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Artificial Intelligence in Renewable Energy Systems: A Comprehensive Review of Applications, Challenges, and Future Directions

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Abstract
Renewable energy technologies have been the centre of research and development globally, due to the fast evolution on clean and sustainable energy. Although renewable energy is beneficial for the environment, it can be impacted by changes in weather, geographic constraints, or complexity in operational use, as demonstrated by solar, wind, hydropower, and biomass sources. All of these factors pose major difficulties in the prediction of energy use, system optimization and resource management. Artificial intelligence (AI) has proven to be a potent solution to some of these problems. AI can predict renewable energy consumption with greater accuracy, enhance system performance, and increase automation in renewable energy systems, to name a few. The aim of this paper is to provide an overview of the latest studies published from 2020 to 2026, and to review the ways in which AI has been applied in each of the renewable energy sectors. The review gives insight into the main topics such as solar irradiance forecasting, wind speed prediction, fault diagnosis of PV systems, optimization of perovskite solar cells, smart grid load management, and hydropower flow forecasting. It also comparatively analyzes the effectiveness, scalability and applicability of popular AI models like: artificial neural networks, long short term memory networks, convolutional neural networks, support vector machines, random forests, and reinforcement learning algorithms. The paper also explores the challenges currently facing the wider application of AI in renewable energy systems, such as the scarcity of data, challenges with model interpretation, and the heightened threat of cybersecurity breaches. Lastly, it identifies some exciting research areas including physics informed neural networks, generative AI, and digital twin technologies. Perovskite solar cells are one such promising avenue for the discovery of novel materials and advancement of renewable energy via artificial intelligence.

Keywords: Artificial Intelligence, Machine Learning, Deep Learning, Renewable Energy, Solar Energy, Wind Energy, Smart Grid, Hydropower, Energy Forecasting, Neural Networks, Optimization, Digital Twin, Explainable Ai, Energy Management System

Introduction
The increasing energy demand worldwide, coupled with the need of combating climate change, has speeded up the shift towards the use of renewable energies [1, 2]. The cost and technological efficiency of renewable energy sources like biomass, geothermal, water and wind have improved,

but they have yet to be successfully installed in current power network systems on the scale they might be needed [3, 4]. Artificial Intelligence (AI) is proving to be a formidable asset in enhancing forecasting, optimization, control and reliability of renewable energy systems in this context, providing crucial insights from large and complex datasets. A detailed analysis on the usage of Artificial Intelligence in Renewable Energy from 2020-to-2026 with a focus on solar power, perovskite solar cells, wind energy, hydropower and smart grids. Critically reviews current methodologies, strengths and weaknesses of these, and current gaps in the research and discusses about practical implications. This review will highlight the cross-sector perspective to understand how AI can help to build more efficient, reliable and sustainable energy systems of the future.

