World Journal of Advanced Engineering Technology and Sciences

eISSN: 2582-8266

Cross Ref DOI: 10.30574/wjaets

Journal homepage: https://wjaets.com/

(Review Article)

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Artificial Intelligence (AI) in renewable energy forecasting and optimization

Ezekiel Ezekiel Smart [1, *], Lois Oyindamola Olanrewaju [2], Joseph Usman [3], Kabiru Otaru [4], Dauda Umar Muhammad [5], Prince Nnamdi Amalu [6] and Emmanuel Toba Popoola [7]

[1] *Department of Mechanical Engineering, Akwa Ibom State University, Nigeria.*
[2] *Department of Electrical and Electronics Engineering, Federal University of Technology Akure, Ondo State, Nigeria.*
[3] *Department of Electrical Engineering, Chulalongkorn University, Thailand.*
[4] *Department of Mechanical Engineering, Bayero University Kano, Nigeria.*
[5] *Department of Electrical and Electronics Engineering, Kebbi State University of Science and Technology Aliero, Nigeria.*
[6] *Department of Electrical and Computer Engineering, Kwara State University, Nigeria.*
[7] *Department of Computer Science and Engineering, Ladoke Akintola University of Technology, Oyo State, Nigeria.*

World Journal of Advanced Engineering Technology and Sciences, 2025, 15(02), 1100-1112

Publication history: Received on 07 March 2025; revised on 13 April 2025; accepted on 15 April 2025

Article DOI: https://doi.org/10.30574/wjaets.2025.15.2.0300

Abstract

The integration of Artificial Intelligence (AI) in renewable energy forecasting and optimization has significantly enhanced the efficiency and reliability of energy systems. The use of AI methods like reinforcement learning, deep learning, and machine learning, to increase the precision of forecasting energy from solar, wind, hydropower, and biomass is examined in this research. AI-driven optimization techniques have proven essential for grid integration, load balancing, energy storage management, and hybrid energy systems. Compared to conventional forecasting methods, AI models demonstrate superior accuracy by effectively processing large-scale, heterogeneous data. Additionally, AI facilitates real-time energy management and predictive maintenance, thereby increasing the sustainability of renewable energy infrastructures. Despite its advantages, challenges such as data quality, computational complexity, cybersecurity risks, and the need for explainable AI remain critical barriers to large-scale adoption. The paper further discusses emerging trends, including the potential of quantum computing and blockchain integration, in advancing AI-driven renewable energy solutions. In order to secure the ethical deployment of AI, future research should concentrate on creating more interpretable AI models, improving energy efficiency, and putting strong regulatory frameworks in place. The insights from this study provide valuable guidance for researchers, policymakers, and industry stakeholders in optimizing renewable energy systems.

Keywords: Artificial Intelligence; Renewable Energy Forecasting; Machine Learning; Deep Learning; Energy Optimization; Smart Grids; Quantum Computing; Blockchain Integration

1. Introduction

The worldwide shift to renewable energy is essential to alleviate climate change and foster sustainable development. Renewable energy sources, such as solar, wind, hydro, and biomass, are essential for diminishing reliance on fossil fuels and mitigating greenhouse gas emissions. As the global energy landscape evolves, ensuring the reliability and efficiency of renewable energy systems remains a significant challenge, particularly due to their intermittent nature [1,2]. Addressing these challenges requires innovative approaches, with artificial intelligence (AI) emerging as a transformative tool for forecasting and optimization.

* Corresponding author: Ezekiel Ezekiel Smart. Email: smartyezekiel@gmail.com

Solar energy harnesses sunlight using photovoltaic cells or concentrated solar power systems to generate electricity. Improvements in photovoltaic technology have enhanced efficiency and lowered prices, rendering solar electricity more attainable. Wind energy transforms the kinetic energy of flowing air into electricity using wind turbines [3]. Technological improvements have led to larger and more efficient turbines, contributing to wind energy's rapid global growth. Hydropower generates electricity by exploiting the energy of moving water, typically through dams or run-of-the-river systems. It continues to be a major global source of renewable power. Utilising combustion or biochemical processes, biomass energy transforms organic materials—such as plant matter and agricultural waste—into energy. This form of energy offers a renewable alternative to fossil fuels, particularly in heating and transportation sectors [4,5].

The incorporation of renewable energy sources into current power networks has distinct problems owing to their fluctuating and sporadic characteristics. Precise forecasting of energy generation is essential for maintaining supply and demand equilibrium, assuring grid stability, and reducing energy loss. For instance, in 2024, nearly 10% of Britain's planned wind output and almost 30% of Northern Ireland's were curtailed due to insufficient capacity to transport or store electricity when demand was low [6]. Optimization is crucial for improving the efficiency and dependability of renewable energy systems. This encompasses enhancing the positioning and functionality of renewable energy systems, improving energy storage solutions, and developing smart grids capable of dynamic responses to fluctuating energy inputs. Effective optimization strategies are essential for reducing costs, maximizing energy output, and facilitating the seamless integration of renewable sources into the broader energy infrastructure [4,6,7].

Artificial intelligence has emerged as a key enabler in renewable energy forecasting and optimization. Machine learning algorithms may considerably increase the accuracy of solar irradiance forecasts and wind speed predictions, hence boosting the dependability of renewable energy systems. AI also plays a role in real-time energy management, enabling smart grids to dynamically modify electricity distribution based on real-time data. As renewable energy adoption accelerates worldwide, integrating AI-driven solutions into energy management strategies will be vital in overcoming existing barriers and maximizing the potential of renewable energy sources [8,9].

