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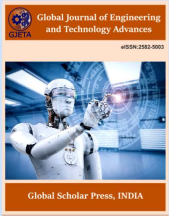


(Review Article)

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# Leveraging machine learning to optimize renewable energy integration in developing economies

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## Abstract

The integration of renewable energy sources into power grids is a critical challenge for developing economies, where infrastructure limitations, unpredictable energy demand, and policy gaps hinder effective energy transitions. Machine learning (ML) offers transformative potential in addressing these challenges, enabling more efficient and reliable energy systems through advanced data analytics, predictive modeling, and real-time decision-making. This review explores how ML can optimize renewable energy integration by improving forecasting accuracy, enhancing grid stability, and optimizing resource allocation in solar, wind, and hydropower systems. Machine learning algorithms are particularly effective in predicting energy demand and renewable resource availability, allowing for better alignment between energy supply and consumption patterns. By leveraging ML-based predictive models, grid operators can mitigate the risks of energy shortages or oversupply, improve grid stability, and reduce operational costs. Furthermore, the application of ML in renewable energy systems provides opportunities for developing economies to leapfrog traditional energy infrastructure limitations by adopting smart grids that integrate real-time data to enhance decision-making and efficiency. This review also reviews case studies from Africa and Latin America, highlighting successful implementations of ML in renewable energy systems. These examples underscore the potential for ML to accelerate the deployment of sustainable energy solutions, while also addressing technical, economic, and policy barriers that exist in developing contexts. With continued advancements in machine learning, combined with supportive regulatory frameworks and investment in digital infrastructure, developing economies have the potential to realize substantial gains in renewable energy integration. This review concludes by discussing future trends, challenges, and opportunities for leveraging machine learning to optimize renewable energy integration, ultimately contributing to sustainable development and energy security in emerging markets.

**Keywords:** Leveraging Machine; Renewable Energy; Developing Economies; Review

## 1. Introduction

The adoption of renewable energy in developing economies has gained significant momentum in recent years, driven by global efforts to transition towards more sustainable energy systems (Cantarero, 2020). Countries across Africa, Latin America, and Asia are increasingly investing in renewable energy sources such as solar, wind, and hydropower, in response to the growing energy demands of their populations and the need to reduce dependence on fossil fuels (Washburn and Pablo-Romero, 2019; Bassey, 2023). These economies, however, face unique challenges that complicate their renewable energy transitions. Limited infrastructure, inconsistent policy frameworks, and financial constraints

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often impede the efficient integration of renewable energy into national grids. Despite these obstacles, the potential for renewable energy in developing regions is vast, with abundant natural resources and a growing political commitment to sustainable development (Majid, 2020). One of the critical components in achieving sustainable development is the efficient integration of renewable energy into existing power systems. For many developing countries, achieving this integration is key to addressing energy poverty, driving economic growth, and mitigating the impacts of climate change. Efficient energy integration ensures that renewable sources, such as solar and wind, are harnessed and distributed effectively to meet demand, stabilize grids, and reduce energy waste (Husin and Zaki, 2021). Inconsistent energy supply due to variability in renewable energy sources like wind and sunlight makes it essential to develop robust systems that can manage supply and demand in real-time. Without such integration, renewable energy initiatives may fail to deliver the full range of environmental, economic, and social benefits that they promise (Al-Shetwi, 2022).

In addressing these energy challenges, machine learning (ML) has emerged as a powerful tool with transformative potential (Ukoba et al., 2024). ML algorithms can analyze vast amounts of data in real time, making it possible to predict energy demand, optimize energy production, and improve grid stability (Ahmad *et al.*, 2022). In renewable energy systems, ML can forecast weather conditions that affect solar and wind power, balance supply and demand, and detect grid anomalies that could lead to disruptions. This ability to process and interpret data at high speeds makes ML especially useful in managing the variability and intermittency associated with renewable energy sources, ultimately leading to more reliable and efficient energy systems. Moreover, ML can help grid operators make data-driven decisions that minimize costs and maximize the use of renewable energy, fostering a more sustainable and resilient energy infrastructure (Alotaibi *et al.*, 2020; Bassey, 2022). This review aims to explore how machine learning can be leveraged to optimize the integration of renewable energy in developing economies. By examining the current challenges these regions face in adopting renewable energy, the review will highlight the specific ways in which ML can enhance energy systems through better forecasting, grid management, and resource allocation. The scope of this analysis includes not only the technical benefits of ML but also the economic and policy implications of adopting advanced technologies in emerging markets. Furthermore, the review will provide case studies from developing regions that have successfully implemented ML in renewable energy projects, offering insight into the practical applications and potential scalability of such systems. Ultimately, the goal of this review is to provide a comprehensive understanding of the role that machine learning can play in optimizing renewable energy integration in developing economies. By doing so, it aims to contribute to the ongoing dialogue on how technological innovation can support sustainable development and energy security in regions that face significant energy challenges. Through the adoption of machine learning, developing economies have the potential to not only overcome current energy limitations but also to build more robust, sustainable, and future-ready energy systems.

