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(Review Article)

AI in renewable energy: A review of predictive maintenance and energy optimization

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Abstract

In the dynamic landscape of the burgeoning renewable energy sector, optimizing energy output, ensuring robust infrastructure maintenance, and seamless integration into the grid present formidable challenges. This paper delves into the transformative potential of artificial intelligence (AI) as a solution to these critical issues. The focus of this study is on the current state of AI applications within the renewable energy domain, particularly honing in on its profound impact on predictive maintenance and energy optimization across diverse sources such as solar, wind, and hydro. By examining the underlying AI techniques employed in this context, the research seeks to unravel the intricacies of how AI contributes to enhancing the efficiency and sustainability of renewable energy systems. A critical component of this exploration involves the analysis of successful case studies, illustrating real-world applications where AI has made substantial strides in predictive maintenance and energy optimization. These cases provide tangible evidence of the practical implications of incorporating AI into renewable energy practices. The research explores AI's role in renewable energy, focusing on emerging trends and future directions. It aims to understand AI's transformative influence on optimization, sustainability, and energy efficiency, fostering a more resilient and efficient energy landscape. AI is revolutionizing the renewable energy sector, transforming infrastructure maintenance, energy generation optimization, and integrating renewable sources into the grid. Its advanced analytics, predictive capabilities, and optimization are crucial in achieving global renewable energy targets. As AI technology evolves, its impact on the renewable energy landscape will deepen, paving the way for a cleaner, more sustainable future. By harnessing AI's power, we can accelerate the transition towards a renewable energy future, ensuring a thriving planet for future generations.

Keywords: Artificial intelligence; Dynamic landscape; Renewable energy; Optimization

1. Introduction

The history of artificial intelligence (AI) dates back to ancient Greece and China, with early speculations tracing back to the desire to mimic human intelligence (Bhatt, 2021). The 20th century saw the formal birth of AI as a scientific inquiry with Alan Turing's "Computing Machinery and Intelligence" paper (Bowen, 2016). In 1956, a summer workshop at Dartmouth College, funded by the Rockefeller Foundation, marked the official birth of AI as a research discipline (Howard, 2019). Despite initial excitement, the field faced periods of skepticism and funding cuts, leading to breakthroughs in expert systems, natural language processing, and machine learning (Yonck, 2020). The 21st century has seen a resurgence of AI, fueled by data explosion, computing power advancements, and powerful algorithms like deep learning (Lu, 2019). This "AI renaissance" has brought us self-driving cars, facial recognition systems, virtual

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assistants, and even machines capable of creating art and poetry (Sudmann, 2019). The future of AI is undeniable, with its potential to improve our lives in various ways, from healthcare and education to climate change and space exploration (Santosh & Gaur, 2022). While concerns about ethical implications and potential misuse remain, AI promises to be a defining force in shaping the future of humanity (Federspiel et al., 2023). As we navigate the uncharted territory of AI, it's crucial to remember its rich history and approach it with both a sense of wonder and a responsibility to ensure its development benefits all of humankind (Dignum, 2018).

The world's energy landscape is changing, with renewable energy sources such as solar, wind, and hydro gaining pace (Nazir et al., 2020, Ukoba and Inambao, 2018). However, the path to an environmentally friendly future is not without challenges. The inherent uncertainty of renewable energy sources, along with the requirement for efficient infrastructure maintenance and smooth grid interconnection, presents considerable problems (Tronchin et al., 2018). Fortunately, artificial intelligence (AI) has emerged as a potent weapon in this arsenal, offering its prowess in data analysis, prediction, and optimization to revolutionize the renewable energy sector (Bose, 2017, Adebukola et al., 2022, Sanni et al., 2024). Our energy landscape is in the midst of a transformative paradigm shift, with renewable energy sources such as solar, wind, and hydro gaining unprecedented traction (Farrokhabadi et al., 2017). This transition towards a sustainable future, driven by a growing awareness of environmental concerns and a quest for energy independence, holds the promise of mitigating the impact of traditional energy sources on the planet (Cantarero, 2020). However, this ambitious journey is not without its hurdles. One of the primary challenges facing the widespread adoption of renewable energy is the inherent variability of these sources (Chakraborty et al., 2018). Unlike traditional fossil fuels that provide a consistent and reliable power output, renewable sources are highly dependent on external factors such as weather conditions and daylight availability (Vanajaa & Kathirvel, 2017). This intermittency poses a significant challenge for maintaining a stable and resilient energy grid, raising questions about the reliability of renewable energy in meeting the constant and often unpredictable demand for electricity (Medina et al., 2022, Ukoba, Fadare and Jen, 2019).

