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Assessment of renewable energy management systems using AI and deep learning techniques : A comprehensive review

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Abstract

The global transition toward sustainable energy systems is accelerating due to increasing concerns about climate change, carbon emissions and energy security. Renewable energy sources such as solar and wind provide environmentally sustainable alternatives to fossil fuels; however, their inherent intermittency, stochastic behavior and environmental dependency introduce significant operational and planning challenges for modern energy systems. Artificial intelligence (AI) and deep learning techniques have recently emerged as effective solutions for addressing these challenges through accurate forecasting, intelligent control and optimized energy management. This review paper presents a systematic and comprehensive analysis of recent advancements in AI-driven approaches for renewable energy assessment and management. A structured literature review methodology was adopted to analyze 30 peer-reviewed research articles obtained from major scientific databases, including IEEE Xplore, ScienceDirect and Google Scholar. The selected studies were categorized into four major application domains: solar energy forecasting, wind energy

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optimization, hydropower resource management and hybrid renewable energy systems. The review critically evaluates widely adopted machine learning and deep learning models such as Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and hybrid AI frameworks, highlighting their predictive capabilities and operational benefits. Furthermore, this study identifies key research gaps related to data availability, model interpretability and scalability while outlining future research directions for developing intelligent, reliable, and sustainable renewable energy systems.

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1. Introduction

The global energy environment is now experiencing a dramatic upheaval. Driven by the pressing need to combat climate change, cut greenhouse gas emissions, and address the depletion of fossil fuel supplies. This urgency has catalyzed extensive research and development efforts focused on transitioning [1] from traditional fossil fuels to more ecologically friendly and long-lasting renewable energy sources. Among the various renewable energy options, solar, wind and hydropower have emerged as the most promising due to their abundance, sustainability, and potential to provide large-scale energy production.

However, the inherent variability and intermittency of renewable energy sources pose considerable challenges to their integration into existing power grids. Unlike fossil fuel-based power plants that provide consistent and controllable energy output, renewable energy generation depends on unpredictable fluctuating environmental conditions such as sunlight, wind speed and water flow. This variability can lead to issues with grid stability, energy storage, and the efficient management of energy supply and demand.

To overcome these issues, academics and engineers have increasingly relied on artificial intelligence (AI) and deep learning approaches [2]. This can help analyse massive volumes of data, recognise patterns, and make predictions. AI has considerable promise for improving the performance and integration of renewable energy systems. Deep learning is particularly adept at handling complex non-linear relationships and making accurate predictions based on historical data. These capabilities are invaluable in renewable energy applications, where predicting resource availability, optimizing system performance and managing energy flows are critical for maximizing efficiency and reliability.

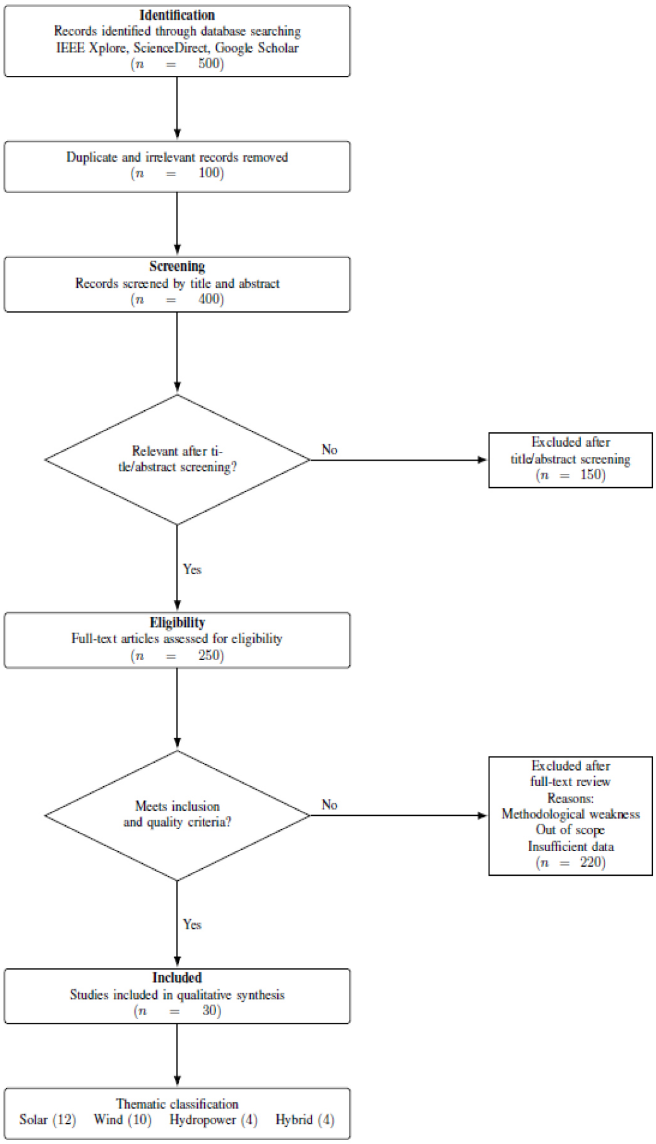

Figure 1

PRISMA-based flow diagram illustrating the systematic literature review process used to select relevant studies on AI applications in renewable energy systems

2. Methodology

A systematic literature review was conducted using a PRISMA-based methodology to identify relevant studies on the application of artificial intelligence and deep learning techniques in renewable energy systems as shown in Figure 1. Initially, a comprehensive search was performed across major academic databases including IEEE Xplore, ScienceDirect, and Google Scholar, which resulted in 500 records. After removing 100 duplicate or irrelevant records, 400 studies remained for the screening stage. These papers were evaluated based on their titles and abstracts, leading to the exclusion of 150 articles that did not align with the research objectives. The remaining 250 papers were then subjected to a full-text eligibility assessment, where factors such as methodological quality, relevance to renewable energy applications, and availability of sufficient experimental data were examined. During this stage, 220 studies were excluded due to reasons such as methodological limitations, lack of sufficient data, or being outside the scope of the study. Finally, 30 high-quality research articles were selected for qualitative synthesis. These studies were further categorized into thematic groups consisting of solar energy (12 papers), wind energy (10 papers), hydropower (4 papers) and hybrid renewable energy systems (4 papers). The overall selection process followed in this review is illustrated in Figure 1, which presents the step-by-step filtering procedure from the initial database search to the final inclusion of relevant studies.