## 2. Machine Learning Applications in Renewable Energy Integration

As developing economies work towards incorporating renewable energy sources like solar, wind, and hydropower, the efficient integration of these resources into the grid becomes a key challenge (Oyekale *et al.*, 2020). Machine learning (ML) has emerged as a transformative technology that can address these challenges by offering

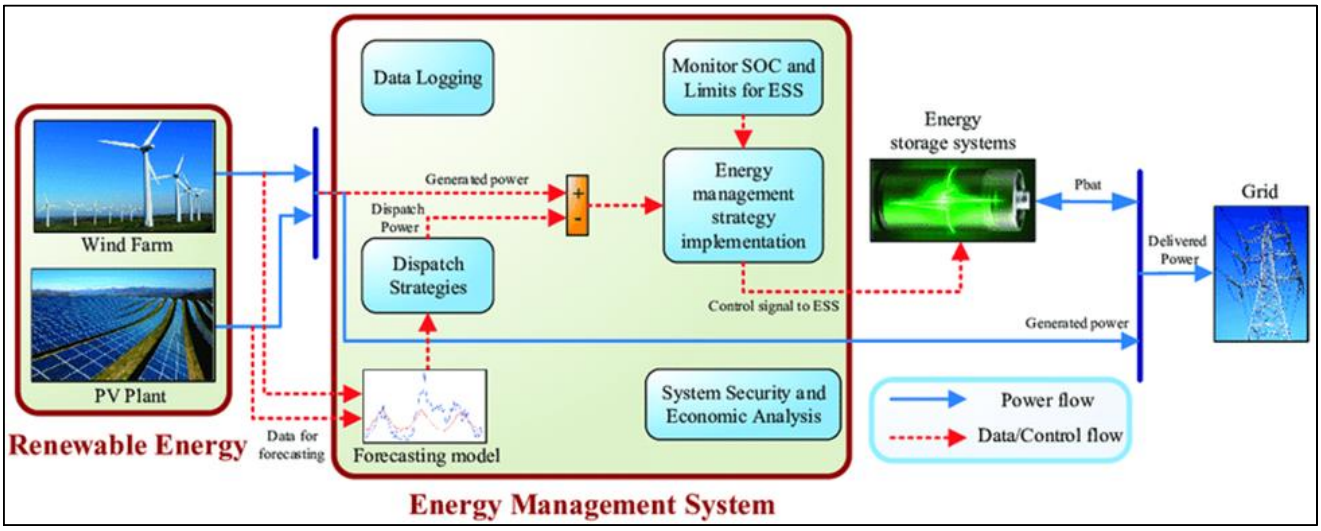


**Figure 1** Renewable energy management system architecture (Zafar *et al.*, 2020)

real-time insights, predictive analytics, and data-driven decision-making. Through various applications such as energy demand forecasting, grid management and stability, and renewable resource prediction, machine learning is revolutionizing how renewable energy is optimized and utilized as illustrated in figure 1 (Zafar *et al*., 2020).

One of the most critical aspects of renewable energy integration is forecasting energy demand accurately. In traditional energy systems, fluctuations in demand can be managed by adjusting the output from fossil-fuel-based power plants. However, with renewable energy sources, the variability in supply especially from solar and wind makes demand forecasting far more complex (Orlov *et al*., 2020). Machine learning offers a solution by enabling predictive analytics that can optimize energy production and ensure that supply meets demand in real time. Predictive analytics models use historical energy consumption data, weather patterns, and even social trends to forecast future energy needs. These models rely on various machine learning algorithms, such as artificial neural networks (ANN), support vector machines (SVM), and decision trees, to predict energy consumption patterns with a high degree of accuracy as explain in figure 2 (Miraftabzadeh *et al*., 2021; Ngo *et al*., 2022' Bassey, 2022).

