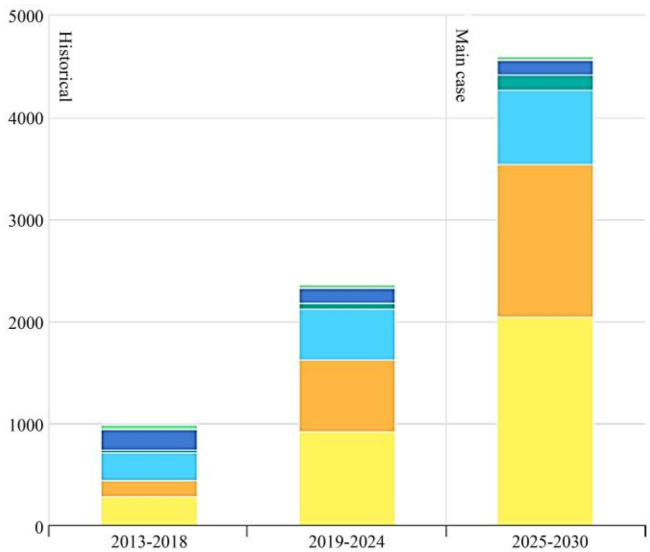

Fig. 1 Renewable electricity capacity growth by technology segment, main case, 2013-2030 [93]

The hydropower plants utilize the stream of water and use the prospects of gravitational power as well. Bioelectrochemical systems transform energy by utilizing biological processes.

The integration of renewable power sources such as solar and wind into the power grid poses significant challenges because of their intermittent and unpredictable nature. Weather prediction is also important to estimate solar and wind installations production since the weather around is directly related to the production (Sarkar, Karthick, Kumar Chinnaiyan, & Patil, 2023).

2.2. Artificial Intelligence Fundamentals

The introduction of AI to renewable energy is multifaceted, and it can resolve technological and strategic challenges. In solar energy, AI-based hybrid systems use deep learning (e.g., CNN-LSTM networks) to make precise irradiance predictions, reinforcement learning to operate real-time surveillance, and Edge AI to operate a decentralized and low-latency control.

All these mechanisms increase the power generation, responsiveness of the system, and the scalability of operations, and combine smart materials to improve efficiency (Mamodiya et al., 2025). Figure 2 illustrates various use cases of AI in the energy sector. Figure 2 illustrates AI techniques used in a renewable energy system.

3. AI Technologies and Methodologies

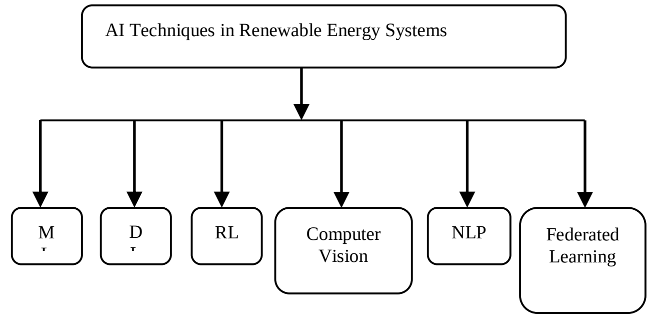

Fig. 2 AI techniques used in a renewable energy system

3.1. Machine Learning

Recent studies have shown that machine learning is a revolutionary technology in the field of renewable energy implementation, overcoming the issue of prediction, optimization, and integration of systems. Machine learning is a set of algorithms that are trained on data to produce predictions or judgments without necessarily being programmed to perform a set of tasks.

3.2. Supervise Learning

Supervised learning is an input-output algorithm training, where the model is trained on characteristics of the map (e.g., weather data, historical power production, or equipment usage) to achieve the target variables (e.g., projected energy generation or power consumption). This technique is important in the management of the natural variability and unpredictability of renewable resources such as solar and wind in renewable energy. Specifically, in photovoltaics, supervised models including XGBoost, Random Forest, and Support Vector Regression have been compared with temperature and humidity prediction, with XGBoost showing the highest accuracy (lowest MAE and RMSE, largest R2), showing the usefulness of model selection and assessment metrics in practice deployments (Abdelsattar, AbdelMoety, & Emad-Eldeen, 2025).

A combination of flexible decomposition and controlled machine learning could bring about uncertainty in the energy production and help stabilize the grid as well as plan (G. Li et al., 2023). These models are important in short-term forecasting, which is necessary because of the uncertainty of renewable resources. Predictive models of power consumption at the equipment or building level are also based on supervised learning to provide more sustainable energy management. Principal Component Analysis to reduce features and ensemble classifiers to predict have been employed to construct strong, understandable models to predict power use (Altayeb & Arabiat, 2025). The selection of a supervised learning technique will be based on the personal factors of the renewable energy challenge. Models that are suitable for time-series forecasting problems can include temporal dependencies, whilst those that are required in classification problems, such as defect detection, require algorithms that have high discriminative capabilities. Proper train- test splitting and cross-validation are essential to permit the model to generalize, as the data in renewable energy is nonstationary.

Additionally, supervised learning can also be used together with more sophisticated data-driven and optimization methods, including few-shot learning and deep autoregressive models, to solve problems such as the scarcity of data and multi-objective optimization in energy- water management (W. Zhao et al., 2025). In spite of the strength of supervised learning, it is important to understand the limitations that are set by the quality and representativeness of training data, and the need to consider the spatiotemporal uncertainty of renewable energy systems (J. Wang et al., 2023).

3.3. Unsupervised Learning

Unsupervised learning is a diverse set of techniques, including clustering, dimensionality reduction, and anomaly detection, which is able to extract valuable information out of unlabeled data. These are especially useful in renewable energy, given the unpredictable character of resources like wind and solar; labeled datasets have frequently been either costly or difficult to obtain. Specifically, an old-fashioned unsupervised method, namely Principal Component Analysis (Khan et al., 2021), is employed to perform data reduction and feature extraction so as to enhance the performance and accuracy of power utilization prediction models (Altayeb & Arabiat, 2025). In the same way, statistical learning methods are used to study the spatiotemporal uncertainty of the renewable energy production, and this shows patterns in the error of prediction and is useful in quantifying the inherent non-predictability of such sources (J. Wang et al., 2023). Figure 3 shows the use cases of PCA. Another crucial role that unsupervised learning makes in estimating the predictability of time series of renewable energy is also necessary for strong decision-making in energy systems. Through comparisons of the different predictability criteria with much caution, researchers are able to identify the most applicable methodologies of various renewable generating data in order to enhance forecasting and investment decision-making (Karimi-Arpanahi, Pourmousavi, & Mahdavi, 2023). Moreover, unsupervised methods are commonly used together with other machine learning models, e.g., reinforcement learning, to improve energy management systems in the real world, as demonstrated in the case of electric car optimization (Y. Wang, Wu, He, Wei, & Sun, 2025).