This paper attempts to give a detailed overview of the present level of AI applications for forecasting and optimising renewable energy. It will examine various AI methodologies applied to different renewable energy sources, assess their effectiveness, and explore existing challenges and future research directions. By synthesizing recent advancements and case studies, this review seeks to offer valuable insights for researchers, policymakers, and industry stakeholders involved in the global transition to sustainable energy systems.

2. Fundamentals of AI and Machine Learning in Renewable Energy

Artificial intelligence (AI) covers computing systems that are able to do tasks like learning, reasoning, and problem-solving that often call for human intelligence. Within AI, various subfields have arisen, particularly deep learning (DL), reinforcement learning (RL), and machine learning (ML), each offering distinct approaches and applications in renewable energy [10,11].

2.1. Explanation of AI, Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL)

A branch of artificial intelligence called machine learning (ML) focusses on algorithms that let systems learn from and make judgements based on data. ML models identify patterns within datasets, facilitating tasks like classification, regression, and clustering [11]. Deep learning (DL), a branch of machine learning, models complex patterns in data by using multi-layered artificial neural networks. Improvements like speech and picture recognition have been made possible thanks in large part to these deep neural networks. Reinforcement Learning (RL) is a distinct paradigm where agents are led by incentives and punishments to learn the best behaviours through trial-and-error interactions in an environment. RL has been pivotal in developing systems that learn from experience, such as game-playing AI and robotics [12,13].

2.2. Overview of AI Algorithms Commonly Used in Energy Applications

In renewable energy, various AI algorithms have been employed to enhance forecasting accuracy and optimize system operations. Artificial Neural Networks (ANNs) are computer models that can approximate complicated nonlinear interactions since they are modelled after the human brain [7]. They have been widely used for predicting energy consumption and generation patterns. Convolutional Neural Networks (CNNs), primarily designed for processing structured grid data like images, have been adapted for spatial data analysis in energy systems, such as assessing satellite imagery for solar farm site selection [14]. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network, are adept at learning temporal dependencies and have been applied to forecast time-series data like wind speed and solar irradiance. Natural selection serves as the inspiration for genetic algorithms (GAs), which are optimization methods used to address challenging issues in energy management, such as optimizing the configuration of renewable energy systems for improved efficiency [15].

2.3. Key Advantages of AI Over Traditional Forecasting and Optimization Techniques

AI offers several advantages over traditional forecasting and optimization methods in renewable energy applications. Traditional techniques often rely on linear models and assumptions that may not capture the inherent complexities and nonlinearities of energy systems. The basic comparisons have been detailed in Table 1. AI algorithms, however, can model these nonlinear relationships more effectively, leading to improved prediction accuracy. For instance, according to research by Xiao et al. [16], employing LSTM networks for wind power forecasting resulted in a significant reduction in prediction error compared to conventional statistical methods. Additionally, AI models can process vast amounts of heterogeneous data, including weather conditions, historical energy production, and real-time sensor data, enabling more comprehensive and dynamic analysis [17,18]. This capability allows for real-time optimization of energy systems, enhancing their responsiveness and efficiency. Furthermore, AI-driven approaches can adapt to changing patterns and anomalies in data, providing robust performance even under unforeseen circumstances. As noted by Safari et al. [19], integrating AI in energy management systems facilitates adaptive learning and decision-making, which is crucial for accommodating the variability inherent in renewable energy sources.

Table 1 Comparison of Traditional vs AI-Based Forecasting Methods

Forecasting Method	**Data Requirements**	**Accuracy**	**Flexibility**	**Adaptability to Real-Time Conditions**
Statistical Methods (e.g., ARIMA, Exponential Smoothing)	Require structured, stationary historical time series data.	Moderate for short-term forecasts; declines with non-linearity.	Low – limited to linear patterns and trends.	Poor – need re-calibration when data patterns shift.
Physical Models (e.g., Numerical Weather Prediction - NWP)	Depend heavily on meteorological and geophysical inputs.	High when all parameters are known; error-prone with missing data.	Moderate – adaptable to different physical systems but require recalibration.	Limited – high computational demand hinders real-time use.
Hybrid Models (Statistical + Physical)	Combine historical data with physical inputs.	Better than standalone traditional models.	Moderate – more robust than single models.	Moderate – improvements possible with dynamic updates.
Artificial Neural Networks (ANN)	Require large datasets with historical and training samples.	High – especially with large, quality datasets.	High – can model complex, non-linear relationships.	Good – can be retrained frequently with new data.
Support Vector Machines (SVM)	Require well-preprocessed, labeled datasets.	High – particularly for classification and regression tasks.	Moderate – effective for small to medium datasets.	Moderate – adaptation needs tuning of kernel parameters.
Random Forests (RF)	Require historical data with feature variability.	High – resistant to overfitting and robust with noisy data.	High – effective for both classification and regression tasks.	Moderate – retraining can improve real-time adaptability.
Deep Learning (DL) (e.g., LSTM, CNN)	Require very large datasets and computational resources.	Very High – excels in capturing long-term dependencies.	Very High – superior for pattern recognition and multi-dimensional data.	Excellent – can be deployed in real-time with online learning.

3. AI for Renewable Energy Forecasting

The integration of artificial intelligence (AI) into renewable energy forecasting has significantly enhanced the accuracy and reliability of predictions across various energy sources. This section explores AI applications in forecasting for solar, wind, hydropower, and biomass energy, emphasizing the methodologies employed, comparative performances, and real-world implementations [7].