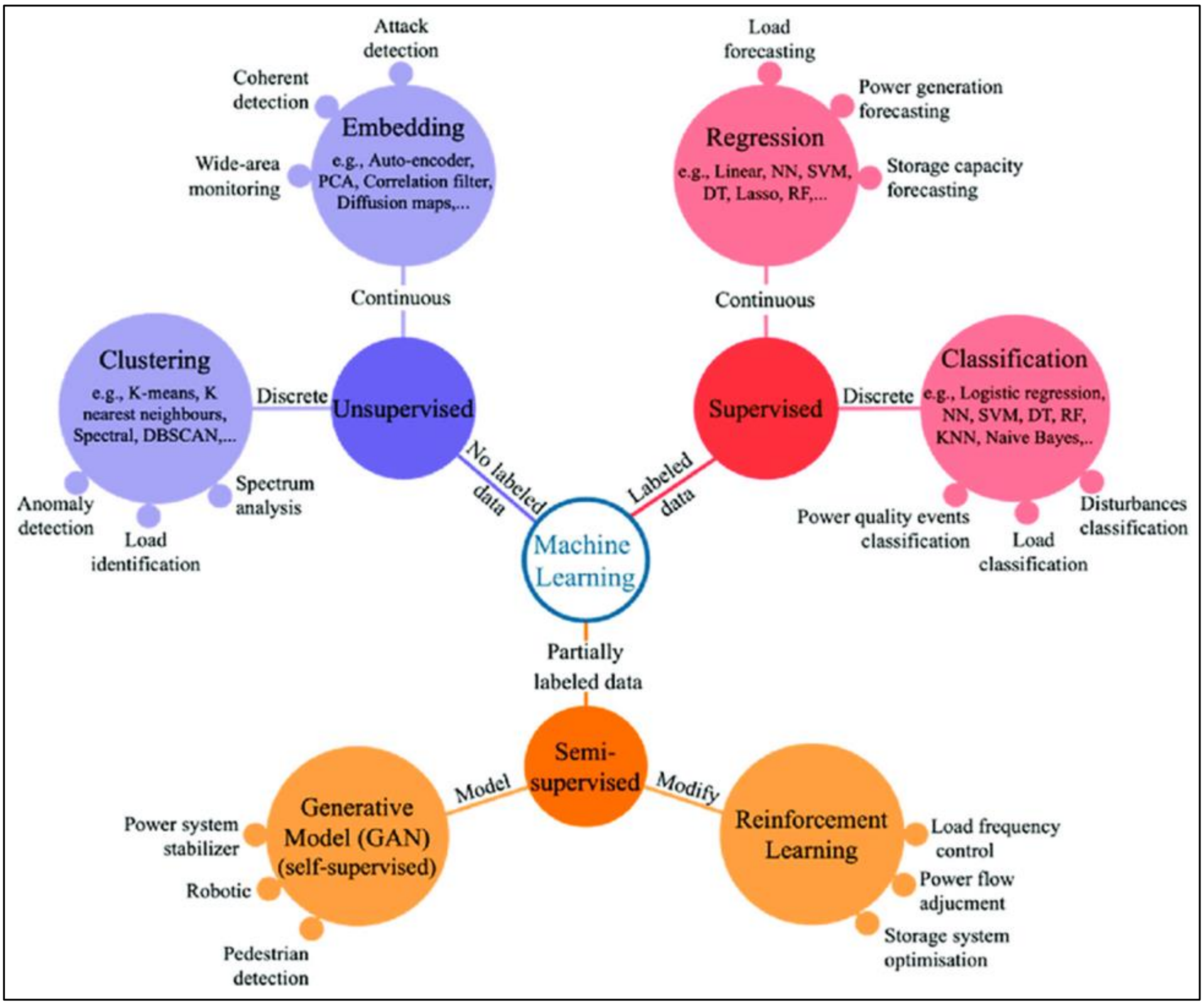


**Figure 2** Power system applications, methods, and paradigms for machine learning (Miraftabzadeh *et al*., 2021)

By forecasting demand more precisely, renewable energy systems can be optimized to ensure that energy production aligns with usage, reducing waste and improving efficiency. Furthermore, ML models are adaptive, meaning they can continuously learn from new data to refine their predictions, thereby enhancing the system's ability to manage fluctuating demand. Machine learning also helps balance supply and demand by making real-time adjustments to energy distribution. For instance, ML can predict when demand will peak and adjust energy output from renewable sources accordingly. In scenarios where renewable energy generation is insufficient, machine learning systems can integrate backup energy sources, such as battery storage or auxiliary power from fossil fuels, to maintain grid stability. This balancing act is essential for ensuring a reliable and resilient energy system, particularly in developing economies with less mature energy infrastructure.

Efficient grid management and stability are critical for the successful integration of renewable energy (Stephanie and Karl, 2020). Renewable sources, due to their intermittent nature, can lead to fluctuations in power generation, potentially causing grid instability. Machine learning enables real-time data analysis and predictive control mechanisms that help maintain grid stability even when there are sudden changes in energy production. One of the primary ways ML enhances grid management is through anomaly detection. Machine learning algorithms can continuously monitor grid performance, identifying any anomalies or irregularities that could signal impending disruptions (Rivas and Abrao, 2020). These anomalies could include voltage fluctuations, frequency shifts, or unexpected power surges. By detecting these issues early, grid operators can take proactive measures to prevent outages or other failures. ML models can even suggest corrective actions based on historical data and patterns, making the grid more resilient to disturbances.

Another application of machine learning in grid management is predictive maintenance. Traditional grid maintenance is often reactive, addressing issues only after they occur. With machine learning, grid operators can predict potential equipment failures before they happen, allowing for preemptive maintenance. This predictive capability reduces downtime and improves overall system reliability, which is crucial in regions where energy disruptions can have significant socio-economic impacts (Kebede *et al*., 2021). Accurately predicting the availability of renewable energy resources, such as solar radiation or wind speed, is essential for optimizing energy production and reducing inefficiencies (Nwachukwu et al., 2023). Weather conditions play a significant role in the variability of renewable energy sources, which directly impacts energy generation. Machine learning techniques can significantly enhance the accuracy of weather forecasting, thus improving resource prediction. For solar energy, ML models use weather data to predict the availability of sunlight, factoring in variables such as cloud cover, temperature, and humidity. For wind energy, machine learning algorithms predict wind speed and direction, enabling wind turbines to adjust their orientation for maximum efficiency. Hydropower systems can also benefit from machine learning by forecasting water availability based on rainfall patterns and river flow data (Bernardes *et al*., 2022). This predictive capacity allows operators to make data-driven decisions about when and how much energy to generate from these renewable sources, ensuring that the maximum possible amount of clean energy is harnessed. Machine learning techniques such as random forests, deep learning, and regression models have been used effectively for resource prediction. These models analyze vast datasets, including historical weather patterns, geographical data, and environmental variables, to provide more accurate forecasts. With improved resource prediction, energy producers can optimize their operations, reduce reliance on backup systems, and better align energy generation with demand. This not only enhances the efficiency of renewable energy systems but also lowers operational costs, making renewable energy more economically viable for developing economies.

The integration of renewable energy in developing economies presents a set of challenges that require innovative technological solutions. Machine learning is playing a pivotal role in overcoming these challenges by enabling more accurate energy demand forecasting, enhancing grid management and stability, and improving renewable resource prediction (Devaraj *et al*., 2021; Bassey, 2023). Through the use of ML, developing economies can optimize their renewable energy systems, ensure a stable energy supply, and make significant strides toward achieving sustainable development. The continuous advancements in machine learning techniques offer promising opportunities for further improving the efficiency and reliability of renewable energy integration, positioning developing regions to better harness their renewable resources and drive economic growth.