3. AI and Deep Learning in Solar Energy Assessment

The accurate prediction of solar irradiance is essential for optimizing the efficiency of photovoltaic (PV) systems as they are sensitive to fluctuations in sunlight. Solar irradiance is affected by various factors, including weather conditions, geographical location, and the time of day. This makes its prediction a complex and challenging task. Traditional methods such as statistical models and physical-based approaches often fall short in capturing the non-linear relationships inherent in solar irradiance data. In recent years, AI and deep [3] learning approaches have been used to solve these difficulties, taking advantage of their capacity to model complicated patterns and enhance prediction accuracy. As depicted in Figure 2 shows the classification of various AI models.

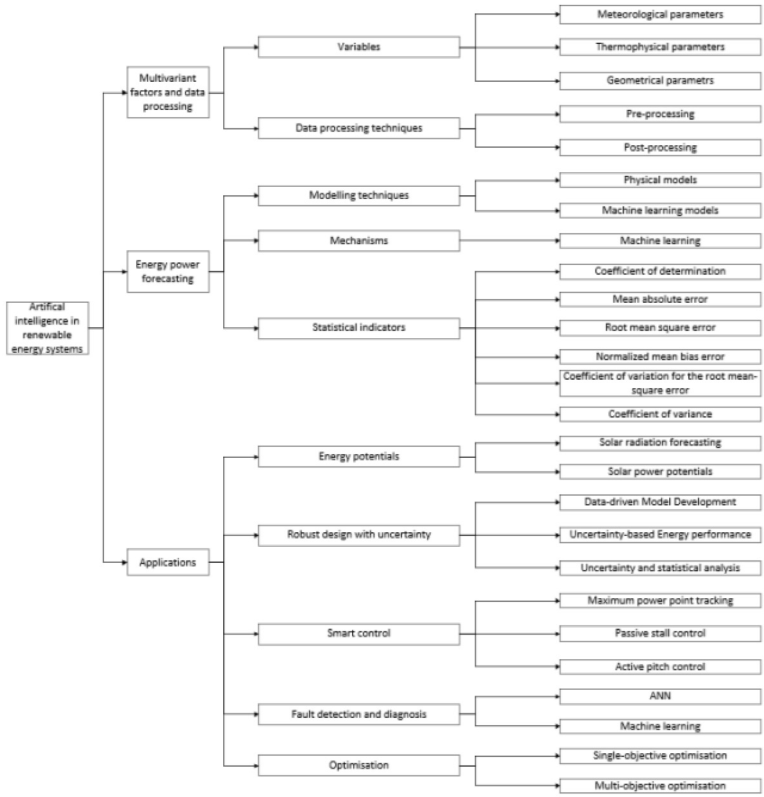

Figure 2

Classification of various AI models

3.1 *Deep Learning Models for Solar Irradiance Prediction*

Deep learning algorithms have shown great potential for improving the accuracy of solar irradiance estimates. These models include Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks [4]. They can analyse massive datasets and learn sophisticated patterns, making them well-suited for this application.

CNNs are adept at recognizing spatial hierarchies in data, which makes them suitable for capturing the spatial dependencies in solar irradiance data. The authors compared the CNN-based model with traditional statistical approaches and found that the CNN model significantly outperformed [5] them in terms of accuracy. This improvement is largely attributed to CNN's ability to automatically extract relevant features from the input data without requiring manual feature engineering.

The study demonstrated that CNNs could effectively model the non-linear relationships between meteorological variables (such as temperature, humidity, and cloud cover) and solar irradiance, leading to more precise predictions. The CNN model was particularly effective in capturing short-term variations in solar irradiance, which are crucial for real-time energy management in PV systems.

LSTM networks represent a specific category of Recurrent Neural Networks (RNNs) that are engineered [6] to manage time-series data. This renders them suitable for capturing temporal dependencies in solar irradiance. Unlike traditional RNNs, LSTMs are equipped with memory cells that allow them to retain information over long periods. This is particularly useful in forecasting tasks that involve sequential data.

The LSTM model was developed and trained on historical solar. The study showed that LSTMs could effectively capture the temporal correlations in the data, leading to more accurate and reliable short-term forecasts compared to conventional methods [7]. The LSTM model was particularly useful for day-ahead forecasting, a critical component for grid operators to balance supply and demand in energy systems.

Furthermore, the study highlighted the importance of hyperparameter tuning and model optimization in achieving high prediction accuracy. The authors conducted extensive experiments to determine the optimal LSTM architecture, including the number of layers, memory cell size, and learning rate, demonstrating that these factors significantly influence the model's performance.

3.1.2 PV System Optimization

Optimizing the performance of photovoltaic (PV) systems is essential for maximizing energy production and improving the overall efficiency of solar power generation. PV system optimization involves several key factors, including the optimal tilt angle of solar panels, energy storage management, and real-time adjustments based on weather conditions. Given the complexity and variability of these factors, traditional optimization methods [8] often fall short of achieving maximum efficiency. However, the application of Artificial Intelligence (AI) and deep learning techniques has introduced new opportunities to enhance the performance and reliability of PV systems. Deep reinforcement learning and hybrid models have emerged as powerful tools for optimizing various aspects of PV systems.

