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Artificial intelligence for optimizing renewable energy systems: techniques, applications, and future directions

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ABSTRACT

The integration of artificial intelligence (AI) is critically transforming the renewable energy sector. This review synthesizes AI's role in optimizing solar and wind energy systems, focusing on power forecasting, system optimization, and predictive maintenance. The research goal was to systematically analyze how diverse AI techniques enhance these critical aspects. Key findings indicate AI's capacity to substantially improve short-term solar irradiance and wind power forecasts (e.g., via SARIMAX, long short-term memory (LSTM), and hybrid deep learning models), dynamically manage energy flow in smart grids and microgrids, optimize maximum power point tracking (MPPT) in photovoltaic (PV) systems, and enable proactive maintenance through anomaly detection in wind turbines using IoT-integrated AI. Key conclusions reveal that AI significantly enhances the efficiency, reliability, and economic viability of solar photovoltaic and wind power generation, offering superior adaptability and predictive capabilities over traditional methods. While AI is important for the global transition to cleaner energy, persistent challenges related to data quality and availability, model interpretability, and cybersecurity must be addressed to fully unlock its potential in practical renewable energy applications.

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1. INTRODUCTION

Fossil fuels, currently prevalent energy sources, are primarily characterized by high emissions of CO2 and other pollutants, uneven distribution, and expensive production [1], [2]. Achieving CO2 neutrality is now the most critical global activity in the fight against climate change, driving all countries to switch to cleaner energy to meet international goals [3]. Artificial intelligence (AI) has become a critical enabler in optimizing renewable energy systems. This review answers how AI can overcome the inherent variability of renewable sources, especially solar and wind, which pose significant challenges to grid stability and efficient energy utilization. AI mitigates this by improving energy generation forecasts and optimizing system operations, thereby enhancing reliability and efficiency [4], [5]. AI-driven predictive maintenance further ensures robust asset management by detecting equipment anomalies early, preventing downtime, and reducing costs [6].

Solar energy, collected through photovoltaic (PV) panels, plays a key role in providing sustainable and renewable energy solutions, offering an environmentally friendly and cost-effective alternative to traditional energy sources, thus reducing dependence on fossil fuels and contributing to environmental protection [7], [8]. Wind energy, for instance, is a clean, free, and inexhaustible source, often characterized by lower initial investment costs [9], [10]. AI also plays an important role in integrating renewables into power grids. AI-enhanced smart grids dynamically manage energy distribution and storage, ensuring stable supply despite variability [11]. Beyond grid management, AI optimizes energy storage systems, improving battery management and extending lifespan [6]. AI's forecasting ability supports demand response, balancing generation with consumption, reducing peak loads, and improving efficiency [4]. Optimizing system operations, AI contributes to lower carbon emissions and reduced operational costs, making renewable energy projects more sustainable and financially viable [12]. Thus, AI is central to the global transition towards cleaner, more efficient energy production and sustainability goals.

Figure 1 summarizes AI applications in renewable energy, encompassing energy prediction, system performance, grid integration, energy storage, and demand response. AI's ability to process complex datasets improves forecasts, optimizing production and reducing inefficiencies [12]. Predictive maintenance minimizes disruptions by identifying failures early, ensuring consistent power generation [13]. In grid management, AI coordinates generation and distribution, maintaining balance and stability [14]. AI also optimizes energy storage and adjusts production based on demand, supporting reduced peak loads and balanced distribution [15]. These applications align with global efforts towards carbon neutrality and climate change mitigation, as AI tools enhance the sustainability and economic viability of renewable energy systems. Through these applications, AI is important for advancing renewable energy performance, making it central to future energy strategies.

Despite these advancements, significant challenges persist that limit AI's full potential in renewable energy. Key issues include concerns related to data quality and availability, the critical need for model interpretability and trustworthiness to facilitate operator adoption, and pervasive ethical and cybersecurity concerns within interconnected energy infrastructures. Addressing these unresolved problems forms a core focus of this review.

This review adopts a structured approach, providing a detailed and focused analysis of specific AI techniques and their transformative role in optimizing solar and wind energy systems. Our distinctive contribution lies in synthesizing the current state-of-the-art specifically within solar and wind contexts, identifying and elaborating on critical challenges (data quality, model interpretability, cybersecurity), and offering future-oriented perspectives and recommendations to drive the strategic and effective use of available AI techniques in the renewable energy sector. This work offers a targeted knowledge base for both researchers and practitioners, showing how a new framework, synthesis, and perspective will provide novel insights into overcoming the variability and operational complexities of renewable energy.