### 2.1. Challenges in Renewable Energy Integration in Developing Economies

The integration of renewable energy into the power grids of developing economies offers immense potential for economic growth, energy security, and environmental sustainability (Strielkowski *et al*., 2021). However, this process is fraught with challenges that hinder the effective adoption of renewable sources like solar, wind, and hydropower. These challenges stem from a combination of infrastructure limitations, inconsistent energy demand and supply, a lack of accurate data and forecasting systems, as well as economic and policy-related barriers. Understanding and addressing these issues is critical to ensuring that developing economies can harness renewable energy for sustainable development.

One of the most significant barriers to renewable energy integration in developing economies is the lack of adequate infrastructure. Unlike developed nations with established energy grids capable of managing diverse energy sources, many developing countries face the challenge of outdated or underdeveloped infrastructure (Iweh *et al*., 2021). This makes it difficult to incorporate variable energy sources like wind and solar into the existing power grids. For instance, renewable energy systems often require advanced grid technologies to manage fluctuations in energy supply and demand. In many developing regions, the existing grid is not flexible enough to accommodate the intermittent nature of renewable energy. Energy storage technologies, which are crucial for managing supply during periods of low renewable generation, are also underdeveloped or too costly for widespread implementation. Moreover, the transmission and distribution networks in these regions may not be capable of efficiently transferring energy from remote renewable energy plants to urban centers, leading to energy losses and inefficiencies (Medina *et al*., 2022; Bassey, 2023). The main challenges faced by developing countries as regard renewable energy integration is shown in table 1.

**Table 1** Key challenges in renewable energy integration in developing economies (Murshed, 2021)

| **Challenge** | **Description** | **Impact** | **Potential Solutions** |
|---|---|---|---|
| Infrastructure Limitations | Insufficient or outdated energy infrastructure, including unreliable grids and lack of storage systems. | Limits capacity for energy distribution and storage, leading to inefficiencies and outages. | Invest in grid modernization, develop off-grid solutions, and improve storage technologies. |
| High Initial Costs | High capital costs for renewable energy technologies and installation. | Financial barriers for adoption and scaling of renewable projects | Implement financial incentives, subsidies, and low-interest loans. |
| Data Availability and Quality | Lack of reliable data for accurate forecasting and optimization due to poor monitoring systems. | Affects the effectiveness of predictive models and operational efficiency | Improve data collection infrastructure and invest in advanced monitoring systems. |
| Technological Expertise | Shortage of skilled professionals and technical expertise in renewable energy and machine learning. | Limits the ability to develop, implement, and maintain advanced technologies. | Invest in education and training programs to build local expertise. |
| Regulatory and Policy Barriers | Inadequate or inconsistent policies and regulations for renewable energy adoption. | Creates uncertainty and hinders investment in renewable energy projects. | Develop and enforce supportive policies and regulatory framework |

The intermittent nature of renewable energy poses another significant challenge for developing economies. Solar energy is dependent on sunlight, and wind energy depends on wind patterns, both of which can be unpredictable. This variability leads to inconsistencies in energy generation, making it difficult to match energy supply with demand (Zeng *et al*., 2021). Without proper mechanisms to balance supply and demand, renewable energy systems may experience periods of excess energy generation followed by shortfalls, leading to grid instability and potential power outages. In developing economies, where energy consumption patterns can be irregular due to fluctuating economic activity or unreliable access to electricity, the challenge of inconsistent energy demand further complicates the integration of renewables. Rural areas may have minimal energy demands at certain times of the day, while urban areas could experience sharp spikes in energy usage. Without advanced energy management systems in place, these inconsistencies can lead to energy waste during periods of excess production and energy shortages during high demand.

The ability to predict energy demand and renewable resource availability is essential for the effective integration of renewable energy (Boza and Evgeniou, 2021). However, many developing economies lack the data collection and forecasting infrastructure required for accurate predictions. Accurate weather forecasting is crucial for predicting the availability of solar and wind energy, but in many developing regions, weather stations are sparse, and the technology to process large datasets is limited. Without accurate forecasts, energy producers are unable to optimize the generation of renewable energy, leading to inefficiencies and reduced reliability of supply. Furthermore, the absence of historical data on energy consumption patterns poses another challenge. Machine learning algorithms and predictive analytics, which could optimize energy production and distribution, require access to large datasets for training (Mostafa *et al*., 2022). In developing economies, where data collection may be inconsistent or incomplete, the use of such advanced technologies is limited, hampering efforts to build smart grids and energy-efficient systems.

Economic barriers also play a critical role in the slow integration of renewable energy in developing economies. Renewable energy technologies, while increasingly cost-effective, still require significant upfront capital investment. Solar panels, wind turbines, and energy storage systems are expensive to install, particularly in regions where financial resources are scarce (Sánchez *et al*., 2022). Developing economies often lack access to affordable financing options, making it difficult for governments, businesses, and communities to invest in renewable energy projects. In addition to financial constraints, there are policy gaps that impede renewable energy integration. Many developing countries lack clear and consistent policy frameworks that encourage the adoption of renewable energy. Subsidies for fossil fuels, inconsistent regulations, and the absence of long-term energy plans create uncertainty for investors and energy producers. Additionally, many governments face competing priorities such as poverty reduction and economic development, which can limit their focus on renewable energy investments.

The integration of renewable energy in developing economies is crucial for achieving sustainable development, but it is hindered by significant challenges (Adenle, 2020). Infrastructure limitations, inconsistent energy demand and supply, a lack of accurate data and forecasting systems, as well as economic constraints and policy gaps, all contribute to the complexity of adopting renewable energy in these regions. Addressing these challenges will require coordinated efforts between governments, private sector investors, and international organizations to create the necessary technological, financial, and regulatory environments for successful renewable energy integration. Overcoming these barriers is key to unlocking the full potential of renewable energy in developing economies, enabling them to meet growing energy demands while reducing their environmental impact (Kylili *et al*., 2021).