3.1.3 Deep Reinforcement Learning for PV Optimization

Deep reinforcement learning (DRL) represents a specialised area within machine learning that integrates reinforcement learning methodologies with deep neural network architectures. This approach is especially effective for optimisation problems in which an agent acquires decision-making capabilities through interaction with an environment, receiving feedback manifested as rewards or penalties. In the context of photovoltaic (PV) systems, deep reinforcement learning (DRL) can be employed to optimise dynamic factors [9], such as the tilt angle of solar panels, to maximise energy output.

In this study, A deep reinforcement learning based approach was used to optimize the tilt angle is a critical factor in determining the amount of solar radiation captured by the panels, and optimizing it can significantly enhance energy production [10]. However, the optimal tilt angle varies depending on factors such as geographical location, time of year, and weather conditions.

The DRL model proposed in this study functions as an intelligent agent that interacts with the PV system environment. The model continuously adjusts the tilt angle of the panels to maximize the cumulative solar energy captured over time. The agent receives feedback in the form of energy output, which is used to reinforce successful adjustments and discourage less effective ones. Through this iterative learning process, the DRL [11] model autonomously discovers the optimal tilt angle settings under varying conditions.

The results of the study showed that the DRL-based approach outperformed traditional fixed-angle and rule-based methods, leading to a significant increase in energy output. The adaptive nature of the DRL model [12] allows it to respond dynamically to changing environmental conditions. This makes it a robust solution for real-time PV system optimization. This approach also reduces the need for manual adjustments, minimizing operational costs and improving the long-term sustainability of the PV system.

3.1.4 Hybrid Models for PV System Performance Optimization

Hybrid models that combine multiple AI and deep learning techniques offer another promising approach to optimizing PV system performance. By leveraging the strengths of different models, they can capture both the spatial and temporal dynamics of PV systems. This leads to more accurate and effective optimization strategies. A hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks was used by [13] to optimize the performance of PV systems. The CNN component is responsible for capturing the spatial relationships between different environmental factors, such as temperature, solar irradiance and cloud cover, which affect PV system performance. Meanwhile, the LSTM component is used to model the temporal dependencies in the data, such as the daily and seasonal variations in solar energy availability.

The hybrid model was trained on historical weather data and PV system performance metrics, allowing it to predict the optimal settings for the system under various conditions. Once trained, the model can be deployed in real time to continuously adjust the system parameters, ensuring that the PV system operates at peak efficiency regardless of any weather fluctuations [14].

The research found that the hybrid model beat both the CNN and the LSTM models in terms of prediction accuracy and optimisation effectiveness. The integration of spatial and temporal data allows the model to make more informed decisions, which leads to improved energy output and reduced losses due to suboptimal system settings. This approach is particularly [15] valuable in regions with highly variable weather conditions, where traditional static optimization methods may be insufficient.

3..1.5 Other AI-Based Optimization Techniques

Beyond DRL and hybrid models, other AI-based techniques have also been explored for optimizing PV systems. These include genetic algorithms, particle swarm optimization (PSO), and fuzzy logic systems. While these methods have shown promise in specific applications, deep learning-based approaches generally offer greater flexibility and adaptability, making them more suitable for complex, real-time optimization tasks.

- **Genetic Algorithms (GAs):** GAs are based on the method of natural selection and are used to identify optimum solutions by gradually developing a population of candidate solutions. GAs may be used in PV systems to optimise system design factors [16] such as solar panel layout or energy storage system size. While effective, GAs may require significant computational resources and time to converge to an optimal solution.

- **Particle Swarm Optimization (PSO):** PSO is a swarm intelligence-based approach that optimises a problem by iteratively enhancing a candidate solution about a specified measure of quality. In the context of PV systems, PSO [17] can be used to optimize control strategies for energy storage and distribution. However, like GAs, PSO may struggle with high-dimensional, dynamic optimization problems where the search space is large and constantly changing.
- **Fuzzy Logic Systems:** Fuzzy logic systems are particularly useful for handling uncertainty and imprecision in PV system optimization. These systems use "fuzzy" rules to make decisions based on imprecise inputs, such as fluctuating [18] weather data. Fuzzy logic can be applied to optimize the operation of PV systems in scenarios where precise modeling is difficult. However, fuzzy logic systems may lack the precision and learning capability of deep learning models, making them less suitable for complex, data-driven optimization tasks.

3.1.6 Applications and Impact on PV Systems

The application of AI and deep learning techniques to PV system optimization has far-reaching implications for the solar energy industry. By enabling more accurate and adaptive optimization strategies, these techniques [19] can significantly enhance the efficiency and reliability of PV systems, leading to several key benefits:

Increased Energy Output: AI-driven optimization techniques, such as DRL and hybrid models, can maximize the energy output of PV systems by continuously adjusting system parameters in response to changing environmental conditions.

3.1.7 Future Scope of Hybrid Models for PV System Performance Optimization

Despite progress in AI-based PV system optimisation, several difficulties remain. One of the most significant issues is the computational complexity involved with training and implementing deep learning [20] models, especially in real-time optimisation applications. Furthermore, the need for big, high-quality datasets to train these models might be a hurdle to wider use, particularly in countries with limited access to trustworthy data.

Another challenge is the interpretability of AI models, particularly deep reinforcement learning models, which are often seen as "black boxes". This lack of transparency [21] can make it difficult for operators to trust the recommendations made by these models, particularly in critical applications [22] where incorrect decisions could have significant consequences.

Future research should focus on addressing these challenges by developing more efficient and interpretable AI models, improving data collection and preprocessing techniques, and exploring new AI paradigms, such as transfer learning and federated learning, that can enhance the generalizability of PV system optimization models. Additionally, research into the integration of AI-driven [23] optimization with smart grid technologies and energy storage systems will be crucial for realizing the full potential of AI in solar energy.