3.1. Solar Energy Forecasting

3.1.1. AI Models Used for Solar Irradiance and Power Output Prediction

Artificial intelligence, particularly deep learning (DL) and machine learning (ML) models, has been extensively applied to forecast solar irradiance and power output. The dependability and effectiveness of solar energy systems are increased by these models' capacity to learn from past weather data and spot intricate patterns that forecast solar irradiance [20]. A thorough analysis by Ghimire et al. [21] found that a number of AI-based models, including as convolutional neural networks (CNNs), support vector machines (SVMs), and artificial neural networks (ANNs), have been employed for solar irradiance prediction, demonstrating superior performance compared to traditional methods. The various AI models for renewable energy forecasting have been summarized in Table 2.

Table 2 Common AI Techniques and Their Applications in Renewable Energy

AI Technique	Typical Applications	Strengths	Limitations
Artificial Neural Networks (ANN)	Solar radiation forecasting, wind speed prediction, power load forecasting	Excellent at modeling complex, non-linear relationships; adaptive learning capabilities	Requires large datasets for training; may overfit if not properly regularized
Support Vector Machines (SVM)	Short-term wind power forecasting, solar energy classification, load prediction	Good generalization for small to medium datasets; robust against overfitting	Kernel selection and parameter tuning can be complex; not ideal for very large datasets
Random Forest (RF)	Energy demand estimation, solar PV output prediction, feature selection	Handles noisy data well; resistant to overfitting; interpretable with feature importance	May struggle with extrapolation; performance can degrade with too many irrelevant features
Decision Trees (DT)	Load forecasting, energy consumption modeling	Easy to interpret; fast to train and deploy	Prone to overfitting when not pruned; lower accuracy than ensemble methods
Deep Learning (DL) (e.g., CNN, LSTM)	Long-term forecasting, multi-variate energy prediction, spatiotemporal modeling	High accuracy; captures complex temporal and spatial dependencies; ideal for large datasets	Requires substantial computational power; long training times; can be a 'black box'
K-Nearest Neighbors (KNN)	Wind direction estimation, anomaly detection in smart grids	Simple to implement; non-parametric; adaptable to different distributions	Computationally expensive with large datasets; sensitive to irrelevant or redundant features
Reinforcement Learning (RL)	Grid optimization, energy storage control, demand response systems	Excellent for dynamic decision-making and sequential optimization tasks	Needs large exploration space and careful reward structuring; longer convergence times
Fuzzy Logic (FL)	Energy flow control in hybrid systems, uncertainty handling in solar/wind models	Effective with uncertain or imprecise inputs; rule-based and interpretable	Rule formulation can be subjective; less accurate than data-driven models in some cases

3.1.2. Performance Comparison of AI-Based vs. Conventional Models

Comparative studies have demonstrated that AI-based models often outperform traditional statistical methods in solar energy forecasting. For instance, a study by Yang et al. [22] compared the performance of ML and DL models against conventional forecasting techniques, finding that AI models provided more accurate predictions of solar irradiance, thereby contributing to more efficient energy management. In table Table 3, the performance metrics used in AI-based models for renewable energy forecasting.

In practical applications, AI-driven models have been successfully implemented to enhance solar energy forecasting. For example, the pvlib python library, an open-source tool, offers functionalities for simulating photovoltaic system performance, aiding in accurate solar energy predictions [23]. This library has been widely adopted in both academic research and industry applications, facilitating the development of advanced forecasting models and contributing to more efficient solar energy systems.

Table 3 Performance Metrics Used in Forecasting

Metric	Definition	Formula	Significance / Interpretation
Mean Absolute Error (MAE)	Average of the absolute differences between predicted and actual values	$MAE = (1/n) * \Sigma\|y_i - \hat{y}_i\|$	Provides a straightforward measure of average magnitude of error without considering direction
Mean Squared Error (MSE)	Average of the squares of the differences between predicted and actual values	$MSE = (1/n) * \Sigma(y_i - \hat{y}_i)^2$	Penalizes larger errors more than MAE, making it sensitive to outliers
Root Mean Squared Error (RMSE)	Square root of MSE	$RMSE = \sqrt{[(1/n) * \Sigma(y_i - \hat{y}_i)^2]}$	Measures the standard deviation of the prediction errors; interpretable in original units
Mean Absolute Percentage Error (MAPE)	Average of the absolute percentage errors	$MAPE = (100/n) * \Sigma\|(y_i - \hat{y}_i) / y_i\|$	Provides error as a percentage, making it useful for comparing forecast accuracy across datasets
Coefficient of Determination (R^2)	Proportion of variance in the dependent variable predictable from the independent variables	$R^2 = 1 - [\Sigma(y_i - \hat{y}_i)^2 / \Sigma(y_i - \bar{y})^2]$	Indicates how well the model fits the data; closer to 1 implies better fit
Normalized Root Mean Square Error (nRMSE)	RMSE normalized to the range or mean of the observed data	$nRMSE = RMSE / (\max(y_i) - \min(y_i))$ or $RMSE / \text{mean}(y_i)$	Allows RMSE comparison across datasets with different scales
Symmetric Mean Absolute Percentage Error (sMAPE)	Modified version of MAPE to avoid division by zero	$sMAPE = (100/n) * \Sigma[\|y_i - \hat{y}_i\| / ((\|y_i\| + \|\hat{y}_i\|)/2)]$	Balances over- and under-forecasts; suitable for data with zero or near-zero values

3.2. Wind Energy Forecasting

3.2.1. Machine Learning Models for Wind Speed and Power Prediction

Neural networks and ensemble techniques are two examples of machine learning models which have been employed to predict wind speed and power output. These models analyze historical wind data to forecast future patterns, thereby enhancing the accuracy of wind energy predictions. For example, the European Centre for Medium-Range Weather Forecasts (ECMWF) has introduced an AI-based system capable of predicting weather up to 15 days in advance, offering global predictions that include wind speeds at turbine height, which is advantageous for the renewable energy sector [24].

