Africa Philanthropy Network
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# Harnessing AI-Driven Simulations for Optimizing Renewable Energy Projects in Energy-Scarce African Regions


## by Winfred Kiaire



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# 1. Introduction

## 1. 1 Background and Context

One of the most pressing global issues today is energy security. With the world's population and energy consumption increasing rapidly, and the demand continues to grow, access, efficiency, and conservation of energy become even more pertinent (Santos et al., 2023). From the 1990s to 2014, global energy consumption increased by 151% (International Energy Agency, 2020).

Africa, in particular, has one of the fastest-growing and youngest populations in the world, thus an increase in energy demand. According to the International Energy Agency (IEA), one in two people added to the global population between now and 2040 is likely to be from Africa (IEA, 2020). Reliable energy access is vital for sustainable development, and for efficiency in sectors such as agriculture, health, transportation, and housing (Nyarko et al., 2023). However, despite the rapid population growth and increased energy demand in Africa, there remains a significant energy access deficit, especially in Sub-Saharan Africa (Quansah et al., 2016). This affects the continent's access to essential resources like electricity and clean cooking fuels, which negatively impacts its development (Nyarko et al., 2023). Figure 1.1 shows how far the continent is lagging compared to the rest of the world in terms of utilization despite the high demand for clean, reliable energy.

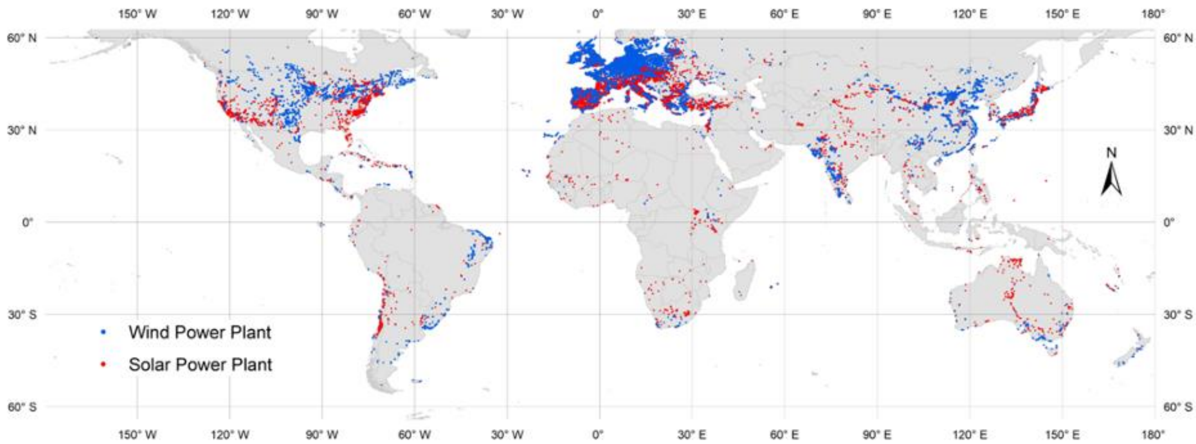


**Figure 1.1 Wind and solar power plants across the globe (Sachit et al., 2022)**

Climate change and environmental degradation are pressing global challenges, with Africa especially vulnerable due to its limited adaptive capacity and reliance on climate-sensitive resources. The Intergovernmental Panel on Climate Change (IPCC) highlights that Africa is experiencing temperature rises faster than the global average, intensifying droughts, reducing water availability, and compromising food security (IPCC, 2023). The World Bank warns that without significant global action, climate change could push an additional 100 million people into poverty by 2030, disproportionately affecting African nations (Roome, 2015). These factors highlight the urgency of transitioning to sustainable energy solutions like renewable energy systems, which are gaining traction worldwide due to their potential to enhance energy security, mitigate environmental impact, and improve air quality (Abualigah et al., 2022; Alam et al., 2020). Particularly in Africa, the shift towards renewable energy technologies especially wind and solar systems is crucial not only for their lower environmental and safety risks compared to conventional energy sources but also as a strategic response to the region's unique vulnerabilities to climate change (Singh et al., 2021).

Solar energy, derived from the sun's radiant energy, is captured through photovoltaic cells or solar thermal systems, which convert sunlight directly into electricity or heat. Meanwhile, wind energy systems harness the kinetic energy of wind using turbines which convert this mechanical energy into electrical energy. These renewable energy (RE) technologies not only provide significant environmental benefits by mitigating climate change but also are becoming more cost-effective due to continual declines in costs and advancements in storage solutions like batteries. AI-driven optimization further enhances the efficiency and cost-effectiveness of these technologies, making them increasingly viable for widespread adoption (Alzain et al., 2023; Behzadi & Sadrizadeh, 2023). As the main drivers of energy system expansion in Africa, solar and wind power are poised to close Africa's energy gap cost-efficiently and in a climate-compatible manner, emerging as the primary carriers of low-cost renewable electricity (Oyewo et al., 2023). Solar photovoltaics (PVs), in particular, are seen as the most cost-effective energy source for the African continent due to their abundant availability and significant cost reductions in technology (Oyewo et al., 2023). A strategic focus on wind and solar energy, supported by advanced AI techniques, will position Africa to leapfrog into a sustainable and demand-oriented energy system for the future.

### 1.2 Problem Statement

The paradox in Sub-Saharan Africa (SSA) is that despite the richness of renewable energy sources, they remain largely untapped, which is unhelpful to the severe energy scarcity that undercuts socio-economic development across the continent (Agoundedemba et al., 2023; Mukhtar et al., 2023). The underutilization of renewable energy in Africa primarily stems from inadequate infrastructure, compounded by low investment levels and multiple uncertainties, including fluctuating weather conditions, inconsistent energy demands, and regulatory challenges. Despite the continent's vast potential, annual investments required to meet energy and climate goals are far from being met, with current investments representing only a fraction of the necessary funding (IEA, 2024). This shortfall is compounded by the "Africa infrastructure paradox," where despite a substantial pipeline of projects and available funding, many initiatives fail to reach financial close due to inadequate feasibility studies, poor planning, and insufficient project management capabilities (Thusi & Mlambo, 2023; Mercer et al., 2021; OECD/ACET, 2020). Additionally, clean energy investments in Africa have drastically declined, receiving just 0.6% of global renewable energy funding, severely limiting the expansion of essential infrastructure (United Nations Development Programme, 2023; RES4Africa Foundation, 2023). The uncertainties surrounding renewable energy projects—caused by fluctuating weather patterns, shifts in energy demand, and technological limitations—further deter investment, as investors and governments are wary of low or no returns on investment (International Renewable Energy Agency (IRENA), 2018; IEA, 2023). These multifaceted challenges highlight the critical need for a more strategic approach to developing the necessary infrastructure and mitigating uncertainties in the renewable energy sector across Africa.