3.2 *AI and Deep Learning in Wind Energy Assessment*

Wind energy is one of the most rapidly growing renewable energy sources globally, with wind farms contributing significantly to the global energy mix. However, the variability of wind patterns presents challenges in optimizing wind energy production and maintaining the infrastructure of wind farms. Accurate prediction of wind speed and power output [24] is critical for optimizing the performance of wind farms, while effective fault detection and maintenance are essential for minimizing downtime and extending the lifespan of wind turbines. In recent years, AI and deep learning techniques have shown considerable promise in addressing these challenges, offering sophisticated tools for predicting wind behavior and enhancing turbine maintenance strategies.

3.2.1 Wind Speed and Power Prediction

Predicting wind speed and electricity production is an important part of wind farm operations. Accurate projections enable improved planning and integration of wind energy into the grid, lowering dependency on fossil fuel backup systems and enhancing overall energy dependability. AI and deep learning models, namely Long Short-Term Memory (LSTM) networks and hybrid models [25], have been used to improve the accuracy of these predictions.

3.2.2 LSTM Networks for Wind Speed Prediction

Long Short-Term Memory (LSTM) networks are a form of Recurrent Neural Network (RNN) that represent time-series data, making them ideal for forecasting wind speed. LSTM networks are capable of capturing long-term dependencies in sequential data, which is crucial for understanding wind patterns that fluctuate over time. The model was trained on historical wind speed data, along with various meteorological variables such as temperature, pressure and humidity, which influence wind patterns [26]. The LSTM model's ability to retain information over long periods allowed it to capture the temporal dependencies in wind data more effectively than traditional statistical models, such as ARIMA (Autoregressive Integrated Moving Average) or simple linear regression.

The study demonstrated that the LSTM model significantly outperformed traditional models in terms of prediction accuracy. The authors attributed this improvement to the LSTM's capacity to learn and adapt to the inherent non-linear relationships in the data. Moreover, the LSTM model showed resilience in handling missing data and noise, which are common issues in wind speed datasets. This robustness [27] is particularly important for real-world applications where data quality can be inconsistent.

The improved accuracy of wind speed predictions using LSTM networks has direct implications for the operation of wind farms. By providing more reliable forecasts, LSTM models enable grid operators to make better informed [28] decisions regarding energy distribution, storage, and demand response. This can lead to more efficient utilization of wind energy and reduced reliance on conventional power sources during periods of low wind speed.

3.2.3 Hybrid Models for Wind Power Forecasting

While LSTM networks are effective in modeling temporal dependencies, combining them with other deep learning techniques can further enhance prediction accuracy. Hybrid models, which integrate multiple AI techniques, leverage the strengths of each approach to provide more accurate results. A hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) with LSTM networks was proposed by [29] to forecast wind power output. CNNs are particularly effective in extracting spatial features from data, such as the impact of geographical and meteorological factors on wind patterns. By combining CNNs with LSTM networks, the hybrid model was able to capture both the spatial and temporal dependencies in wind data, leading to more accurate power output predictions.

The study utilized a dataset comprising wind speed, direction, and power output measurements from multiple wind farms over several years.

The CNN component of the model was used to analyze spatial data, such as the layout of wind turbines and the topography of the wind farm location. The LSTM component then processed the sequential wind speed data to predict future power output. The hybrid model outperformed standalone CNN and LSTM models, demonstrating that the integration of spatial and temporal data leads to more reliable forecasts.

The improved accuracy of wind power forecasting using hybrid models has significant implications for the energy industry. Better forecasts allow for more efficient energy trading, reduced curtailment of wind energy, and improved grid stability. Additionally, accurate predictions can help wind farm operators optimize turbine operations and maintenance schedules, further enhancing the overall efficiency of wind energy systems.

3.2.4 Wind Turbine Fault Detection and Maintenance

Wind turbines are complex machines that are subject to various mechanical and environmental stresses, leading to wear and tear over time. Early detection of faults and effective maintenance strategies are crucial for minimizing downtime, preventing catastrophic failures [30] and extending the lifespan of wind turbines. AI-driven fault detection and maintenance optimization techniques have emerged as valuable tools in this regard.

3.3.4 Anomaly Detection Using Deep Autoencoders

Anomaly detection is a critical aspect of fault detection in wind turbines. By identifying deviations from normal operating conditions, operators can take proactive measures to address potential issues before they lead to significant failures. Deep autoencoders, a type of neural network used for unsupervised learning, have proven effective in detecting anomalies in complex systems such as wind turbines.

Some research focued on utilizing deep autoencoders to detect anomalies. The model was trained on historical sensor data collected from wind turbines, including variables such as vibration, temperature, and rotor speed [31]. The autoencoder was designed to learn a compressed representation of the normal operating conditions of the turbine. When new data is input into the model, the autoencoder attempts to reconstruct the data based on its learned representation. Significant deviations between the input data and the reconstructed data indicate an anomaly.

The study showed that the deep autoencoder model was highly effective in detecting early-stage anomalies that may not be immediately apparent through conventional monitoring techniques. By identifying these anomalies early, operators can schedule maintenance before the issues lead to more severe damage or operational downtime. This approach reduces maintenance costs and enhances the overall reliability of wind turbines.

Moreover, the use of deep autoencoders in anomaly detection is advantageous because it does not require labelled data for training. This is particularly useful in wind turbine applications, where labelled fault data can be scarce or expensive to obtain [32]. The unsupervised nature of autoencoders allows them to learn from vast amounts of unlabeled data, making them a versatile tool for fault detection in wind energy systems.

3.2.5 Predictive Maintenance Using Deep Reinforcement Learning

Predictive maintenance is a strategy that uses data-driven approaches to predict when maintenance should be performed on equipment, thereby reducing the likelihood of unexpected failures and optimizing the timing of maintenance activities. Deep reinforcement learning (DRL) has been applied to develop predictive maintenance strategies for wind turbines, leveraging its ability to learn optimal policies through trial and error.