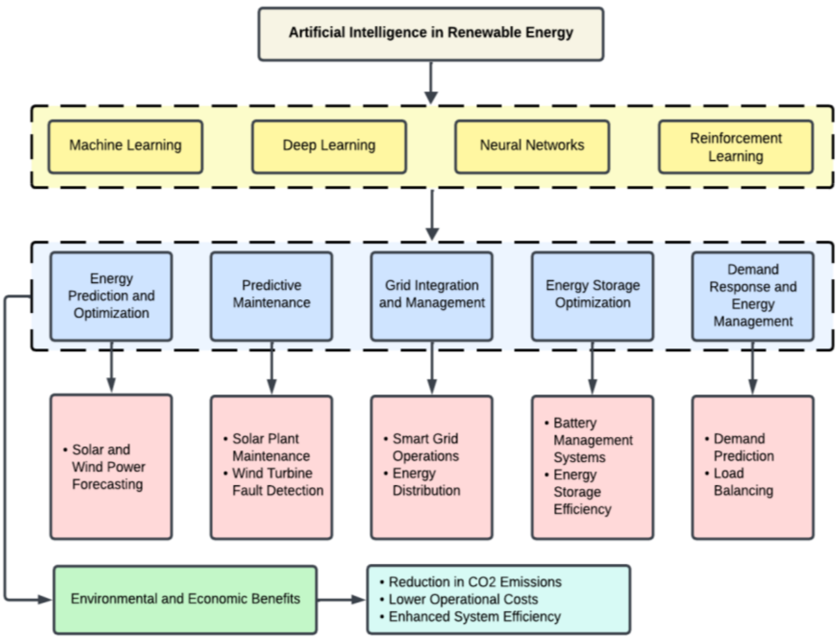

Figure 1. Overview of AI applications in renewable energy systems

2. METHODOLOGY

This narrative and thematic review systematically synthesizes existing knowledge on AI's transformative role in optimizing renewable energy systems, with a particular focus on solar and wind energy. The research goal was to identify and categorize key AI techniques and their applications in power forecasting, system optimization, and predictive maintenance; discuss associated challenges and limitations; and propose future research directions and recommendations. This approach emphasizes transparency and replicability despite its narrative nature, ensuring a comprehensive and reliable synthesis of the literature, providing the necessary foundation for validating the methods employed and confirming the findings.

2.1. Literature search strategy

The primary database for literature identification was Scopus, selected for its extensive coverage and quality control. The search was conducted periodically up to the finalization of this manuscript to ensure inclusion of the most recent advancements. A structured search string combined keywords related to AI techniques ("artificial intelligence," "machine learning," "deep learning," "reinforcement learning," "neural network"), renewable energy types ("solar energy," "wind energy," "photovoltaic"), and specific applications ("optimization," "forecasting," "predictive maintenance," "smart grid"). Boolean operators (AND, OR) were used. The search was limited to "article" and "review article" document types and English-language papers.

2.2. Inclusion and exclusion criteria and selection process

Studies were selected based on specific inclusion/exclusion criteria. Inclusion focused on peer-reviewed journal articles and review articles directly addressing AI applications in optimizing, forecasting, or maintaining solar and/or wind energy systems, providing experimental or field-based insights. Exclusion filtered out studies not directly addressing AI in renewable energy, those focused on other energy sources (unless part of a hybrid system explicitly including solar or wind), non-peer-reviewed literature, and papers solely discussing hardware design without significant AI integration. The two-stage selection process involved initial title and abstract screening for relevance, followed by full-text review of selected articles to confirm compliance.

2.3. Data extraction and thematic analysis

Data extraction focused on gathering key information: specific AI technique(s), renewable energy type, application area, key findings, challenges, and proposed future directions. This data then underwent thematic analysis, involving familiarization through reading, initial coding for recurring concepts, grouping similar codes into broader themes (e.g., "deep learning for forecasting," "challenges in data quality," "AI-IoT integration"), and refining these themes for accuracy. The review's findings are structured around these identified themes, providing a coherent narrative that synthesizes advancements, challenges, and future directions, offering valuable insights for researchers and practitioners.

3. RESULTS AND DISCUSSION

3.1. Overview of AI techniques in renewable energy

3.1.1. Machine learning

Machine learning (ML) optimizes renewable energy systems by enhancing predictive accuracy and detecting anomalies. Supervised learning improves solar and wind energy generation predictions, while unsupervised learning identifies irregular consumption patterns, contributing to grid stability. Reinforcement learning (RL) optimizes control strategies in dynamic grid environments, improving efficiency and reducing storage needs [16]. These methods effectively manage energy variability, enabling informed production and distribution decisions.

In practical applications, ML significantly improves renewable energy output. Genetic algorithms (GA) increase solar PV output by up to 15%, and RL optimizes maximum power point tracking (MPPT) even under challenging conditions [17], [18]. Neural networks (NN) improve wind turbine efficiency by 12% [17]. The ramifications of these advancements are significant: they not only enhance energy yield and enable operation closer to theoretical maximum efficiencies, but also translate into tangible economic savings and reduced reliance on non-renewable backup systems, directly contributing to sustainability goals.