The uncertainties in the renewable energy sector present complex challenges that can be effectively managed through the use of artificial intelligence (AI) and machine learning (ML) technologies. These advancements are achieved through data-driven insights, predictive analytics, and sophisticated optimization techniques. This involves geospatial analysis to determine areas with the highest solar irradiance and wind speed, which can significantly enhance energy output (Salleh et al., 2022). Moreover, AI and ML help in selecting the appropriate technologies for specific sites. For instance, they can determine whether a location would benefit more from thin-film solar panels or crystalline-based solar panels, or dictate the specific type of wind turbine that would maximize efficiency based on local wind patterns (Kurniawan & Shintaku, 2022). These algorithms also streamline the distribution of essential resources—such as land, materials, and labor—needed to establish and maintain these installations. They can predict the optimal layout of solar panels and wind turbines to avoid shadowing and wake effects, thereby maximizing the generation capacity (Babawarun et al., 2023). This optimization not only streamlines project development processes but also enhances the overall effectiveness of investments in renewable energy. Furthermore, AI and ML technologies enable the prediction of maintenance needs for renewable energy infrastructure by analyzing data from sensors and monitoring equipment to identify potential issues before they become critical (Flaieh et al., 2020; Concepcion II et al., 2021; Bustamam et al., 2020). This proactive maintenance approach reduces downtime, extends equipment lifespan, and improves system reliability (Capote-Leiva et al., 2022). AI and ML aid professionals in the renewable energy sector in making informed decisions, enhancing system performance, and accelerating the shift toward sustainable energy (Danish, 2023). Figure 1.2 shows an overview of the history of AI applications in the energy sector.

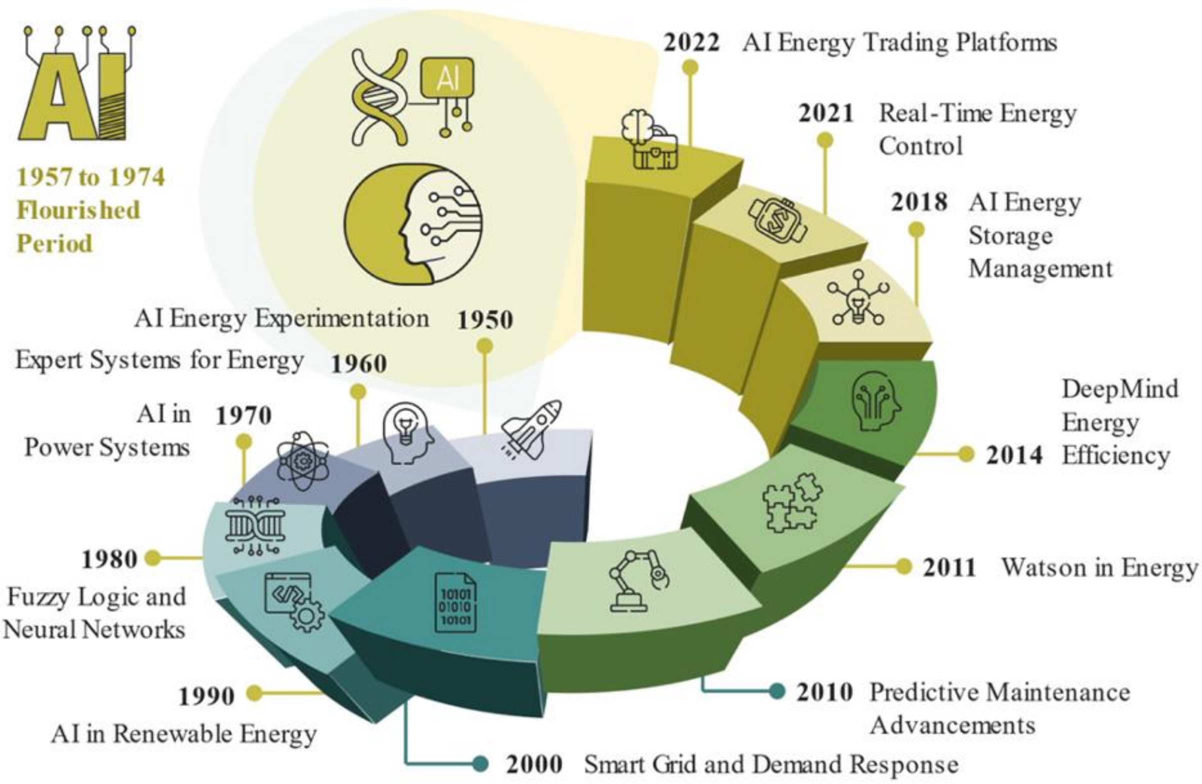


**Figure 1.2 History of AI in the energy sector (Danish, 2023)**

The following study on the application of Artificial Intelligence (AI) and Machine Learning (ML) in the optimization of renewable energy is highly beneficial for multiple reasons. It addresses the critical need for sustainable energy solutions by demonstrating how AI and ML technologies can improve the efficiency, reliability, and efficiency of renewable energy systems (Danish, 2023; Nguyen et al., 2024). This research highlights the interdisciplinary nature of this developing field in Africa, linking renewable energy studies with advancements in AI and ML. By synthesizing current research in Africa and emphasizing key trends and challenges, it informs decision-makers, policymakers, and industry stakeholders about the potential impacts of integrating AI and ML into renewable energy. This literature review will serve as an educational resource for students, researchers, and professionals seeking to explore the potential of AI/ML applications in renewable energy. The aim is for this research to expand knowledge, foster innovation, and accelerate the transition towards clean and sustainable energy in Africa.

### 1.3 Research Objectives and Questions

**General Objective**
Explore the implementation of AI-driven simulations in optimizing wind and solar photovoltaic (PV) energy farms in Africa.

**Research Questions**
The research questions designed to guide this study include:

i. What are the potential benefits and limitations of applying AI-driven simulations in the planning and executing of renewable energy projects in energy-scarce African regions?
ii. How can AI-driven simulations help overcome the infrastructural and financial barriers that currently impede renewable energy adoption in Africa?

### 1.4 Methodology

This research adopts a robust methodology centered around an extensive literature review. It is designed to rigorously examine the integration of AI-driven simulations in enhancing the design and implementation of renewable energy projects. The methodology is meticulously crafted to evaluate the potential of AI technologies in transforming the renewable energy sector in energy-scarce African regions, focusing specifically on the applicability of modeling and simulations.

#### 1.4.1 Rationale for Study Selection

Selection of the studies involved systematically searching databases such as IEEE Xplore, ScienceDirect, and the Web of Science to identify articles that meet the inclusion criteria. Keywords such as "case study," "AI models," "wind energy," "solar energy," "existing data," "reanalysis," and "renewable energy" are used to filter relevant studies. Each article is then evaluated based on its abstract and methodology to ensure it provides insight into the application of AI-driven simulations in renewable energy.

a. Inclusion Criteria:

- Studies that focus on the application of AI technologies in renewable energy systems, particularly those employing modeling and simulations.
- Articles published in peer-reviewed academic journals and reputable industry reports.
- Research conducted or reviewed within the last ten years, to ensure relevance to current technology and market conditions.
- Studies that provide empirical data on the outcomes of AI applications in energy systems.
- Articles that include case studies or real-world applications of AI in energy contexts in regions in or analogous to the Sub-Saharan environment.

b. Exclusion Criteria:

- Articles published more than ten years ago, to avoid outdated technological insights.
- Studies that do not focus on renewable energy sources.
- Papers that lack empirical evidence or adequate methodological detail.
- Research focuses solely on theoretical AI models without practical or applied testing.
- Studies done outside Africa.