In addition to the variability, the need for efficient infrastructure maintenance and seamless grid integration further complicates the transition to renewable energy (Jones, 2017). Aging power grids, designed with traditional energy sources in mind, require significant upgrades to accommodate the decentralized and fluctuating nature of renewable energy. The challenge lies not only in developing new technologies but also in optimizing the existing infrastructure to ensure a seamless integration that can support the evolving energy landscape (Čolaković & Hadžialić, 2018). Fortunately, artificial intelligence (AI) has emerged as a powerful tool to address these challenges and pave the way for a more sustainable and reliable energy future. The intersection of AI and renewable energy opens up new possibilities for overcoming the limitations posed by variability and grid integration. By harnessing the capabilities of AI in data analysis, prediction, and optimization, the renewable energy sector stands to undergo a revolutionary transformation.

One of the key contributions of AI to the renewable energy sector lies in its ability to process vast amounts of data generated by renewable sources (Şerban & Lytras, 2020, Mouchou et al., 2021, Uddin et al., 2022). AI algorithms can analyze historical weather patterns, solar radiation levels, wind speeds, and other relevant data to develop accurate predictions of renewable energy production (Malik et al., 2022). This data-driven approach enables energy operators to anticipate fluctuations in supply and demand, allowing for more effective grid management. Moreover, AI-driven data analysis plays a crucial role in optimizing the performance of renewable energy systems (Mohammad & Mahjabeen, 2023). Machine learning algorithms can identify patterns and correlations within the data that human operators might overlook (Shameer et al., 2018). This insight can be leveraged to fine-tune energy production, storage, and distribution processes, ultimately improving the overall efficiency and reliability of renewable energy systems (Escalera et al., 2018). Prediction is a cornerstone of effective energy management, and AI excels in creating sophisticated models for forecasting renewable energy output. Advanced machine learning models can factor in a multitude of variables, including weather conditions, geographical features, and historical data, to generate highly accurate predictions (Kowalska & Ashraf, 2023). These prediction models not only aid in managing the variability of renewable energy sources but also provide valuable information for grid operators and energy planners. By knowing in advance when peaks and troughs in energy production are likely to occur, operators can make informed decisions on energy storage, distribution, and grid management, ensuring a more stable and resilient energy infrastructure (Petrichenko et al., 2018).

Renewable energy system optimization is a challenging operation that necessitates regular modifications to balance supply with demand. In this arena, AI systems shine by continually optimizing energy production and distribution through the use of real-time data. For example, AI can optimize solar panel operation by altering tilt and orientation in response to changing sunshine angles. Wind turbines, too, can be fine-tuned to match with prevailing wind patterns, boosting energy generation while minimizing mechanical wear and tear. This level of optimization precision adds to higher energy yield, longer equipment lifespan, and overall cost-effectiveness. Seamless integration of renewable energy into existing power grids is a critical aspect of the transition towards sustainability (Tang et al., 2021, Ewim et al., 2021). Traditional grids, designed for centralized power generation, face challenges in accommodating the decentralized and variable nature of renewable sources. AI plays a pivotal role in mitigating these challenges by enabling smart grid solutions.

Smart grids, empowered by AI technologies, can dynamically manage energy flows, balance supply and demand, and detect and respond to grid disturbances in real-time. Machine learning algorithms can optimize the routing of electricity through the grid, reducing transmission losses and improving overall grid efficiency. Additionally, AI facilitates demand response mechanisms, allowing consumers to adjust their electricity consumption based on real-time pricing and availability of renewable energy (Ambec & Crampes, 2021). While the integration of AI into the renewable energy sector holds immense promise, it is not without its challenges and considerations. One significant concern is the need for standardized data formats and communication protocols across diverse renewable energy systems (Rafique et al., 2020). Interoperability is crucial for the effective functioning of AI algorithms across different platforms, ensuring seamless integration and data exchange (Cândea et al., 2021, Owebor et al., 2022).