3.2.2. Short-Term vs. Long-Term Wind Energy Forecasts

For both short-term and long-term wind energy forecasts, AI models have been developed. While long-term forecasts, which span days to weeks, help with strategic planning and maintenance scheduling, short-term predictions, which span minutes to hours, are crucial for real-time grid management. According to a study by Kaur et al. [25], AI-based models have demonstrated superior performance in both short-term and long-term wind energy forecasts compared to traditional methods, highlighting their potential in enhancing the reliability of wind energy systems.

3.2.3. AI-Based Hybrid Models and Their Accuracy

In wind energy forecasting, hybrid models that integrate AI with conventional physics-based techniques have demonstrated increased accuracy. For instance, the ECMWF's AI-based system integrates numerical weather prediction models with machine learning techniques, resulting in more accurate and reliable wind forecasts [24,26]. This hybrid approach has been particularly effective in predicting the trajectory of tropical cyclones, providing crucial warnings for severe weather events [26].

3.3. Hydropower and Biomass Energy Forecasting

3.3.1. AI Applications in Streamflow Prediction and Hydropower Generation

AI has been applied to predict streamflow, a critical factor in hydropower generation. By analyzing hydrological data, AI models can forecast water availability, optimizing hydropower operations and improving energy reliability. A study by Di Grande et al. [27] demonstrated that AI-based models could accurately predict streamflow, leading to more efficient hydropower generation and better management of water resources.

3.3.2. AI in Bioenergy Feedstock Supply Chain Forecasting

In the biomass energy sector, AI has been utilized to forecast the supply chain of bioenergy feedstocks. By predicting the availability and quality of biomass resources, AI aids in optimizing logistics and ensuring a steady supply for energy production. According to a study by Senocak et al. [28], AI models have been effective in forecasting biomass availability, contributing to more efficient bioenergy production and supply chain management.

4. AI for Renewable Energy Optimization

Artificial Intelligence (AI) has emerged as a key instrument for improving renewable energy systems' dependability and efficiency. AI enables a more robust and sustainable energy infrastructure by optimising a number of components, including energy storage, load balancing, grid integration, and hybrid energy systems. Various AI algorithms for the optimization of renewable energy have been summarized in Table 4.

Table 4 AI Algorithms Used in Renewable Energy Optimization

AI Algorithm	Typical Applications in Renewable Energy	Advantages	Limitations
Genetic Algorithm (GA)	Optimal sizing and placement of renewable energy systems, load dispatch, and scheduling.	Good global search capability, effective for nonlinear problems.	Can be computationally expensive and slow to converge.
Particle Swarm Optimization (PSO)	Power flow optimization, energy storage control, and parameter tuning.	Simple to implement, fast convergence, and fewer parameters.	Prone to premature convergence in complex landscapes.
Ant Colony Optimization (ACO)	Optimal routing in energy distribution networks, resource allocation.	Effective in combinatorial optimization, adaptive to changes.	Sensitive to parameter settings, may require long computation time.
Artificial Neural Networks (ANNs)	Forecasting of solar and wind power, load prediction, energy demand estimation.	Highly flexible and powerful in capturing nonlinear relationships.	Requires large datasets, can overfit without regularization.

Fuzzy Logic Systems	Energy management in microgrids, demand response systems.	Handles imprecise data well, easy to integrate with control systems.	Rule formulation can be subjective and complex.
Reinforcement Learning (RL)	Real-time energy management, smart grid optimization, battery management.	Learns optimal strategies through interaction with environment.	Requires a large number of trials and careful reward shaping.
Support Vector Machines (SVM)	Renewable power forecasting, energy price prediction.	Effective in high-dimensional spaces, good generalization.	Computationally intensive for large datasets.
Deep Learning (DL)	Complex pattern recognition in energy consumption and generation forecasting.	Excellent for unstructured data (e.g., time series, images), high accuracy.	Requires significant computing resources and tuning.

4.1. Grid Integration and Load Balancing

4.1.1. AI-Driven Demand Response Strategies

AI-driven demand response strategies enable the dynamic adjustment of energy consumption to align with supply conditions, thereby enhancing grid stability. For instance, Zhukovskiy et al. [29] developed an algorithm that regulates the load schedule of educational institutions based on electric consumption forecasts, effectively implementing demand response mechanisms.

4.1.2. Smart Grid Applications and Real-Time Energy Management

Real-time energy distribution monitoring and management are made easier by the use of AI into smart grids. The U.S. Department of Energy has recognized AI's potential to address the substantial backlog of renewable energy projects awaiting grid connection, offering up to $30 million to expedite the interconnection review process with AI assistance [30].

4.2. Energy Storage Optimization

4.2.1. AI for Battery Storage Scheduling and Efficiency Improvement

Efficient scheduling of battery storage systems is crucial for balancing supply and demand in renewable energy systems. Companies like GridBeyond utilize AI to enhance the operation of distributed energy resources, including battery storage systems, supporting the transition to net-zero energy systems [31,32].

4.2.2. Predictive Analytics for Battery Health Monitoring

Predictive analytics powered by AI is essential for tracking battery health, facilitating preventative maintenance, and increasing the longevity of energy storage devices. For example, AI applications in building energy management systems have led to significant reductions in HVAC energy consumption, indirectly benefiting battery health by optimizing overall energy usage [33,34].