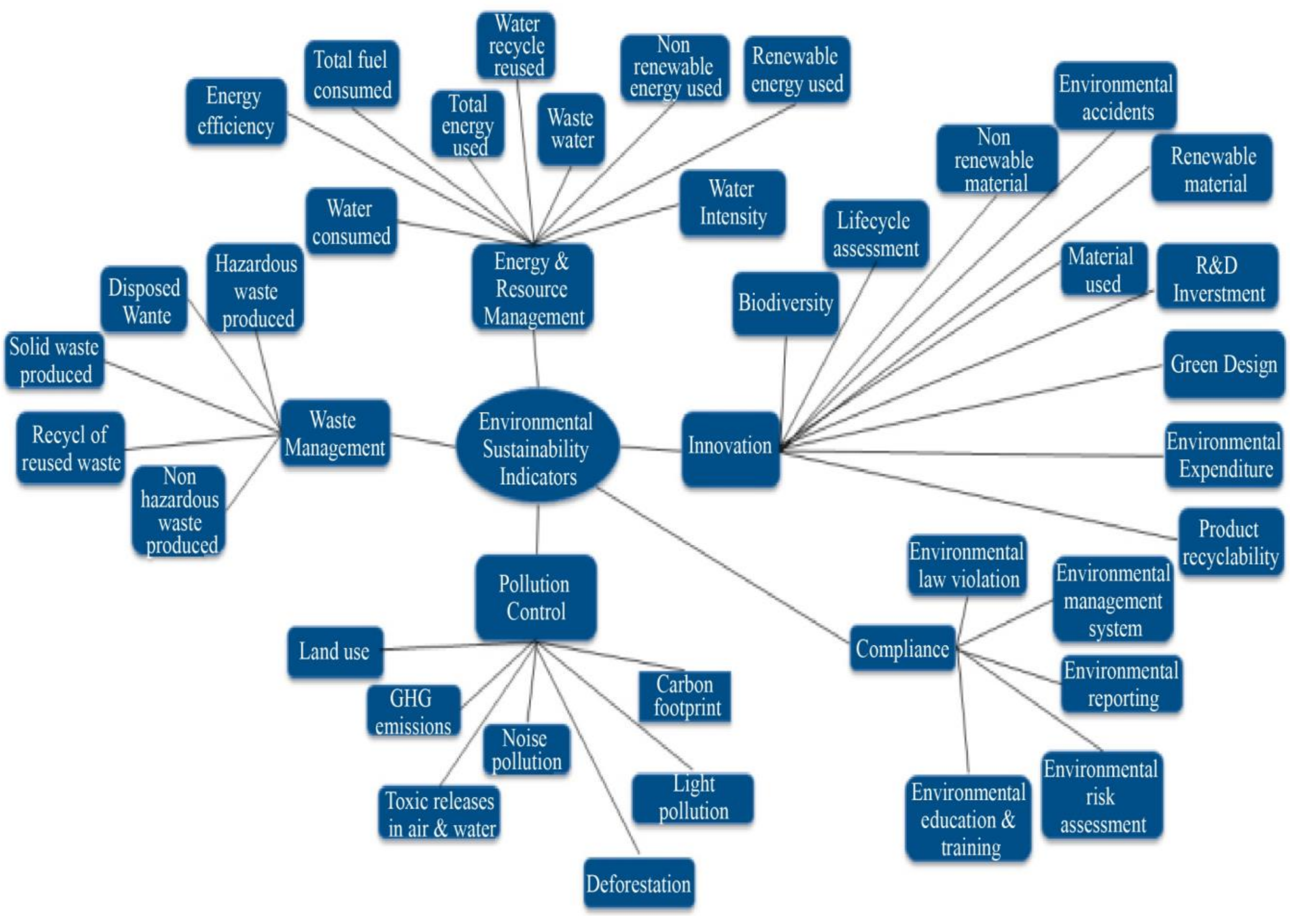

Fig. 3 Principal Component Analysis use cases [40]

3.4. Deep Learning

Deep learning (Alazemi, Darwish, & Radi, 2024) has developed a robust method for renewable energy applications, especially for controlling highly complex and high-dimensional information and retrieving subtle temporal and spatial features. Deep learning in grid management, especially Generative Adversarial Networks (GANs), can be used to simulate different photovoltaic generation-consumption scenarios, providing real-time adaptive control and achieving up to 96% operating efficiency, 20% cost savings, and 30% carbon savings (Z. Gu, Li, Zhang, & Li, 2025). Systematic reviews affirm that deep learning models, such as deep neural networks and hybrid models, are always superior to physical and statistical models in predicting renewable energy outputs, particularly when there is a lot of uncertainty.

Long Short-Term Memory networks, also known as recurring neural networks, have become the standard methodology of renewable energy time-series forecasting due to their ability to capture long-term temporal dependencies. These architectures are very good in modeling the sequential character of energy generation patterns, which depend on cyclic weather patterns and seasonal changes (Sharma, Sharma, & Jindal, 2021). Figure 4 displays the process flow of the Long Short-Term Memory (LSTM) model. Convolutional Neural Networks have also been useful in the field of spatial-temporal forecasting of renewable energy, when the source of distributed generation is involved. CNNs can work with multi-dimensional sensor data of wind farms or solar arrays to detect spatial relationships among various units of generation and temporal patterns at any given time. Deep learning has also been used to improve resource management in coupled systems like energy- water networks, whereby few-shot learning and deep autoregressive models have been used to make precise predictions with minimal data, which leads to better cost and emission results (W. Zhao et al., 2025).

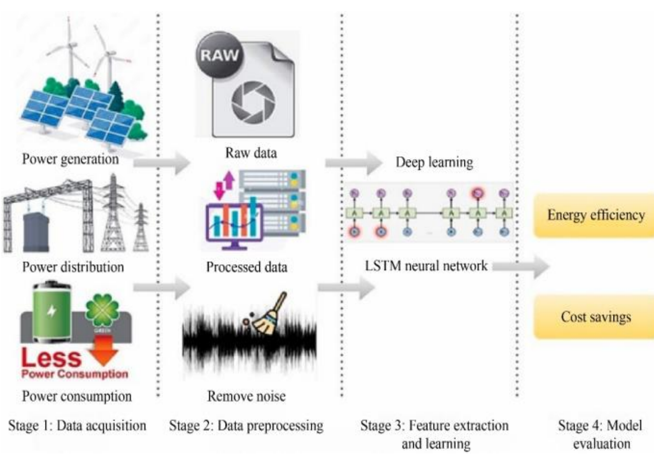

Fig 4. Process flow of Long Short-Term Memory (LSTM) [10]

U-Net-based segmentation and deep regression models are useful in the maintenance of PV systems as they offer granular thermal analysis, which allows the optimization of the cooling system to be more effective and thus yields more power. More recent advances have demonstrated that hybrid deep learning models combining various architectural paradigms can be very useful. CNN-LSTM hybrid architectures combine the spatial representation power of CNNs and the temporal representation power of LSTMs, resulting in the state-of-the-art in solar irradiance prediction and wind power prediction (Sharma et al., 2021). These hybrid methods are capable of handling both spatial sensor configurations and time series, and offer them specifically to a huge renewable energy installation. The comparative analysis of the Q-learning, SARSA, and the deep Q-networks used in the context of microgrid energy control shows that deep RL systems, when aided with model predictive control and Kalman filters, offer more flexibility and control in dynamic and stochastic systems (Ramesh et al., 2025). Figure 5 depicts renewable energy integration in a microgrid.