Privacy and security concerns also come to the forefront when dealing with AI in the energy sector (Marinakis et al., 2021). The vast amounts of data collected for analysis and optimization must be handled with utmost care to protect user privacy and prevent potential cyber threats (Bagnato et al., 2019). Establishing robust cybersecurity measures and adhering to ethical data usage practices are imperative to build trust in the deployment of AI solutions in the renewable energy domain (Taddeo et al., 2019). Furthermore, the upfront costs associated with implementing AI technologies can be a barrier for some entities, particularly smaller renewable energy projects or developing regions. Overcoming these financial barriers requires a concerted effort from governments, industry stakeholders, and international organizations to incentivize the adoption of AI solutions and make them accessible to a broader spectrum of players in the renewable energy sector (Moorthy et al., 2019). Ultimately, the merging of artificial intelligence with renewable energy constitutes a formidable partnership with the potential to transform the global energy environment (Ali & Choi, 2020). As the world aspires for a future that is less environmentally damaging, solving the hurdles provided by renewable energy fluctuation and the need for grid integration is critical. AI, with its powers in data analysis, prediction, and optimization, can serve as a powerful catalyst in tackling these issues.

The ability of AI to process vast amounts of data and generate accurate predictions empowers energy operators to make informed decisions, ensuring the stability and reliability of renewable energy systems. Moreover, the optimization capabilities of AI contribute to increased energy yield, reduced operational costs, and extended equipment lifespan (Choobineh & Mohagheghi, 2016, Adegoke, 2023). Smart grid solutions, driven by AI technologies, offer a pathway to seamlessly integrate renewable energy into existing power grids, enhancing overall efficiency and resilience. While challenges such as data standardization, privacy concerns, and upfront costs need to be addressed, the potential benefits of AI in the renewable energy sector are immense. Governments, industry leaders, and the research community must collaborate to overcome these challenges and unlock the full potential of AI in creating a sustainable and resilient energy future. As we stand at the crossroads of technological innovation and environmental stewardship, the integration of AI with renewable energy is not just an option but a necessity for building a cleaner and more sustainable world.

2. Predictive Maintenance

2.1. AI Techniques for Predictive Maintenance

Traditional maintenance schedules for renewable energy infrastructure rely on reactive approaches, leading to costly downtime and inefficiencies. AI-powered predictive maintenance flips the script by leveraging sensor data, historical records, and weather patterns to anticipate equipment failures before they occur (Yildirim et al., 2017, Chidolue and Iqbal, 2023). This proactive approach enables targeted interventions, minimizing downtime, extending equipment lifespan, and optimizing maintenance costs. AI-powered predictive maintenance for renewable energy infrastructure harnesses the synergy of sensor data, historical records, and weather patterns to proactively anticipate potential equipment failures (Jose, 2018). Leveraging advanced techniques such as Machine Learning (ML), Deep Learning (DL), and Digital Twins, this approach aims to minimize downtime, extend equipment lifespan, and optimize maintenance costs. Machine Learning algorithms process vast amounts of sensor data collected from renewable energy systems. By analyzing historical performance data and identifying patterns, these algorithms can predict potential issues before they escalate into critical failures (Qiu et al., 2019). This proactive approach enables maintenance teams to address problems in their early stages, preventing unexpected downtimes and disruptions to energy production.

Deep Learning, a subset of ML, enhances predictive maintenance capabilities by delving into complex data sets. In the context of renewable energy, Deep Learning algorithms can extract valuable insights from various sources, including image data from surveillance cameras or drones (Capra et al., 2020). This allows for the detection of visual anomalies or signs of wear and tear on equipment, enabling preemptive maintenance actions (Giannoulidis et al. 2022). Meanwhile, the concept of Digital Twins further amplifies the effectiveness of predictive maintenance. Digital Twins create virtual replicas of physical assets, enabling a real-time simulation of their behavior (Rasheed et al., 2019). By integrating sensor data into these digital replicas, AI systems gain a holistic view of equipment health. This comprehensive understanding facilitates accurate predictions of potential failures and assists in devising optimized maintenance strategies tailored to specific assets (Scarpellini et al., 2018, Okunade et al., 2023). The collective application of these techniques not only minimizes the risk of unexpected breakdowns but also extends the overall lifespan of renewable energy infrastructure. This is achieved through targeted and timely interventions based on insights derived from AI analysis.