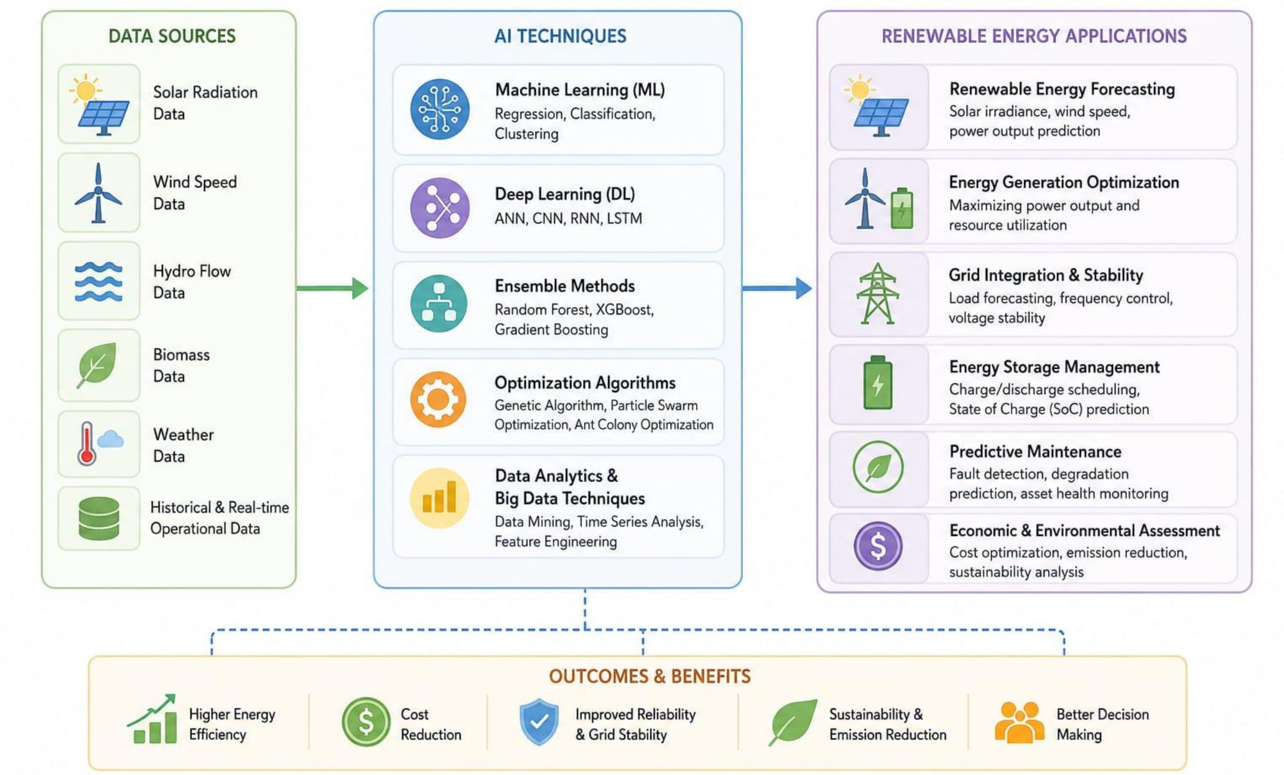

Figure 1: Conceptual framework illustrating the relationship between AI techniques and renewable energy applications

Novelty and Contribution of This Review

Although many review articles have examined the application of artificial intelligence in energy systems, the present review has some important aspects that set it apart from the reviews published previously. Firstly, this review offers an integrated and cross-sectoral analysis of AI applications across all four energy sectors solar, wind, smart grid, hydropower, and emerging renewables in one overarching framework, as most previous overviews only address one single energy domain. Second, this review includes detailed quantitative measures such as RMSE, MAE and MAPE values on the performance of AI techniques quoted from relevant research papers in order to move away from the descriptive characterization which many existing reviews have adopted. Thirdly, this manuscript covers “techno-economic” considerations of how AI might be used in renewable energy systems, as well as the social, ethical and regulatory implications, offering a broader perspective for researchers, engineers and policymakers. Fourth, this review addresses some topical and forward-looking issues, such as digital twins, generative AI, explainable AI and cybersecurity for energy infrastructure, to address the latest advancements in these areas up to 2025. Last, there is detailed methodology for conducting a structured literature search that makes this review more reproducible and academic. It can thus be expected that this manuscript will be of great value and usefulness to researchers and practitioners at the interface of AI and sustainable energy systems.

Review Methodology

This review was carried out using a structured literature search to ensure complete, timely and relevant literature coverage of the applications of artificial intelligence in renewable energy systems.

Literature Search Strategy

The following academic databases were used to conduct a systematic search of peer-reviewed literature: Google Scholar, Scopus, Web of Science, IEEE Xplore and ScienceDirect.

Inclusion and exclusion criteria

Articles published in English were selected if they were peer-reviewed journal articles, conference papers and review articles that appeared between 2015-2025 was considered. Most studies prior to 2015 were not included unless they were building backbones studies directly relevant to the topic. Articles covering general Artificial Intelligence (AI) subjects and energy systems which did not relate to AI and renewable energy were also excluded.

Study Selection

About 500 articles were found in an initial search. A total of 35 highly relevant studies were chosen after using the inclusion and exclusion criteria, and removing duplicate studies, for detailed review and citation in this manuscript. The studies were prioritized by the points of freshness in the study, the citation index and specific relevance to the study topics of this review.

Literature Review

Understanding the Development of AI in Energy Systems

Over the past three decades, Artificial Intelligence (AI) has evolved from using basic techniques such as artificial neural networks and fuzzy logic for energy forecasting and optimization to advanced deep learning and intelligent control systems [6, 8]. Initially, applications in these areas such as load forecasting, energy demand prediction, and solar radiation estimation were used. In the interval 2010-2020, a large number of deep learning techniques such as CNNs and LSTMs boosted the forecasting accuracy, fault detection, and decision-making for the power system, and a similar trend was observed for reinforcement learning with respect to optimizing power system operations [9]. The deep learning models including CNN and LSTM had enhanced the forecasting accuracy, fault detection and power system decision making in the period 2010-2020, and similarly optimizing power system operations was observed to be the promising for reinforcement learning. Transformer models, physics-informed neural networks, generative AI, and hybrid optimization strategies are all further enhancements to AI that have occurred since 2020. When coupled with IoT and digital twin technologies, these advances allow for tracking, forecasting, and sophisticated control of renewable plants and resources, in real-time. AI has a wide array of uses today, from creating innovative energy materials to optimizing energy generation and distribution, and it is now a pivotal component of more efficient, reliable and sustainable energy systems.