## 2. Literature Review

## 2.1 Energy Scarcity in Sub-Saharan Africa (SSA)

Mukhtar et al. (2023) report that more than 600 million in SSA face acute energy poverty and 900 million people do not have access to clean cooking fuels. Unfortunately, the efforts to address this energy deficit are still being outpaced by the region's population growth. The 20 least electrified countries in the world are located in Sub-Saharan Africa (Statista, 2023). Ritchie (2023) reports that the number of people without electricity worldwide has halved over the last two decades. Nevertheless, in Sub-Saharan Africa, the figure has remained fairly constant; 8 out of 10 people do not have electricity. Additionally, there is a great disparity between electrification in the urban and rural areas where 80% of people in the urban dwellers have access to electricity while in rural areas, only 30% of people have electricity. Countries with less than 30% of electricity access rate in the world in 2021 are in SSA including South Sudan (7.7%), Burundi(10.2%), Chad(11.3%), Malawi(14.2%), Central African Republic(15.7%), Niger(18.6%), Burkina Faso (19%), Dem. Republic of the Congo(20.8%), Sierra Leone(27.5%) and Liberia(29.8%) (Statista, 2023).

This lack of access to energy has multifaceted effects on both individuals and communities. A report by the World Bank highlights that inadequate access to clean energy for cooking results in indoor air pollution, leading to respiratory diseases that disproportionately affect women and children in rural areas (The World Bank, n.d.). Also, hospitals often lack electricity to power medical devices and refrigerate vaccines, affecting healthcare delivery and exacerbating health outcomes (Adair-Rohani et al., 2013). The situation also exacerbates the economic challenges, as energy is a fundamental economic growth and development driver. Power outages cost African economies about 2-4% of their GDP annually (Copinschi, 2022; RES4Africa Foundation, 2023; African Development Bank, 2019). Furthermore, inadequate access to electricity impacts access to information and technology, exacerbating the digital divide and hindering educational opportunities and overall quality of life on the continent (Sarkodie & Adams, 2020). And not forgetting the heavy reliance on coal, oil, and natural gas, which constitute approximately 80% of total electricity production in the continent, continues to contribute to environmental degradation and carbon emissions, thus countering global efforts to combat climate change (Agoundedemba et al., 2023).

## 2.2 Untapped potential of renewable energy resources in Africa/SSA

Africa is endowed with abundant renewable energy resources, including wind, solar, hydro, biomass, and geothermal power. These resources present a significant opportunity to address the energy access challenge and promote sustainable development across the continent. The continent receives ample sunlight throughout the year, making solar energy particularly promising, with vast solar potential estimated at 11 terawatts (TW) (African Development Bank, 2019). Wind energy capacity is also substantial, estimated at 110 gigawatts (GW) (RES4Africa Foundation, 2023). These renewable sources offer decentralized and scalable solutions suitable for both grid-connected and off-grid applications, particularly in rural areas (Agoundedemba et al., 2023; Samatar et al., 2023). Average electricity consumption per capita in sub-Saharan Africa stands at around 180 kWh, with stark contrasts within the region, such as rural areas consuming approximately 5 kWh monthly compared to urban centers like Nairobi where usage reaches 200 kWh (Castellano et al., 2015; Tesfamichael et al., 2020; African Development Bank Group, 2019). A single gigawatt of wind power, sufficient for approximately 166,000 to 400,000 households based on regional energy usage variations, means the 110 gigawatts of estimated wind capacity could power between 18.3 million and 44 million homes. Just 50% of the Solar energy in the region could theoretically meet the electricity needs of the entire continent several times over, highlighting its capability to significantly exceed Africa's current and projected residential energy demands.

Sub-Saharan Africa (SSA) with its high solar irradiance and substantial wind potential, is well-suited to harness these resources to meet growing energy demands sustainably (Adedeji et al., 2021; Ebhota & Tabakov, 2023). Deploying wind and solar energy systems can enhance energy security by reducing dependence on imported fossil fuels and diversifying the energy mix, thereby decreasing supply disruptions (Bilal et al., 2022; Bouabdallaoui et al., 2023). Moreover, decentralized, modular, and scalable systems such as solar PVs and wind power are less prone to cost overruns and technical failures compared to large hydropower projects. While hydropower has historically been a dominant energy source due to its significant power output, it is increasingly being reconsidered in the energy transition. The shift is driven by faced challenges including technical failures, environmental impacts, and the growing incidence of droughts exacerbated by climate change (Sovacool et al., 2023; International Energy Agency, 2023). Moreover, wind and solar power technologies present lower investment barriers, with initial setup costs being more affordable and AI and machine learning advancements further optimizing their efficiency and cost-effectiveness (Adun et al., 2022; Alzain et al., 2023). AI-driven predictive models have significantly improved the operational efficiency of these systems, making them more financially viable and reliable (Behzadi & Sadrizadeh, 2023). Additionally, wind and solar technologies significantly reduce greenhouse gas emissions, aiding global climate change mitigation efforts and supporting sustainable development goals in SSA (Al-Buraiki & Al-Sharafi, 2021). Their decentralized nature makes them ideal for deployment in remote and underserved areas, providing clean energy access where traditional grid extensions are impractical or too costly (Nyarko et al., 2023; RES4Africa Foundation, 2023).

### 2.3 What is Artificial Intelligence (AI)?

Artificial Intelligence (AI) refers to using computer systems to perform tasks that normally require human intelligence. These tasks include learning from data, making decisions based on this data, and solving complex problems. AI is particularly suited for the renewable energy sector because of its ability to process and analyze vast amounts of data quickly and accurately, which is crucial for optimizing energy systems and integrating renewable sources efficiently (Benti et al., 2023). Three types of AI are relevant to renewable energy optimization. Machine Learning (ML) is a subset of AI that involves training a system to learn from data and improve its performance over time without being explicitly programmed (Benti et al., 2023). ML is applied in renewable energy to forecast demand and supply, optimize energy distribution, and predict equipment maintenance needs (Forootan et al., 2022). Deep learning is an advanced form of ML that uses neural networks and is particularly effective in processing and interpreting vast amounts of unstructured data, such as satellite images, to monitor solar farms or wind parks (Abualigah et al., 2022). Reinforcement learning is a subset of AI that involves algorithms that learn to make sequences of decisions by trial and error, optimizing the operation of energy systems, such as dynamically adjusting power loads or storage systems to balance supply and demand in real time (Specht & Madlener, 2023).