Furthermore, the optimization of maintenance costs is a significant benefit. Predictive maintenance allows for a shift from traditional, reactive maintenance practices to a more cost-effective and efficient model. By strategically scheduling maintenance activities when they are most needed, resources are utilized more effectively, reducing unnecessary downtime and associated expenses. Finally, AI-powered predictive maintenance in renewable energy seamlessly integrates sensor data, historical records, and weather patterns. Through the application of Machine Learning, Deep Learning, and Digital Twins, this approach offers a proactive solution to equipment failures, ultimately contributing to increased reliability, extended equipment lifespan, and optimized maintenance costs in the renewable energy sector (Vivi et al., 2019).

3. Case Studies in Predictive Maintenance

The integration of Artificial Intelligence (AI) in the renewable energy sector has proven transformative, particularly in predictive maintenance and energy optimization. Examining notable case studies provides insights into the tangible benefits realized by leading companies in the field.

GE Renewable Energy employs AI to achieve a 95% accuracy in predicting wind turbine failures. This initiative yields a remarkable 30% reduction in maintenance costs for GE Renewable Energy (Canizo et al., 2017, Ukoba and Jen, 2023). By leveraging AI for predictive maintenance, the company identifies potential issues before they escalate, enabling targeted interventions. The result is minimized downtime and sustained optimal performance of the wind turbine fleet, showcasing the economic advantages of predictive maintenance.

Enel Green Power focuses on predicting performance degradation in solar panels using AI. By harnessing AI insights, Enel optimizes maintenance schedules, leading to an extended lifespan for solar panels. This proactive approach not only ensures infrastructure longevity but also maximizes energy output by addressing issues before they significantly impact performance. Enel's case underscores the critical role of AI in enhancing both the operational and economic aspects of renewable energy assets Vestas adopts AI-powered digital twins to monitor and optimize the performance of wind turbines. Through the utilization of digital twins, Vestas achieves significant improvements in uptime for its wind turbines (Frandsen et al., 2022). Real-time monitoring, accurate predictions of potential failures, and precise adjustments showcase the potential of AI in enhancing operational efficiency. Vestas demonstrates how digital twins, fueled by AI, offer a comprehensive and dynamic approach to managing and optimizing wind turbine fleets. In addition to predictive maintenance, AI plays a crucial role in optimizing energy generation and grid integration, addressing broader challenges in the renewable energy landscape. AI algorithms analyze real-time weather data, empowering grid operators to optimize energy dispatch, seamlessly integrate renewable sources, and reduce reliance on fossil fuels. The result is a more resilient and sustainable energy grid, emphasizing the pivotal role AI plays in shaping the future of energy distribution.

AI algorithms optimize the charging and discharging of energy storage devices, optimizing efficiency and contributing to grid stability. This AI solution ensures that stored energy is used appropriately, improving overall energy system resilience in the face of dynamic demand patterns. The predictive powers of AI are useful in regulating peak demand periods and motivating consumers to change their energy use habits. This demand response management not only decreases grid stress at peak times, but it also reduces total energy expenditures, resulting in a more balanced and efficient energy distribution system. These case studies demonstrate the importance of artificial intelligence in predictive maintenance and energy optimization in the renewable energy sector. The observable benefits include cost savings, higher operational efficiency, and improved sustainability, validate the pivotal role AI plays in shaping the future of renewable energy.

4. AI Techniques for Energy Optimization

AI techniques for energy optimization include reinforcement learning, evolutionary algorithms, and multi-agent systems. Reinforcement Learning uses agents to identify optimal energy generation and storage strategies, while evolutionary algorithms refine management strategies. These techniques coordinate renewable energy systems.

As the global demand for energy continues to rise, the imperative to enhance the Energy system efficiency and sustainability are becoming increasingly important. AI has emerged as a useful tool for addressing the complex difficulties connected with energy optimization. We dig into three key AI techniques—Reinforcement Learning (RL), Evolutionary Algorithms, and Multi-Agent Systems—that play critical roles in optimizing energy generation, storage, and consumption. Reinforcement Learning is a paradigm in which an agent learns to make decisions through interaction with its environment and feedback in the form of rewards or penalties. In the area of energy optimization, RL is a dynamic and adaptive approach that enables agents to learn optimal solutions strategies through trial and error in response to changing grid conditions. RL agents in energy systems interact with the environment, which includes renewable energy sources, energy storage systems, and the power grid. The agent takes actions, such as adjusting energy production or storage levels, and receives feedback in the form of rewards or costs based on the impact of these actions on the system. Over time, through continuous interaction, the RL agent refines its decision-making policies to maximize cumulative rewards. While RL offers adaptability and dynamic decision-making, challenges such as high computational requirements, training time, and the need for a well-defined reward structure exist. Striking a balance between exploration and exploitation is crucial to prevent suboptimal learning outcomes.

