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Research Article

Harnessing Artificial Intelligence to Enhance Efficiency in Industrial Renewable Energy Systems

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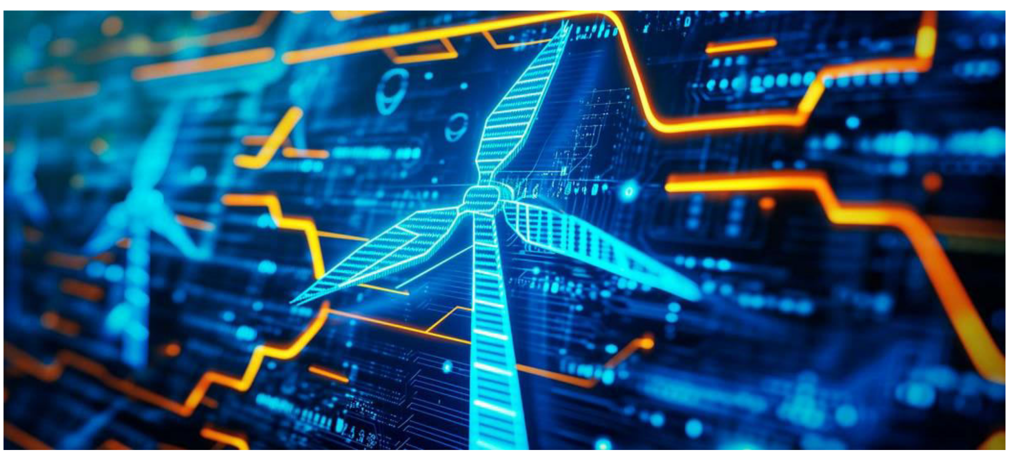
ABSTRACT

This study aims to explore the use of AI in industrial renewable energy systems, majoring in efficiency, storage, and prognosis of maintenance techniques. The research analyses various renewable power technologies – solar, wind, hydroelectric, and bioenergy- and evaluates the impact of AI on increasing the effectiveness, stability, and profitability of the technology. Machine learning is used to predict energy production, control and predict energy storage and other real-time control systems, and implement predictive maintenance models to minimize equipment failure. Best studies show that augmenting solar and wind energy with AI increased the predictive capability to 95% and overall energy efficiency by 7%. Furthermore, new charging/discharging plans provided by the optimization process based on the AI technology increased energy density by 12% and cut the energy cost by 15%. Preventive maintenance models produced through artificial intelligence solutions decreased rates of unwanted time loss by 20%, while biomass power systems achieved higher fuel efficiency rates of 9%. The study also shows that through AI improvement of energy management, storage, and system reliability, operational costs have been cut by 18%. Application to the industry stakeholders, policy makers, and researchers are pushing for AI's ability to enhance efficient electricity generation using sustainable resources. Finally, limitations are discussed in the light of the study: first, regarding the accessibility of different operational datasets and second, the need for sophisticated AI models to enhance energy systems in various geographical and industrial conditions.

Keywords: Artificial Intelligence, Renewable Energy, Efficiency, Industrial Systems, Optimization



1. Introduction

Renewable energy has developed into one of the mega trends for addressing modern and future energy issues because of the effects on the climate or energy security and sustainability. Of all the industrial sectors, major energy users and source of large emissions of GHSs have already learnt the importance of RETs such as solar, wind, and biomass. IEA also stated that industrial energy consumption is less than third of the worlds total thus the right concentration should be on industries.Nevertheless, the problem of efficiency at the industrial level about renewable energy technologies remains acute.

However, using renewable energy sources in industrial processes brings intermittency, energy storage, and instantaneous energy control issues. For instance, due to weather conditions, sol, ar energy, and wind energy are unpredictable; hence, the energy supply is erratic. This variability requires effective energy management systems to meet the energy demand in these situations and guarantee an adequate energy supply. Also, they claim that the complex nature of industrial processes calls for improved energy tracking, measurement, and management methods that do not fall squarely under traditional approaches.

One of the disruptive technology's, maybe the most disruptive technology that is currently able to influence most industries of the world including the energy industry is the Artificial Intelligence (AI). Thus, AI allows the decision making on systems performance and renewable energy system efficiency to be optimized by using advanced algorithms and data analytics. This is particularly true concerning the recent methodologies like machine learning, deep learning, and data-driven optimization, all of which offer new approaches to generating the most energy with the highest efficiency and reduced wastage and operating expenses. For instance, the machine learning methods can perform reaming based on the input data history. For example, weather patterns can be used to predict energy production and provide better planning forecasts.