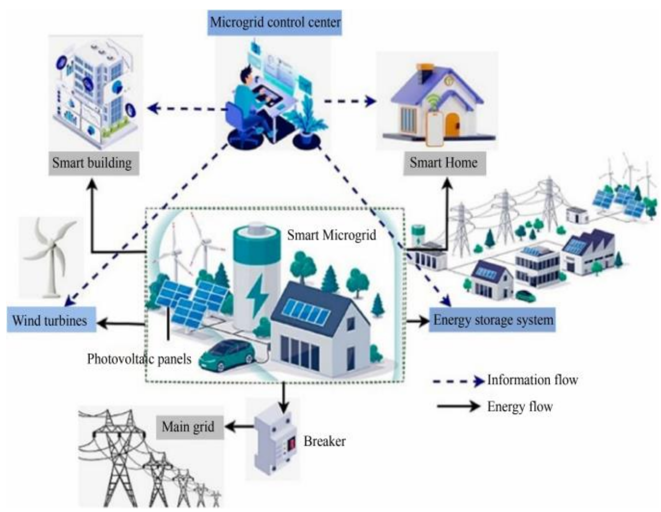

Fig 5. Utilizing renewable energy sources in a microgrid [19]

3.5. Reinforcement Learning

Reinforcement learning is effective for optimizing renewable energy systems in unpredictable conditions. In renewable energy settings, RL agents find optimal control policies through trial-and-error interactions with the system, where incentives are based on performance measures like energy efficiency, cost reduction, or grid stability. Reinforcement learning (Du, Chatterjee, Bhattacharya, Dutta, & Halappanavar, 2023) is a successive decision-making framework that is data-driven and acquires knowledge of optimal policies in the context of interaction with dynamic environments. In cases of renewable energy, RL, and more specifically, deep learning versions, have been applied to manage the natural instabilities, nonlinearities, and operational challenges of incorporating renewable resources into power systems.

In hybrid renewable energy systems, DRL has been successfully applied to the optimal power flow problem, surpassing classical metaheuristic methods by offering improved handling of uncertainty and nonlinear conditions. (Gurumoorthi, Senthilkumar, Karthikeyan, & Alsaif, 2024). Multi-timescale scheduling algorithms based on DRL have been extended to maximize the free deployment of wind, solar, and wave energy in maritime renewable energy, with real-world meteorological data and state-of-the-art neural network predictors (Xu et al., 2024). The other critical role of RL is risk-based robust control of cyber-physical energy systems, which provides automated and adaptive control in the face of uncertainty, and concerns remain in the area of generalizability and safety (Du et al., 2023). DRL methods have been suggested in the context of distribution networks, where the high renewable penetration presents a combinatorial complexity and operational constraints in the large-scale power distribution (R. Wang, Bi, Bu, & Tang, 2025).

Reinforcement learning solves the basic problems of applying RL to real- world energy systems, in which safety violations may cause damaged equipment, destabilization, or economic losses of the grid. The framework usually presents the energy systems as Constrained Markov Decision Processes (CMDP), where agents are required to maximize rewards and observe safety constraints (S. Gu et al., 2024). The Markov process and its role in verifying the total future reward are highlighted in Figure 6. Hard limits need to be imposed on the operation parameters of the energy systems. As an example, the battery storage systems should be in safe voltage and temperature operation, whereas the grid-connected renewable sources should be stable in voltage and frequency (Achiam, Held, Tamar, & Abbeel, 2017).

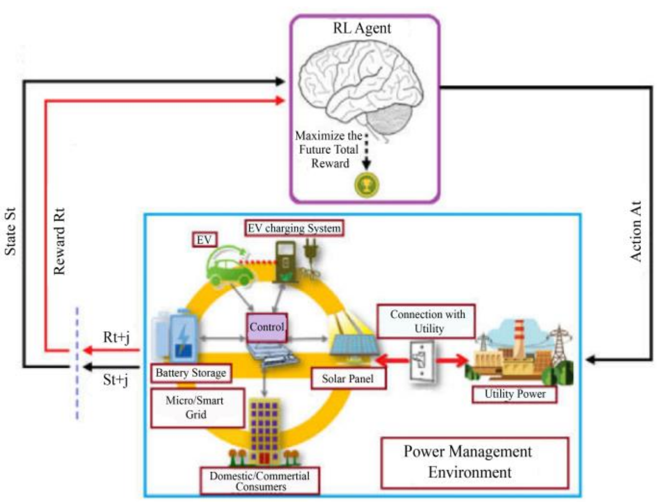

Fig 6. Markov process and the verification of the total future reward [7]

Safe RL algorithms directly incorporate these limits into the learning objective to ensure that policies learned during training respect safety limits when deployed. Recent methods combine model-based and model-free methods in order to strike a balance between sample effectiveness and adaptability. As an example, constrained policy optimization has been used to solve the problem of electric vehicle charging coordination, energy storage management, and renewable energy dispatch (H. Li, Wan, & He, 2019).

3.6. Computer Vision

Computer Vision (CV) is a branch of artificial intelligence that enables machines to perceive and process graphic data of the world, typically in the form of digital photographs or video feeds. CV is finding application in renewable energy to solve problems of monitoring, preservation, and efficient optimization of power systems. Specifically, in photovoltaic solar energy, CV models based on deep learning, including U-Net architectures, are applied to identify solar panels in thermal images, which can be used to perform accurate spatial analysis of temperature distributions and to achieve improved thermal control. This results in improved determination of cooling system operation and streamlines the enhancement of PV system maintenance, hence affecting power output (Elmessery et al., 2024).

Another important field of intersection between CV and machine learning is forecasting renewable energy extraction. Combining adaptive decomposition methods with machine learning, scientists will be able to improve the quality of short-term energy production forecasts of wind and solar power, which will allow balancing the volatility and uncertainty of renewable sources (G. Li et al., 2023). CV can also be used in the larger-scale environmental and system monitoring, where infrared and visible spectrum imaging can be used to give real-time, non-contact information on systems, environmental conditions, or even worker safety in an indoor or outdoor environment (Yang et al., 2023). These are applications of a broader tendency of the combination of AI, IoT, and robots in order to make the renewable energy infrastructure smarter and more robust.