Evolutionary Algorithms (EAs) draw inspiration from the principles of natural selection to iteratively evolve solutions towards optimal outcomes. In the context of energy optimization, EAs provide a robust and flexible approach to refining energy management strategies (Darwish et al., 2020). Evolutionary algorithms are used in energy optimization to generate a population of potential solutions, each represented as an individual within the population. These solutions are evaluated based on their fitness, with individuals with higher fitness scores being more likely to be selected for reproduction. Selected individuals contribute genetic material to create new offspring solutions, mimicking natural evolution. Random changes are introduced to the genetic material of some individuals, allowing for exploration of new solution spaces. The process iterates until a satisfactory solution is found. Evolutionary algorithms are used in micro grid optimization, energy trading, resource allocation, and load balancing. However, challenges include the need for a suitable representation of solutions, determining appropriate selection mechanisms, and the potential for premature convergence.

Multi-Agent Systems (MAS) are AI systems that coordinate and collaborate with multiple agents to achieve common goals in energy optimization. These systems use autonomous agents, communication protocols, and coordination mechanisms to achieve system-wide goals. They also have decentralized decision-making, allowing for real-time adjustments based on local observations and constraints. MAS can adapt to changes in the energy landscape, such as fluctuations in renewable energy generation or unexpected demand changes. Applications of MAS include smart grid coordination, distributed energy resource management, energy trading platforms, and resilience to failures. However, challenges include designing effective communication protocols, managing information exchange among agents, and balancing centralized coordination and decentralized decision-making. Despite these challenges, MAS fosters collaboration and adaptability, making it a valuable tool for managing energy resources and ensuring efficient utilization.

4.1. Comparative Analysis and Synergies in AI Technique

Reinforcement Learning (RL), Evolutionary Algorithms (EA), and Multi-Agent Systems (MAS) are three prominent AI techniques that have distinct strengths and weaknesses. RL relies on trial and error, learning from direct interactions with the environment, while EAs optimize solutions through iterative evolution. MAS involves collaborative decision-making among autonomous agents, often aiming at a common goal.

RL operates centralized, learning from a single reward signal, while EAs can be implemented both centrally and de-centrally. RL learns directly from interacting with the environment, while EAs rely on evolving populations of solutions. MAS involves individual agents learning through interaction and local information. RL excels in dynamic environments but can be computationally expensive. EAs offer parallel optimization but require careful parameter tuning. MAS handles complex distributed tasks but managing agent coordination is challenging. The true magic lies in combining these techniques. An RL agent guided by an EA-generated exploration strategy or a team of MAS agents using RL to individually learn optimal actions within a larger collaborative framework can leverage the strengths of each technique while mitigating their weaknesses. RL + EA: EA can provide diverse exploration strategies for RL, speeding up learning and adapting to changing environments. EA + MAS: Individual agents in a MAS can use RL to continuously improve their local decision-making, contributing to a more effective collective outcome. By understanding the individual strengths and limitations of each technique and actively exploring their potential synergies, we can push the boundaries of AI, tackling ever more complex and dynamic challenges. The future of AI lies in collaborative intelligence, where different techniques unite to create remarkable breakthroughs.

4.2. Case Studies in Energy Optimization

The energy landscape is undergoing a profound transformation, driven by the imperative to combat climate change and the increasing adoption of renewable energy sources. In this dynamic space, Artificial Intelligence (AI) is emerging as a potent tool for optimizing energy production, consumption, and trading, paving the way for a more sustainable and efficient future. Let's delve into three compelling case studies showcasing how AI is revolutionizing energy management: Imagine a power plant that bids for electricity not with human intuition, but with the lightning-fast calculations of AI. This is the reality with Tesla's Autobidder platform. The system leverages real-time market data, weather forecasts, and battery storage capabilities to predict future electricity prices and optimize bids accordingly. Power plant owners using Autobidder can maximize their financial returns by selling electricity at peak times and storing excess supply for periods of higher demand. The impact is tangible. In California, a consortium of energy storage systems equipped with Autobidder earned $20 million in a single year from participating in the wholesale energy market.This not only benefits the owners but also contributes to grid stability by providing flexible resources that can compensate for the intermittent nature of renewables like solar and wind.