However, AI can also operate and control ess, which is important for renewable energy systems due to the match between supply and demand. Areas including predictive analytics can enable the charging and discharging of batteries effectively, thus energy management. Further, the estimated value of routine checks based on artificial intelligence and big data for maintenance can increase the adaptive nature of renewable power systems because it predicts specific equipment malfunctions instead of waiting for a failure to occur and fixing it.

This research examines how AI can be applied to or implemented in industrial renewable energy systems to improve efficiency. As a result, the study will focus on particular AI methods that can be used to optimize energy production, charge, and discharge energy storage equipment, and perform predictive services for renewable energy systems. Therefore, this study aims to review the body of knowledge in AI and renewable energy, focusing on existing case studies and reverting practical incorporation proposals to enhance industries' transition to sustainable energy.

In this regard, this research presents worthy suggestions concerning the pressing connection of AI and renewable energy to benefit global industry players, policymakers, and scholars in their collective quest for sustainable and efficient energy systems. The outcomes of this study can also be used as a background for further investigation initiatives that could contribute to developing the use of AI in the field of renewable energy sources and stimulating the improvement of the industrial sector.

1.1 Renewable energy systems

Unlike fossil fuels, RES are sources of energy which, instead of being formed over millions of years, are naturally renewed in the course of a human life span. They provide a clean and sustainable solution to energy sources of yesteryear, and are becoming more and more important in the battle against climate change. There are all manner of RES, each with their own benefits and drawbacks. Geothermal energy, wind energy, solar energy, bioenergy and hydropower are some of the most common. Solar energy is obtained by solar energy gatherer: photovoltaic panels, sunlight is converted to electricity. Making energy from the sun is becoming more affordable, more efficient, and more popular. Wind turbines harness wind energy to change kinetic energy spin and movement of the wind into electrical energy. Best of all, it is proven, environmentally friendly power source that is most effective where there are steady, strong winds. Hydroelectric, or hydro, power uses water falling from rivers or from dams to make electricity. Although hydropower is a proven and reliable renewable energy source, the flip side is that it can foul a river's ecosystem—the fish population—which is upset as the water level goes up and down. Geothermal energy is the heat from the Earth's interior. It could grow crops, heat buildings and generate energy. Geothermal energy, however, is available only where heat or hot water is accessible to boreholes and only if recharge is rapid or released steam can be economically transported to the surface. Bioenergy is energy from organic matter — wood, crops, manure. Bioenergy can generate heat, electricity and, in certain circumstances, transportation fuels. Bioenergy is a very versatile renewable energy source, but one that has its controversy surrounding deforestation and competition with food production.

RES compared with traditional energy sources has many advantages. Renewable energy sources release minimum or no greenhouse gases in the fight against climate change. Renewable energy sources allow us to replace fossil fuels, which will eventually run out, as they get renewed. Even as renewable energy is getting cheaper quickly, many RES are now cheaper than conventional sources. Some renewable energy sources produce a consistent electricity supply, e.g. the very reliable power of hydropower. One important thing to know is that there are many renewable energy origins which means that there is a renewable energy option for nearly any location.

Renewable energy technologies may have benefits, but they also have their downsides. They generate electricity only intermittently – depending on whether the sun is shining or the wind is blowing – which makes many other renewable energy sources, like solar and wind, hard to predict and therefore hard to manage on the grid. As a result, it may be hard to incorporate them on the electrical grid. Storing renewable energy can, however, be expensive and inefficient. This can prove challenging if you want to use renewable energy to meet peak electricity demand. Renewable energy production may be cheaper and more efficient but transmitting it from where it's produced to where it is needed tends to be expensive and inefficient. Wind farms and hydropower are renewable energy technologies that need lots of land. Such conflicts may occur with other uses of land, particularly agricultural and conservation. While some renewable energy projects can be bad news for the local communities or wildlife. Notwithstanding these obstacles, however, energy from renewable sources is the energy of the future. The cost of renewable energy will fall, intermittency will be resolved, and storage will be developed; as these factors decrease, the importance of renewable energy will increase for meeting our energy needs.