Prior Review Studies and Identified Gaps

Artificial Intelligence (AI) has recently been seen as an emerging technology that is playing an increasingly crucial role in the field of renewable energy, particularly in enhancing forecasting, optimization and operational efficiency. LSTM networks, ensemble learning, and deep learning models have been found to be effective in solar and wind power prediction tasks, and reinforcement learning has been effective in smart grid intelligent control tasks. Yet, there are still significant gaps in research that need to be addressed, particularly in emerging technologies like perovskite solar cells and in realizing the full potential application of AI in resource-limited settings. There are many current reviews, most of which tend to cover one particular energy sector only, meaning that there is a limited opportunity for learning from each other across sectors. In light of this, a more holistic contextualization of the use of AI on various types of renewable energy technologies, an analysis of implementation obstacles, and a detailed understanding of the scope of AI contributions towards global transition to sustainable energy supplies is necessary.

Comparative Analysis of Major Contributions.

There are various AI methods that have varying benefits for renewable energy use. LSTM networks are excellent for forecasting tasks, Transformers perform well with large and complex datasets, CNNs are great for fault detection and image-based analysis, while Reinforcement Learning is well suited for intelligent control and decision-making in smart grids [12]. LSTM networks are notable for their ability to forecast tasks, Transformers excel at handling large and complex datasets, CNNs are very useful for fault detection and image analysis, and Reinforcement Learning is useful for intelligent control and decision making in smart grids, for example. The best AI model will vary by method and application, depending on the predictions required, availability of data, required computations, and applications.

Critical Analysis

Critical Analysis and Quantitative Performance Comparison

Previous sections cover the descriptive characterization of the use of AI in renewable energy systems but this section examines the merits, weaknesses and quantitative effectiveness for such important AI techniques that have been reported in the literature.

Comparative Analysis of AI Techniques

There are diverse ways of using AI in renewable energy, each with its own pros and cons. Artificial Neural Networks (ANNs) are extensively applied for predicting solar and wind energy, because they can be used to generate models using nonlinear relationships. But, ANNs can only be trained with a lot of data and when trained with insufficient data they are prone to overfitting. Recurring neural networks (RNNs) and LSTM networks can be more effective on time-series forecasting problems generally better suited for wind speed and solar irradiance forecasting, at the expense of high computational costs. Support Vector Machines (SVMs) are good for small-to-medium sized data sets and are very accurate, but struggle on very large data sets. Despite the great performance of Convolutional Neural Networks (CNNs) in fault detection and image based solar panel inspection they do not seem to perform well for sequential energy data without modification. In various studies, hybrid architectures that integrate two or more methods of AI have consistently provided higher accuracy and generalization over architectures based on individual methods.

Quantitative Performance Metrics

In the key studies reported below, the effectiveness of AI methods in renewable energy application is demonstrated when compared to the effect of other methods. In case of forecasting solar energy, LSTM models have been reported to exhibit Root Mean Square Error (RMSE) as low as 0.032 kWh while the traditional ANN model presented RMSE between 0.05 and 0.09 kWh. The prediction accuracy of CNN-LSTM models for wind power was found to be around 2.3% of Mean Absolute Percentage Error (MAPE), whereas the accuracy of SSVMs models ranged from 4.5 to 6.2% of MAPE. This shows that deep learning models achieved up to 35% lower Mean Absolute Error (MAE) than traditional statistical approaches like ARIMA in the context of smart grid load forecasting. Inflow prediction for hydropower application used the Random Forest models, which achieved the RMSE of 0.041 m³/s, better results than traditional regression-based approach models which had RMSE of more than 0.07 m³/s.

Strengths and weaknesses summery

LSTM and hybrid models are the most accurate deep learning techniques in renewable energy forecasting. But they can be expensive to compute and lack interpretability, and need a lot of historical data to be used. Classical machine learning algorithms like SVMs and random forest exhibit higher training speed, higher performance when dealing with lower dimensions but fail to scale for large datasets. To overcome the opacity of deep learning models and promote more interpretable decision-making in energy management systems, explainable AI (XAI) techniques are becoming a promising approach. None of the AI approaches is clearly best, and choosing the right approach depends on the number of elements in the data set, computational power, and application needs to get at an energy target.