### 2.2. Case Studies and Applications of Machine Learning in Renewable Energy Integration

The integration of renewable energy into existing power grids is a critical step toward achieving global sustainability goals. Machine learning (ML) has emerged as a powerful tool to optimize this integration by improving the efficiency, reliability, and scalability of renewable energy systems. This presents success stories of ML applications in renewable energy integration, focusing on solar energy management in Africa and wind energy forecasting in Latin America. Additionally, a comparative analysis of ML applications across different regions is provided.

Africa is endowed with abundant solar resources, making it an ideal location for solar energy development (Aboagye *et al*., 2021). However, the continent faces challenges in managing and optimizing solar energy production due to variability in solar irradiance and the need for efficient energy storage solutions. Machine learning has played a pivotal role in addressing these challenges. In Kenya, for instance, ML algorithms have been employed to optimize solar energy production by predicting solar irradiance and adjusting energy storage systems accordingly. By analyzing historical weather data and real-time satellite images, ML models can forecast solar energy production with high accuracy. These forecasts enable better grid management and reduce the need for fossil fuel-based backup power, leading to cost savings and reduced carbon emissions. The success of these ML-driven solutions has led to increased adoption of solar energy across the region, contributing to Africa's efforts to expand access to clean energy (Singh *et al*., 2022).

Latin America has vast wind energy potential, particularly in countries like Brazil and Mexico. However, the intermittent nature of wind energy poses challenges for grid operators in maintaining a stable power supply. Machine learning has been instrumental in overcoming these challenges through advanced wind energy forecasting (Yan *et al*., 2022). In Brazil, a country with one of the largest wind energy capacities in the world, ML models have been developed to predict wind speed and direction with high precision. These models utilize large datasets, including meteorological data, turbine performance metrics, and historical wind patterns, to generate accurate short-term and long-term wind forecasts. The implementation of these ML-based forecasting systems has significantly improved the reliability of wind energy integration into the grid, reducing the need for costly reserve power and enhancing the overall stability of the energy supply. The success of wind energy forecasting in Brazil has set a precedent for other Latin American countries, encouraging the expansion of wind energy projects across the region.

The application of machine learning in renewable energy integration varies across regions, reflecting differences in resource availability, technological infrastructure, and regulatory environments (Nam *et al*., 2020). In Africa, the focus has been primarily on optimizing solar energy management due to the continent's rich solar resources. Machine learning models have been successful in enhancing solar energy production and storage, particularly in regions with limited grid infrastructure. The success in Africa demonstrates the potential of ML to address energy access challenges in developing economies. In contrast, Latin America's ML applications have been more focused on wind energy forecasting. The region's abundant wind resources and established wind energy infrastructure have driven the development of sophisticated ML models for accurate wind predictions (Reja *et al*., 2022). The success of these models has not only improved grid stability but has also encouraged investment in wind energy projects. Comparatively, ML applications in developed regions, such as Europe and North America, have been more diverse, covering a wide range of renewable energy sources, including solar, wind, hydro, and bioenergy. These regions benefit from advanced technological infrastructure and large datasets, allowing for the development of more complex and integrated ML systems. With successful applications in wind energy forecasting in Latin America and solar energy management in Africa, machine learning has shown to be a revolutionary tool in the integration of renewable energy sources. The comparative analysis demonstrates how adaptable machine learning is across various locations, highlighting its potential to handle regional difficulties and support global renewable energy goals. It is anticipated that machine learning (ML) technology will play an increasingly important role in optimizing renewable energy systems as they develop, propelling global progress toward energy sustainability (Inbamani *et al*., 2021).

### 2.3. Technical and Economic Considerations of Machine Learning in Renewable Energy Integration

The integration of machine learning (ML) into renewable energy systems presents numerous technical and economic opportunities, but also challenges (Ibrahim *et al*., 2020). While ML can enhance efficiency and optimize energy production, the implementation process is influenced by factors such as cost, data availability, and technological infrastructure. This explores the cost implications of machine learning implementation, data availability and quality challenges, and the technological infrastructure and digital literacy in developing economies.

Implementing machine learning in renewable energy systems involves significant financial investment, which includes the costs associated with hardware, software, and human resources (Forootan *et al*., 2022). For renewable energy operators, integrating ML-based systems requires advanced computing infrastructure capable of processing large datasets and performing complex algorithms in real-time. This involves high-performance servers, cloud computing platforms, and robust data storage solutions. In addition to hardware costs, the development and deployment of machine learning models demand specialized software and expertise. ML models must be custom-built and fine-tuned to address specific challenges within renewable energy systems, whether it's predicting solar energy output, optimizing wind turbine performance, or managing energy storage (Perumalla *et al*., 2022; Zaman *et al*., 2022). Skilled data scientists, software engineers, and energy experts are needed to design and maintain these systems, adding to the overall cost. As the demand for AI and ML talent grows, particularly in the energy sector, the cost of hiring and retaining skilled professionals continues to rise. For large-scale renewable energy projects, these costs are often justified by the long-term benefits of increased energy efficiency, reduced operational downtime, and improved grid stability. However, for smaller projects, particularly in developing economies, the initial investment may pose a significant barrier to adoption. In regions with limited financial resources, the cost of machine learning implementation can hinder the broader deployment of these technologies.