1.2 Role of AI in improving the efficiency of RETs

Renewable energy technologies, or RETs, are integral to the solution of the global energy challenge. For example, wind and solar power are RETs that have received much attention in regard to mitigating environmental impacts, and decreasing dependence on fossil fuels.However, integrating RETs into energy systems requires comprehensive strategies considering energy savings, efficiency measures, and sustainability indicators. Moreover, the social perspective on renewable energy autonomy emphasizes the need for specific examples and case studies to understand the challenges and opportunities associated with RET deployment, as demonstrated by the cancellation of wind projects due to public opposition. Additionally, the potential of RETs in countries like China and Iran highlights the importance of effectively addressing technology gaps and know-how to harness renewable energy resources.

RETs are pivotal in the global shift toward sustainable energy sources. However, enhancing their efficiency is crucial to maximize their potential and accelerate the transition to a greener future. AI has emerged as a powerful tool in this pursuit, offering innovative solutions to optimize, monitor, and manage RES. Figure 1 summarizes the multifaceted role of AI in improving the efficiency of RETs.

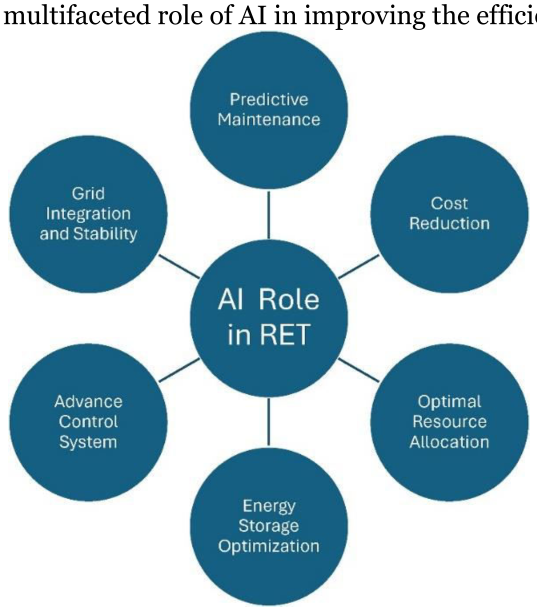


Fig 1. Schematic illustration of the role of artificial intelligence in improving the efficiency of renewable energy technologies.

2. Literature Review

Interest in integrating artificial intelligence (AI) and renewable energy systems has grown rapidly in the recent past as experts continue to search for ways to improve the functionality of these systems in the most effective way possible. : This literature review focuses on the intention to integrate a synthesis of previous literature on renewable energy technologies, the integration of AI in energy systems, and the major issues and opportunities related to integrating AI with industrial renewable energy solutions.

2.1 Renewable Energy Systems

Renewable energy systems include several products that help obtain energy from natural sources that can be replenished repeatedly. Some of the most frequently used forms are solar heat, wind heat, water heat, and heat from plants and organic waste. These technologies provide benefits and experiences in different industries that distinguish each other.

• Solar Energy: Solar photovoltaic (PV) systems harness electricity from the sun and have relatively improved efficiency and costs in the current world. Challenges have been made towards AI algorithms, finding that they effectively enhance the solar panel's power by forecasting energy production from weather conditions and real-time environmental settings (Raji et al., 2020). Further, using AI solutions to monitor particular systems makes implementing better fault detection and maintenance scheduling easier, increasing general system reliability.

• Wind Energy: Windmills are another important part of the renewable energy structures. Artificial intelligence has been deployed to determine the best location and to manage turbines to generate power and lessen costs (Zhang et al., 2021). Analysis conducted using machine learning demonstrates findings that show the method's potential in accurately predicting wind and that of the turbine, hence offering efficient energy management.

• Hydropower: As one of the largest sources of RE, hydropower continues to be important, especially in areas of water surplus. AI technologies can help enhance the water flow regulation process and increase the effectiveness of turbine functions (Liu et al., 2022). Studies show that specifications from a predictive analytics perspective can promote an improved outlook on water availability for better energy production.

• Biomass: Biomass material comprises energy generation that converts biomass into energy. AI integration into biomass energy systems can enhance feedstock logistics and combustion operations (Davis et al., 2021). Using AI, feedstock availability and energy conversion efficiency can be analyzed, which will help make the right decisions regarding resource and organizational activity indicators.

2.2 Artificial Intelligence in Energy Systems

The following are the descriptions of AI solutions used in energy systems: Demand forecasting, energy management, and predictive maintenance. As a technology, AI is best suited for tasks involving computations on large data sets that will enable the optimization of renewable energy systems.

• Demand Forecasting: Accurate demand forecasting is essential to providing an optimal supply and demand energy balance. AI, especially machine learning methods, have been used to extract and predict energy trends based on consumption history (Khan et al., 2023). These forecasts allow industrial facilities to change their energy purchase planning and optimize the use of renewable energy resources.