4.3. Hybrid Energy Systems Optimization

4.3.1. AI-Based Optimization for Multi-Source Renewable Energy Systems

Hybrid energy systems, combining multiple renewable energy sources, benefit from AI's ability to manage complexity and variability. In order to optimise hybrid energy systems, researchers at École Polytechnique Fédérale de Lausanne created the Commelec framework, which offers distributed and real-time control of electrical grids using specific setpoints for active/reactive power absorptions and injections [35].

4.3.2. Role of AI in Microgrid and Smart Grid Optimization

In microgrids and smart grids, AI is essential for integrating renewable energy sources, balancing supply and demand, and ensuring stable operation. Gabriela Hug's research emphasizes the need for distributed cooperative control strategies to coordinate energy storage systems within the grid, demonstrating that AI can effectively manage the charging and discharging of these systems to maintain balance and minimize losses [36].

5. Challenges and Limitations of AI in Renewable Energy

Artificial Intelligence (AI) has a lot of promise to improve the efficiency and dependability of renewable energy systems. However, several challenges and limitations must be addressed to fully realize these benefits. These challenges include data quality and availability issues, computational complexity and model interpretability, the need for explainable AI (XAI) in energy systems, and cybersecurity and ethical concerns [37,38]. These have been summarized in Table 5.

Table 5 Key Challenges in AI-Based Forecasting and Optimization

Challenge	Description	Impact on AI Models	Potential Solutions
Data Quality and Availability	AI models require large volumes of high-quality, labeled, and representative data for training and validation.	Poor or insufficient data leads to inaccurate predictions and reduced model generalizability.	Implement robust data collection infrastructure, use data augmentation techniques, and leverage transfer learning.
Model Interpretability and Transparency	Many advanced AI models, especially deep learning, act as 'black boxes' with limited insight into how decisions are made.	Reduces trust and adoption by stakeholders in critical sectors like energy.	Use explainable AI (XAI) methods, incorporate interpretable models where possible, and visualize model behavior.
Computational Requirements	Training and deploying AI models, especially for real-time or large-scale forecasting, can be resource-intensive.	Limits implementation in regions with low computational infrastructure or budget constraints.	Adopt lightweight models, leverage cloud computing resources, and use efficient model architectures.
Generalization to New Conditions	AI models trained on historical data may struggle to adapt to unseen patterns, especially in dynamic energy systems.	Decreases forecast accuracy in evolving scenarios like climate changes or technology upgrades.	Incorporate continual learning strategies and domain adaptation techniques.
Integration with Physical Models	AI models often function separately from domain-specific physical laws and constraints.	Can produce physically inconsistent or unrealistic outputs in optimization tasks.	Combine AI with physics-informed models or hybrid approaches integrating empirical and data-driven models.
Cybersecurity and Privacy	AI systems in energy infrastructure are vulnerable to data breaches, attacks, and misuse of sensitive information.	Compromises data integrity and public safety; may lead to system outages or manipulation.	Apply robust encryption, access controls, and cybersecurity frameworks; consider federated learning for privacy.
Regulatory and Ethical Concerns	Lack of standardized regulations for deploying AI in renewable energy systems.	Creates uncertainty and slows adoption; may lead to unethical data use or biased decision-making.	Develop and adhere to industry-specific AI governance standards and ethics guidelines.

5.1. Data Quality and Availability Issues

High-quality data is fundamental for the effective application of AI in renewable energy. However, challenges such as inconsistent data collection methods, missing values, and limited access to real-time data can hinder the development of reliable AI models. According to Zhang et al. [39], the variability and unpredictability of renewable energy sources like solar and wind power necessitate robust data collection and management strategies to improve AI model performance. Moreover, Luqman et al. [40] state that data privacy and security are key considerations, especially when sensitive data is employed in cloud-based models. These challenges underscore the importance of establishing standardized data protocols and ensuring data integrity to enhance AI applications in renewable energy.

5.2. Computational Complexity and Model Interpretability

The training and implementation of AI models, particularly deep learning techniques, sometimes need significant computational resources. This high energy consumption contributes to a significant carbon footprint, raising environmental concerns. Strubell et al. [41] highlight that the development and use of AI models, particularly large-scale models, consume large amounts of electricity, which could offset some environmental benefits achieved through renewable energy. Additionally, the complexity of these models often results in limited interpretability, making it difficult for stakeholders to understand the decision-making processes. Bender et al. [42] discuss the challenges in developing machine learning techniques that are both effective and interpretable, noting that the "black-box" nature of AI can hinder trust and acceptance among energy professionals and policymakers. Addressing these issues requires the development of more energy-efficient algorithms and enhancing the transparency of AI models.

5.3. Need for Explainable AI (XAI) in Energy Systems

The necessity of Explainable AI (XAI) in renewable energy applications is highlighted by the opacity of complicated AI models. In order to improve trust and cooperation between AI systems and human operators, XAI seeks to make AI decision-making procedures clear and intelligible. According to Gafni and Levy [43], implementing XAI can enhance the reliability of AI-driven energy management systems by allowing stakeholders to comprehend and validate AI-generated recommendations. Furthermore, Ali et al. [44] emphasize that ensuring model explainability is vital, since sophisticated AI systems must be made interpretable for non-technical stakeholders. By incorporating XAI, energy professionals can better understand AI-driven insights, leading to more informed decision-making in renewable energy management.