AI holds significant promise for optimizing the transition towards renewable energy sources due to its advanced computational capabilities and efficiency in managing complex systems. AI's ability to predict when renewable energy system components will likely fail or require maintenance is revolutionary. According to Onwusinkwue et al. (2024), AI algorithms can analyze data from sensors on wind turbines to anticipate equipment failures before they occur. This predictive capacity reduces downtime and minimizes maintenance costs, enhancing renewable energy installations' overall efficiency and lifespan. AI significantly enhances the accuracy of energy demand and supply forecasts. Bouquet et al. (2023) implemented an LSTM-based Deep Learning model for precise solar electricity forecasting, demonstrating its effectiveness in aiding power grid operators with stable electricity supply planning in short-term forecasting within minutes. AI facilitates more efficient grid management and helps mitigate the variability associated with renewable energy sources.

Google's DeepMind is one example of AI in big data analysis for renewable energy. This AI application predicts wind power output 36 hours ahead of actual generation (Elkin & Witherspoon, 2019). Such predictive capability is invaluable for grid operators, as it allows for better integration of intermittent wind power into the power grid, optimizing both renewable resources and grid operations. Another example is Siemens Energy which utilizes AI-powered digital twins to create virtual models of wind farms before actual construction (Scopelliti, 2023). This technology enables operators to optimize the layouts and operations of these farms, ensuring maximum efficiency and effectiveness from the planning stage through to operation.

## 2.4. Review of Solar power systems and AI Applications + Simulations and Modelling

### 2.4.1 Review of Solar Energy Power Systems and AI Application

Although many regions in Africa receive over 2,000 kWh of solar radiation annually, the continent has yet to experience significant development in solar energy power plants (Quansah et al., 2016). This immense and ubiquitous energy source has the potential to meet SSA's energy demands (Santos et al., 2023). Despite the promising outlook, several critical obstacles must be overcome for Africa's power sector to fully harness the potential of utility-scale solar PV systems. The primary challenges are linked to the technical capacity of grid infrastructure and the reserve capacity in most Sub-Saharan African (SSA) countries (Nyarko et al., 2023). Solar energy availability fluctuates significantly throughout the day and is non-existent at night, leading to variability in power output (Alderman et al., 2023). This inconsistency presents substantial difficulties for grid operators, which must maintain balance and stability in electricity transmission and distribution systems. According to an IEA report on integrating variable renewable resources into electricity grids, grid systems need to incorporate flexible resources to handle the intermittency of renewable energy production (International Energy Agency, 2020).

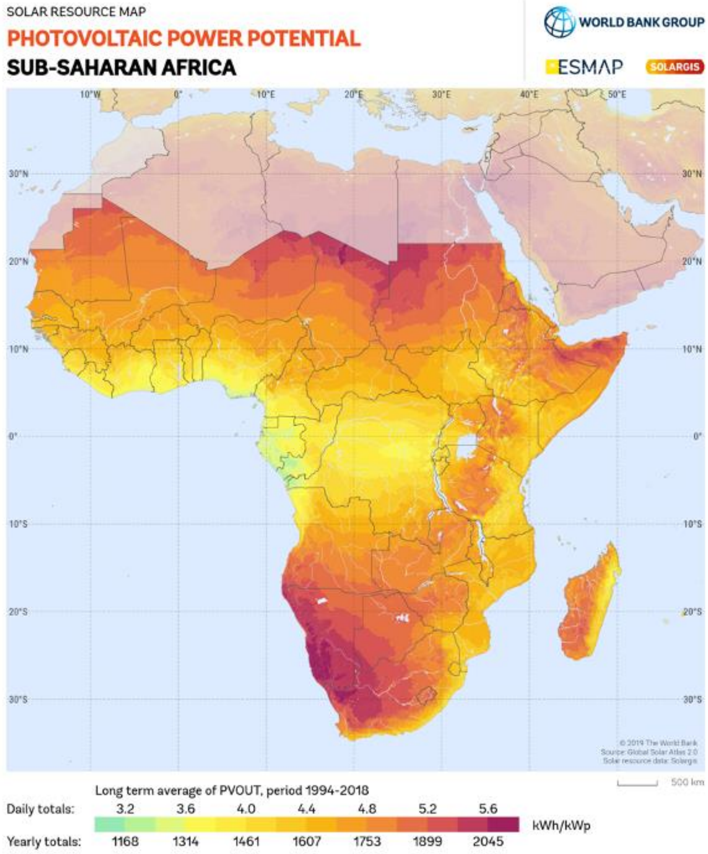


**Figure 2.1 Solar energy potential in Africa (Global Solar Atlas, n.d.)**

In the realm of solar energy, artificial intelligence has become increasingly vital, offering innovative methods to enhance output and efficiency (Shirole et al., 2021). Machine learning advances, particularly in predictive analytics and panel layout optimization, have made solar energy more reliable and easier to integrate into existing power networks (Ghaithan et al., 2021; Behzadi & Sadrizadeh, 2023). One key application of artificial intelligence in solar energy is predictive analytics, where algorithms analyze historical weather patterns, solar radiation levels, and various environmental factors to forecast solar power output with high accuracy (Cheng et al., 2023; Al-Buraiki & Al-Sharafi, 2021). This capability is crucial for efficient grid management, enabling better integration of solar energy with other electricity sources, thereby ensuring a steady energy supply and reducing reliance on non-renewable backups (Jafari et al., 2022; Adun et al., 2022).

Moreover, artificial intelligence plays a critical role in optimizing the positioning and orientation of solar panels. By analyzing sunshine patterns, topography, and other geographic features, artificial intelligence algorithms can recommend optimal locations and angles for solar panel deployment to maximize energy capture (Wang et al., 2020; Said et al., 2022). This optimization not only enhances the efficiency of large-scale solar farms but also ensures that smaller installations, such as rooftop panels, significantly contribute to electricity production (Quitiaquez et al., 2021; Damayanti et al., 2021). Additionally, artificial intelligence aids in the maintenance and operation of solar power plants by predicting equipment faults and detecting when solar panels are underperforming due to issues like dirt accumulation or damage. This predictive maintenance capability allows for proactive issue resolution, minimizing downtime and maximizing the efficiency and longevity of solar energy systems (Zhang et al., 2023; Kallio & Siroux, 2023; Chakraborty et al., 2023).

A survey done on the application of artificial intelligence (AI) and mathematical models in optimizing power grids driven by renewable energy sources reported that AI techniques such as machine learning algorithms, neural networks, and reinforcement learning could enhance load forecasting, fault detection, and grid stability. For instance, the implementation of a machine learning-driven demand-response scheme was shown to reduce operational expenses by 30% and improve grid reliability by 25% ( Srinivasan et al., 2023). Additionally, the study quantified a 20% increase in the integration efficiency of renewable sources. However, it also highlighted limitations, such as the need for large datasets to train accurate models and the significant computational resources required. These findings suggest that AI-driven simulations could address the infrastructural and financial barriers in energy-scarce African regions by optimizing the allocation and utilization of renewable energy resources. Specifically, by enhancing grid stability and load forecasting, AI can reduce the need for expensive infrastructure upgrades and minimize financial risks associated with renewable energy projects.