Despite progress, ML implementation in renewable energy faces limitations. Models may struggle with unpredictable real-world conditions, raising robustness concerns. Challenges arise from ML's reliance on high-quality data and complex integration into existing infrastructure. Moreover, the technical depth of these models can also hinder interpretability, making it difficult for operators to trust AI-driven decisions [19]. This 'black box' nature is a critical barrier to widespread adoption in high-stakes energy applications where transparent decision-making is paramount. Future advancements like explainable AI (XAI) and edge computing offer promising solutions to address these challenges in renewable energy applications [20]. These innovations aim to build trust and accessibility, accelerating AI adoption in the transition towards a sustainable energy future, making them highly valuable for future practical deployment.

3.1.2. Deep learning

Deep learning (DL) is critical for forecasting and control in renewable energy systems, due to its ability to model complex, nonlinear relationships. Long short-term memory (LSTM) networks excel at temporal dependencies in load forecasting [21], while convolutional neural networks (CNNs) suit spatial data analysis [22]. A key comparison reveals that hybrid CNN-LSTM models often leverage both temporal and spatial features, offering improved performance over single-architecture models by capturing richer patterns [21]. These models process vast datasets (historical consumption, weather patterns), effectively forecasting energy load and PV power production, facilitating better renewable energy integration and enhanced power system reliability compared to traditional statistical models by capturing non-linear relationships more effectively [21], [22].

Beyond forecasting, DL optimizes control strategies by providing accurate short-term and long-term forecasts, enabling precise balancing of supply and demand within smart grids. This is essential for systems with high intermittent renewable penetration [23]. DL-based control methods improve grid stability and operational efficiency by managing energy flows effectively in complex systems with electric vehicles and distributed energy resources [24].

However, DL deployment faces challenges. Interpretability is a significant issue; these "black box" models limit trust among engineers and grid operators who need transparent outputs for real-time decisions [25]. This lack of transparency is a major impediment to their widespread adoption in critical infrastructure, where accountability and understanding model rationale are important, representing a significant ramification. Model performance heavily depends on data quality and availability; inadequate data limits accuracy and generalization [26]. High computational demands also hinder scalability. This implies that future developments are likely to focus on creating more interpretable models, enhanced data processing, and edge computing to reduce computational demands, including lightweight, scalable neural networks (e.g., TinyML) tailored for edge deployment [24], [27]. These advancements are essential for DL to enhance efficiency, reliability, and sustainability, directly addressing what will come in handy in the future.

3.1.3. Reinforcement learning

Reinforcement learning (RL) has shown significant promise in the adaptive management of renewable energy systems, providing robust solutions for handling uncertainty and dynamic environments. In the context of energy management within buildings, RL models, such as those utilizing the upper confidence bound (UCB1) algorithm, have been effectively applied to manage energy consumption, generation, and storage. These models demonstrate superior adaptability to ongoing environmental changes, outperforming traditional methods like EXP3 and simpler RL algorithms in selecting the best actions for energy optimization [28]. This adaptability is particularly important in the face of fluctuating energy generation from renewables like solar and wind, where RL-based models can continuously learn and adjust their strategies to optimize energy use. Similarly, in the realm of microgrid management, RL algorithms such as deep Q-networks (DQN), proximal policy optimization (PPO), and twin delayed deep deterministic policy gradient (TD3) have proven valuable. A critical interpretation of these RL approaches reveals their advantages over traditional methods like rule-based and model predictive control (MPC), particularly in managing the complexities of energy flows within microgrids due to their ability to learn optimal policies without explicit system models and adapt to unforeseen changes [29].

Advanced applications of RL in renewable energy include multi-agent reinforcement learning (MARL) frameworks, which allow for the autonomous management of renewable energy microgrids. By using multiple agents that learn and adapt to different parts of the system, MARL significantly enhances grid reliability, energy efficiency, and cost reduction compared to traditional rule-based approaches [30]. The ramifications of this decentralized approach are profound, as it is especially advantageous in complex, distributed energy systems where real-time coordination among different energy sources and consumers is required to maintain stability and optimize resource allocation, leading to more resilient and efficient grids. Additionally, RL has proven effective in energy storage optimization, with strategies like reinforcement learning-optimal power flow (RL-OPF) being used to maximize storage capacity in power systems. These methods excel in situations where accurate stochastic models are unavailable, using RL's flexibility to handle real-time variations in grid conditions [31]. For building energy management, methods like the soft actor-critic combined with transformer deep neural networks have shown success in controlling heat pumps and thermal storage, leading to better energy efficiency than rule-based approaches [32]. In zero-energy houses, model-based RL approaches such as DQN and deep deterministic policy gradient (DDPG) have been instrumental in optimizing PV generation usage, achieving fast convergence and cost-effective energy management, with DDPG standing out for its ability to maximize self-consumption and self-sufficiency ratios [33].