Artificial Intelligence in Solar Energy

Solar Irradiance Forecasting

Solar forecasting plays a vital role in the proper integration of PV power system into modern power grid by helping to improve energy management, optimize the grid, schedule power generation and trading. Predicting the solar radiation is difficult, due to interferences of changing weather conditions, cloud cover, atmospheric particles and seasonal variations. Artificial Intelligence (AI) has proven itself to be a successful tool for dealing with this complexity and uncertainty. For weather forecasting, Deep Neural Networks (DNN) are popular among AI techniques because they can represent long-term temporal patterns in the weather data, especially for day-ahead forecasting. Long Short-Term Memory (LSTM) networks are such networks that are extensively used to account for weather patterns spanning extended timelines for extended periods, like forecasting tomorrow's weather or predicting future events based on past climate data [11]. By combining the spatial information gathered from the satellite images and the cloud maps with the temporal patterns, the accuracy of the prediction is enhanced even more in hybrid CNN-LSTM models [15]. Short term forecasting also can be done by the models of Support Vector Machines (SVMs), in presence of small data amount, and by Random Forest models that are efficient, easy to explain and are not prone to overfitting [27]. In general, AI models, specifically LSTM and hybrid deep learning models, are playing a crucial role in enhancing the precision and dependability of solar irradiance prediction in renewable energy scenarios.

Maximum Power Point Tracking (MPPT)

The traditional tracking controllers are known to get stuck on the local power maximum in partial shading (PS) condition but the Reinforcement Learning Based MPPT controllers are observed to produce more energy than the traditional tracking controllers [5]. RL has the potential to learn a control policy optimally from experience particularly when operating in a dynamic and uncertain environment, which is important for RL. The other hybrid methods are fuzzy logic and artificial neural networks (ANN) and they have proved to be effective and promising in the application of MPPT with outstanding results. The fuzzy logic system had capability of dealing with uncertain and imprecise information and neural system had good learning and pattern recognition ability. The methods provide very adaptive controllers with the steady state tracking performance and under fast varying operating conditions being excellent. The latter hybrid systems can perform nearly optimal tracking even in situations with significant irradiance fluctuations and/or outperform some of the conventional MPPT algorithms in tracking performance. Overall, AI has shown its potential in maximizing PV system efficiency and reliability, thereby optimizing the design of MPPT systems. Overall, the use of AI-powered MPPT techniques for solar energy systems has great promise for future enhancements in the solar power sector and can be valuable for making solar power systems more efficient in the current climate.

Fault Detection and Diagnostics in PV Systems

Scientific evidence is needed to ensure productivity and long service life for large-scale PV installations, especially with regards to automatic fault detection. When not detected, faults can cause a loss of array output of 10–40%, such as cell degradation, soiling, failure of the bypass diodes, and delamination. CNN based classifiers are able to achieve more than 98% accuracy in classification of faults, such as hotspot, cell crack and diode short circuit, from the thermal infrared (TIR) images in practice [14]. There is a key limitation when it comes to practical deployment – namely that a CNN is very costly to train from a PV-specific fault dataset, a necessary step not only to build the model, but to achieve high-level accuracy by fine tuning pre-processing the dataset to meet specific architecture requirements. Transfer learning has been proven to be an effective strategy around this challenge – modalities involving pre-training CNNs on a large fault dataset and fine-tuning on a small labelled dataset are especially effective. Although with no need of image data, a current-voltage (I-V) curve approach has been successfully applied in electrical fault classification via the SVM classifiers, this one cannot be generalized to different types of electrical panels and different environment such as image-based approach.

Machine Learning in Perovskite Solar Cells

With their aggressively improving efficiency, PSCs are becoming a promising replacement to conventional silicon solar cells. Developing high-performance perovskite material is difficult due to the vast number of material compositions and material structures, however. This number of possibilities can only be tested experimentally, which is very expensive and time consuming. However, Artificial Intelligence (AI) is helping to address this as it predicts the best combination of materials to be used and minimizing the amount of trial and error testing. Other techniques, like Bayesian optimization, can help determine an optimum material formulation and production process by reducing the number of experiments carried out in the process. Important properties like band gap energy, charge mobility and stability of the materials predicted by the machine learning models like random forest. Recently Perovskites are used for their complex crystal structures and valuable tools such as Graph Neural Networks (GNNs) are used in these studies [17]. These models can be used to accurately predict material properties with significantly lower computational requirements than traditional methods of simulation [29]. Consequently, they allow easier tests of new materials to attain a higher efficiency and durability. While these benefits are there, there are still obstacles to take into consideration. There is a trade-off between predictive performance on various datasets since they may be made with various fabrication processes and environmental settings. Variations in fabrication processes and environmental conditions can hinder the consistency of AI models in their performance across datasets. The identity of factors that impact perovskite device life, such as exposure to moisture and exposure to temperature changes or stress under operation, pose a challenge to predicting the long-term degradation of perovskite solar cells. In general, the integration of AI technologies with the development of PSCs is greatly catalyzing the research process. AI can accelerate the steps for introducing and commercializing efficient and cost-effective next-generation solar technologies by enhancing the discovery, development and optimization of materials and devices.