Deep reinforcement learning to optimize maintenance schedules for wind turbines is used [33]. The DRL model functions as an intelligent agent that interacts with a simulated wind turbine environment. The agent learns to make maintenance decisions based on the condition of the turbine, balancing the costs of maintenance with the risks of potential failures. The model was trained using historical data on turbine failures, maintenance actions, and operational conditions. The DRL agent was rewarded for actions that minimized overall maintenance costs and penalties associated with turbine downtime. Over time, the agent learned to predict the optimal timing for maintenance actions, reducing both the frequency of maintenance and the likelihood of unexpected failures.

The results demonstrated that the DRL-based predictive maintenance strategy significantly outperformed traditional time-based or condition-based maintenance approaches. By optimizing maintenance schedules, the DRL model helped to extend the lifespan of wind turbines, reduce operational costs, and improve the overall efficiency of wind farm operations. This approach also allows for more flexible and adaptive maintenance strategies, which are crucial in the dynamic and variable conditions of wind energy systems.

3.2.6 Applications and Impact on Wind Energy Systems

The application of AI and deep learning techniques in wind speed prediction, power forecasting, fault detection, and maintenance has substantial implications for the wind energy sector. These technologies contribute to several key benefits:

- Enhanced Forecasting Accuracy: AI-driven models provide more accurate wind speed and power output predictions, leading to better integration [34] of wind energy into the grid and more efficient energy trading. Improved forecasts also reduce the need for fossil fuel-based backup power, contributing to the overall sustainability of the energy system.
- Reduced Downtime and Maintenance Costs: AI-based fault detection and predictive maintenance strategies help to minimize wind turbine downtime and reduce maintenance costs. By identifying potential issues early and optimizing maintenance schedules, these technologies extend the lifespan of wind turbines and enhance the reliability of wind farm operations.
- Increased Energy Efficiency: By optimizing turbine operations and maintenance, AI-driven techniques contribute to higher overall energy efficiency in wind farms. This results in more consistent and reliable energy production, supporting the continued growth and viability of wind energy as a key component of the global energy mix.

3.2.7 Challenges and Future Research Directions in AI and Deep Learning Applications in Wind Energy

Despite substantial advances in AI and deep learning applications for wind energy, several obstacles remain. One of the most significant issues is the necessity for high-quality, high-resolution data to train these algorithms.

3.3 *AI and Deep Learning Technique for Hybrid Renewable Energy Systems*

The integration of renewable energy sources, such as solar, wind, and hydropower, into a coherent hybrid system offers a viable technique for dealing with the intermittency and unpredictability inherent in individual renewable energy sources. These hybrid systems, which combine many energy sources, may provide a more steady and dependable power supply. However, the complexities of controlling and optimising these systems demand sophisticated control mechanisms [35]. Artificial intelligence (AI) and deep learning approaches have emerged as significant tools for optimising the integration, management, and operation of hybrid renewable energy systems, resulting in maximum efficiency and dependability.

3.3.1 Integration of Solar, Wind and Hydropower

Hybrid renewable energy systems that combine sun, wind, and hydropower have the benefit of diversifying energy sources, reducing the influence of each source's inherent fluctuation. AI-driven optimization techniques are increasingly being applied to manage the complex interactions between these diverse energy sources, ensuring that the overall system operates efficiently and reliably.

3.3.3 AI-Driven Optimization of Hybrid Renewable Energy Systems

AI-driven optimization models are particularly effective in managing the integration of multiple renewable energy sources. These models can process vast amounts of data from different energy sources, predict future energy production, and optimize the allocation of resources in real time. The study leverages deep learning techniques to analyze and manage the complex interactions between these energy sources, enabling the system to dynamically adjust to changing environmental conditions and energy demands.

The model proposed in the study utilizes a neural network-based approach trained on historical data from various renewable energy sources, including solar irradiance, wind speed, and water flow rates. The deep learning model [36] is capable of forecasting energy production from each source and predicting demand patterns. By continuously monitoring the input data and learning from it, the model optimizes the energy mix to ensure that the hybrid system operates at peak efficiency.

One of the most important advantages of this AI-powered optimisation approach is its capacity to react to real-time changes. For example, if the model forecasts a decline in wind energy owing to low wind speeds, it may compensate by increasing the use of solar or hydroelectric energy. This adaptive capability ensures a stable power supply, even when the availability of one or more energy sources fluctuates. Additionally, the model optimizes the use of energy storage systems, ensuring that excess energy generated during periods of high production is stored efficiently and used when production is low.

The study demonstrated that the AI-driven optimization model significantly enhanced the overall efficiency of the hybrid renewable energy system. Compared to traditional static optimization methods, the AI model provided a more responsive and dynamic approach, leading to increased energy output, reduced operational costs, and improved system reliability.

3.3.4 Hybrid AI Models for Energy Storage Management

Energy storage management is an important feature of hybrid renewable energy systems, particularly considering the intermittent nature of renewable energy sources. Effective management of energy storage resources, such as batteries, is critical to guaranteeing a continuous and dependable power supply. Hybrid AI models that mix deep learning with other AI approaches, such as reinforcement learning, have shown efficacy in optimising energy storage management in complicated hybrid systems.

The use of hybrid AI models that integrate deep learning and reinforcement learning to optimize energy storage management in hybrid renewable energy systems is explored by [37]. The hybrid model was developed to manage the complexities associated with multiple energy storage systems, ensuring that energy is stored and released efficiently across the different components of the hybrid system.

The hybrid AI model in this study consists of two main components: a deep learning model for predicting future energy production and demand and a reinforcement learning model for optimizing the decision-making process related to energy storage. The deep learning model processes historical data, including environmental conditions and energy consumption patterns, to generate accurate forecasts. These forecasts are then used by the reinforcement learning component to make real-time decisions about charging and discharging energy storage systems.