Despite RL's potential, its implementation in renewable energy systems faces certain challenges, such as the requirement for extensive training data, high computational demands, and prolonged training times needed to learn optimal strategies in complex, non-linear environments. Such factors may limit deployment in resource-constrained settings. These limitations present significant hurdles to broader adoption, and their resolution is critical for RL to scale effectively. Future research could focus on improving interpretability to foster greater trust among energy operators, exploring data-efficient RL algorithms and edge computing to reduce computational load, including offline and federated RL for decentralized, privacy preserving policy learning suitable for real-world energy systems [30], [31], [33]. By addressing these challenges, RL has the potential to further enhance the efficiency and sustainability of renewable energy systems, making it adaptable to the evolving demands of the energy market and ensuring its utility in future energy infrastructure.

3.1.4. Hybrid models

Hybrid models, which integrate AI with physical models, offer a powerful approach for improving the accuracy and efficiency of renewable energy predictions and optimization. By leveraging the strengths of both AI techniques—such as machine learning and deep learning—and traditional physical models, these systems can deliver more precise energy forecasts and better resource management. For example, the Kuwait Renewable Energy Prediction System (KREPS) combines numerical weather prediction with statistical learning models and an analog ensemble approach, providing accurate short-term and long-term forecasts for energy production [34]. This blend of data-driven insights and physically based models allows for a more nuanced understanding of complex energy systems, representing a key advantage and making hybrid models particularly valuable in scenarios where variability in renewable energy generation poses significant challenges due to their ability to incorporate physical constraints and known system behavior, leading to more robust and reliable predictions.

One of the key advantages of hybrid models is their ability to optimize energy systems through the integration of advanced AI algorithms with traditional mathematical frameworks. Techniques such as artificial neural networks (ANN) and LSTM networks are often combined with classical methods to streamline the optimization process, reducing computational burdens while maintaining accuracy [35], [36]. This approach is an important interpretation of their utility: it enables fast and precise predictions of energy production, which is critical for real-time energy management in renewable energy systems, offering a superior balance of accuracy and computational efficiency compared to purely data-driven or purely physics-based models. Additionally, AI-driven models within these hybrid frameworks can process large datasets, including weather forecasts and historical production records, to fine-tune energy system performance leading to reduced energy waste and improved overall efficiency. By utilizing stochastic uncertainty analysis and statistical methods, this also enhances the robustness of energy predictions, ensuring reliable performance even under fluctuating environmental conditions [37].

The adaptability of hybrid models extends to real-time operations, where they enable dynamic adjustments to energy generation and distribution. This capability is particularly beneficial for managing decentralized energy systems like microgrids, where variability in energy supply and demand requires constant monitoring and adjustment [38]. For large-scale applications, such as renewable energy parks, systems like KREPS showcase the potential of hybrid models to integrate multiple renewable energy sources—including wind, solar, and storage technologies—into a cohesive management framework [5], [34]. The versatility and precision of hybrid models make them a robust solution for optimizing renewable energy systems, offering significant improvements in forecasting accuracy, system efficiency, and overall stability [39]. Their ability to combine theoretical understanding with data-driven learning suggests they will come in handy as increasingly important tools for ensuring reliable and sustainable energy production in increasingly complex future energy landscapes.

3.2. AI in solar energy systems

AI advances solar energy by enhancing efficiency, reliability, and grid integration. In power forecasting, AI improves predictions for grid stability and energy planning. For optimization, AI maximizes energy capture, adapts to conditions, and streamlines monitoring. AI-driven predictive maintenance enables early fault detection, anomaly identification, and real-time diagnostics, ensuring consistent performance and reducing costs.

3.2.1. Solar power forecasting

AI-based techniques have seen its significant effects for improving solar power forecasting and grid stability. Advanced models like LSTM show superior performance in predicting solar electricity generation beyond two hours, enabling better planning [40]. Enhanced ANNs incorporating weather data improve accuracy, suitable for variable climates [41]. Ensemble methods (LSTM, XGBoost, ridge regression) provide robust forecasting [42]. Hybrid models (1D CNN with gated recurrent unit (GRU)) excel in short-term forecasts, capturing complex patterns with higher precision [43]. A critical comparison of these methods indicates that while deep learning models (LSTM, CNN-GRU) often offer higher precision for complex, non-linear patterns, traditional methods and ensembles can provide a balance of interpretability and robustness, making their suitability dependent on the specific forecasting horizon, data availability, and operational requirements.