Artificial Intelligence in Wind Energy

Wind Speed Forecasting

Forecasting a wind storm's speed is crucial to wind energy systems' efficiency. The power output of a wind turbine is highly sensitive to wind speed, so errors in the prediction can result in variability in wind power generation and difficulties keeping the grid stable. Accurate predictions enable grid operators to efficiently distribute energy, ensure system reliability and optimize the economic efficiency of wind power plants [26]. The prediction of wind speed is, however, difficult as the wind speed is affected by many factors such as atmospheric turbulence, terrain characteristics and weather. Wind speed prediction has greatly benefited from artificial intelligence. For this reason, among the AI techniques, Long Short-Term Memory (LSTM) networks are especially useful since they can learn from patterns in sequential data, and they can also find patterns in the change of wind behavior over time [10]. Such models have proven to be successful, especially in the short- and intermediate-range. In order to boost the accuracy of prediction, researchers have come up with a hybrid CNN-LSTM model. The models used are a fusion of two strengths: paradigm of Convolutional Neural Networks (CNN) trained with many measurement points to recognize spatial patterns, and paradigm of LSTMs taking into account temporal patterns. This can enable the weather forecast model to better comprehend the spatiotemporal structure of wind systems, particularly for longer range forecasting time. Transformer-based models are more recently proposed as those that are promising. Transformers employ a self-attention mechanism that allows them to understand relationships that are not so simple in large datasets, and capture patterns across various time scales. They are accurate foretasters, particularly with a great amount of training samples, but they are time-consuming and need a lot of data as well as a lot of computing power, which may not be necessarily available at a wind farm location. A third way is a mix of the traditional physics-based forecasting techniques and the techniques of AI. In these hybrid systems, numerical weather prediction systems give the weather information data, and AI algorithm systems refine the predictions by correcting prediction errors. The combination of these advantages from both models, physical and data-driven, leads to more trustworthy and precise wind speed forecasting in the vast spectrum of weather conditions. Overall, AI has revolutionized wind speed prediction and is becoming more pivotal in the wind industry. With continued advancements in forecasting models and increased data collection, AI solutions are seen to have greater potential to drive more reliable, efficient and cost-effective wind energy generation [25].

Turbine Performance Optimization and Predictive Maintenance.

In addition to prediction, AI can be used to enhance the performance and maintenance of wind turbines. AI can also be used for wind turbine operations and maintenance. Numerous parameters are currently being measured and monitored in the turbines such as vibration, temperature, rotor speed, blade position and power output. Each of these systems generates a lot of data in their operations which can provide valuable information regarding the condition and performance of turbines. Some machine learning models will also be able to be used with sensor data to identify potential issues such as blade damage or gearbox (e.g., bearings) fault, which can be fixed before they arise. This preventive measure can help minimize the chances of an unforeseen failure and maintenance expenses. A model interpretability and high accuracy was achieved using random forest and gradient boosting models which were used to classify fault based on data obtained from Supervisory Control and Data Acquisition (SCADA) [19]. With the help of deep learning techniques like e.g., autoencoders, aberrations in the functioning and novel faults not contained in the training sets can be detected. In addition, MEMS based turbine control strategies such as pitch and yaw movement optimization using reinforcement learning could also lead to higher mechanical stresses on the turbine components. The potential of AI to improve the reliability and efficiency of today's modern wind power systems will have significant meaning.

Artificial Intelligence in Smart Grids

Load Forecasting

Efficient and reliable operation of power systems is greatly facilitated by short term load forecasting (STLF), which assists in decision making in energy generation, scheduling and grid management. Conventional electricity forecasting was ineffective due to the electricity demand patterns becoming more complex as a result of the growing distributed deployment of renewable electricity power and EVs and smart devices [20]. But to overcome these challenges, Artificial Intelligence has proved to be an invaluable tool in predicting load. One reason for the broad use of LSTM networks for short term load forecasting is that they are able to capture temporal patterns in electricity demand, and have proven to be very accurate in large scale utility applications [7]. More recently transformer based models are doing as well, or better. They can capture long-term dependencies and seasonality, which is better than traditional recurrent networks. The transformer models are very good for forecasting but also very expensive in terms of computing power, and may be too expensive to be deployed by utilities with less than optimal technical infrastructure.