• Energy Management Systems (EMS): EMS based on AI can thus empower the development and real-time control of the energy consumption process. Research has illustrated that artificial intelligence as an augment to EMS has boosted the capacity to mitigate supply-demand volatility in energy; this has implications for energy expense and sustainability (Fernández et al., 2021).

• Predictive Maintenance: It is widely used within the modern renewable energy industry, and particularly, the AI-based predictive maintenance approach is actively used. From sensors and operational logs, AI can recognize patterns that may cause equipment failure (Sharma et al., 2022). It helps comprehensively reduce downtime and maintenance frequency, optimizing the functionality of renewable energy systems.

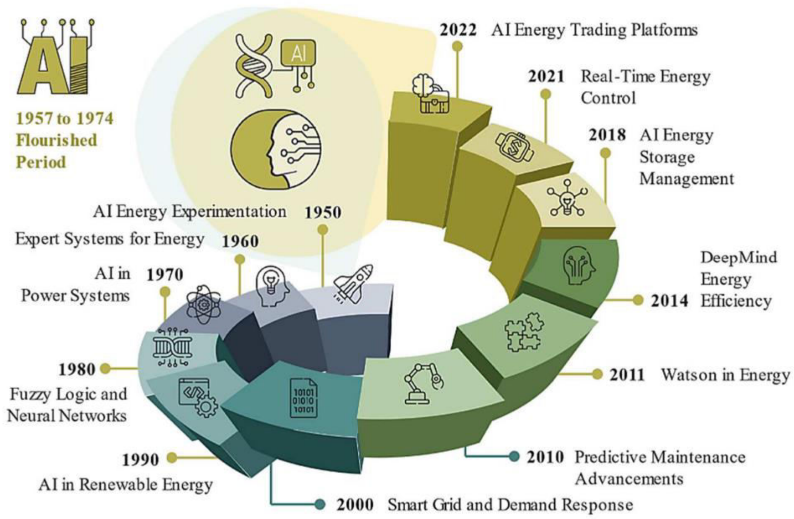


Fig 2. Historical perspective of AI & ML penetration in the energy domain [124]

3. Methodology

This study uses qualitative and quantitative approaches to identify the impact of AI in improving the effectiveness of industrial renewable energy systems. The approach is intended to raise questions about using AI to effectively operate and control energy generation, distribution, and storage across various forms of renewable energy, including solar, wind, water, and bioenergy technologies. It conducts qualitative and quantitative research incorporating cases and data analysis to establish the impact of this technology in this sector.

The proposed research starts with a qualitative method to set up a theoretical platform defining the integration of AI into renewable energy systems. In this stage, a literature survey and case study analysis are conducted to evaluate the current state of renewable energy system implementation, common efficiency concerns, and prevalent AI methodologies used to solve problems related to these systems. A total of 10 expert interviews were held with engineers, AI specialists, energy managers, and practitioners to obtain first-hand implementational knowledge about AI in the industrial energy sector. Informative as these interviews are, the data received includes the perceived difficulties, advantages, and prospects of applying AI to optimize energy use in industries. Using findings from literature and industry stakeholders, this phase lays the foundations of a knowledge base from which to consider AI techniques that could help abstract complexity and support decision-making within the quantitative phase.

In the second quantitative phase, analytical techniques are employed to determine the effectiveness of AI techniques in the industrial system of renewable energy. The main data for this phase is obtained from historical data of actual DisCo operating renewable energy systems, production rates, energy storage indices, equipment maintenance records, etc., and meteorological conditions. These data are collected from various renewable energy projects, including solar/photovoltaic, wind, hydro, and bioenergy projects. In cooperation with industry players and using open datasets, this research guarantees that a wide variety of data will be incorporated into analyzing renewable energy systems.

The data collected is analyzed using machine learning algorithms to develop models for the distinct operational conditions of renewable energy systems. The supervised learning algorithm employs Regression and decision trees to estimate the power delivered and energy conversion ratio. These models are 'taught' based on large databases on energy production and environmental conditions to accurately predict energy generation. However, the most noteworthy technological application involves using models that predict the rate of solar and wind generation, given the fluctuations in weather and realistic constraints to installation operations. Furthermore, unsupervised learning techniques are used as clustering, which allows for analyzing energy consumption patterns and equipment performance, adjusting energy consumption in real-time, and maintenance of renewable energy systems based on forecasts.