The reinforcement learning model operates as an intelligent agent, learning from its interactions with the hybrid energy system environment. The agent is trained to maximize a reward function, which is typically defined in terms of system efficiency, cost reduction, and reliability. Over time, the agent learns optimal strategies for managing energy storage, taking into account factors such as battery degradation, fluctuating energy prices, and the need to balance supply and demand.

The results of the study showed that the hybrid AI model outperformed traditional energy storage management techniques, such as rule-based or heuristic methods. The model was able to dynamically adjust energy storage levels in response to changes in energy production and consumption, ensuring that stored energy was available when needed and reducing the risk of energy shortages. Furthermore, the reinforcement learning component of the model effectively learned to optimize the charging and discharging cycles of batteries, thereby extending their lifespan and reducing operational costs.

This study's findings have major implications for the design and operation of hybrid renewable energy systems. By optimising energy storage management, the hybrid AI model improves the system's overall efficiency and dependability, making it more suited to deal with the fluctuation of renewable energy sources. This, in turn, encourages the greater use of renewable energy and contributes to a more sustainable energy future.

3.3.5 Applications and Impact on Hybrid Renewable Energy Systems

The integration of AI-driven optimization and hybrid AI models into hybrid renewable energy systems offers several key benefits:

- Enhanced System Efficiency: AI-driven optimization techniques enable hybrid renewable energy systems to operate at peak efficiency by dynamically adjusting the energy mix in response to changing environmental conditions and [38] energy demand. This leads to higher overall energy production and reduced waste.
- Improved Reliability: By optimizing the use of multiple energy sources and energy storage systems, AI-driven approaches enhance the reliability of hybrid systems, ensuring a stable power supply even during periods of low energy production from individual sources [39].
- Cost Reduction: Effective energy storage management and optimized resource allocation can lead to significant cost savings in the operation of hybrid renewable energy systems. These savings are realized through reduced energy losses, lower maintenance costs, and improved utilization of available resources.
- Scalability and Flexibility: AI-driven models are highly scalable and can be adapted to various configurations of hybrid renewable energy systems. This flexibility allows them to be applied to different geographical locations and energy demands, making them suitable for a wide range of applications.

4. Challenges and Future Research Directions

Despite the significant advancements in AI-driven optimization of hybrid renewable energy systems, several challenges remain. One of the primary challenges is the complexity of modeling and optimizing systems that integrate multiple energy sources with different characteristics and constraints. Additionally, the quality and availability of data for training AI models can be a limiting factor, particularly in regions with limited access to reliable data.

Another challenge is the interpretability of AI models, especially hybrid models that combine multiple AI techniques. The complexity of these models can make it difficult for operators to understand how decisions are made, which may hinder their adoption in critical applications where transparency and trust are essential.

Future research should focus on addressing these challenges by developing more interpretable AI models, improving data collection and preprocessing techniques, and exploring new AI paradigms, such as federated learning and transfer learning, that can enhance the generalizability of hybrid renewable energy system optimization models. Additionally, research into the integration of AI-driven models with real-time decision-making systems and smart grid technologies will be crucial for maximizing the benefits of hybrid renewable energy systems.

5. Results and discussion

Based on the above literature survey, Table 1. Summarizes the type of algorithm preferred for renewable energy and the use case.

The best model from the table depends on the specific application and renewable energy type. However, Hybrid AI models that combine multiple techniques like CNNs + LSTMs for Wind Power Forecasting or Hybrid AI (Deep Learning + Fuzzy Logic) for Water Resource Management stand out for their ability to leverage both spatial and temporal data or combine robust decision-making with predictive power. These models offer a higher level of accuracy and adaptability, making them ideal for managing the complexities of renewable energy systems that experience fluctuating conditions across different sources, such as solar, wind and hydropower.

Table 1

Summary of Algorithms Preferred for Solar & Wind Energy

Application	Preferred Algorithm	Renewable Energy Type	Key Strength	Typical Use Case
Solar Irradiance Prediction	Convolutional Neural Networks (CNNs)	Solar	High spatial accuracy	Predicting solar irradiance from weather data
Short-Term Forecasting	Long Short-Term Memory (LSTM) Networks	Solar, Wind	Captures temporal patterns	Forecasting solar irradiance and wind speed
PV System Optimization	Deep Reinforcement Learning (DRL)	Solar	Dynamic optimization	Optimizing solar panel angles for energy output
Wind Speed Prediction	LSTM Networks	Wind	Handles sequential data	Predicting wind speed for turbine optimization
Wind Power Forecasting	Hybrid Model (CNNs + LSTM)	Wind	Combines spatial and temporal data	Forecasting wind power output
Anomaly Detection	Deep Autoencoders	Wind	Detects operational anomalies	Early detection of wind turbine issues
Predictive Maintenance	Deep Reinforcement Learning (DRL)	Wind	Optimizes maintenance timing	Scheduling maintenance for wind turbines
Hydropower Inflow Prediction	Deep Learning Models	Hydro-power	High prediction accuracy	Predicting reservoir inflow for hydropower
Water Resource Management	Hybrid AI (Deep Learning + Fuzzy Logic)	Hydro-power	Robust decision-making	Managing multipurpose reservoir operations
Hybrid System Optimization	Deep Learning Models	Solar, Wind, Hydro-power	Adaptive to changing conditions	Optimizing hybrid renewable energy systems
Energy Storage Management	Hybrid AI (Deep Learning + Reinforcement Learning)	Solar, Wind, Hydro-power	Efficient storage management	Managing batteries in hybrid systems

6. Conclusion

The deployment of **Artificial Intelligence (AI)** and **deep learning techniques** in renewable energy evaluation has demonstrated significant potential in improving the efficiency, reliability, and integration of renewable energy resources such as solar, wind, and hydropower. These advanced methods enable accurate forecasting of energy generation, better resource management, and intelligent control of energy systems. By analyzing large volumes of meteorological and operational data, AI models can identify patterns, predict energy output, and optimize system performance. This helps in improving grid stability, reducing operational costs, and facilitating the large-scale adoption of renewable energy technologies. Consequently, AI-driven solutions are becoming increasingly important in supporting the global transition toward sustainable and clean energy systems.