5.4. Cybersecurity and Ethical Concerns

The integration of AI into renewable energy infrastructures introduces cybersecurity vulnerabilities, as interconnected systems become potential targets for cyberattacks. Protecting sensitive data and ensuring the resilience of energy systems against malicious activities are critical challenges. Hoffman [45] argues that AI will increase 'first strike' incentives and could lead to more aggressive and destabilising assaults, further exacerbating the already unbalanced game between cyber attackers and cyber defenders. Additionally, ethical considerations arise concerning data privacy, the environmental impact of AI's energy consumption, and the potential displacement of jobs due to automation. Bender et al. [42] highlight that under-represented groups may be further marginalised by big language models that encode hegemonic and biassed ideas. A multidisciplinary strategy is needed to address these issues, integrating technological know-how with moral and legal considerations to guarantee the safety and equity of AI applications in renewable energy.

6. Future Research Directions

Advancements in artificial intelligence (AI) have significantly impacted renewable energy forecasting and optimization. However, emerging technologies and methodologies present new avenues for research to increase the renewable energy systems' dependability and efficiency.

6.1. Emerging Trends in AI for Energy Forecasting and Optimization

Recent developments in AI have introduced sophisticated techniques for energy forecasting and optimization. For example, the intricate, non-linear dynamics of power pricing have been modelled using computational intelligence techniques like support vector machines and artificial neural networks. These models demonstrate an improved ability to handle the volatility and spiky nature of energy markets compared to traditional statistical methods [46,47]. Additionally, the integration of deep learning models, including distributional neural networks, has shown promise in capturing intricate patterns in energy data, leading to more accurate predictions [48].

6.2. Potential of Quantum Computing in Renewable Energy AI Models

Quantum computing offers the potential to revolutionize AI applications in renewable energy by solving complex optimization problems more efficiently than classical computers. Researchers like Veeramachaneni [49] have explored the integration of quantum computing with AI to enhance the intelligence of power grids, suggesting that such integration could lead to more efficient energy distribution and management. However, challenges remain in developing practical quantum algorithms and ensuring their scalability for real-world energy systems.

6.3. Integration of AI with Blockchain for Decentralized Energy Management

The combination of AI and blockchain technology presents opportunities for decentralized energy management systems. Peer-to-peer energy trade can be facilitated by the transparent and safe ledger of blockchain technology, and

AI can optimise patterns of energy generation and consumption. This integration could lead to more resilient and efficient energy systems. According to a report by Mohamed [50], companies are employing generative AI to analyze and forecast data in the energy freight market, highlighting AI's transformative potential in energy management. Further research is needed to address scalability, interoperability, and regulatory challenges associated with integrating these technologies.

6.4. Policy Implications and Regulatory Considerations

The rapid adoption of AI in renewable energy necessitates the development of policies and regulations that ensure ethical use, data privacy, and system security. Policymakers must balance fostering innovation with protecting consumer interests and maintaining grid stability. The UK's recent withdrawal of £1.3 billion in investment in technology and AI projects has raised concerns about the country's competitiveness in fields like quantum computing, which could impact advancements in energy AI applications [51]. Governments, corporate stakeholders, and academic institutions must work together to create frameworks that enable technology growth while addressing possible hazards.

7. Conclusion

This study highlights the transformative impact of AI on renewable energy forecasting and optimization. AI models, such as genetic algorithms, long short-term memory networks, and artificial neural networks, have demonstrated superior accuracy in predicting solar irradiance, wind speed, hydropower streamflows, and biomass feedstock availability. AI-driven optimization strategies, such as smart grid management, battery storage scheduling, and hybrid energy system control, have significantly improved energy efficiency and grid stability. Compared to traditional methods, AI enables more precise energy demand-supply matching, reducing curtailment losses and enhancing renewable energy integration into power grids.

The adoption of AI in renewable energy systems presents significant opportunities for research and industrial applications. Future research should prioritize the development of interpretable AI models to enhance transparency and trust in energy management systems. Additionally, AI's integration with quantum computing and blockchain technology could revolutionize decentralized energy markets and optimize large-scale power distribution networks. For AI-driven solutions to be deployed responsibly and sustainably, however, issues including computational complexity, cybersecurity flaws, and regulatory concerns must be resolved. Industry stakeholders should invest in AI-enhanced predictive maintenance, demand response strategies, and autonomous energy management systems to maximize operational efficiency.

By facilitating autonomous energy optimisation, predictive analytics, and intelligent decision-making, artificial intelligence is poised to play a significant role in the future of renewable energy. AI will become even more useful in renewable energy systems as it develops and is integrated with cutting-edge technologies like edge computing, federated learning, and digital twins. A sustainable and resilient global energy future will need strategic cooperation between researchers, policymakers, and industry leaders, despite the benefits and difficulties that come with the shift to AI-driven energy management. AI-driven solutions will help achieve net-zero emissions and fight climate change in addition to speeding up the adoption of renewable energy.

Compliance with ethical standards

Acknowledgments

The authors would like to thank all of the participating academics and colleagues who worked together to co-author and co-edit this review article. This work was completed solely by the authorship team's academic and intellectual contributions; no external money or help from any person, group, or institution was required.

Disclosure of conflict of interest

The authors declare that they have no conflict of interest to be disclosed.

References

[1] Paraschiv, L. S., & Paraschiv, S. (2023). Contribution of renewable energy (hydro, wind, solar and biomass) to decarbonization and transformation of the electricity generation sector for sustainable development. *Energy Reports*, *9*, 535-544.