### 2.4.2 Simulations and Modelling in the Solar Energy Domain

Daghsen et al. (2023) proposed a universal model for solar radiation exergy accounting focusing on Tunisia. Exergy is the measure of how much of the sunlight’s energy is potentially usable for conversion into other forms of energy, like electricity, under specific environmental conditions. Using meteorological data, including solar radiation, ambient temperature, and relative humidity, the model provided a detailed quantification of solar radiation exergy. The study presented results showing an average exergy efficiency of 35% under typical Tunisian climatic conditions, with peak efficiencies reaching up to 45% during optimal conditions. Validation against empirical data showed a mean absolute percentage error (MAPE) of less than 5%, confirming the model's accuracy and reliability. This model can be particularly effective in optimizing solar energy projects in diverse African environments by providing precise exergy calculations that can guide the efficient design and operation of solar power systems. By offering accurate exergy accounting, this model helps overcome infrastructural barriers by ensuring that solar projects are designed to maximize efficiency and minimize resource wastage.

Seane et al. (2024) investigated the optimization of microgrid systems using real-time residential data in Palapye, Botswana. The hybrid model, integrating solar PV, wind, and battery storage, achieved an optimal energy management strategy with an efficiency improvement of 20% and a cost reduction of 15%. The study utilized advanced optimization algorithms, resulting in a reliable and efficient microgrid system capable of addressing the region's energy needs. This optimization is critical for overcoming the infrastructural challenges and financial constraints in deploying microgrids in rural and urban settings. By optimizing energy management, AI-driven simulations reduce the need for costly infrastructure and enhance the financial viability of microgrid projects.

Fumtchum et al. (2024) proposed a model for predicting the efficiency of solar photovoltaic energy injection into a localized subtropical grid, using Douala as a case study. The model incorporated actual generation trend curves, achieving an efficiency prediction with an RMSE of 4.2%. This approach provided accurate predictions of energy injection, enhancing the reliability and efficiency of the local grid and reducing energy costs by 12%. By providing precise efficiency predictions, AI-driven simulations can help optimize energy injection into local grids, addressing both infrastructural and financial barriers. Accurate efficiency predictions ensure that energy injection is maximized, reducing the need for additional infrastructure and enhancing the financial viability of renewable energy projects.

Dobreva et al. (2015) developed an energy yield model for PV systems operating under Namibian conditions. The model predicted an annual energy yield of 1,800 kWh/kWp, with a model accuracy of 95% as validated against empirical data. This high level of accuracy underscores the significant potential for solar energy generation in Namibia, with an estimated LCOE of $0.05 per kWh. By providing precise energy yield predictions, AI-driven simulations can optimize the design and operation of PV systems in similar climatic conditions, addressing both infrastructural and financial barriers.

Accurate yield predictions ensure that projects are economically viable and technically sound, reducing the risk of financial loss and underperformance.

Ebhota and Tabakov (2023) conducted an assessment of the solar photovoltaic potential in selected site locations across sub-Saharan Africa using geographical information systems (GIS) and meteorological data. The assessment revealed that locations such as Lagos, Nairobi, and Accra exhibited high solar irradiance levels, with annual averages of 5.5 kWh/m²/day. The economic analysis predicted a levelized cost of electricity (LCOE) ranging from $0.04 to $0.06 per kWh, making solar PV a financially viable option for these regions. This assessment provides valuable insights into the most effective locations for solar energy projects and can guide strategic planning and investment in renewable energy infrastructure. By identifying optimal sites for solar PV installations, AI-driven assessments help overcome infrastructural barriers by ensuring that projects are developed in locations with the highest potential for energy generation, thus reducing the risk of underperformance and financial loss.

Similarly, Gerbo et al. (2020) conducted a study aimed at identifying high-potential solar sites by integrating various spatial and meteorological data, including solar irradiance, land use, and proximity to existing electrical infrastructure. The study used a GIS-based approach to model the potential sites for grid-connected solar power in the East Shewa Zone of Ethiopia. The results showed that the identified sites had an average solar irradiance of 6 kWh/m²/day, making them highly suitable for solar power generation. The GIS-based modeling effectively pinpointed optimal locations for solar installations, facilitating strategic planning and infrastructure development. By providing detailed spatial analysis, this approach helps overcome infrastructural barriers by ensuring that solar projects are sited in locations with the highest potential for energy generation, thus maximizing efficiency and financial returns.