AI also ensures grid stability through interpretable insights. Explainable AI (XAI) methods (LIME, SHAP, ELI5) help operators understand AI forecasts, important for decision-making [44]. The ramification of transparent XAI is increased operator trust and quicker adoption of AI tools, which is essential for stable grid operations, particularly when autonomous decisions are involved. Traditional methods (decision trees, random forest) remain useful for solar irradiance forecasting due to reliability and interpretability [45]. Tiny machine learning (TinyML) offers on-device predictions for resource-constrained settings [46]. These AI models contribute to grid stability by adapting to conditions, providing precise forecasts, and offering scalable solutions. However, their effective implementation requires addressing interpretability and integration challenges. Future efforts will focus on making these advanced models more accessible and interpretable, directly contributing to their practical utility and enabling wider adoption in diverse operational environments.

3.2.2. Optimization of PV systems

AI plays an important role in enhancing the efficiency and performance of PV systems through various optimization techniques that address challenges such as fluctuating weather conditions and the need for precise energy management. AI-based MPPT (neural networks, fuzzy logic) outperforms traditional methods like perturb and observe (P&O) by offering greater stability and adaptability to changing weather [47], [48]. This superiority is interpreted as AI's capacity to dynamically adjust the operating point of PV systems in response to real-time changes in sunlight intensity and temperature, ensuring that PV systems always operate at their optimal power point, even under rapidly changing conditions like partial shading [48], [49]. The ramification of this adaptability is particularly valuable in regions with highly variable weather, where even subtle changes in irradiance can significantly affect power output, leading to sub-optimal energy capture. By continuously optimizing energy capture, these AI techniques increase overall efficiency, providing a stable supply and reducing reliance on supplementary sources.

Beyond MPPT, AI enhances hybrid PV systems by integrating with other energy sources (e.g., fuel cells), improving decision-making, performance, efficiency, and cost savings [12]. AI-based forecasting tools (e.g., evolving generative adversarial fuzzy networks - EGAFN) provide accurate solar energy predictions, critical for planning and managing resources [50]. This capability helps grid operators manage energy flows, reducing overproduction or shortages. AI algorithms enable automated monitoring and fault detection, identifying inefficiencies and facilitating timely maintenance, thus reducing downtime and operational costs [51]. Despite advances, challenges remain: large training datasets, computational demands, and selecting the most suitable AI approach. Addressing these through research could enhance AI's practicality in PV systems, making them more efficient and adaptable. These ongoing improvements in AI-driven optimization hold promise for making PV systems a more reliable and cost-effective solution for sustainable energy production, clearly indicating what will come in handy in the future for broad deployment and improved grid stability.

3.2.3. Predictive maintenance for solar plants

AI-driven predictive maintenance transforms solar energy by enhancing reliability, efficiency, and reducing operational costs. Supervised learning algorithms predict and classify faults, enabling early detection before significant power losses occur [52]. Unsupervised learning detects anomalies in sensor data, identifying potential failures early. RL optimizes maintenance scheduling and resource allocation while digital twins provide virtual replicas for real-time diagnostics and planning, reducing reliance on manual inspections [52]. Deep learning monitors soiling on PV panels, optimizing cleaning schedules, and internet of things (IoT) devices collect real-time data for predictive insights [53], [54].

A challenge in adopting AI-driven predictive maintenance is model interpretability. XAI techniques (LIME, SHAP) make AI decisions transparent, building trust in automated maintenance [44], [55]. The critical ramification of improved XAI is not just technical understanding but also increased human confidence in automated systems, which is important in high-stakes environments where understanding the rationale behind actions can impact system safety and efficiency, and where regulatory compliance demands transparent operations. Despite challenges, AI strategies improve economic viability by minimizing downtime, reducing manual maintenance costs, and maximizing energy production [38]. As AI advances, these predictive maintenance approaches will become more refined, making solar energy systems more resilient, cost-effective, and capable of meeting demand, representing what will come in handy for future large-scale, reliable, and sustainable solar energy deployment.

3.3. AI in wind energy systems

AI is important in advancing wind energy systems, improving forecasting, optimization, and predictive maintenance. AI models enhance wind power predictions for better grid integration and energy management. For turbine optimization, AI-driven control systems adjust settings using real-time data, maximizing efficiency and reliability. In predictive maintenance, AI detects potential issues early via data analysis, reducing downtime and extending component lifespan. This integration makes wind energy more efficient, reliable, and cost-effective.

3.3.1. Wind power forecasting

AI techniques enhance wind speed and power predictions, improving energy management by boosting accuracy and efficiency. ML and deep learning models use historical data, forecasts, and sensor information for precise wind energy forecasts, enabling effective planning [56], [57]. These methods, including hybrid CNN-LSTM, offer up to a 15% improvement over traditional models, increasing energy efficiency by 10% and improving grid integration [57], [58]. A key interpretation of these advances is that they help utilities significantly reduce operational costs and improve overall grid responsiveness by minimizing the need for expensive reserve power, optimizing energy dispatch, and facilitating more efficient scheduling within the grid network.