[2] Amponsah, N. Y., Troldborg, M., Kington, B., Aalders, I., & Hough, R. L. (2014). Greenhouse gas emissions from renewable energy sources: A review of lifecycle considerations. *Renewable and Sustainable Energy Reviews*, *39*, 461-475.

[3] Firoozi, A. A., Hejazi, F., & Firoozi, A. A. (2024). Advancing Wind Energy Efficiency: A Systematic Review of Aerodynamic Optimization in Wind Turbine Blade Design. *Energies*, *17*(12), 2919.

[4] Darwish, A. S., & Al-Dabbagh, R. (2020). Wind energy state of the art: present and future technology advancements. *Renewable Energy and Environmental Sustainability*, *5*, 7.

[5] Saleem, M. (2022). Possibility of utilizing agriculture biomass as a renewable and sustainable future energy source. *Heliyon*, *8*(2).

[6] Jerez, L. E. C., & Nour, M. (2025). A Cost-Optimizing Analysis of Energy Storage Technologies and Transmission Lines for Decarbonizing the UK Power System by 2035. *Energies*, *18*(6), 1489.

[7] Ukoba, K., Olatunji, K. O., Adeoye, E., Jen, T. C., & Madyira, D. M. (2024). Optimizing renewable energy systems through artificial intelligence: Review and future prospects. *Energy & Environment*, *35*(7), 3833-3879.

[8] Ssekulima, E. B., Anwar, M. B., Al Hinai, A., & El Moursi, M. S. (2016). Wind speed and solar irradiance forecasting techniques for enhanced renewable energy integration with the grid: a review. *IET Renewable Power Generation*, *10*(7), 885-989.

[9] Benti, N. E., Chaka, M. D., & Semie, A. G. (2023). Forecasting renewable energy generation with machine learning and deep learning: Current advances and future prospects. *Sustainability*, *15*(9), 7087.

[10] Korteling, J. H., van de Boer-Visschedijk, G. C., Blankendaal, R. A., Boonekamp, R. C., & Eikelboom, A. R. (2021). Human-versus artificial intelligence. *Frontiers in artificial intelligence*, *4*, 622364.

[11] Raihan, A. (2023). A comprehensive review of artificial intelligence and machine learning applications in energy sector. *Journal of Technology Innovations and Energy*, *2*(4), 1-26.

[12] Naskath, J., Sivakamasundari, G., & Begum, A. A. S. (2023). A study on different deep learning algorithms used in deep neural nets: MLP SOM and DBN. *Wireless personal communications*, *128*(4), 2913-2936.

[13] Gronauer, S., & Diepold, K. (2022). Multi-agent deep reinforcement learning: a survey. *Artificial Intelligence Review*, *55*(2), 895-943.

[14] Shanmuganathan, S. (2016). *Artificial neural network modelling: An introduction* (pp. 1-14). Springer International Publishing.

[15] Husein, M., & Chung, I. Y. (2019). Day-ahead solar irradiance forecasting for microgrids using a long short-term memory recurrent neural network: A deep learning approach. *Energies*, *12*(10), 1856.

[16] Xiao, Z., Tang, F., & Wang, M. (2023). Wind power short-term forecasting method based on LSTM and multiple error correction. *Sustainability*, *15*(4), 3798.

[17] Sharma, S., Sharma, K., & Grover, S. (2024). Real-time data analysis with smart sensors. In *Application of Artificial Intelligence in Wastewater Treatment* (pp. 127-153). Cham: Springer Nature Switzerland.

[18] Selvam, A. P., & Al-Humairi, S. N. S. (2023). The impact of iot and sensor integration on real-time weather monitoring systems: A systematic review.

[19] Safari, A., Daneshvar, M., & Anvari-Moghaddam, A. (2024). Energy Intelligence: A Systematic Review of Artificial Intelligence for Energy Management. *Applied Sciences*, *14*(23), 11112.

[20] Elsaraiti, M., & Merabet, A. (2022). Solar power forecasting using deep learning techniques. *IEEE access*, *10*, 31692-31698.

[21] Ghimire, S., Nguyen-Huy, T., Deo, R. C., Casillas-Perez, D., & Salcedo-Sanz, S. (2022). Efficient daily solar radiation prediction with deep learning 4-phase convolutional neural network, dual stage stacked regression and support vector machine CNN-REGST hybrid model. *Sustainable Materials and Technologies*, *32*, e00429.

[22] Yang, D., Wu, E., & Kleissl, J. (2019). Operational solar forecasting for the real-time market. *International Journal of Forecasting*, *35*(4), 1499-1519.

[23] Holmgren, W. F., Hansen, C. W., & Mikofski, M. A. (2018). pvlib python: A python package for modeling solar energy systems. *Journal of Open Source Software*, *3*(29), 884.

[24] Kosovic, B., Haupt, S. E., Adriaansen, D., Alessandrini, S., Wiener, G., Delle Monache, L., ... & Prestopnik, P. (2020). A comprehensive wind power forecasting system integrating artificial intelligence and numerical weather prediction. *Energies*, *13*(6), 1372.

[25] Kaur, A., Nonnenmacher, L., Pedro, H. T., & Coimbra, C. F. (2016). Benefits of solar forecasting for energy imbalance markets. *Renewable energy*, *86*, 819-830.

[26] Koldunov, N., Rackow, T., Lessig, C., Danilov, S., Cheedela, S. K., Sidorenko, D., ... & Jung, T. (2024). Emerging AI-based weather prediction models as downscaling tools. arXiv preprint arXiv:2406.17977.