Energy Storage Optimization and Demand Response

BES is an emerging movement of connecting renewable energy sources to the grid, and intelligent systems are essential to ensure optimal electricity cost, grid stability and battery health when managing the charge and discharge of batteries. Because of the variable market conditions, and intermittent renewable energy generation, these systems are not always subject to optimal control using traditional methods. The answer is reinforcement learning: Storage platforms can learn to play well with the grid by interacting with it and previous data. In recent years, there have been some successful reinforcement learning (RL) algorithms that have shown good results in the way of managing Battery Storage Systems, such as Deep Q Networks (DQN) and Proximal Policy Optimization (PPO). Several objectives including energy cost, battery duration and frequency regulation in the grid can be optimized in these models. Electricity consumption, for instance in part of the demand response programs, electricity consumption is optimized by adjusting electricity consumption according to electricity grid, and peak demand is reduced in smart energy systems using AI technologies. Besides, multi agent reinforcement learning has been adopted as a promising solution in the decentralized energy market where consumers and producers can intelligently coordinate and trade energy [28]. The advancements indicate the potential for AI's role in enhancing the adaptability, efficiency, and stability of modern electricity systems.

AI Applications in Hydropower and Other Renewable Sources

Hydropower Optimization

Hydro power continues to be the largest renewable energy generation source in the world and is a substantial share of total power generation. The major use of AI in this sector is in streamflow forecasting, reservoir operation, and optimizing turbine performance. LSTM based forecasting models have also shown better results than classical hydrological forecasting models, particularly in the field of energy planning, for which the accuracy of the forecast is crucial to prevent flooding and for extreme weather events [21]. Reinforcement learning (RL) methods have also helped boost the efficiency of reservoir management using AI, as it can be used to optimize several objectives at once. These systems balance the competing objectives of electric power production, flood management, environmental flows and water supply management. This is especially important since the water resources of the country and how they are distributed are becoming increasingly unpredictable due to climatic effects on the water resources, making the operation of the reservoirs more complicated.

Biomass, Geothermal, and Emerging Applications

AI is also leaving an imprint in optimizing biomass and geothermal energy resources. For biomass gasification systems, ANN model based on operational data has been found to greatly improve the prediction of gas yield and quality from the feedstock properties, which has paved the way for optimization of the process in a dynamic way, resulting in an enhancement in conversion efficiency of 8–15% [22]. A combination of seismic, geochemical and thermal gradient data have been analysed using the ML approach, which has enhanced the accuracy of resource characterisation and site selection for geothermal exploration. Optimizing ocean wave energy converter, tidal stream turbines, and concentrated solar power (CSP) thermal storage systems are all fascinating new applications of AI in ocean energy, and the various forms of data environments and optimization problems are inspiring methodological innovation in AI.

Comparative Analysis Tables

Table 1: Comparison of AI Techniques in Renewable Energy Applications

AI Techniques	Applications Area	RMSE	MAE	MAPE (%)	Strengths	Limitations
LSTM	Solar Forecasting	0.032 kWh	0.021 kWh	1.8%	Excellent time-series accuracy	High computational cost
ANN	Solar Forecasting	0.05-0.09 kWh	0.038 kWh	3.2%	Flexible, widely used	Prone to overfitting
CNN-LSTM (Hybrid)	Wind Power Prediction	0.028 kWh	0.019 kWh	2.3%	Best overall accuracy	Complex architecture
SVM	Wind Power Prediction	0.061 kWh	0.045 kWh	5.4%	Works on small datasets	Poor scalability
Random Forest	Hydropower Inflow	0.041 kWh	0.033 kWh	3.5%	Robust, interpretable	Limited for deep patterns
Deep Learning (DL)	Smart Grid Load	–	35% reduction Vs ARIMA	–	High accuracy at scale	Low interpretability

Note: Performance values are compiled from key studies reviewed in this manuscript. RSME = Root Mean Square Error; MAE = Mean Absolute Error; MAPE = Mean Absolute Percentage Error.