3.7. Natural Language Processing

NLP is also a part of artificial intelligence that enables computers to understand and read human language. Its most salient techniques include text mining, data mining, sentiment analysis, and topic modeling, which are frequently driven by strong machine learning and deep learning algorithms (Bobba et al., 2023; López-Úbeda, Martín-Noguerol, Aneiros-Fernández, & Luna, 2022). Systematically investigating the quickly growing corpus of scientific research, patents, and even technical documentation, NLP may be applied in the background of renewable energy to help researchers and policymakers find new trends, gaps, and opportunities. The recent view by (Bobba et al. (2023) considers how NLP, in combination with network analysis, can map the terrain of materials scientific literature, in particular, energy-related components, including batteries, catalysis, and organic electronics. The method allows tracking the most significant research topics, their development throughout the years, and the connections between subdisciplines, which are directly related to the research of renewable energy. NLP reduces the human load on researchers and improves evidence-based decision-making by automating the process of extracting and distilling knowledge out of large volumes of text corpora.

The most significant challenges to the application of NLP to renewable energy are the inconstancy of data sources, domain-related vocabularies, and the fact that enormous annotated datasets are required to train the models. Nevertheless, as can be seen in materials science and healthcare, even the simplest NLP methods can help extract useful information, and network analysis can further increase the possibility of visualizing and interpreting complex research environments (Brito, Oliveira, Oliveira, Silva, & Amancio, 2023).

3.8. Federated Learning

The idea behind federated learning is to allow a large number of clients (i.e., IoT devices, smart meters, or energy management systems) to jointly train machine learning models rather than sharing their raw data. It can be used particularly effectively in the areas of renewable energy where data privacy, compliance with regulations, and heterogeneity of data are critical issues (A. Chen, Fu, Sha, & Lu, 2022). FL can be broadly divided into horizontal FL, vertical FL, and federated transfer learning, which apply to varying data distribution conditions (Wen et al., 2023). FL is used in renewable energy in smart grids, energy expenditure prediction, and IoT-focused energy management using edge and cloud technologies to process data safely and in an effective manner (Jerkovic, Sarkar, & Ali, 2025; Wen et al., 2023). The recent studies have shown the incorporation of FL with other advanced security techniques like homomorphic encryption (A. Chen et al., 2022) in order to enhance the security of user information in smart grid systems to make energy consumption prediction safe and privacy-protecting (Jerkovic et al., 2025). Also, FL structures are being streamlined to be energy-efficient and scalable in IoT networks, through metaheuristic algorithms and directed acyclic graph systems to optimize the lifetime of devices and communication effectiveness (Nalinipriya et al., 2024).

One of the central issues with the application of FL to renewable energy is that the data across devices is not IID (independent and identically distributed), and this could affect the performance of the models. To address this, adaptive hyperparameter optimization, hierarchical aggregation, and personalized federated learning approaches are being developed. These solutions group similar energy profile devices together, use multi- task learning, and adjust model parameters to local data distributions, thus leading to better predictions with robustness (Hsu, Keoy, Chen, Chao, & Lai, 2023; Toderean et al., 2025). The customized federated learning trend, particularly in the cloud-edge systems, is especially relevant to intelligent IoT services in renewable energy. These models are aimed at dealing with device, statistical, and model heterogeneity, thus rendering FL more practical and effective in actual, massive-scale energy systems (Wu, He, & Chen, 2020). Table shows the AI technologies and their applications in the field of renewable energy.

Table 1. AI Technologies and Their Applications in Renewable Energy

AI Technology name	Key Techniques	Primary Applications	Advantages	References
Machine Learning	XGBoost, Random Forest, SVM	Energy forecasting, power consumption prediction	High accuracy, handles time-series data	[1, 9,25]
Deep Learning	CNN, LSTM, CNN-LSTM hybrids, GANs	Solar irradiance prediction, grid management, scenario simulation	Captures complex temporal/spatial patterns	[54, 89, 74]
Reinforcement Learning	Q-learning, SARSA, Deep Q-Networks, DRL	Microgrid energy control, optimal power flow, multi-time-scale scheduling	Adaptive control in dynamic environments	[33, 68, 87]
Computer Vision	U-Net, Deep CNN	Thermal analysis of PV systems, panel detection, and environmental monitoring	Non-contact monitoring, spatial analysis	[28, 88]
Federated Learning	Horizontal FL, Vertical FL, Hierarchical FL	Smart grid energy prediction, privacy-preserving learning	Data privacy, distributed learning	[20, 41, 78]

4. AI and Renewable Energy

4.1. Energy Generation Forecasting

Renewable energy is being transformed by AI technologies to overcome major challenges of variability, coordination, and optimization of investments. Machine learning and deep learning models are used in energy generation to enhance short-term predictions of wind and solar energy, reducing uncertainty and enhancing the stability of a system (G. Li et al., 2023). Recent studies indicate that machine learning has been applied in the forecasting of renewable energy power generation. Adaptive decomposition and ML integrated techniques have been demonstrated to mitigate uncertainty and enhance grid security, especially in wind and solar energy, as they give more accurate short-term predictions (G. Li et al., 2023).

Comparative analysis of nine ML models in PV systems established that XGBoost was superior to other models in the prediction of temperature and humidity, and it had a high accuracy (MAE=1.544, RMSE=1.242, R2=0.947), which was essential in optimization of PV system (Abdelsattar et al., 2025). Real-time evaluation and prediction in renewable energy with the help of AI involves a complex set of procedures managing the fundamental challenges of fluctuation, nonlinearity, and environmental uncertainty. These systems rely on more complex machine learning models, such as hybrid architectures (e.g., CNN-LSTM, RF-LSTM), Recurrent Neural Network (focused), and ensemble models. These models handle massive volumes of spatiotemporal information, including solar irradiance, wind speed, and environmental variables, in order to produce trustworthy short and long-term forecasting (G. Li et al., 2023; Mamodiya et al., 2025). A common process starts with the data collection of distributed sensors and IoT devices, decomposing it adaptively (e.g., CEEMDAN) to isolate complex nonstationary signals into more predictable ones (Sarkar et al., 2023). Then, machine learning models are trained on the following components: high-frequency variations can be processed by random forests or SVMs, whereas long-term dependencies and trends are identified by LSTM or Hybrid Neural Networks (Kim & Nam, 2025).

4.2. Predictive Maintenance

Predictive Maintenance (PdM) is an AI-based approach to renewable energy systems, which involves using data-driven models to predict upcoming problems in the system, reducing the downtime and maintenance costs of the system. AI approaches like digital twins and real-time analytics are also becoming common in wind energy, as in a case study of wind turbine condition monitoring and predictive analytics based on a distributed digital twin framework in an IoT architecture (Abdullahi, Longo, & Samie, 2024). This method provides wellness control and optimization of utilization in real time along wind farms. Machine learning algorithms, such as LSTM with spatio-temporal attention, and regression models are also used in solar energy to make photovoltaic predictions and optimize system operation (L. Zhao, Nazir, Nazir, & Abdalla, 2022), e.g., in a case study of solar-powered irrigation and PV energy production prediction. These models are helpful in solving problems that are brought about by ecological variability and system complexes. Although the hydro-specific AI PdM case studies are not so evident in the given search, the literature on the power industry at large addresses the shift towards the idea of predictive maintenance, in which the idea of AI-based analytics to monitor the system and prevent failures is integrated (Molęda, Małysiak-Mrozek, Ding, Sunderam, & Mrozek, 2023). In all industries, the implementation of IoT-based PdM and digital twins is a characteristic of Industry 4.0, which facilitates proactive maintenance and enhanced asset management (Bongomin et al., 2025).