Challenges include prediction uncertainties and data quality/quantity issues affecting reliability. Non-stationarity and complex variable interactions make consistent accuracy hard to attain. These issues present significant ramifications, as unreliable forecasts can lead to grid instability, higher operational costs, increased curtailment of renewable energy, and reduced confidence in wind power as a primary energy source, thereby impeding the energy transition. Addressing these requires improved data preprocessing and model interpretability. High computational requirements also limit real-time application, indicating a need for more efficient approaches [56].

Future advancements in AI for wind speed and power prediction aim to tackle these challenges through the integration of meta-heuristic algorithms, which enhance the adaptability and optimization of predictions. Improving feature selection and using advanced data-driven techniques can further refine forecasting accuracy, making AI models more responsive to changing weather conditions. These advancements will enable better integration of wind power into energy systems, reducing energy waste and making renewable energy sources more reliable and cost-effective, directly illustrating what will come in handy for future energy management and grid modernization.

3.3.2. Turbine optimization and control

AI-enabled control schemes optimize wind turbine coordination within wind farms. They allow real-time control, bypassing time-consuming optimization processes with high computational efficiency for MPPT and set point tracking (SPT) modes [59]. ML-based wind turbine control systems (MLBWTCS) use sensor data (wind speed, blade pitch angle, generator torque) to predict optimal settings, enhancing efficiency and reliability [60]. ANN and fuzzy logic (FL) are applied in wind energy for MPPT, maintaining optimal output under fluctuating wind [61]. RL, ANNs, and metaheuristic optimization algorithms optimize turbine placement within wind farms, considering energy output, cost-efficiency, and environmental impact [62].

Implementing AI in wind turbine systems faces challenges, such as reliability in offshore wind technology, where AI is important for improving performance, particularly in predicting failures in unsupervised components like yaw brakes [63]. Cybersecurity is another concern; AI-based converter controllers are proposed to mitigate cyber-attacks (e.g., data spoofing, DoS) using anomaly detection and encryption [64]. The ramifications of these cybersecurity vulnerabilities are significant, potentially leading to grid instability, operational disruption, financial losses, and even national security threats if not effectively managed through robust AI-enabled defenses. Despite these challenges, AI boosts energy production by optimizing efficiency and reducing costs [15]. It also improves wind power forecasting and enables early detection of turbine failures via SCADA data [65]. Integrating AI into wind turbine operations holds great potential for optimizing energy production, enhancing forecasting capabilities, and proactively addressing key challenges like reliability and cybersecurity, showing what will come in handy for the future of large-scale, secure, and efficient wind energy development.

3.3.3. Predictive maintenance for wind plants

Predictive maintenance for wind turbines leverages AI to enhance reliability, reduce downtime, and lower operational costs. ML algorithms (random forest, LSTM, ANFIS) predict failures and classify faults. Analyzing historical and real-time data, these models detect anomalies and forecast issues, allowing proactive intervention before escalation [30], [63]. This proactive approach is a critical interpretation of AI's value: it not only minimizes unplanned downtime but also extends the lifespan of turbine components by ensuring timely and targeted maintenance, leading to substantial economic and operational benefits by reducing costly reactive repairs and lost revenue from outages. AI enhances maintenance schedules by recognizing patterns preceding failures.

AI-driven predictive maintenance often integrates cloud platforms and IoT systems for real-time data processing, enabling scalable, centralized monitoring of turbines across geographies [66], [67]. Rapid analysis of sensor data supports quicker decision-making. Cloud computing makes AI solutions cost-effective by reducing on-site infrastructure needs. This combination highlights a shift towards data-driven, efficient maintenance.

Digital twins further enhance capabilities, providing virtual replicas for real-time condition monitoring, data analysis, and feedback [67]. This insight allows operators to simulate scenarios and predict maintenance needs. Sensor data is critical for predicting the remaining useful life (RUL) of components [66]. Autoencoders and isolation forests assist in anomaly detection [30]. Combining AI insights with human expertise improves fault detection accuracy, supporting less experienced technicians [68]. This human-AI collaboration represents an important future direction for practical implementation, ensuring that the technology complements human skills rather than replacing them entirely. As a result, AI-driven predictive maintenance offers significant benefits, including greater operational efficiency, reduced costs, and enhanced reliability, making renewable energy production more sustainable and cost-effective [65], [66]. These advancements directly contribute to what will come in handy in the future for large-scale, resilient, and economically viable wind power deployment across diverse environments.