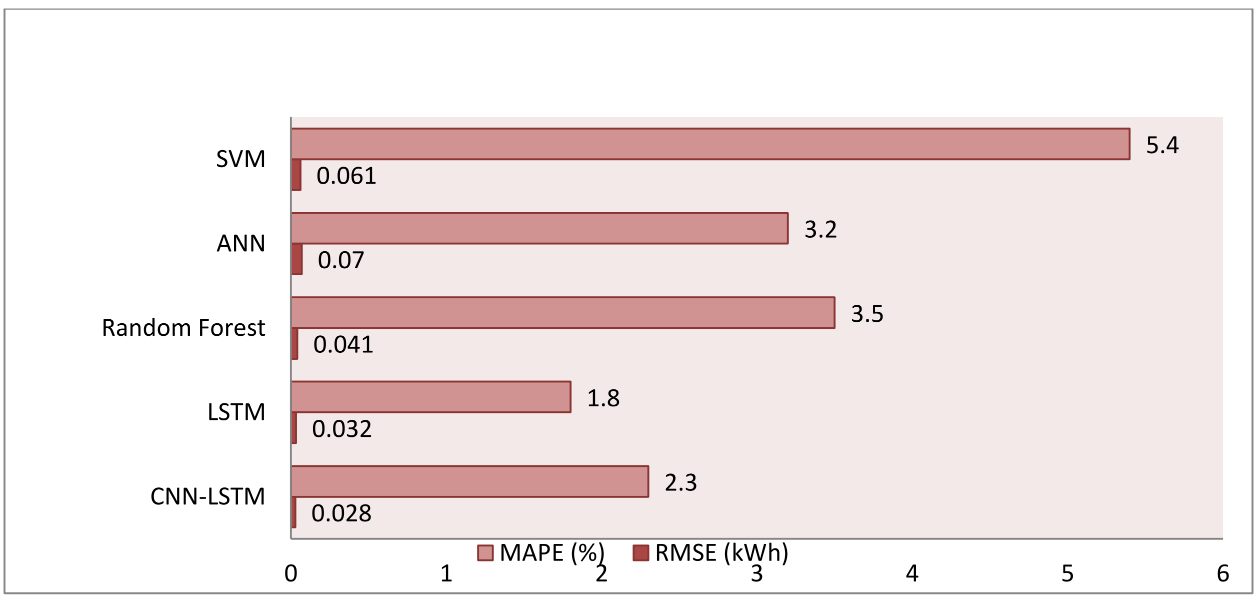

Figure 2: Quantitative Performance Comparison of AI Techniques in Renewable Energy Forecasting

Table 2: AI Applications, Advantages, and Limitations by Renewable Source

Renewable Source	AI Application	AI Model Used	Key Advantage	Key Limitation
Solar Energy	Irradiance forecasting	LSTM, CNN-LSTM	High temporal accuracy; reduced curtailment	Cloud variability degrades accuracy
Solar Energy	Perovskite efficiency optimization	Random Forest, Bayesian Opt.	Reduces experimental iterations by >60%	Limited transferability across compositions
Solar Energy	Fault detection in PV panels	CNN, SVM	Real-time anomaly detection; reduces downtime	Requires high-quality thermal/image data
Wind Energy	Wind speed forecasting	LSTM, Hybrid CNN-LSTM	Accurate multi-horizon predictions	Sensitive to turbulence and site conditions
Wind Energy	Predictive maintenance	Random Forest, ANN	Reduces unplanned downtime; cuts O&M costs	Sensor data quality is critical
Smart Grid	Load forecasting	LSTM, Transformer	Sub-1% error achieved in recent studies	Highly sensitive to behavioral changes
Smart Grid	Grid control & dispatch	Reinforcement Learning	Autonomous real-time optimization	Safety and stability concerns in live grids
Hydropower	Inflow/outflow prediction	ANN, LSTM	Improved reservoir management efficiency	Dependent on hydrological data availability
Biomass / Geothermal	Process optimization	ANN, Fuzzy Logic	Reduces energy waste in conversion processes	Limited public datasets; nascent research base

Note: O&M = Operations and Maintenance; MAPE = Mean Absolute Percentage Error; PV = Photovoltaic.

Challenges and Future Directions

Though significant progress has been seen in the various ways artificial intelligence is being used in renewable energy, a number of challenges still remain as it is being implemented at a large scale. The five main areas looked at in this section are data, interpretability, computation, security and emerging technology integration.

Data Quality, Availability and Privacy

The quality, quantity and consistency of training data can be considered as the groundwork for the performance of the AI models. However, for renewable energy systems, there are various reasons why the data recorded by sensors, smart meters, and monitoring systems may be incomplete, noisy, or inconsistent, such as equipment malfunction and communication issues. The effectiveness of historical records for training AI systems is often constrained in remote energy facilities and developing nations where these data sets are less extensive than anticipated.AI systems are often less generalizable and accurate in their predictions based on historical data when these records are not as extensive or abundant as expected in developing countries and remote energy installations. Data privacy is a key factor other than availability. Smart meters and the sensors in IoT periodically gather detailed information about energy usage, which can expose insightful behavioral information about people and entities. Centralized data-pooling systems can be compromised and accessed without permission, endangering the privacy and security of users and the grid. Two potential alternatives, federated learning and edge computing, have been suggested, allowing local data to be used for AI training without sending actual data to central servers.