One of the key technical considerations in the successful implementation of machine learning is the availability and quality of data (Lwakatare *et al*., 2020). ML models rely on large, high-quality datasets to make accurate predictions, optimize performance, and identify patterns within renewable energy systems. In many cases, renewable energy operators need access to historical weather data, real-time sensor data, and performance metrics from energy generation equipment such as solar panels and wind turbines. In developing economies, however, data availability can be a major challenge. Many regions lack the necessary infrastructure to collect and store data in a consistent and comprehensive manner. Additionally, data quality may be compromised due to inadequate monitoring systems or poorly maintained sensors. Inaccurate or incomplete data can severely limit the effectiveness of ML models, leading to suboptimal outcomes such as inaccurate energy forecasts or inefficient maintenance schedules (Pachouly *et al*., 2022). To address these challenges, efforts are being made to improve data collection systems in renewable energy projects, including the deployment of advanced sensors, satellite imagery, and Internet of Things (IoT) devices. Nevertheless, ensuring data consistency and accuracy remains a significant hurdle, especially in remote or underserved areas.

Another critical factor affecting the deployment of machine learning in renewable energy integration is the state of technological infrastructure and digital literacy in developing economies. In many low- and middle-income countries, the lack of robust technological infrastructure such as high-speed internet, cloud computing services, and modern energy grids—poses a major barrier to implementing ML solutions. Renewable energy operators in these regions often struggle to access the necessary computing power and digital tools required for machine learning deployment (Kotsiopoulos *et al*., 2021). In addition to infrastructure challenges, digital literacy among the workforce is a significant concern. The successful implementation of machine learning requires not only advanced technology but also skilled individuals capable of designing, managing, and maintaining these systems. However, in many developing economies, there is a shortage of workers with the necessary digital skills to implement and utilize ML technologies effectively. Building local capacity through education and training programs is essential to overcome this challenge. By investing in digital literacy initiatives and fostering partnerships with international tech companies, developing economies can gradually enhance their workforce's ability to leverage machine learning in renewable energy systems. This, in turn, would contribute to greater adoption of AI-driven solutions for energy optimization and sustainability.

The integration of machine learning into renewable energy systems presents both opportunities and challenges (Duchesne *et al*., 2020). The cost of implementing ML solutions can be significant, particularly for small-scale projects in developing economies. Data availability and quality remain ongoing challenges, as many regions lack the necessary infrastructure for consistent data collection and maintenance. Furthermore, technological infrastructure and digital literacy play a crucial role in the success of machine learning deployment, particularly in low-resource settings.

Addressing these technical and economic considerations requires collaborative efforts between governments, private sector stakeholders, and educational institutions. By investing in infrastructure, promoting digital literacy, and ensuring access to high-quality data, developing economies can unlock the full potential of machine learning to accelerate renewable energy adoption and achieve sustainable energy goals (Choudhuri *et al.*, 2021).

### 2.4. Policy and Regulatory Frameworks for Renewable Energy and AI Integration

The integration of artificial intelligence (AI) into renewable energy systems represents a significant step toward achieving more efficient, sustainable, and reliable energy production (Abdalla *et al.*, 2021). However, the success of this integration depends heavily on the policy and regulatory frameworks that govern the energy sector. Supporting policies for AI and renewable energy integration, the role of governments and international organizations, and recommendations for future policy development are essential components of fostering AI-driven advancements in renewable energy.

Effective policy frameworks are critical for enabling the integration of AI into renewable energy systems. These frameworks can help bridge the gap between technological innovation and large-scale adoption by creating incentives for investment, research, and development in AI applications within the renewable energy sector. Governments play a central role in formulating policies that provide financial and regulatory support for AI-based solutions aimed at optimizing renewable energy systems (Liu *et al.*, 2022). Key policies that support AI integration include tax incentives, subsidies, and grants for AI-driven projects in renewable energy. For instance, tax credits for investments in AI technology used in solar and wind energy optimization can stimulate private sector involvement. Furthermore, research and development (R&D) grants can encourage universities, research institutions, and private companies to explore AI's potential in energy systems. These financial mechanisms lower the barrier to entry for AI technologies and foster innovation. In addition to financial incentives, supportive policies may include regulations that mandate the use of smart grids and AI-based forecasting tools to improve the efficiency and reliability of renewable energy generation. For instance, governments can require utilities to adopt AI-enhanced predictive maintenance systems that minimize downtime in energy infrastructure. Smart grid policies that enable AI to balance energy loads and predict consumption patterns can also accelerate the integration of renewable energy into national grids (Omitaomu and Niu, 2021).

Governments and international organizations play pivotal roles in promoting the integration of AI into renewable energy systems. National governments can lead by setting ambitious renewable energy targets and creating a regulatory environment conducive to AI innovation (Ren *et al.*, 2021). For example, the European Union's Renewable Energy Directive has set targets for renewable energy adoption while fostering an environment for advanced technology integration. Similarly, governments in regions such as North America and Asia have implemented AI-focused energy policies that encourage the use of advanced technologies to enhance grid stability and increase renewable energy capacity. International organizations, including the International Renewable Energy Agency (IRENA) and the International Energy Agency (IEA), play an equally important role by providing technical assistance, policy recommendations, and platforms for international collaboration (Hattori *et al.*, 2022). These organizations help governments identify best practices for AI integration and renewable energy development. They also facilitate knowledge sharing, offering access to cutting-edge research and case studies that highlight successful AI applications in energy systems. The United Nations and the World Bank, through their sustainable development initiatives, further promote renewable energy adoption by funding AI-enabled projects aimed at improving energy access in developing regions. These efforts ensure that developing economies, often hindered by a lack of infrastructure and technical expertise, can benefit from AI's potential to optimize renewable energy production and distribution.