4.2.1. Fault Detection and Diagnosis

The principle of AI-based fault diagnosis in a renewable energy system works by analyzing large volumes of operational and environmental data to uncover anomalies that may suggest faults. Specifically, noise-resistant classification models such as the Perturbed-Random Forest (P-RF) algorithm are used in wind turbines to classify the SCADA data with high precision despite the presence of noise, thereby providing an opportunity to respond and reduce downtime (Irfan et al., 2025). In the case of PV plants, electrical and environmental variables, including irradiance, temperature, and energy output, are monitored by the use of recursive linear models to identify and categorize faults in real-time to aid in the real-time and historical performance evaluation (Lazzaretti et al., 2020).

Microgrids use supervised machine learning algorithms, in particular Support Vector Machines (Lazzaretti et al., 2020), to classify and detect faults, even in the case of unknown fault resistance. The approach will reduce the need for significant communication infrastructure and improve the efficiency of microgrid protection schemes (Barkhi, Pourhossein, & Hosseini, 2024). There is also the application of edge AI to real-time defect detection and condition monitoring in industrial settings, which allows decentralized and low-latency assessment and quick response to new faults (Gültekin, Cinar, Özkan, & Yazıcı, 2022). In the case of wind turbine blades, hybrid models that combine methods of optimization algorithms (ex, Tyrannosaurus Optimization Algorithm) and SVMs are used to examine noise signals to promote the detection accuracy and reliability of harsh environmental conditions (Lei, Lin, Tang, Xiong, & Wen, 2025).

4.2.2. Anomaly Detection

Anomaly detection can be an important component in the operation and maintenance of renewable energy to prevent expensive failures and optimize performance, such as that of wind turbines and electric vehicles, where anomalies or deviant behavior can be identified early to prevent failure. The recent advancements in AI, namely, deep learning, have enabled more accurate and robust anomaly detection. There are a number of case studies that outline the importance of AI in this field. In particular, deep ensemble models, including RNNs, LSTMs, and CNNs, have been demonstrated to be effective in multivariate time series analysis to ensure short- and long-term relationships to identify subtle anomalies (Iqbal, Amin, Alsubaei, & Alzahrani, 2024). The LSTM-autoencoders applied to the vibration data in the context of wind energy can obtain high rates of anomaly detection (up to 97%), especially when complemented with advanced preprocessing methods such as wavelet packet transformation and principal component analysis (Jankauskas et al., 2023; Lee, Park, Kim, Ahn, & Jeong, 2024). These techniques are superior in distinguishing between normal and abnormal functioning conditions, particularly in noisy conditions. In addition to wind turbines, AI-based anomaly detection has been extended to the driving behavior of electric vehicles, with models based on a hybrid between LSTM- autoencoder, LOF, and Mahalanobis distance assessed on the basis of clustering metrics and chaos theory metrics in order to detect unsteady or inefficient driving behavior (Savran, Karpat, & Karpat, 2024). These do not only enhance safety but also result in system lifetime and energy efficiency.

4.2.3. Energy Optimization

Such artificial intelligence tools are essential to both the grid operators and energy producers because they should minimize uncertainty, ensure system stability, and enable the regulation of energy trade. The use of intelligent devices and adaptive control also enhances the system efficiency by enhancing the energy harvesting and reducing maintenance requirements (Mamodiya et al., 2025). In general, the combination of developed AI models, adaptive decomposition, and real-time control is the basis of the current renewable energy monitoring and forecasting systems. Big data streams and the computational needs of smart grids are handled using cloud and fog computing frameworks and AI-driven optimization algorithms such as Rock Hyrax Optimization to optimize response time and energy consumption (Singhal et al., 2023). Real-time energy management in hybrid renewable energy systems is done with adaptive neuro-fuzzy inference systems (Toumia & Hassine, 2021) and other intelligent controllers, which guarantee efficient power flow between resources and storage and overcome nonlinearities. Smart grids are also secured with the help of AI. With the increasing susceptibility to cyber-attack due to digitalization, novel intrusion detection systems (Rossi, Parisi, Maranghi, Basosi, & Sinicropi, 2020) using hybrid feature selection and deep learning classifier have been developed to identify sophisticated attacks such as False Data Injection, and therefore ensure the integrity of the grid (Mohammed et al., 2025). Management AI-driven models make it possible to have adaptive, stochastic energy management contracts between prosumers and the grid, which allow real-time, flexible, and adaptive energy trading and balancing of supply-demand in the face of uncertainty.

4.3. Grid Integration and Planning

Closely related to these generation forecasts are demand forecasting and grid management. The smart grid technologies are characterized by Artificial Neural Networks, support vector machines (Pandey, Singh, Nawaz, & Kushwaha, 2023), as well as optimization algorithms to forecast power output and usage, and thereby allow balancing the supply and demand dynamically. On-site high-resolution datasets, including China State Grid ones, have further allowed the creation and testing of solid forecasting models, which are critical to day-ahead scheduling and grid stability (Y. Chen & Xu, 2022). Systems with integrated forecasting that combine adaptive decomposition methods with machine learning have been shown to minimize uncertainty in renewable production, thus contributing to grid security and operational strategy (G. Li et al., 2023). As proposed in the cross-regional analysis, e.g., the models of the gray forecasting models, it is necessary that the model selection is required, besides the optimization of the various energy available and the regional conditions (Pandey et al., 2023). Finally, there must be a feedback mechanism inserted into the system to ensure successful renewable energy integration, where the weather forecasting determines what should be produced, which is in turn forwarded to the demand estimate algorithm and grid management algorithm. The identification of the best portfolios of renewable energy projects that were able to balance the profitability and the risk was achieved with the help of the sophisticated AI-based optimization algorithms that could consider some of the aspects, such as the project life, and workforce demands (Goli, 2024).