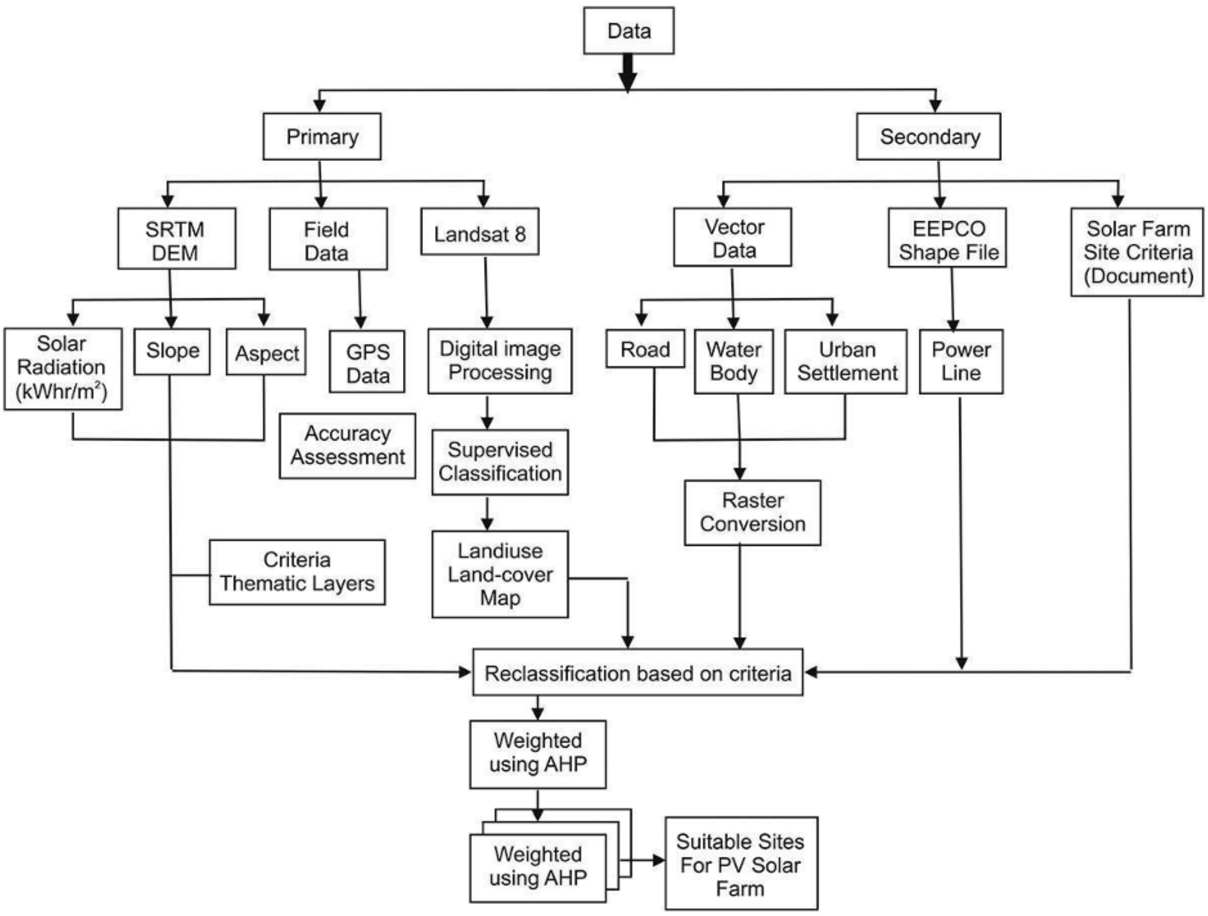

**Figure 2.4 Model structure for identifying high-potential sites for solar farms in Africa (Gerbo et al., 2020)**

Van Vuuren et al. (2019) proposed a simulation-based theoretical preconstruction process for implementing solar photovoltaic (PV) technology in South African shopping centers. Detailed simulations indicated a potential energy yield of 1,200 MWh per year for a 1 MW installation, with a predicted return on investment (ROI) of 7 years. The simulation accounted for local climatic conditions, resulting in a model accuracy with a mean bias error (MBE) of 4%. This preconstruction process significantly reduced the financial risks associated with large-scale solar PV projects. AI-driven simulations can provide a thorough assessment before construction and therefore help overcome infrastructural barriers and ensure the feasibility and economic viability of renewable energy projects. Simulating different scenarios allows these models to optimize planning that minimizes costs and maximizes energy output, thus addressing financial barriers.
Building on previous research, Van Vuuren et al. (2021) validated a simulation-based pre-assessment process for rooftop solar PV technology in South African shopping centers. Using actual performance data, the validation showed an energy yield prediction accuracy with an RMSE of 5% and an ROI of 6 years. This validation process supported the pre-assessment model's reliability and its effectiveness in predicting the economic viability of rooftop solar PV installations. AI-driven simulations provide accurate pre-assessment data which enable mitigation of financial risks and support the successful implementation of renewable energy projects. The accurate predictions of energy yields and financial returns reduce uncertainty and enhance investor confidence, addressing financial barriers to project funding.

The table below provides a summary of the reviewed articles, highlighting their respective outcomes, AI techniques, and the types of data used.

## 2.5 Review of Wind Energy Power Systems and AI Application + Simulations and Modelling

### 2.5.1 Review of Wind Energy Power Systems and AI Application

Wind is an abundant energy source that can be harnessed without producing carbon emissions. Wind power represents a rapidly advancing sector within renewable energy technologies, demonstrating significant growth compared to other energy sources under exploration (Correa-Jullian et al., 2022). Worldwide, the potential of wind energy in SSA exceeds the region's energy consumption, with considerable room for further expansion (Global Wind Energy Council, 2022). Despite these advantages and the ongoing development of wind power, integrating it into existing power grids presents various challenges. Fluctuating wind patterns can introduce harmonics, disrupt voltage levels, compromise grid stability, and cause issues with unit commitment and scheduling (Weschenfelder et al., 2020). To address these issues, Artificial Intelligence (AI) techniques, particularly Artificial Neural Networks (ANN), are pivotal in enabling faster and more cost-effective predictions across short-term, medium-term, and long-term forecasts.

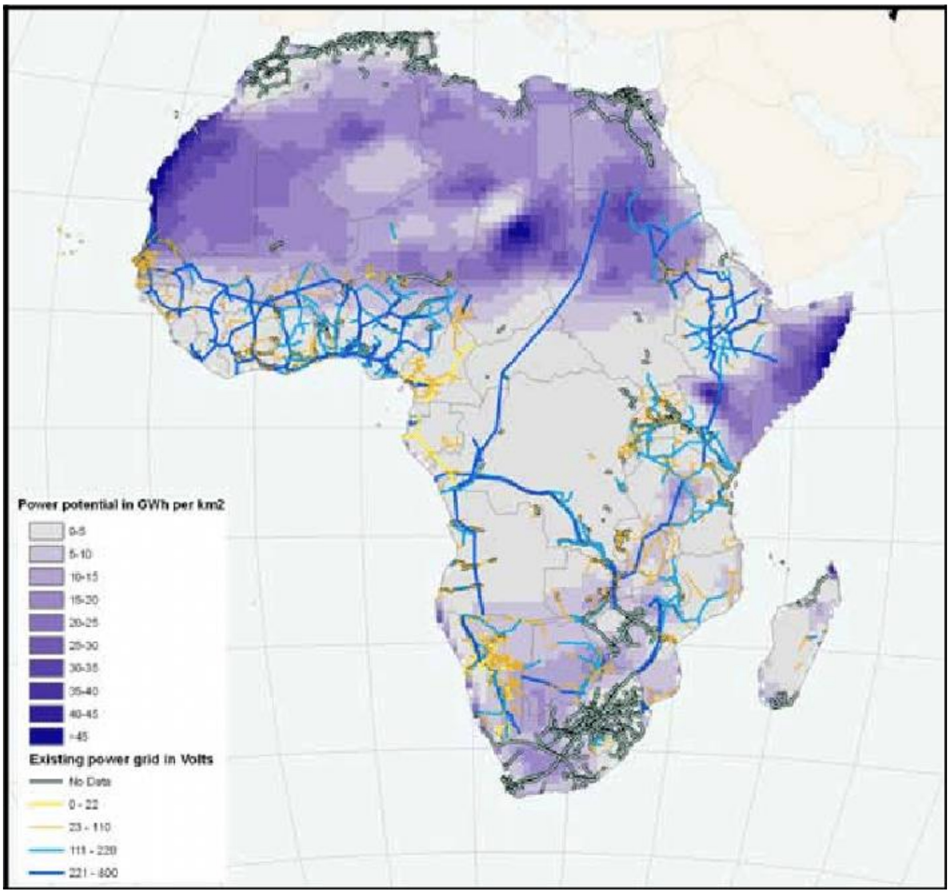


**Figure 2.2 Wind power potential (Belward et al., n.d.)**

Figure 2.2 shows the potential for wind power generation calculated in GWh per km², with regions containing water bodies, forests, cities, and protected areas excluded. This estimate assumes a density of 5 turbines per km². The figure also includes the locations of existing power grid infrastructure, marked with their respective voltage capacities in volts. Wind turbines are used to convert the kinetic energy of wind into usable energy forms, such as electricity. Consequently, the installation of wind turbines has significantly increased due to their negligible carbon emissions (Global Wind Energy Council, 2022; Weschenfelder et al., 2020). However, the number of WTs that can be installed is constrained by concerns related to species protection, as well as geopolitical and supply risks (Global Wind Energy Council, 2022). Additionally, the high production and maintenance costs associated with WTs are significant factors to consider before installation (Njiri & Söffker, 2016). Therefore, given the limitations on increasing the number of WTs, it is crucial to maximize zero-carbon energy generation from wind by further optimizing the energy efficiency of turbines.