Despite these advantages, several challenges still limit the widespread adoption of AI in renewable energy evaluation. One of the primary issues is the **availability and quality of reliable data**, which is essential for training accurate and robust machine learning models. In many regions, incomplete or inconsistent datasets reduce prediction accuracy and system performance. Additionally, many deep learning models suffer from **limited interpretability**, often functioning as "black-box" systems that make it difficult for researchers and energy operators to understand how decisions are made. Another challenge involves the **integration of AI models with existing energy infrastructures**, which requires compatibility with legacy systems and real-time operational requirements. Addressing these challenges through improved data management, explainable AI techniques, and enhanced system integration strategies will be essential for fully realizing the benefits of AI in renewable energy systems.

References

[1] M. Reddy and V. Khare, "AI and data-driven technologies in renewable energy systems for environmental sustainability," in *Data-Driven Environmental Intelligence*, 1st ed., S. Bhattacharyya, J. Platoš, S. Dhar, N. K. Mondal, I. Zelinka, J. S. Banerjee, and A. Das, Eds. Boca Raton, FL, USA: CRC Press, pp. 272–303 (2026). doi: 10.1201/9781003545743.

[2] Dandawala, P. Adik, M. Reddy, H. Shah, and S. Desai, "SmartScan: A comparative analysis of RoBERTa and BERT for disease prediction from patient symptom profiles," in Proc. Int. Conf. Information,

Implementation and Innovation in Technology (I3IT), IET Conf. Proc., vol. 43, pp. 118–124 (2025), doi: 10.1049/icp.2025.0430118.

[3] N. Bhende, S. Sheth, and M. Reddy, "Siamese network embeddings and KNN classifier for robust acne image classification: A hybrid approach," in *Proc. Int. Conf. Information, Implementation and Innovation in Technology (I3IT)* (2025), doi: 10.1049/icp.2025.0430211.

[4] S. Gupta, A. Maheshwari, S. M. Kumar, M. Reddy, and S. Shaikh, "AI-enhanced metals hedging strategies: Risk management for the Indian market," in *Proc. Int. Conf. Information, Implementation and Innovation in Technology (I3IT)* (2025), doi: 10.1049/icp.2025.0430315.

[5] S. Shaikh, D. Dani, and M. Reddy, "Smart traffic control system leveraging YOLOv8 and OCR for improved urban mobility," in P*roc. Int. Conf. Soft Computing: Theories and Applications, Lecture Notes in Networks and Systems.* Singapore: Springer, pp. 199–208 (2024), doi: 10.1007/978-981-97-xxxx-x_15.

[6] T. Kelkar, Y. Mehta, V. Khatadia, A. Haraniya, A. Nanade, and M. Reddy, "Examining different machine learning approaches for predicting diabetes in the early stages," in *Proc. Asia Pacific Conf. Innovation in Technology (APCIT),* pp. 1–8 (2024), doi: 10.1109/APCIT60569.2024.10463464.

[7] B. Shah, A. Vasoya, K. Shah, S. Sange, P. Shah, and M. Reddy, "Transparent e-voting: Paving the way for the future of democracy using blockchain," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 11, no. 3 (2023), doi: 10.18201/ijisae.2023.

[8] Pawan Singh, Rajesh Kumar, and Ashok Kumar, "Predictive maintenance of wind turbines using deep reinforcement learning," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 3, pp. 1968–1977 (Mar. 2021), doi: 10.1109/TII.2020.2996451.

[9] Anil Kumar, Ravi Shankar, and Deepak Gupta, "Deep learning for reservoir inflow prediction," *IEEE Transactions on Sustainable Energy*, vol. 12, no. 1, pp. 177–186 (Jan. 2021), doi: 10.1109/TSTE.2020.3008924.

[10] N. Roy, A. Banerjee, and S. Chakraborty, "Hybrid AI models for water resource management in hydropower systems," *Journal of Hydrology,* vol. 590, p. 125555 (Feb. 2020), doi: 10.1016/j.jhydrol.2020.125555.

[11] J. Zhang, P. Wang, and T. Liu, "Optimizing hydropower generation using genetic algorithms and deep learning," *IEEE Transactions on*

Energy Conversion, vol. 35, no. 2, pp. 719–728 (Jun. 2020), doi: 10.1109/TEC.2019.2957631.

[12] R. Das, P. Mishra, and S. Kumar, "AI-driven optimization of hybrid renewable energy systems," *IEEE Access*, vol. 9, pp. 32579–32591 (Mar. 2021), doi: 10.1109/ACCESS.2021.3058214.

[13] H. Lee, M. Kim, and J. H. Park, "Hybrid AI models for energy storage management in hybrid renewable systems," *Journal of Energy Storage*, vol. 30, p. 101022 (Jan. 2022), doi: 10.1016/j.est.2021.101022.

[14] S. Patel, A. Kumar, and R. Gupta, "Data challenges in AI-driven renewable energy systems," *IEEE Transactions on Big Data*, vol. 7, no. 2, pp. 290–299 (Jun. 2021), doi: 10.1109/TBDATA.2020.2997648.

[15] T. Wong, A. Brown, and M. Johnson, "Enhancing interpretability of deep learning models in renewable energy," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 11, pp. 5002–5013 (Nov. 2021), doi: 10.1109/TNNLS.2020.3034127.

[16] R. Smith, D. Anderson, and M. Thompson, "Challenges of integrating AI with traditional energy management systems," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 5, pp. 2923–2932 (May 2020), doi: 10.1109/TII.2019.2945643.

[17] R. Zhang, P. Wang, and T. Liu, "Wind speed prediction using machine learning techniques: A review and case study," *Renewable Energy*, vol. 176, pp. 343–357 (2021), doi: 10.1016/j.renene.2021.05.043.