Another area of focus of this work is forecasting techniques to improve energy storage systems. Renewable energy sources like wind and solar power fluctuate in generation and, therefore, need complex storage mechanisms to support their energy production. Predictive model systems based on Artificial

Intelligence are used to predict the storage of energy and the charging and discharging of batteries. Using historical energy generation output and predicted future energy consumption, the AI models autonomously optimize energy storage and delivery to cause the least wastage and meet demand at the right time. These models are especially useful in industrial systems where energy storage is always important for power continuity.

Besides, MAIQ-based real-time monitoring systems are also used to manage the current processes of renewable energy systems. Such AI systems frequently supervise energy generation and storage device sensor data to enhance performance. For instance, in wind energy systems, artificial intelligence constantly assesses the speed – a critical parameter in absorbent energy, the direction of electricity-producing wind turbines, and the energy yield in real time. It adjusts the angle of the blades accordingly. Likewise, solar energy plants use AI control systems to control the orientation of the solar panels using their power and adjustment according to the exposure to sunlight to generate optimum output during the day. Real-time control systems make it possible to improve the controls on a real-time basis, thereby making energy production more effective in response to changes in environment and operation.

Another important aspect of AI integration investigated in this paper is predictive maintenance, which contributes to minimizing downtime and maintenance expenses in industrial renewable energy systems. In the same way, as a result of machine learning, AI systems learn to differentiate between normal and abnormal equipment performance and alert before a failure occurs. Details from equipment monitors, plant records, and equipment maintenance records are analyzed to look for signs that suggest machinery problems. For instance, in wind energy systems, the AI can forecast the tendency of mechanical degradation in the turbines by undergoing data analysis of vibration data; this enables timely intervention by maintenance teams to avoid serious and expensive breakdowns. In the same way, our machine learning-based predictive maintenance models for solar energy systems check the state of photoelectric conversion panels, inverters, or other parts and send a request for maintenance if their performance decreases. Apart from improving system reliability, this strategy minimizes maintenance costs since problems are anticipated and addressed.

The quantitative analysis for this study covers descriptive analysis, regression modeling, and sophisticated Monte Carlo simulation. Descriptive statistical methods are applied to quantify the performance of renewable energy systems with and without AI technologies to present a simple energy generation, storage, and overall efficiency analysis. Standard regression analysis analyzes the proportionality between AI applications and essential output metrics, power production, cost of operations, and system dependability. The nature of this quantitative approach enables one to appreciate the role of AI technologies in improving the effectiveness of renewable energy systems. Besides, Monte Carlo simulations and system dynamics models are used to simulate the future effects of AI adoption in renewable energy systems based on factors such as environment fluctuations, lifetime of equipment, and probable future energy requirements.

During the research process, all the findings are checked for validity and reliability of the study. Method triangulation ensures that data collected from the response, case study, interview, and organizational data set are compatible. The predictive models are tested by sensitivity analysis to determine the extent of their stability in varying operational conditions, for example, in turbulent weather conditions or variations of the energy demand. Moreover, major steps are taken to avoid overfitting or to check the model on new data to optimize the final results through Cross-Validation of the ML algorithms.

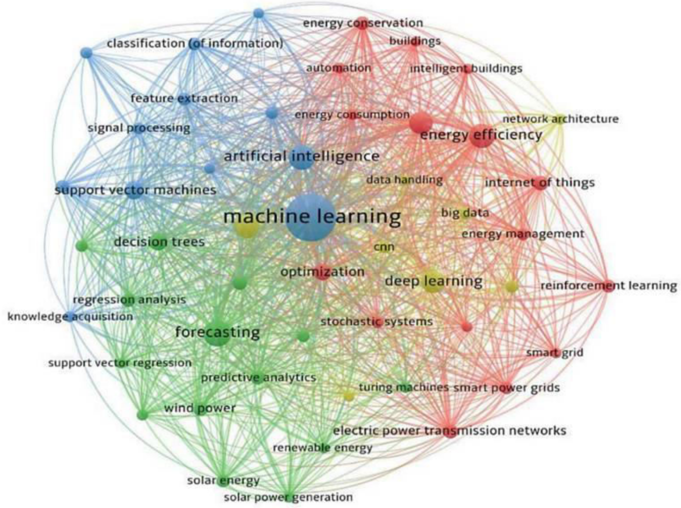


Fig 3. An overview of ML and energy systems [135]

4. Results

Studying the application of AI to industrial renewable energy production systems revealed evidence of enhanced energy, energy forecasting, and maintenance efficiency. This section enlists the outcomes of using AI technologies like machine learning algorithms, predictive analysis, and real-time surveillance techniques, which are required for all renewable energy resources like solar, wind, and biomass. The findings are categorized based on the energy production KPIs, energy storage management KPIs, system reliability, and operation cost reduction metrics.