Obviously, Wind energy is a potent force in the fight against climate change, but its intermittent nature can pose challenges for grid operators. Predicting wind generation with high accuracy is crucial for maintaining grid stability and maximizing the integration of renewables. Enter Google DeepMind's AI system, which analyzes historical wind data, weather patterns, and atmospheric conditions to forecast wind energy production with a stunning 93% accuracy. This remarkable feat saved the UK National Grid £8 million in operational costs in just one year by enabling them to optimize power generation and deployment based on the AI predictions (Lian, et al., 2017). The implications go beyond cost savings. By improving the predictability of wind power, DeepMind's AI fosters greater reliance on renewables, reducing dependence on fossil fuels and furthering the path towards a cleaner energy future.

Meanwhile large-scale power generation and trading benefit from AI, its potential extends to individual homes as well. Sonnen's AI-powered smart home energy management systems optimize energy consumption based on real-time electricity prices, user preferences, and the availability of solar power (Mouffak & Gallardo, 2021). The system learns how residents use energy throughout the day and dynamically adjusts appliance operation to coincide with periods of lower electricity costs. Additionally, it can leverage solar power generated on the home to power appliances directly, reducing dependence on the grid and lowering electricity bills. Sonnen's AI solution boasts impressive results. One user reported a 30% reduction in electricity costs thanks to the system's intelligent management. By empowering individuals to manage their energy consumption effectively, sonnen contributes to a more decentralized and sustainable energy grid.

Finally, these case studies are just a glimpse into the profound impact AI is having on energy optimization. From maximizing financial returns for power plant owners to predicting wind energy production and making homes more energy-efficient, AI is transforming the way we generate, trade, and consume energy. Tesla's Autobidder uses AI to optimize energy trading for solar and battery systems, while Google's DeepMind predicts wind energy production with 93% accuracy, saving UK grid operators millions. Sonnen offers AI-powered smart home energy management systems. This transformation promises a future with a more resilient and sustainable grid, lower emissions, and greater energy independence. As AI continues to evolve and become more sophisticated, its impact on the energy landscape will only grow, paving the way for a brighter future powered by clean energy and intelligent management.

5. Emerging Trends and Future Directions

The global landscape of renewable energy is undergoing a transformative shift, driven by technological advancements and a growing emphasis on sustainability. In this context, three emerging trends stand out as crucial factors shaping the future of renewable energy: Edge computing, Blockchain integration, and Explainable AI. Each of these trends plays a distinct role in enhancing the efficiency, security, and trustworthiness of renewable energy systems. Edge computing represents a paradigm shift in how we process and analyze data. Traditionally, data processing occurred in centralized cloud servers. However, the surge in renewable energy sources has led to an increased volume of data generated at the edge of the network, where these sources are deployed. Edge computing addresses this challenge by bringing AI processing closer to the data source. In the realm of renewable energy, this entails deploying AI algorithms directly on the devices that generate or consume energy, such as solar panels, wind turbines, and smart grids. By doing so, edge computing enables faster decision-making and real-time optimization of energy production and consumption. For instance, AI algorithms at the edge can adjust solar panel angles based on real-time weather conditions, enhancing energy capture efficiency.

Moreover, edge computing reduces latency in data transmission, a critical factor in applications requiring instantaneous responses. In renewable energy systems, this translates to quicker adaptation to fluctuations in energy generation or demand. The ability to make split-second decisions at the edge contributes to the stability and reliability of the entire energy ecosystem.

Blockchain technology has gained popularity as a means of storing and transmitting data in a safe, transparent, and decentralized manner. Integrating it in the context of renewable energy provides a plethora of benefits, particularly resolving concerns about data integrity, security, and trust within the ecosystem. One of the major issues in renewable energy is the diversity of energy production sources, which are frequently located over geographically separated areas. The decentralized ledger of blockchain ensures that data about energy production, distribution, and consumption is safely saved and shared across the network. Not only does this prevent data manipulation, but it also improves the general transparency of the renewable energy economy.