The complex interactions between atmospheric flow and wind blades influence the energy efficiency of wind turbines. Atmospheric flow, characterized by turbulent boundary layer flow with moving boundaries and external energy sources, is highly non-linear (Shin et al., 2022). The interaction between this turbulent flow and the wind blades also exhibits non-linearity, depending on factors such as wind direction, angle of attack, and blade geometry. Therefore, designing WTs requires simulations or experiments that capture the full interactions between turbulent atmospheric flow and turbine blades (Jie et al., 2020). Recently, several studies have utilized artificial intelligence to enhance WT energy efficiency (Wang et al., 2021; Lin & Liu, 2020) and to improve WT maintenance (Gustavo et al., 2021; Correa-Jullian et al., 2022). For instance, neural networks (NN), a type of ML model, have shown significant promise in wind energy harvesting due to their advanced capability to learn non-linear patterns, such as the chaotic patterns found in atmospheric flows (Shin et al., 2022).

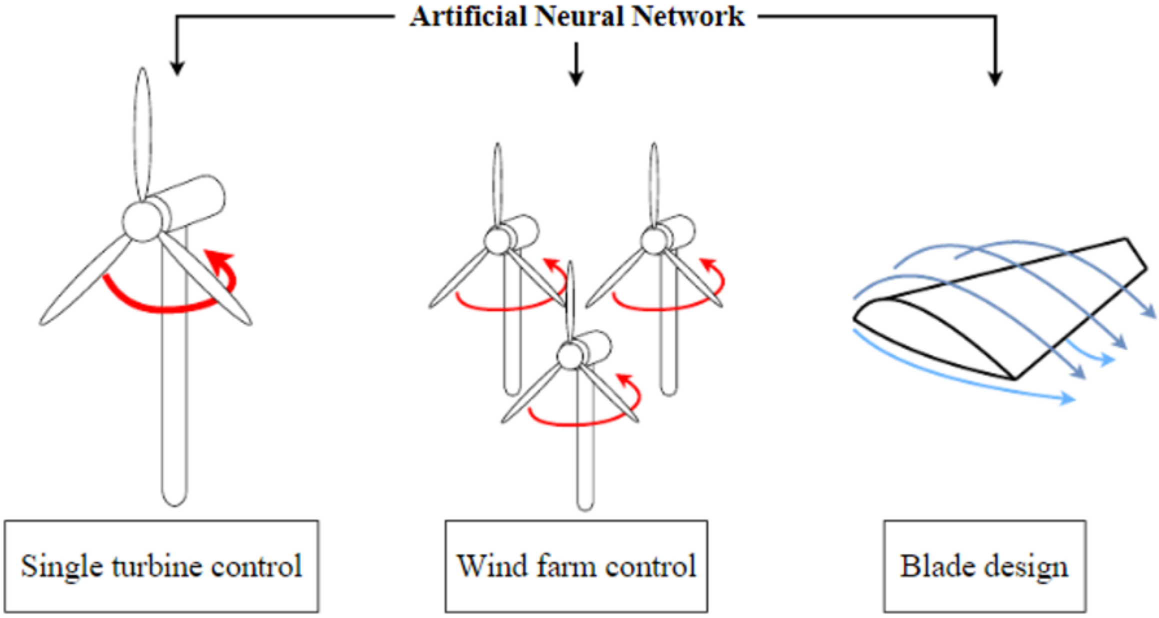


**Figure 2.3 Using AI to improve the energy efficiency of Wind Turbines (Shin et al., 2022)**

### 2.5.2 Simulations and Modelling in the Wind Energy Domain

Odero et al. (2022) conducted a study focused on wind energy resource prediction and optimal storage sizing to ensure dispatchability within the Kenyan power grid. The researchers utilized a combination of wind resource data and storage sizing algorithms to develop a predictive model. The results indicated that integrating optimal storage solutions with wind energy could significantly enhance the reliability of the power supply. Specifically, the study found that the optimal sizing of storage systems could reduce energy wastage by 15% and improve dispatchability by 20%. This approach helps address the infrastructural and financial barriers by ensuring a stable and predictable energy supply from wind resources.

Adedeji et al. (2021) employed a hybrid neuro-fuzzy system to investigate the short-term variability of wind resources in South Africa, aiming to enhance site suitability analysis for wind energy projects. A hybrid neuro-fuzzy system combines neural networks and fuzzy logic to create a model that leverages the learning capabilities of neural networks with the intuitive, human-like reasoning of fuzzy logic. This integration allows the system to handle uncertain and imprecise data effectively, making it highly suitable for predicting environmental variables like wind speed and direction. The researchers developed a model that significantly improved prediction accuracy by 18% over traditional methods, achieving an RMSE of 2.8%. This approach provides a robust tool for site selection, ensuring optimal locations for wind energy projects and thus mitigating financial risks and improving project feasibility.

Fuzzy logic tools were also applied by Placide and Lollchund (2024) to conduct a study on wind farm site selection in Burundi using GIS-based mathematical modeling. The study combined spatial data and fuzzy logic to evaluate the suitability of various sites for wind farm development. The results identified several high-potential sites with optimal wind conditions and minimal environmental impact. The use of GIS-based fuzzy logic modeling enhanced the precision of site selection, leading to more informed decision-making and efficient resource allocation. This method helps overcome infrastructural barriers by ensuring that wind farms are located in the most suitable areas, reducing the risk of underperformance.

On the other hand, Bilal et al. (2022) investigated the application of adaptive neuro-fuzzy inference systems (ANFIS) for identifying wind power conversion system models. The study applied ANFIS to optimize the performance of wind turbines, achieving an accuracy improvement of 20% over conventional methods. The results demonstrated that ANFIS could effectively model the non-linear dynamics of wind power conversion, leading to enhanced system performance and reduced operational costs. This approach helps address financial barriers by improving the efficiency and cost-effectiveness of wind energy projects.

Dotche et al. (2019) explored the use of support vector regression (SVR) for wind speed prediction at the Lome Site. The study developed an SVR model to predict wind speeds based on historical meteorological data. The results demonstrated that the SVR model achieved a prediction accuracy of 92%, with an RMSE of 3.1%. This high level of accuracy in wind speed prediction supports the efficient planning and operation of wind energy projects. The SVR model helps reduce the uncertainty and financial risks associated with wind energy investments by providing reliable wind speed forecasts.

Habtemariam et al. (2023) utilized a Bayesian optimization-based Long Short-Term Memory (LSTM) model for wind power forecasting in the Adama District of Ethiopia. The study aimed to improve the accuracy of wind power predictions by integrating Bayesian optimization with LSTM neural networks. The results showed a significant reduction in forecast errors, with an RMSE of 2.5%. This advanced forecasting model enhances the reliability of wind power predictions, aiding in better grid integration and energy management. By optimizing wind power forecasts, this model addresses both infrastructural and financial challenges in wind energy deployment.