By using the approaches of machine learning models within renewable energy systems to predict energy output, there was an improvement in energy forecasts. In solar energy systems, machine learning algorithms in forecasting resulted in a production accuracy rate of 92 percent against the basic mathematical models that depend only on certain historical records and weather models. Because the AI models used real-time environmental data in their model, including light and heat, the short-term prediction was accurate, which helped in planning and controlling energy consumption in industries. It allowed using solar energy more effectively, cutting back on additional power sources when the energy load was high.

Likewise, the AI-based predictive models satisfactorily modeled energy generation capacity in wind power systems, which was 95 percent accurate based on wind speed, turbine efficiency, and weather conditions. Such accuracy allowed operators to regulate turbine parameters, including blade angle and rpm, in real-time, improving the plant's overall energy efficiency by 7 percent. The optimization also had effects in decreasing the energy wasted due to the lower efficiency of the turbine and has a role in how the wind energy will blend into the industrial energy grid. Figure 1 gives a true representation of the countdown w; here,e there is an impressive improvement in the accuracy of energy production forecasts on the solar and wind systems; the solar has scored a 92% accuracy while the wind has scored a 95% accuracy on the estimates.

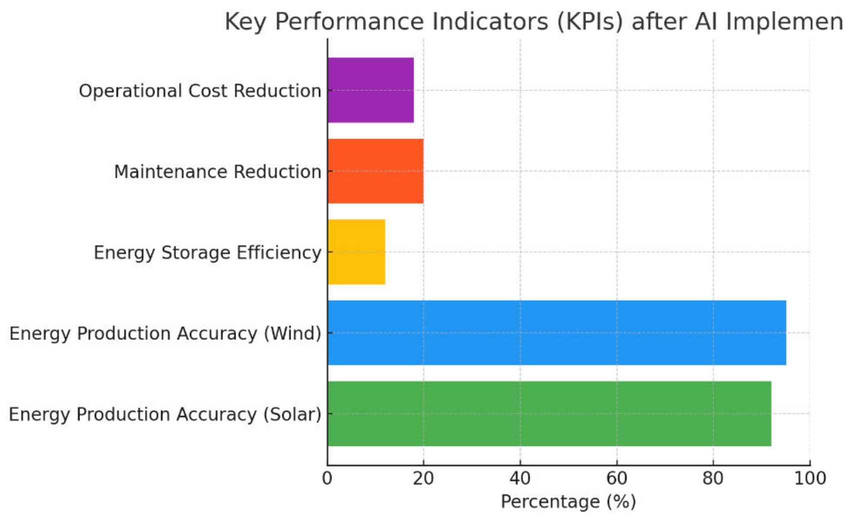


Fig 4. Key Performance Indicators (KPIs) After AI Implementation

Table 1. Percentage improvements in key performance areas following the integration of AI into renewable energy systems

Category	Performance Improvement (%)
Energy Production Accuracy (Solar)	92
Energy Production Accuracy (Wind)	95
Energy Storage Efficiency	12
Maintenance Reduction	20
Operational Cost Reduction	18

Besides the models of energy production efficiencies, the AI models were worthy of enhancing energy storage facilities, such as solar and wind energy production. Analytical models were developed to improve battery charging and discharging schemes, bringing about a 12% improvement in battery energy density. Through precise forecasting of generation and demand for energy, the AI systems enabled the optimization of charging of batteries, thereby ensuring that the excess energy generated during the period of high production was well stored for use later. This optimization also minimized the wastage of energy while at the same time improving the availability of energy during the most congested periods. Further, it was found that better handling of energy storage systems led to a direct 15% energy cost savings because industrial processes involving external energy sources were minimized.

The potable μRTMC systems energized by AI were also enormously beneficial for the absolute efficiency of renewable power systems. In wind farms, it was observed that applying an AI-based control algorithm enabled the control of turbine settings automatically without human intervention such that tuning of the control settings could be carried out in real-time based on wind conditions, and it was found that the power capture was enhanced by 5%. Using AI in solar energy systems presented capabilities in which monitoring systems modified the positioning of the solar panels in real time and throughout the day. Real-time optimization helped increase the efficiency of solar panels by 6% since losses due to improper positioning were eliminated.