4.4. Integration with IoT and Edge Computing

4.4.1. IoT and Sensor Networks

The present-day renewable energy systems are based on Artificial Intelligence, the Internet of Things (IoT), and Sensor Networks. IoT sensors and sensor nets are spread over the renewable energy resources (wind turbines, solar panels, and microgrids) to gather real-time data on the environmental conditions, the system state, and power production. This information is then computed with the help of modern AI and machine learning algorithms to provide estimates of electricity production, anomaly detection, and enhanced operational choices. Integrated forecasting systems use adaptive breakdown and machine learning to reduce the uncertainty of renewable energy production, and eventually increase grid stability and reliability (G. Li et al., 2023). In solar PV waste control, smart bins that use IoT technology and machine learning methods such as k-NN and LSTM provide real-time monitoring and classification of garbage, which improves recycling efficiency (Muthusamy, Velusamy, Thandavan, Govindasamy, & Savarimuthu, 2022). Computational intelligence solutions also improve autonomous system decision-making by relying on data gathered by IoT to forecast the condition of a system and optimize communication among machines (Jin, Khan, Alturki, & Ikram, 2023). Multi-agent systems founded on IoT can be used in microgrid applications to provide distributed, peer-to-peer control of networked renewable resources, which can be optimized locally and globally using layered control architectures (Toumia & Hassine, 2021). High-dimensional sensor data of wind farms are fed through deep learning models like CNN-LSTM hybrids to enhance the accuracy of power prediction, which is crucial to environmental sustainability and grid integration (Khan et al., 2021). Combined with these methods, the problems of intermittency, the increase in operational efficiency, and the possibility of expanding the renewable energy systems are addressed.

4.4.2. Edge Computing

The application of artificial intelligence in Edge Computing in Renewable Energy is a new paradigm that enjoys the computational capacity of edge computing devices to compute and analyze data, instead of relying solely on centralized cloud networks. This is the case in the realm of renewable energy, as the AI models can be fitted onto and within the wind and solar systems, or in a cluster of devices interconnected with one another, i.e., smart inverter systems, the controllers of microgrids, and IoT sensors. This local processing is also known to enable quick selection to such activities as resource allocation, fault correction, predictive maintenance, and demand-response optimization in addition to making the reduction of latency or even bandwidth needs (Alhasnawi, Jasim, Rahman, Guerrero, & Esteban, 2021; Elgendy, Muthanna, Shaiba, Ünal, & Khayyat, 2021). The more obscure explanation of such a direction is that renewable-powered plants are gradually becoming increasingly more productive and that hurried and spontaneous autonomous administrations are required to respond to fluctuation to counter intermittency. The decentralized design that can be implemented using edge AI can be applied to Peer-To-Peer (P2P) microgrids and the Internet of Energy (IoE) in order to enable the distributed agents to communicate with each other and coordinate the flows of energy and the grid stability (Alhasnawi et al., 2021; Alsalemi, Amira, Malekmohamadi, & Diao, 2023). Algorithms of more advanced complexity are also being resource-constrained, e.g., deep reinforcement learning, lightweight classification algorithms, etc., such that they can run at low resource requirements and will not consume excessive local hardware (Elgendy et al., 2021). Overall, Edge Computing AI in Renewable Energy is at the boundary of AI, IoT, and energy informatics, and it offers radical opportunities to sustainable environment development, grid innovation, and the achievement of international energy and climate objectives.

5. Renewable Energy Sectoral Trends and Key Insights

5.1. Solar Energy

Implementations of AI in solar energy have a very broad range, including enhancing the precision of solar irradiance and estimating energy production, in addition to streamlining production operations and enabling intelligent energy distribution. As an example, hybrid AI systems, which integrate Convolutional Neural Networks (CNNs), Long Short-Term Memory models, as well as reinforcement learning, are being applied to predict solar radiation, regulate two-axis monitoring, and enable decentralized energy trade, thus increasing the efficiency and adaptability of solar energy generation (Mamodiya et al., 2025). Explainable AI and deep learning in manufacturing. In manufacturing, high-dimensional sensor data can be analyzed using explainable AI and deep learning to understand process dynamics that could not be analyzed previously by humans and speed up the journey to scalable, high-quality manufacturing (Klein et al., 2024).

Another important contribution that AI makes to energy distribution is in remote or off- grid settings. Artificial Intelligence-Driven Peer-To-Peer (P2P) energy trading networks are designed to optimize the distribution of energy produced by the Sun to the community and residential use, overcoming such issues as storage capacity and fluctuating demand [81]. Hybrid models combine deep learning through generative Large Language Models (LLMs) not only to enhance prediction accuracy but also to increase interpretability, making solar predictions even more actionable to grid operators and planners. The comparative analysis of AI models predicting solar irradiance reveals that hybrid and deep learning techniques (e.g., CNN-LSTM-ANN) tend to perform better than the traditional regression and tree-based models, particularly when the prediction time span and time horizon are varied (Bamisile et al., 2022). Finally, to visualize and analyze large-scale solar infrastructure and to aid land use planning and policy development with a high-accuracy geospatial dataset, spatially explicit machine learning techniques are currently being employed (Ortiz et al., 2022).

5.2. Wind Energy

Artificial intelligence in wind energy can solve a number of typical issues: the inherent variability of wind, the complexity of turbine systems, and the need to have accurate forecasting and successful grid integration. The traditional statistical models often fail to capture the multivariate, non-linear nature of wind energy systems. In much the same way as in the optimum operation and maintenance of turbines, AI methods, such as deep learning and neural networks, as well as hybrid models, have proven more successful in predicting wind velocity and energy production. More sophisticated diagnostics and performance evaluation, multivariate power curve models are being constructed using explainable AI methods (Astolfi, De Caro, & Vaccaro, 2023), instead of simplistic univariate methods, and enable much more subtle diagnostics. Kolmogorov-Arnold Networks, Multilayer Perceptrons, and other advanced models are also effective in forecasting and are better than traditional methods since they are scalable and can be better understood (Mubarak et al., 2024). Hybrid deep learning models that combine techniques like Gradient Boosting, Random Forest, and LSTM with empirical mode decomposition can improve the accuracy of daily wind speed forecasts by a significant margin (Band et al., 2025).

The other use of the AI is the enhanced prediction of wind energy. The mathematical resolution of data into trend and fluctuation data on wind speeds and the deep learning carried out on each subdivision of these data help the researcher to generate quality and more valid predictions about the grid stability (Zhang, Li, & Zhang, 2021). The ANNs have been utilized to control wind turbines to enhance the operation of the Doubly Fed Induction Generator (DFIGs) and reduce the variability of power, and attained good quality of power in the actual wind condition (Dardabi et al., 2024). Along with massive appraisals, wind energy expectations, that is to say, equipment management, and grid incorporation, indicate the relevance of AI in a bid to minimize the cost and technical and environmental complexities that emerge in connection with the diversified utilization of renewable energy.

5.3. Hydropower

The artificial intelligence process in which the hydro power is exposed to is not only that which handles the technical issues, but also the ecological issues. The immersive analytics can be referred to as the systems that assemble the sensor data with the simulations, enabling the engineers to visualize and estimate the life cycles of the hydro turbine, which are essential in the problems regarding the maintenance and reliability. Efficient algorithm optimization, particularly with evolutionary methods, can yield significant energy efficiency (Dardabi et al., 2024).

Specifically, one of the cases of the moth swarm algorithm resulted in the generation of more significant power production (more than 65 percent as compared to the real one), which might be explained by the fact that the AI is capable of optimizing the expenditures of the resources (Sharifi, Akbarifard, Madadi, Qaderi, & Akbarifard, 2022). In addition to technical enhancement, AI is essential to digitization and real-time control systems that can help reduce the environmental implications of hydropower.