To fully leverage AI's potential in renewable energy, several key policy recommendations should be considered. First, governments should adopt flexible regulatory frameworks that allow for rapid innovation while maintaining oversight of AI applications (Smuha, 2021). These frameworks should encourage experimentation with AI technologies while ensuring consumer protection, data privacy, and energy security. Sandboxing initiatives, where AI technologies are tested in controlled environments before large-scale implementation, can help balance innovation with regulation. Second, education and capacity-building programs should be incorporated into policy frameworks. As AI integration in renewable energy systems increases, the demand for skilled workers proficient in both AI and renewable energy will grow. Governments should promote educational initiatives that focus on building digital literacy and technical expertise in AI and energy sectors (Rahman *et al.*, 2021). By fostering local talent, countries can ensure a steady supply of professionals capable of designing, deploying, and maintaining AI-enhanced renewable energy systems. Third, governments and international organizations should promote collaboration between the private sector, research institutions, and energy companies. Public-private partnerships can accelerate the development and deployment of AI technologies in renewable energy. Policymakers should incentivize these partnerships through tax breaks, grants, and streamlined regulatory processes that reduce bureaucratic hurdles for innovative projects. Finally, global cooperation is essential for addressing the technical and economic challenges of integrating AI into renewable energy. International treaties and agreements should include provisions for AI technology transfer, ensuring that all countries, particularly developing economies, have access to the latest AI-driven renewable energy solutions. This would help reduce the global digital divide and ensure equitable access to clean energy technologies.

Artificial Intelligence (AI) integration with renewable energy systems offers a singular potential to maximize energy output, enhance grid stability, and hasten the shift to sustainable energy (Behara and Saha, 2022). However, strong legislative and regulatory frameworks are required for this promise to be fully realized. A favorable environment for the integration of AI and renewable energy can be established by governments and international organizations through financial incentives for AI-based renewable energy projects, international collaboration, and digital literacy promotion.

### 2.5. Future Trends and Opportunities in Machine Learning for Renewable Energy

The integration of machine learning (ML) into renewable energy systems is driving significant advancements, helping optimize energy generation, storage, and distribution (Kim *et al*., 2022). As energy demands continue to rise alongside the global push for sustainability, future trends in ML and artificial intelligence (AI) offer numerous opportunities for enhancing renewable energy systems (Oviroh et al., 2023, Ukoba et al., 2023). This explores advancements in ML for renewable energy optimization, the potential for AI-driven smart grids, and opportunities for cross-sector collaboration that can accelerate these developments.

Machine learning has already demonstrated its capacity to optimize various aspects of renewable energy systems, but ongoing advancements are expected to bring even more profound improvements as explain in figure 3 (Husin and Zaki, 2021; Abualigah *et al*., 2022).

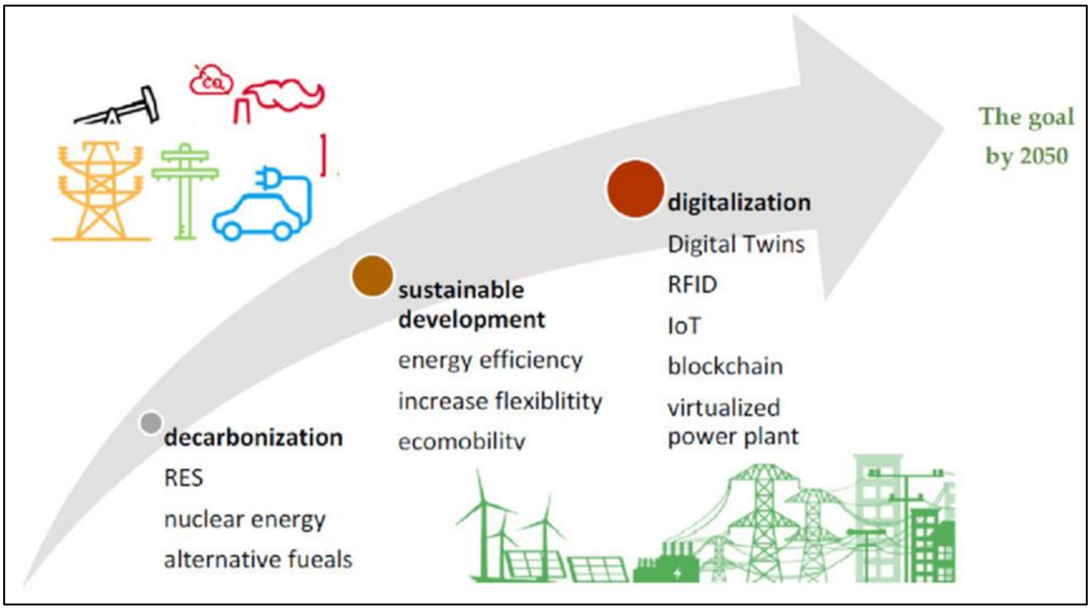


**Figure 3** Direction of energy sector growth (Husin and Zaki, 2021)

One major trend is the development of more sophisticated predictive models capable of improving energy production forecasts. These models analyze vast amounts of weather data, energy consumption patterns, and historical performance metrics to more accurately predict solar, wind, and hydropower output. This increased forecasting accuracy allows energy producers to better match supply with demand, thereby enhancing grid stability and reducing reliance on fossil fuels. Moreover, ML is set to play an increasingly important role in optimizing energy storage systems. As the use of renewable energy grows, the need for efficient energy storage becomes critical, given the intermittent nature of sources like wind and solar (Lukong et al., 2023). Advanced ML algorithms can manage energy storage by predicting periods of high and low demand and charging or discharging energy accordingly. This helps minimize energy waste, extend the lifespan of storage batteries, and ensure a reliable energy supply. Technologies like reinforcement learning, where algorithms learn to make better decisions over time, are particularly promising for optimizing energy storage in real-time (Dreher *et al*., 2022). Another key area of advancement is in predictive maintenance for renewable energy infrastructure. ML algorithms can analyze data from sensors installed in wind turbines, solar panels, and hydroelectric systems to identify early signs of equipment failure or inefficiency. This allows operators to address maintenance issues before they escalate into costly breakdowns, thereby reducing downtime and maximizing the lifespan of renewable energy assets. As sensor technology and ML models become more advanced, predictive maintenance will become even more effective, further reducing operational costs and improving energy efficiency.