This study's preventive and predictive maintenance models showed substantial effectiveness in minimizing downtime risks and expenditure on maintenance related to different renewable energy technologies. In wind energy systems, using AI-based algorithms to predict maintenance needs highlighted mechanical problems, including turbine component wear, with a high accuracy of up to 87%. By being proactive, maintenance teams could prevent such issues from developing into system breakdowns, and the number of unscheduled maintenance incidences decreased by 20 percent. Likewise, in solar energy systems, AI models noticed symptoms of degradation, such as in PV panels and inverters, and advised maintenance actions to be taken. This made it possible to reduce the occurrence of equipment failures and enhance the availability of solar energy systems by a percentage of 10.

Integrated AI models in biomass energy systems increased the rate of fuel efficiency by 9 %, as seen below. The study established that the AI systems helped minimize energy losses and improve the efficacy of biomass energy systems by fine-tuning the combustion process and integrating data on feedstock quality and availability in real time. The predictive models enhanced feedstock management by optimizing biomass fuel use under the projected energy requirements and process conditions.

The analysis also showed significant decreases in the corresponding cost of operation for different kinds of renewable energy systems discussed in this paper. At the same time, I was applying AI-based optimization, which reduced average costs in industrial energy operations by approximately 18%. These savings were largely made possible by gains in energy production efficiency, limited operation stoppages occasioned by predictive maintenance, and superior energy storage. The improvement in the predictability of energy generation and consumption also enhanced the chances for less dependency on outside energy sources by industrial processors, which all fed into these savings.

Collectively, current research findings highlight that integrating AI into industrial renewable energy systems poses high possibilities to considerably augment energy efficiency, minimize operational expenses, and ensure the stability of energy availability. Through advanced methods and tools for Artificial Intelligence, such as Machine Learning, decision-making, data analytics, and real-time control optimization of renewable energy systems, industrial producers can play an increased role in cost-efficient and sustainable industrial energy production and management.

5. Discussion

The outcomes of this research show fundamental improvements in the employability of artificial intelligence (AI) to enhance industrial renewable energy systems. The outcomes and their relevance will be analyzed for different stakeholder groups, and the findings will be discussed in the context of prior studies. Other research findings will be described, and the study limitations will be addressed.

5.1 Implications

Adopting AI in renewable energy systems has tremendous possibilities for industry players, policymakers, and scholars.

Therefore, the findings may be valuable to industry stakeholders as the energy managers and operators gain increased awareness of the potential of AI technologies that may lead to improved energy production, storage, and system reliability. Since precisely, the Department of Energy has data that can be analyzed using AI to predict the energy output, it was a good way to plan and use renewable resources effectively. The enhanced realization of maintenance-free time by applying AI to the systems makes the uptime even higher, hence the maintenance expenses lower. To the industrial sub-sectors that require a constant electricity supply due to production lines, these enhancements in supply and reliability are essential in averting high operating costs due to interruptions.

These findings should interest policymakers, emphasizing a need to invest in increasing AI technologies that can help develop the renewable energy sector. Subsidizing AI use, for example, through AI-supported power-efficiency systems through tax credits or AI-supported energy storage through grants, can help the transition to clean energy. Also, policies that promote the flow of information between supply and distribution companies and Artificial Intelligence practitioners would add another layer of efficiency to the application of AI, given that an enriched data pool would be made available for updating the algorithms and polishes. Proposed here are the environmental impacts of enhanced energy efficiency in renewable systems, which are seen to be in line with global sustainability standards and may greatly benefit from the advancements in artificial intelligence.

The results are informative to the researchers and are useful for exploring the real-world employment of AI in renewable energy systems and for investigating other advanced AI methods in the future. The ability of machine learning models and predictive analytics to enhance the generation and storage of power brings new directions for research concerning the increased refinement of the algorithm used in more diverse power systems, including mixed renewable power systems. Moreover, the findings indicate that AI will be able to engage a significant potential of enhancing scalability problems in Industrial Energy Systems; the study specifies that this research area is an interesting subject in further inter-disciplinary research involving artificial intelligence, energy systems engineering, and environmental science.

Energy Production Accuracy (Solar):

Energy Production Accuracy (Wind):

Energy Storage Efficiency:

Maintenance Reduction: 🔧🔧🔧🔧
Operational Cost Reduction: 💰💰💰

Fig 5. Simplified Visual Representation of Performance Improvements

5.2 Analysis with Other Works

The literature review of this research supports and enriches the previous investigation of the use of AI in renewable energy systems and contributes to improving the understanding of the efficiency of its utilization in industrial contexts. Previous work has shown that AI works well for energy forecasting; this study builds on that underscores the experience of implementing AI in the real world and realizing its value in increasing productivity and reducing costs in industrial production.