3.4. Challenges and limitations

3.4.1. Data availability and quality

AI applications in renewable energy systems (RES) face significant challenges related to data quality and integration, hindering effectiveness in optimization, forecasting, and maintenance. Resolving these is essential for improved system performance. Data quality concerns include timeliness, completeness, consistency, and accuracy. AI models require real-time data from IoT devices for quick responses to fluctuating conditions [6]. Delays or incomplete datasets reduce prediction accuracy and hinder model training [15]. The inherent variability of RES data leads to inconsistencies, complicating long-term forecasting [6], [69]. Inaccurate sensor or weather data distorts AI-driven decisions, with significant ramifications for system reliability and efficiency, potentially leading to suboptimal energy dispatch and increased operational costs.

Data integration involves combining diverse data sources (weather, sensor outputs, historical records), often in varying formats and resolutions [5], [6]. These sources differ in frequency and precision, complicating standardization and alignment [70]. Effective alignment is important for accurate, real-time insights that enhance energy yield, reduce operational costs, and improve grid reliability [37]. These challenges limit AI's ability to fully capture complex RES dynamics and provide optimal solutions.

3.4.2. Model interpretability and trustworthiness

Despite AI's important role, its effectiveness and adoption depend on model interpretability, trustworthiness, and user engagement. Building trust and ensuring responsible deployment requires AI systems designed with transparency, accountability, and usability. Anomaly detection is core to AI-driven energy systems, identifying equipment faults and disruptions. Techniques like autoencoders and isolation forests detect abnormal patterns in wind and solar data, supporting predictive maintenance that minimizes downtime [45]. This proactive capability significantly improves system performance.

To ensure transparency, by-design frameworks like user-centric explainable AI (XAI) embed interpretability from early development stages. This integrates transparency into tasks like power forecasting and fault prediction, making AI decisions understandable and regulatory-compliant [71]. A user-centric approach prioritizes end-user needs, allowing operators and engineers to interact with understandable, tailored AI models.

Building trustworthy AI also requires addressing reliability, transparency, ethics, and accountability. Users must trust consistent model performance across diverse conditions. Fairness and bias must be monitored, especially when AI influences decisions with operational and safety implications [9]. Interpretability techniques like SHAP and LIME demystify complex AI models, explaining feature contributions to predictions, enabling informed decisions [71], [72]. In high-stakes renewable energy applications, interpretability is not optional but essential for trust, accountability, and long-term adoption. Without it, the ramifications include reduced adoption, operational risks, a lack of accountability in automated decision-making, and a significant hindrance to scaling intelligent energy solutions in real-world scenarios. By incorporating explainability, trustworthiness, and user-centered design, AI models can not only enhance operational efficiency but also become trusted tools in the renewable energy sector. As energy systems grow more intelligent and interconnected, these elements will be important for ensuring AI serves as a sustainable and reliable force in clean energy transformation.

3.4.3. Ethical and security concerns

Integrating AI into renewable energy systems presents significant ethical and security concerns. A primary ethical challenge is data privacy, as large volumes of operational and user data are collected. Without safeguards, sensitive information is vulnerable to misuse, undermining trust and compliance [11], [73]. Transparency is also important, enabling stakeholders to understand AI-driven decisions. XAI frameworks make AI models interpretable and trustworthy. Equitable access to AI-driven technologies is another major ethical concern; the digital divide must be addressed to ensure all communities benefit, preventing further inequalities.

On the security front, the increasing digitalization of energy infrastructure exposes systems to cyber threats. Strong cybersecurity measures (encryption, access control, regular audits) are essential for protecting critical assets [70]. AI-enabled threat detection using machine learning enhances security by identifying real-time anomalies. However, challenges remain, including the need for quality datasets and interpretable security models [74]. The ramifications of failing to address these security concerns include potential grid instability, operational disruption, financial losses, and even national security threats, jeopardizing the very infrastructure AI aims to optimize.

Addressing these concerns requires comprehensive regulatory frameworks that enforce standards on data privacy, transparency, and cybersecurity. Such policies must ensure AI technologies are deployed ethically and securely, aligning with societal values while maintaining system integrity [73]. By creating clear regulations, the renewable energy sector can confidently adopt AI technologies, ensuring systems remain secure, ethical, and resilient.

3.5. Future trends and directions

3.5.1. Emerging AI techniques for renewable energy

Emerging AI techniques like deep reinforcement learning (DRL), generative adversarial networks (GANs), and hybrid AI-physical models are expected to significantly enhance renewable energy systems. DRL is effective in real-time decision-making in dynamic energy environments, optimizing storage and distribution. Its ability to continuously learn and adapt is valuable in smart grids and decentralized systems, where real-time adjustments are critical for supply-demand balance [17], [29]. GANs can improve energy forecasting by generating synthetic data for areas with insufficient historical records, enhancing AI model training. Their ability to simulate diverse scenarios improves accuracy and robustness of forecasts, especially in regions with high weather variability.