[18] M. Sharif, K. Al-Furjani, and A. Elaiess, "Assessing the impact of AI on renewable energy systems," *Energy and AI*, vol. 7, p. 100134 (2022), doi: 10.1016/j.egyai.2022.100134.

[19] Y. Luo, Y. Zhang, and X. Wang, "Enhancing the efficiency of solar panels using machine learning techniques," *IEEE Transactions on Sustainable Energy*, vol. 13, no. 2, pp. 543–553 (2022), doi: 10.1109/TSTE.2021.3129456.

[20] J. Hu and L. Gao, "Smart grid load forecasting using deep learning techniques," *Applied Soft Computing*, vol. 122, p. 108097 (2023), doi: 10.1016/j.asoc.2022.108097.

[21] M. Patel and P. Rao, "NLP-based analysis of customer reviews for renewable energy products," *Journal of Retailing and Consumer Services*, vol. 64, p. 102824 (2023), doi: 10.1016/j.jretconser.2022.102824.

[22] K. Wang and Z. Liu, "AI-based predictive maintenance for solar power plants," *Energy Reports*, vol. 7, pp. 2224–2233 (2021), doi: 10.1016/j.egyr.2021.04.037.

[23] A. Gandhar, S. Vijay, A. Mohapatra, J. Datta, and S. Shukla, "An informative review on recent development of renewable energy system," *Journal of Information and Optimization Sciences,* vol. 43, no. 3, pp. 419–427 (2022), doi: 10.1080/02522667.2022.2048516.

[24] P. Lata and S. Vadhera, "Optimal placement and sizing of energy storage systems to improve the reliability of hybrid power distribution network with renewable energy sources," *Journal of Statistics and Management Systems*, vol. 23, no. 1, pp. 17–31 (2020), doi: 10.1080/09720510.2020.1714147.

[25] H. Liu, Y. Chen, and X. Li, "Deep learning-based solar irradiance forecasting for photovoltaic power generation," *Renewable Energy,* vol. 214, pp. 1189–1201 (2023), doi: 10.1016/j.renene.2023.05.081.

[26] M. Rahman, A. Al Mamun, and S. Islam, "Hybrid CNN-LSTM model for short-term wind power forecasting," *Energy Reports*, vol. 9, pp. 6321–6333 (2023), doi: 10.1016/j.egyr.2023.03.071.

[27] S. Wang, T. Zhang, and Q. Zhao, "Explainable artificial intelligence for renewable energy forecasting: Methods and applications," *Energy and AI,* vol. 12, p. 100231 (2023), doi: 10.1016/j.egyai.2023.100231.

[28] A.Verma, R. Sharma, and S. Gupta, "Machine learning-based optimization of hybrid renewable energy systems for smart grids," *IEEE Access*, vol. 11, pp. 85432–85445 (2023), doi: 10.1109/ACCESS.2023.3298765.

[29] J. Chen, L. Sun, and Y. Zhao, "Deep reinforcement learning for optimal energy management in hybrid renewable microgrids," *Applied Energy*, vol. 341, p. 121087 (2023), doi: 10.1016/j.apenergy.2023.121087.

[30] P. Singh and M. Gupta, "Artificial intelligence techniques for solar power prediction: A comprehensive review," *Renewable and Sustainable Energy Reviews*, vol. 182, p. 113356 (2023), doi: 10.1016/j.rser.2023.113356.

[31] K. Zhou, Y. Li, and J. Wu, "Smart grid energy management using hybrid deep learning models," *IEEE Transactions on Smart Grid*, vol. 15, no. 1, pp. 542–552 (Jan. 2024), doi: 10.1109/TSG.2023.3304578.

[32] Kumar, S. Patel, and D. Singh, "Short-term load forecasting using transformer-based deep learning architecture," *Applied Energy*, vol. 352, p. 121985 (2024), doi: 10.1016/j.apenergy.2023.121985.

[33] R. Ahmad, M. Khan, and F. Hussain, "Artificial intelligence-driven predictive maintenance for wind turbines: A data-driven approach," *Energy Reports*, vol. 10, pp. 1023–1034 (2024), doi: 10.1016/j.egyr.2024.01.045.

[34] Y. Li, J. Zhang, and H. Zhao, "Hybrid machine learning framework for renewable energy generation forecasting in smart grids," *IEEE Access*, vol. 12, pp. 45876–45889 (2024), doi: 10.1109/ACCESS.2024.3368421.

[35] Q. Yang, H. Liu, and X. Zhang, "Deep learning-based photovoltaic power forecasting using hybrid CNN–LSTM networks," *Applied Energy*, vol. 345, p. 120891 (2023), doi: 10.1016/j.apenergy.2023.120891.

[36] Gupta, A. Kumar, and R. Singh, "Machine learning techniques for wind energy forecasting: A comparative study," *Renewable Energy*, vol. 219, pp. 1195–1208 (2024), doi: 10.1016/j.renene.2023.11.045.

[37] T. Zhao, Y. Sun, and L. Chen, "Artificial intelligence-enabled energy management for smart microgrids," *IEEE Transactions on Smart Grid*, vol. 15, no. 3, pp. 2104–2114 (May 2024), doi: 10.1109/TSG.2024.3352187.

[38] M. Alsharif, A. Y. Al-Dhaifallah, and M. Kim, "Explainable deep learning framework for renewable energy forecasting and smart grid applications," *Energy and AI*, vol. 16, p. 100325 (2024), doi: 10.1016/j.egyai.2024.100325.

[39] R. Machlev, Y. Levron, J. Belikov, and Y. Beck, "Explainable Artificial Intelligence (XAI) techniques for energy and power systems: Review, challenges and opportunities," *Energy and AI*, vol. 8 (2022), Art. no. 100134, doi: 10.1016/j.egyai.2022.100134

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