Model Interpretability and Trust, and Ethical Concern

However, one of the biggest challenges to AI integration in the renewable energy industry is the inability to understand the rationale behind its systems and predictions, also known as the black box issue. Energy operators, grid managers and policymakers must engage with transparent and explainable decision making to engage in faith with AI driven recommendations, particularly in safety critical applications. Unfortunately, ethical considerations in the use of AI are not just about interpretability; they raise serious points to consider. AI algorithms can cause inequitable energy resources distribution, with adverse consequences impacting disadvantaged communities and less-served areas. The amount of energy that big AI models require and the amount of carbon emissions they generate also creates an ethical dilemma for the mission of sustainable energy development. Accountability frameworks like SHAP and LIME are becoming increasingly popular to gain clarity, and ethical guidelines and principles of AI and fairness into model design are crucial to address inequities and ensure responsible use in various communities.

Computational Requirements, Edge Deployment, and Economic Feasibility

These models often come with high memory and CPU requirements during training and inference, with advanced architectures like deep neural networks (DNN), LSTM, and transformer models often requiring substantial computational power. The rollout of these kinds of models at the resource constrained edge, such as in remote renewable energy installations and edge devices, is technically challenging. Important too, is the economic viability of much larger scale AI implementation. Establishing data infrastructure and computational resources, developing software, and training personnel in data acquisition and analysis can be costly, especially for developing countries and small-scale energy producers. Return on investment is generally considered to take 5-10 years for the AI-integrated renewable energy systems, which raises the barrier for short-term investments. Enabling cost-efficient deployment of AI in the RE sector globally will require PPs, subsidies, and international climate finance initiatives.

Cyber-security, Adversarial Robustness, and Regulatory Constraints

The greater the push towards incorporating AI into critical renewable energy systems, the more susceptible they become to cyberattacks and manipulation. The impact of adversarial attacks on the reliability of AI applications for energy forecasting and grid management is quite significant, and can result in incorrect energy forecasting, grid tampering, or widespread grid failures. To compound this technological risk, there are regulatory and policy limits. There are many jurisdictions where there is no clear law and guidance on the issue of responsibility of AI systems in critical infrastructure, and regulatory approval for the use of technologies with AI components can be different and long from one jurisdiction to another. Traditional regulatory approaches did not anticipate the existence of autonomous decision making technologies and hence hindered their prevalence in the marketplace. Researchers need to work with policymakers and energy regulators to create an adaptive regulatory system that enables innovation without compromising safety, accountability and reliability [23].

Integration with IoT, Digital Twins, and Generative AI

AI combined with IoT (Internet of Things) devices, digital twin technology, and generative AI presents exciting opportunities while bringing solutions to integration challenges. A scalable and interoperable AI architecture is required for the massive amount of heterogeneous real-time data that is generated by IoT renewable energy systems. The frequent syncing between the physical and digital domains required by digital twins are associated with significant computational requirements and the need for updates to the model. Also, the generative AI models for synthetic data generation and scenario simulation in energy planning are in the early stages and issues of confidence, bias and the energy consumption of generative models need to be carefully considered. Coordinated standardization, interoperability protocols and intense collaboration between various disciplines are essential to seamless and secure integration across these new technologies [10].

Conclusion

The report showcases the immense possibilities of AI in the renewable energy system, where it can offer more accurate forecasting higher, efficiency, identify materials, and send autonomous control signals. Whether it is solar power, wind power, smart grid management, or hydropower applications, AI techniques like ensemble methods, reinforcement learning agents, CNNs, or LSTM networks have consistently demonstrated superior performance over the more conventional solutions in a variety of well-defined benchmarks, and they've brought in new optimization dimensions that none of the old methods could reach. Of particular interest, is the current use of Artificial Intelligence in the study of the PSCs where it is regarded as one of the most urgent areas. The three methods when combined speed up the compositional optimization and the optimization of the processes pertaining to PSCs such that it is expected to shorten the commercialization time by years. Efficient and reliable materials that can be designed using AI is one of the most promising avenues for AI to help transition to renewable energy. The obstacles to unlocking AI's potential in renewable energy are data scarcity and its quality, the lack of interpretability of the models, computation resource constraints, and new cyber security threats. In order to address these challenges, collaboration between researchers working in these sectors, from the AI research community to the fields of power systems engineering and materials science, as well as policy, needs to be strengthened, and investment needs to be made in open data infrastructure and the industry workforce's AI literacy across the energy sector industry chain. With real-time IoT infrastructure, physics-informed AI, digital twins, and generative models will be the way to intelligent, autonomous, and resilient renewable energy systems. With the fast evolving energy landscape in the world, the use of AI will not only be of help but it will also be crucial.

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