To achieve energy generation at the expense of ecosystem conservation, digital, data, communication, and control technologies (Medeiros, Kaufmann, & Schmidt, 2025) are being implemented, usually powered by AI, in support of a wider sustainability agenda like the EU Green Deal (Quaranta et al., 2023).

The AI applications in the broader water field are divided into modeling, prediction and forecasting, decision support, and operational management, and the latter is increasingly focused on responsible and ethical AI applications (Doorn, 2021). Integration of AI and energy systems is a dimension of a greater change in the direction of Energy 4.0, which is a digitization and smartness of energy industries that transform the face of traditional energy. This integration is not just enhancing operational efficiency, but regional and national energy transition is also being encouraged, as seen in large-scale research in China (Dong, Zhang, Zhu, & Sun, 2021). Although most of the literature is on wind and solar, the principles and concerns are extremely applicable to hydropower, especially on prediction, grid integration, and equipment management (L. Zhao et al., 2022). Table 2 displays sector-specific AI applications.

Table 2. Sector-Specific AI Applications

Energy Sector	AI Methods Used	Specific Applications	Key Performance Metrics	Reference
Solar Energy	CNN-LSTM, XGBoost, Reinforcement Learning	Irradiance prediction, two-axis tracking, P2P energy trading, temperature/humidity prediction	MAE=1.544, RMSE=1.242, R^2=0.947	[1, 12, 54]
Wind Energy	LSTM, Random Forest, Gradient Boosting, P-RF algorithm	Wind speed forecasting, turbine performance monitoring, and fault detection	96% operating efficiency, 20% cost reduction	[13, 38, 59]
Hydropower	Evolutionary algorithms, Moth Swarm Algorithm, Digital Twins	Energy generation optimization, condition monitoring, lifecycle analysis	>65% power generation improvement	[2, 55, 73]

6. Challenges and Limitations

6.1. Data Quality and Availability

The AI applications in renewable energy are based on data quality and availability, which are still significant hindrances. In renewable energy technologies, including wind and solar, there are enormous volumes of various data produced by various sources. Nevertheless, this information is usually inadequate, incoherent, or disjointed, which limits its use to the development of effective AI models [59]. Specifically, the prediction of wind speed, which is a crucial factor in the development of wind energy, requires sufficient meteorological data, but any change in the data period and quality may significantly affect the functioning of AI models [83]. In addition, the lack of established data collection and sharing strategies do not enable integrating and analyzing project or region-wide data, which also complicates such issues.

6.2. Model Interpretability and Complexity

Highly developed AI models, particularly those built on deep learning, operate as black boxes, creating barriers to trust and limiting their adoption in critical infrastructure. The stakeholders would want to know whether there is transparency in the process of making decisions during the time that the AI systems are undertaking the basic processes or making risky investments.

6.3. Computational Requirements

The cost of building and operating complex AI models can involve costly computations that can potentially require specially designed hardware and use a lot of energy. This is a contradiction in that AI machines that target the maximization of renewable energy can cause massive environmental footprints.

6.4. Interoperability and Standardization

The other issues that are related are interoperability and standardization. The technology in the renewable energy industry is diverse in format and platforms, as well as actors that possess their own data formats and protocols. This is discouraged non-uniformity within artificial intelligence frameworks that need data sharing and integration effortlessly to allow the systems to be applicable in vast volumes. The implementation of these principles has been advocated by the adoption of the FAIR (Findable, Accessible, Interoperable, Reusable) data standards, but the implementation of these principles is in progress, and too many loopholes in the implementation processes are still evident in the industry. The distributed registry technologies defined as blockchain technologies have been cited as the possible source of interoperability, but they are not new and also have their own technical and legal challenges (Henninger & Mashatan, 2022). These are not only technical issues but also have dire consequences for the reliability, transparency, and scalability of AI-based solutions to renewable energy. They require the integration of the information, standardization, and intersectoral collaboration.

6.5. Scalability Issues

Most of these AI systems that have been demonstrated in controlled settings, or in small-scale pilot projects, are very difficult to scale to commercial or grid-level usage. The obstacles involve the restriction of the computing facilities, a real-time operations environment, and the interface of the old infrastructure.

6.6. Security and Privacy

Perhaps, AI applications in the infrastructure of renewable energy, particularly with respect to smart grids, shared energy resource and peer-to-peer, are subject to considerable cybersecurity, as well as privacy concerns. More significant is the volume of IoT devices and data management systems that directly relate to the clouds, and the mechanism of energy is more susceptible to any information spillage, computer attacks, and access to the data by people at any price. Especially, the full life cycle of energy big data, including its collection to destruction, offers distinct threats in security and privacy, and consequently demands specific risk assessment frameworks and technological breakthroughs in risk reduction, e.g., encryption, integrity checks, and high-security systems of conveying messages (Rai, Shukla, Tightiz, & Padmanaban, 2024). Although there are royal goals of efficiency and resiliency in decentralization of energy systems, it is bound to increase the decentralization-security-privacy trilemma. The social welfare maximization intentions achieved by the implementation of decentralized AI schemes may unintentionally jeopardize one's security or privacy, just as it has been the case with the emergent management orders (Sun, Ma, Zhao, Xin, & Chen, 2024). To do away with these issues, permissioned ledger and blockchain have also been suggested in the recent past to provide verifiable and recoverable data on transactions and privacy-enabling mechanisms. These solutions, however, pose a huge bottleneck to performance, especially the challenge of opening up to liberated market environments (Pradhan, Singh, Sudha, Reddy, & Roy, 2023).

6.7. Regulatory and Ethical Issues

Relatively and ethically, the pace of AI and digital technology advancement in the energy markets is higher than the implementation of the complicated legal and moral framework. This is a regulatory gap that would introduce uncertainty for the stakeholders and may make the execution of breakthrough AI solutions complex. Some of the ethical aspects encompass the safeguarding of the ownership of data, reduction of algorithmic bias, and transparency in the computerized decision-making processes (Dhirani, Mukhtiar, Chowdhry, & Newe, 2023). Moreover, the threat of social polarization and environmental uncertainty supports the need to develop inclusive and multi-level management and involve stakeholders (Nazir, Ali, Bilal, Sohail, & Iqbal, 2020). All in all, even though technical breakthroughs such as blockchain, reliable multi-party computation, and advanced risk assessment models provide promising mitigation methods, the point at the intersection of technical, regulatory, and ethical worlds is still a significant issue in current studies and policy formulation.

6.8 Economic Challenges

The large initial cost required to meet the AI infrastructure requirements of sensors, computer resources, and qualified people can be prohibitively expensive to smaller businesses or developing countries. Furthermore, defining the unquestionable return on investment and quantifying the value of AI deployments is a problematic issue, especially when the benefits are distributed among multiple stakeholders or obtained over a long period.