[27] Di Grande, S., Berlotti, M., Cavalieri, S., & Gueli, R. (2024, September). Harnessing Multivariate AI to Enhance Hydropower Generation Forecasting. In 2024 AEIT International Annual Conference (AEIT) (pp. 1-6). IEEE.

[28] Senocak, A. A., & Goren, H. G. (2022). Forecasting the biomass-based energy potential using artificial intelligence and geographic information systems: A case study. Engineering Science and Technology, an International Journal, 26, 100992.

[29] Zhukovskiy, Y. L., Kovalchuk, M. S., Batueva, D. E., & Senchilo, N. D. (2021). Development of an algorithm for regulating the load schedule of educational institutions based on the forecast of electric consumption within the framework of application of the demand response. Sustainability, 13(24), 13801.

[30] Touriño Jacobo, J. (2024, November 27). US DOE launches US$30 million funding seeking AI to accelerate interconnection process. PV Tech. https://www.pv-tech.org/us-doe-launches-us30-million-funding-seeking-ai-to-accelerate-interconnection-process/

[31] Qurator. (n.d.). GridBeyond company profile. Qurator. Retrieved April 7, 2025, from https://www.qurator.com/vendors/gridbeyond

[32] Liu, Z., Sun, Y., Xing, C., Liu, J., He, Y., Zhou, Y., & Zhang, G. (2022). Artificial intelligence powered large-scale renewable integrations in multi-energy systems for carbon neutrality transition: Challenges and future perspectives. Energy and AI, 10, 100195.

[33] Hanafi, A. M., Moawed, M. A., & Abdellatif, O. E. (2024). Advancing sustainable energy management: a comprehensive review of artificial intelligence techniques in building. Engineering Research Journal (Shoubra), 53(2), 26-46.

[34] Ali, D. M. T. E., Motuzienė, V., & Džiugaitė-Tumėnienė, R. (2024). Ai-driven innovations in building energy management systems: A review of potential applications and energy savings. Energies, 17(17), 4277.

[35] Grammatikos, P. (2024). Fair real-time control of energy storage systems in active distribution networks in the presence of uncertainties (No. 10586). EPFL.

[36] Hug, G., Kar, S., & Wu, C. (2015). Consensus+ innovations approach for distributed multiagent coordination in a microgrid. *IEEE Transactions on Smart Grid*, *6*(4), 1893-1903.

[37] Machlev, R., Heistrene, L., Perl, M., Levy, K. Y., Belikov, J., Mannor, S., & Levron, Y. (2022). Explainable Artificial Intelligence (XAI) techniques for energy and power systems: Review, challenges and opportunities. *Energy and AI*, *9*, 100169.

[38] Hoenig, A., Roy, K., Acquaah, Y., Yi, S., & Desai, S. (2024). Explainable AI for cyber-physical systems: Issues and challenges. *IEEE access*.

[39] Zhang, Y., Dong, C., Guo, W., Dai, J., & Zhao, Z. (2022). Systems theoretic accident model and process (STAMP): A literature review. *Safety science*, *152*, 105596.

[40] Luqman, A., Mahesh, R., & Chattopadhyay, A. (2024). Privacy and security implications of cloud-based AI services: A survey. *arXiv preprint arXiv:2402.00896*.

[41] Strubell, E., Ganesh, A., & McCallum, A. (2020, April). Energy and policy considerations for modern deep learning research. In *Proceedings of the AAAI conference on artificial intelligence* (Vol. 34, No. 09, pp. 13693-13696).

[42] Bender, E. M., Gebru, T., McMillan-Major, A., & Shmitchell, S. (2021, March). On the dangers of stochastic parrots: Can language models be too big?. In *Proceedings of the 2021 ACM conference on fairness, accountability, and transparency* (pp. 610-623).

[43] Gafni, R., & Levy, Y. (2024). The role of artificial intelligence (AI) in improving technical and managerial cybersecurity tasks' efficiency. *Information & Computer Security*, *32*(5), 711-728.

[44] Ali, S., Abuhmed, T., El-Sappagh, S., Muhammad, K., Alonso-Moral, J. M., Confalonieri, R., ... & Herrera, F. (2023). Explainable Artificial Intelligence (XAI): What we know and what is left to attain Trustworthy Artificial Intelligence. *Information fusion*, *99*, 101805.

[45] Hoffman, W. (2021). AI and the Future of Cyber Competition. *CSET Issue Brief*, 1-35.

[46] Pourdaryaei, A., Mohammadi, M., Karimi, M., Mokhlis, H., Illias, H. A., Kaboli, S. H. A., & Ahmad, S. (2021). Recent development in electricity price forecasting based on computational intelligence techniques in deregulated power market. *Energies*, *14*(19), 6104.

[47] Wang, J., Liu, F., Song, Y., & Zhao, J. (2016). A novel model: Dynamic choice artificial neural network (DCANN) for an electricity price forecasting system. *Applied Soft Computing*, *48*, 281-297.

[48] Wang, J., Liu, F., Song, Y., & Zhao, J. (2016). A novel model: Dynamic choice artificial neural network (DCANN) for an electricity price forecasting system. *Applied Soft Computing*, *48*, 281-297.

[49] Veeramachaneni, V. (2025). Optimizing Renewable Energy Integration in AI-Driven Data Centers Using Quantum Algorithms. *Journal of Network Security and Data Mining*, *8*(1), 36-48.

[50] Mohamed, O. A. M. (2023). How generative AI transforming supply chain operations and efficiency?.

[51] Guo, J., Duan, Z., Flanigen, C., Hsu, E., Simon, V., & Floridi, L. (2024). Energy Consumption Ramifications of US-China AI Competition. *Available at SSRN*.