Hybrid AI-physical models combine AI with traditional physics-based approaches for more accurate predictions and optimization. Blending data-driven insights with physical modeling addresses nonlinear dynamics of renewable energy systems, as shown by KREPS, which enhances forecasts by integrating AI with weather predictions [34]. These advanced AI techniques will play a pivotal role in overcoming current challenges related to data variability, prediction accuracy, and system reliability, representing what will certainly come in handy for future RES development and increased grid resilience.

3.5.2. Integration of AI with IoT in renewable energy

The integration of AI with IoT will revolutionize renewable energy management through real-time monitoring, analysis, and control. IoT devices (sensors, smart meters) generate vast amounts of real-time data, which AI models analyze to optimize production, detect anomalies, and predict maintenance [53], [54]. This is particularly beneficial for solar and wind, where environmental factors fluctuate constantly.

AI-driven IoT systems enable continuous monitoring and real-time adjustments for peak efficiency. AI’s role in predictive maintenance is enhanced by IoT sensors collecting performance data, allowing early detection of equipment failure, minimizing downtime, and extending asset lifespan [53], [54]. In decentralized systems, AI-IoT integration provides real-time coordination for managing dispersed energy sources and optimizing energy flows [38]. As IoT spreads, future research will focus on improving data integration, enhancing system scalability, and ensuring the security of AI-IoT networks, which will be important for its widespread adoption and utility in fostering smarter, more autonomous energy systems.

3.5.3. AI for decentralized energy systems

AI is essential for advancing decentralized energy systems, including microgrids and distributed networks, critical for energy access and resilience. MARL is a key AI technique applied here, enabling autonomous coordination among diverse energy sources (solar, wind, storage). MARL ensures decentralized systems respond to real-time supply and demand changes, optimizing energy distribution without reliance on a central grid [30], [33].

AI also improves energy storage management within decentralized systems, using models like RL to optimize charging/discharging cycles, ensuring efficient energy use and cost reduction [31]. AI-driven predictive maintenance enhances reliability by analyzing sensor data to predict equipment failures [53], [54]. AI's ability to adapt to local conditions and optimize energy usage will be important as decentralized systems become more widespread, particularly for off-grid solutions, highlighting their indispensable future role in achieving energy equity and resilience globally.

4. CONCLUSION

AI has emerged as a key enabler of advancements and innovation in solar and wind energy systems, delivering measurable improvements in power forecasting, system optimization, and predictive maintenance. These capabilities contribute not only to enhanced operational efficiency and reliability but also reduce carbon emissions and lower energy costs, thereby supporting the global shift toward sustainable and economically viable energy systems. The scientific justification of this research lies in its focused synthesis of AI applications specifically in solar and wind energy contexts, which are two of the most prominent and rapidly growing renewable technologies.

This study bridges a critical gap in understanding how diverse AI techniques are currently deployed and where future research is most needed. Unlike broad, general-purpose reviews, this work highlights domain-specific advancements, challenges, and opportunities, providing a targeted knowledge base for both researchers and practitioners. Despite the evident progress, significant challenges persist, particularly around data quality, model transparency, and cybersecurity, which continue to constrain AI's full potential in renewable energy. Addressing these challenges will be essential for scaling intelligent energy solutions across regions and use cases.

By addressing the identified gaps and emerging AI methods tailored for renewable energy, future work can unlock the full potential of intelligent, resilient, and decentralized energy systems. This scoping review provides a foundation for such endeavors, offering a roadmap for researchers and practitioners to build upon existing knowledge and contribute to the global energy transition. The continuation of this research could focus on the following key areas: i) Improve data quality and integration: Future studies should explore standardized data schemas, real-time data collection methods, and effective integration of IoT devices and weather data to strengthen AI system accuracy and responsiveness. Studies could also assess the impact of missing or noisy data on model performance; ii) Enhance model interpretability and trust: Continued development of XAI tools tailored to energy systems is needed. Future work can focus on how interpretability affects operator decision-making and system safety, especially in high-stakes applications like grid control and maintenance planning; iii) Strengthen cybersecurity measures: Research into AI models that can detect, prevent, and adapt to cybersecurity threats in real time is needed, including the development of resilient architectures and learning algorithms that maintain functionality under attack; iv) Expand AI-IoT synergies: Further studies should investigate scalable architectures for real-time AI-IoT integration, particularly for off-grid systems. Emerging areas like edge AI and federated learning can be explored to reduce latency and improve adaptability; and v) Support decentralized energy systems with AI: There is a need for applied research on multi-agent systems and reinforcement learning in optimizing decentralized microgrids, peer-to-peer trading, and rural electrification. Pilot implementations and comparative studies across geographies would strengthen this domain.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
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O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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