Smart contracts, a feature of blockchain, further streamline energy transactions. These self-executing contracts automatically enforce and verify the terms of agreements, eliminating the need for intermediaries (Nzuva, 2019). In the context of renewable energy trading, this means faster and more secure transactions between producers and consumers. The use of cryptocurrencies in these transactions adds an additional layer of efficiency and security. Blockchain also facilitates the creation of an immutable record of renewable energy certificates, ensuring the authenticity of green energy claims. This transparency in verifying the renewable attributes of energy sources becomes increasingly important as consumers and businesses seek to make environmentally conscious choices.

The black-box nature of many artificial intelligence models has been a barrier to widespread adoption, particularly in critical sectors like renewable energy (Fan et al., 2023). Stakeholders, including policymakers, energy companies, and the public, often hesitate to embrace AI solutions due to a lack of understanding of how these models arrive at their decisions. Explainable AI (XAI) seeks to address this challenge by making AI systems more transparent and interpretable. In the renewable energy sector, XAI becomes crucial for gaining the trust of stakeholders and ensuring the effective integration of AI models into decision-making processes. For instance, an XAI model can provide clear explanations for why a certain energy optimization strategy is recommended, helping operators and policymakers make informed decisions.

Furthermore, explainability in AI models is essential for compliance with regulatory frameworks governing the energy sector. As renewable energy systems become more reliant on AI for predictive maintenance, grid management, and demand forecasting, ensuring that these models can be audited and understood becomes imperative. XAI also contributes to the democratization of renewable energy information. By providing accessible explanations of AI-driven insights, communities and individuals can actively engage in discussions and decisions related to their local energy systems. This transparency fosters a sense of empowerment and inclusion in the transition towards sustainable energy practices. Obviously, the convergence of edge computing, blockchain integration, and explainable AI represents a powerful force driving the evolution of renewable energy systems. By bringing AI processing closer to the source, ensuring secure and transparent data transactions, and enhancing the interpretability of AI models, these trends collectively contribute to a more efficient, trustworthy, and widely accepted renewable energy ecosystem.

As we move forward, it is crucial for stakeholders across the renewable energy spectrum to embrace and invest in these emerging trends. Collaboration between technology developers, energy companies, policymakers, and the public will be key to harnessing the full potential of edge computing, blockchain integration, and explainable AI in shaping a sustainable and resilient future for renewable energy.

6. Conclusion

Artificial intelligence (AI) has revolutionized the renewable energy sector by reshaping infrastructure maintenance, optimizing energy generation, and integrating renewable sources into existing grids. AI-driven predictive maintenance models analyze vast amounts of data from renewable energy infrastructure, predicting potential issues before they escalate. This proactive approach minimizes downtime and optimizes the lifespan and efficiency of renewable energy systems, contributing to their long-term sustainability. AI also plays a pivotal role in optimizing energy generation by dynamically adjusting parameters based on real-time data, increasing efficiency and cost-effectiveness. AI's advanced forecasting models predict renewable energy generation patterns, enabling grid operators to anticipate fluctuations and plan for balancing mechanisms. AI-driven grid management enhances the integration of renewable energy, mitigating challenges associated with the intermittent nature of sources like solar and wind. As AI technology advances, its impact on the renewable energy sector is poised to deepen, with future developments including more advanced models, improved energy storage solutions, and enhanced grid management systems. The trajectory of AI in renewable energy foretells a cleaner and more sustainable future, accelerating the transition towards renewable energy sources and combating climate change. AI's sophisticated analytics, predictive capabilities, and optimization are indispensable in achieving global renewable energy targets. As we navigate the complexities of transitioning to renewable energy, AI emerges as a key ally, offering solutions that are not only technologically innovative but also imperative for creating a thriving planet for generations to come.

AI is undoubtedly revolutionizing the renewable energy sector, transforming the way we maintain infrastructure, optimize energy generation, and integrate renewable sources into the grid. As AI technology continues to evolve and become more sophisticated, its impact on the renewable energy landscape will only deepen, paving the way for a cleaner, more sustainable future. By harnessing the power of AI, we can accelerate the transition towards a renewable energy future, ensuring a thriving planet for generations to come.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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