AI-driven smart grids are among the most promising future trends in the energy sector. Smart grids use AI and ML to manage the flow of energy in real-time, optimizing the distribution of electricity across various sources and consumers (Ali and Choi, 2020). These systems can detect energy surpluses or shortages, automatically adjusting energy production and storage to maintain a balanced grid. As renewable energy sources, particularly wind and solar, become more widespread, the need for smart grids capable of managing their variability will become increasingly important. One key advantage of AI-driven smart grids is their ability to facilitate decentralized energy systems, where individual households and businesses produce, store, and even sell excess renewable energy back to the grid. Machine learning algorithms can optimize these transactions, balancing energy supply and demand dynamically and ensuring that renewable energy is used efficiently across the network. This would lead to a more resilient energy grid, less reliant on centralized energy production, and better able to handle fluctuations in energy supply from renewable sources. Furthermore, smart grids will play a crucial role in integrating emerging energy technologies, such as electric vehicles (EVs) and distributed energy resources (DERs). Machine learning models will be essential for managing the increased complexity that comes with multiple energy inputs and outputs, helping smart grids allocate energy more effectively and reduce overall grid strain (Banik *et al*., 2021).

The future of machine learning in renewable energy will be shaped by opportunities for cross-sector collaboration. The intersection of energy, AI, and other industries offers significant potential for innovation and optimization. Collaboration between the energy sector, tech companies, research institutions, and governments will be crucial in accelerating the development and deployment of AI-powered renewable energy solutions. For instance, partnerships between energy providers and technology companies can help leverage advanced computing power, cloud-based solutions, and AI expertise to develop more robust machine learning models. Tech giants such as Google and Microsoft have already started investing in renewable energy optimization through AI initiatives, and future collaborations could further enhance these efforts. By pooling resources and expertise, these partnerships can develop cutting-edge AI tools that push the boundaries of renewable energy systems. In addition to industry partnerships, collaboration with academic and research institutions will play a pivotal role in advancing machine learning applications. Universities and research organizations can contribute to the development of new ML algorithms, as well as conduct pilot projects to test and refine AI-driven renewable energy technologies. Collaborative research efforts can also help address common challenges such as data availability and quality, ensuring that ML models have access to the best possible datasets for making accurate predictions and optimizations (Munappy *et al*., 2022). Government involvement in cross-sector collaboration will be vital as well, particularly in terms of setting regulatory frameworks and providing funding for AI-driven renewable energy projects. Governments can facilitate public-private partnerships, incentivize research and development, and promote international cooperation on large-scale renewable energy initiatives. By fostering collaboration across sectors, governments can help ensure that AI's full potential in renewable energy optimization is realized.

The future of machine learning in renewable energy integration is filled with promising trends and opportunities. Advancements in ML models will continue to optimize energy production, storage, and maintenance, making renewable energy systems more efficient and cost-effective. AI-driven smart grids will enable real-time energy management and support decentralized energy systems, contributing to a more resilient and sustainable energy infrastructure. Cross-sector collaboration between the energy industry, technology companies, academic institutions, and governments will be essential in driving these advancements forward (Vogel *et al*., 2022). Together, these trends and opportunities position machine learning as a key enabler in the global transition to clean, renewable energy systems.

## 3. Conclusion

Machine learning (ML) has emerged as a transformative force in the realm of renewable energy, driving significant advancements in efficiency, optimization, and integration. Key findings from recent analyses underscore the profound impact of ML on various aspects of renewable energy systems. Notably, ML has proven instrumental in enhancing predictive maintenance, optimizing energy storage, and refining energy production forecasts. These advancements not only improve the operational efficiency of renewable energy infrastructure but also contribute to more reliable and sustainable energy supply. The potential impact of machine learning on renewable energy integration is substantial. AI-driven technologies, such as advanced predictive models and AI-powered smart grids, promise to revolutionize how energy is managed and distributed. By optimizing energy production, balancing supply and demand, and integrating decentralized energy sources, ML can significantly enhance grid stability and reduce reliance on fossil fuels. The ability of ML to analyze vast amounts of data in real-time and make informed decisions ensures a more responsive and adaptable energy system, paving the way for a cleaner and more efficient energy future.

In developing economies, the future of renewable energy holds immense promise, albeit with specific challenges. ML offers opportunities to address critical issues such as energy access and infrastructure limitations. For instance, AI-driven solutions can optimize off-grid solar systems and enhance energy management in regions with unreliable grids. However, overcoming barriers related to data availability, technological infrastructure, and digital literacy is essential for realizing these benefits. With targeted investments in technology and education, and supportive policy frameworks, developing economies can harness the full potential of ML to advance their renewable energy goals and achieve sustainable development.

Machine learning has the potential to be a key component in the development of renewable energy systems. With the power to change the energy landscape globally, even in developing nations, machine learning (ML) has the potential to significantly advance sustainability and energy efficiency by tackling present issues and seizing new opportunities.

## Compliance with ethical standards

*Disclosure of conflict of interest*

No conflict of interest to be disclosed.

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