6.9. Safety and Reliability Constraints

The introduction of AI in renewable energy systems presents some critical safety concerns that must be considered even before the mass application. In contrast to the case of software applications, where bugs can cause inconvenience, the failure of energy systems can result in either the degradation of equipment, financial losses, or even safety risks. Renewable energy systems are usually carried out in safety-sensitive locations where any wrong decision can be catastrophic. As an example, inadequate battery control may lead to thermal runaway, and poor choices during grid integration may lead to voltage issues or blackouts (S. Gu et al., 2024). Simulation training AI models have a high risk of not transferring safely to real-world systems because of modeling uncertainties and unmodeled dynamical effects. This is especially difficult with renewable energy because system dynamics may be complicated and may be different in installations (S. Gu et al., 2024). Energy systems should be reliable in various situations, such as extreme weather events, equipment malfunctions, and cyberattacks. Safe RL protocols include robustness-related factors by using adversarial training and worst-case optimization (Moldovan & Abbeel, 2012).

6.10. Environmental Impact of AI

Although AI is aimed at assisting in optimizing renewable energy systems, there are ecological impacts associated with the technology. Training massive AI models requires a massive number of computational resources and energy, which adds to carbon emissions. The data centers used to support AI activities have a high-power demand as well as cooling requirements. This creates the need for green AI technologies that reduce the environmental footprint of AI creation and usage.

7. Future Directions and Opportunities

7.1. Emerging AI Technologies

The recent developments in AI have made it possible to use sophisticated tools to solve the issues faced by renewable energy systems. Generative models such as Generative Adversarial Networks (GANs) are being applied to simulate a high-resolution realistic energy generation and consumption setting, which is essential to optimizing grid integration of intermittent resources such as photovoltaics Adding GAN-generated scenarios to an existing real-time adaptive control scheme made the grid significantly more efficient (up to 96%), reduced energy costs by 20% and carbon emissions by 30% (Z. Gu et al., 2025). Federated learning is an innovation that allows numerous edge devices (such as smart meters in households) to collaborate without storing sensitive information in a single location. This approach addresses the issue of privacy and takes advantage of local data diversity. Nevertheless, it is difficult with non-IID (non-independent and identically distributed) data. Recent research has suggested hierarchical federated learning, which is tuned by adaptive hyperparameters, household clustering with similar profiles to enhance prediction accuracy and model robustness (Toderean et al., 2025). It will be easier to determine the amount of energy green buildings will consume by combining various types of deep learning architectures, including Variational Autoencoders (VAEs) and Autonomous Gated Recurrent Units (GRUs). These models consider complex time interrelations as well as anomalies in complex data sets, and therefore, the projections of the models are more reliable and useful (Zeng, Peng, & Han, 2025). Machine learning in general is used to optimize bioenergy systems, but this has not yet been widely adopted. ML allows you to model, make decisions, and make guesses about what will occur, but there remain problems with the quality of the data, its accessibility to comprehend, and its effectiveness in utilizing domain knowledge.

7.2. AI and Sustainability

The use of AI in sustainability is seen in different areas. Within the framework of SDGs, AI will stimulate green technology innovation and renewable energy transition, as will be seen in the case of India, where AI and green technology innovation will play a significant role in facilitating long-term green growth, which is in line with SDG 8 (Decent Work and Economic Growth), and SDG 9 (Industry, Innovation, and Infrastructure) (Ueda et al., 2024). The scope of AI goes to carbon neutrality, where household-level green technology implementation can be optimized with behavioral training and subsidies, being able to expedite carbon-neutral transitions (Ren, Abbas, Hussain, Hu, & Li, 2024). Carbon capture technologies are also highly dependent on AI. It applies machine learning and deep learning technology in order to streamline carbon sequestration processes and broaden them, which should not be permitted to become climate change. Nevertheless, it is not only the biological impact of AI that we can exclude. One can be highly concerned by the amount of energy consumed to train AI models and deploy them, not to mention that data centers have a high carbon footprint. These issues must be addressed holistically that is, it will involve the implementation of energy efficient AI frameworks, which will be managing the data centers in an environmentally friendly fashion and recycling the electronic waste in a sustainable manner (Ueda et al., 2024). AI has been demonstrated to lessen ecological footprints on the planet, particularly in advanced nations. The effect is even greater, as the sustainability activities powered by AI are being popularized through the help of globalization (Q. Wang, Sun, & Li, 2023).

8. Conclusion

8.1. Summary of Key Findings

The application of Artificial Intelligence (AI) within the renewable energy enterprise is a novel concept; the adoption is an excellent trend towards a sustainable energy future. This review has explained the fact that AI technologies are enhancing the renewable energy market in an enormous positive manner. The machine learning and deep learning models have exposed that it is the most efficient weapon in the undertaking of solar and wind power generation, which has the challenge of intermittency squarely facing it. Powered by AI predictive maintenance in operations, it reduces the number of disruptions and costs incurred by predicting the breakdown of systems in resources such as wind turbines and solar farms. In addition, through reinforcement learning, grid stability is being optimized, and dynamic peer-to-peer power trading is possible in complex systems with high renewable penetration. Empirically, AI is also a green innovation driver, which helps to grow the world in the long run and helps to achieve significant Sustainable Development Goals (SDGs). Nonetheless, the integration has significant challenges. Data quality and interoperability, computational cost and environmental footprint of AI models, cybersecurity risks in smart grids, and the nature of complex and black-box algorithms themselves, which may discourage trust and adoption, are the challenges faced by the field.

8.2. Critical Insights

The precision and availability of training data are very critical to the effectiveness of AI in renewable energy. The inconsistency of the renewable energy systems and the lack of standardization remain a problem. Nonetheless, the multidimensionality of the renewable energy issues has been revealed to be highly promising when it comes to hybrid AI techniques, where other methodologies are used. According to the studies associated with industry, AI has developed to be very prevalent in terms of solar and wind energy, whereas hydropower and new technologies, including bio-electrochemical systems, are the prospects. The emergence of AI + IoT and edge computing is enabling more responsive and decentralized energy systems, which adhere to the paradigm of centralized control.

8.3. Final Thoughts

AI interaction with renewable energy is gradually becoming more of a tool to achieve gradual efficiency in a part of the new energy system. AI will be the very heart of the nervous system that surrounds our clean energy systems of the future buildings in the form of multilayered and decentralized.

The stakeholders will be able to open the doors of the future in which a smart, flexible energy system will be able to hasten the process of sustainability in the world, and this will not be a possibility, but will also be efficient and resilient when the issue of data and security, as well as transparency, is solved. The next-generation highway requires more advancements in AI systems, long-term investment in material infrastructure and human resources, an inflexible system of regulations creating balance between innovation and safety, and socially responsible interdisciplinary and industrial cooperation. With renewable energy quickly replacing non-renewable energy at the center of the world's energy structures, the role of AI will be even higher, and even closer to a sustainable, efficient, and equalitarian energy future than ever before. It will be open to every individual.

Conflicts of Interest

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