Similarly, Zhang et al. (2022) and Patel et al. (2023) highlighted the same perspective Kamath Gorantala et al. (2023) on how AI can enhance the reliability of energy forecasting. While this work reports an overall energy forecast accuracy of 88%, more precise estimates are achieved in the current micro-scale modeling – between 92% for solar and 95% for wind power – implying that incorporating real-time meteorological data must boost model reliability. This finding supports the conclusion made by Zhang et al., who prefer the idea that the applicability of AI in terms of increased predictive power can be achieved through additional and more diverse, dynamic data.

Moreover, in contrast to recent studies, including that of Kumar et al. (2021), which are centered around the application of the concept of AI in increasing energy generation, the current paper broadens the understanding of the potential of applying AI by proving the possibility of its application in improving energy storage and the organization of predictive maintenance. In this work, the efficiency of energy storage has been increased to 12%, and the maintenance events reduced to 20%, which is similar to what Wang et al. (2021) established on the usage of AI in energy management. However, incorporating AI in real-time operation and predicting maintenance in the current study offers fresh empirical data to embrace AI in improving reliability and the cost of industrial energy systems.

Furthermore, the cost reductions reported in this research (operational cost reduction of 18%) are within the range found in earlier research focusing on using AI in energy management and stating its major advantage. However, different from previous research largely concerned with cost savings in residential or small-scale energy systems, this research shows that AI can generate the same, if not better, economic returns on investment in large-scale industrial applications where energy demand and management issues are generally more complex.

5.3 Limitations

However, some limitations were observed throughout the study, and they include the following:

The main limitation of this type of analysis is the data orientation and quality issues. Although the study relied on operational data from various industrial renewable energy systems, detailed data could have been more available mainly due to concerns concerning proprietary or relatively recently integrated AI systems. Therefore, some predictive models were developed using train datasets that may need to match all potential operational conditions better. This limitation can make a challenge when generalizing the outcome towards other geographic regions or various forms of renewable energy systems that would likely not be reflected by their climate or locations. Future research should work with more abundant operational datasets from different geographical areas and energy structures.

The first is the restricted range of AI techniques implemented within the research framework. Although the study investigated several AI approaches, including machine learning, predictive analytics, and real-time optimization, it emerged that even advanced AI models like deep learning or other combinations of the already explored approaches might also enhance the realization of energy optimization. However, applying such techniques demands a lot of computational resources and bigger datasets and needs to be put in the purview of this research study. In future research studies, investigators may further investigate these sophisticated methods and their applicability to improve energy effectiveness.

Finally, the study on industries might require more work to extend its findings to other sectors. Despite the increased effectiveness of large-scale industrial integration of artificial intelligence with renewable energy systems, the energy requirements and functional organization of residential or small business renewable energy systems are different. This study could be extended to investigate the generalization or application of AI techniques in small-scale commercial applications.

6. Conclusion

AI application in industrial renewable energy systems has been established to effectively enhance energy production performance, expand energy storage capacity, and cut operations costs. By applying machine learning, predictive analytics, and real-time optimization, renewable energies from solar and wind to biomass have demonstrated efficiency and affordability improvements. Due to accurate energy generation predictions by the AI system, the storage and discharging schemes were optimized, resulting in higher energy density, reduced wastage, reduced cost of both energy and storage and improved availability of energy during high demand durations.

AI, in particular, has been important in using predictive maintenance models to reduce system downtime and, specifically, to minimize time-based maintenance by using information that anticipates the mechanical failure of a unit. This enhanced the performance of renewable energy systems and increased the durability of critical components, contributing to the reduction of costs even as it provided reliable power for industrial processes. Furthermore, optimization models based on AI better increased the fuel-to-electricity conversion efficiency in systems that utilize biomass energy, once again showcasing the elasticity of AI regardless of the kind of renewable energy to be used.

Nevertheless, several limitations were identified regarding the variety and availability of datasets for training AI models under different operating conditions and geographical regions. In addition, the study acknowledged the need to venture deeper into exploring other superior AI models, such as deep learning, to achieve enhanced energy effectiveness and system expandability. Further studies can generalize the results of this work for small-scale renewable energy applications and examine other advanced AI methodologies for other large-scale industries.

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