## 3. Data availability

A notable challenge in applying AI-driven simulations and models is the need for comprehensive, high-quality data. Many regions in Sub-Saharan Africa (SSA) need more data, particularly high-resolution meteorological, environmental, and operational datasets necessary for accurate modeling. The success of AI in optimizing renewable energy systems hinges on the availability of robust datasets, as incomplete or low-quality data can significantly undermine the reliability of predictive models (Adedeji et al., 2021; Alzain et al., 2023). For instance, studies like those by Bilal et al. (2022) and Bouabdallaoui et al. (2023) highlight how data limitations can impede the accurate identification of wind power conversion systems and short-horizon wind energy predictions, respectively. Moreover, Adun et al. (2022) emphasize that while AI models can optimize solar thermal applications, their effectiveness is constrained by the quality and granularity of input data. This challenge underscores the need for enhanced data collection infrastructure and integrating existing reanalysis data to bridge gaps, ensuring AI-driven models can perform effectively and reliably in SSA's renewable energy landscape.

Ayik et al. (2021) note that investigating wind and solar resource potential and developing wind energy projects can significantly enhance using existing reanalysis data. The researchers used data ranging from 1981 to 2019 for 33 locations from Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) to develop statistics for each area, considering annual and long-term monthly averages, wind direction, and hub heights between 30m and 50m above ground level. They attributed the data to five different distribution functions to assess wind power density, with results showing wind speeds of 2.36m/s to 5.08m/s and wind power density between 14.39W/m2 and 128.36W/m2, concluding that utility-scale wind power plants are negligible. At the same time, there is great potential for small wind turbines. The potential benefit of utilizing existing data has also been demonstrated by various studies. McKenna et al. (2021) emphasized the need for high-resolution, large-scale assessments to define wind potential accurately, pointing to the critical role of existing datasets, methodologies, and future research in refining these assessments. Ahmad et al. (2022) effectively employed reanalysis data for offshore wind resource assessment, highlighting its utility in capturing wind patterns and informing project development. Similarly, Dabar et al. (2022) conducted a techno-economic analysis in Djibouti, reinforcing the viability of wind energy and green hydrogen production based on pre-existing data. Moreover, Chen and Ji (2024) reviewed solar and wind energy projections, underscoring the importance and potential of models based on existing datasets in forecasting and optimizing renewable energy resources. Petrenko et al. (2023) supported the reanalysis of data for the projection of wind speed and energy calculations, while Souza et al. (2023) highlighted its application in the Northern Amazon for both wind and solar energy generation. Collectively, these studies affirm the conclusion by Ayik et al. (2021) on the potential of leveraging existing data for investigating and developing solar and wind energy projects, demonstrating the breadth and depth of research supporting this approach.

## 4. Conclusion

Renewable energy initiatives in Sub-Saharan Africa (SSA) confront numerous barriers, including inadequate grid infrastructure, financial constraints, limited technical expertise, regulatory challenges, and the scarcity of quality data, which collectively hinder the integration and efficiency of renewable sources such as wind and solar energy (IEA, 2022; Adun et al., 2022; IRENA, 2021; Odero et al., 2022). These systemic and operational challenges necessitate strategic interventions to improve infrastructure, secure investments, enhance expertise, and refine regulatory frameworks. The integration of AI can significantly mitigate these challenges by enhancing forecast accuracy, optimizing operational efficiency, and improving management practices in renewable energy systems. AI applications, including machine learning algorithms, have successfully predicted solar irradiance and wind patterns, facilitating better project planning and operational efficiency (Mfetoum et al., 2024). Notable projects like the Garissa Solar Power Plant in Kenya and blockchain-based mini-grids have demonstrated the benefits of AI in enhancing reliability and efficiency in renewable energy systems (Chirchir et al., 2023; Finke et al., 2022). Moreover, AI-driven simulations help in optimizing resource allocation, reducing operational costs, and increasing economic viability through predictive maintenance and accurate energy yield predictions, thereby enhancing investment appeal and project sustainability (van Vuuren et al., 2019, 2021; Ebhota & Tabakov, 2023; Gerbo et al., 2020; Placide & Lollchund, 2024).

In conclusion, AI-driven simulations can be critical in overcoming the infrastructural and financial barriers that impede renewable energy adoption in Sub-Saharan Africa (SSA). These simulations enhance solar and wind energy project planning, deployment, and operational efficiency through advanced predictive analytics and optimization algorithms. By accurately simulating weather patterns, energy production, and consumption demands, AI enables investors and developers to identify the most advantageous sites for renewable energy projects and predict their future outputs with high precision. This level of predictability and precision in planning significantly reduces the financial risks typically associated with the high initial capital costs of establishing renewable energy systems. Furthermore, developers can use AI-driven simulations to streamline and optimize the construction and maintenance processes. AI can predict potential system failures or maintenance needs before they become critical, thus extending the lifespan of the infrastructure and reducing unexpected downtime. This predictive maintenance capability minimizes operational costs while maximizing system uptime and reliability.

Despite the potential of AI-driven simulations to optimize renewable energy projects, application in SSA is hindered by technological, infrastructural, financial, socio-political, and environmental aspects. The lack of computational resources and specialized technical expertise limits the development and maintenance of these advanced systems (Behzadi & Sadrizadeh, 2023; Nyarko et al., 2023). Infrastructural issues are significant, with outdated grid infrastructure unable to support the variability of renewable energy sources (International Energy Agency, 2020), and poor connectivity in remote areas hampering real-time monitoring and optimization (Wang et al., 2020). Furthermore, high initial costs and ongoing maintenance expenses can be prohibitive in resource-constrained environments, making it difficult to secure necessary investments (Adedeji et al., 2021; Adun et al., 2022). Socio-political barriers, such as inconsistent regulatory environments and resistance to adopting new technologies, further impede progress. Regulatory uncertainty can deter investment, while the resistance from stakeholders often stems from a lack of understanding and trust in AI-driven solutions (Fumtchum et al., 2024; Bilal et al., 2022). Additionally, environmental and geographical limitations include the need for region-specific models due to diverse climate conditions and the environmental impact of deploying large-scale AI-driven renewable energy systems (Gerbo et al., 2020; Said et al., 2022). These multifaceted challenges necessitate a holistic approach and will to overcome the barriers to implementing AI technologies in Africa's renewable energy sector.

For all stakeholders, integrating AI into renewable energy systems represents a move towards more sustainable, reliable, and financially viable energy solutions. The technology enables a shift from traditional speculative planning to a data-driven approach that offers enhanced accuracy, efficiency, and profitability. Adopting AI-driven simulations in renewable energy projects in Africa could serve as a model for SSA regions facing similar infrastructural and economic challenges, paving the way for the continent's transition to more sustainable energy solutions. Therefore, private investors, government investors, policymakers, and developers must consider leveraging AI-driven simulations when planning and implementing wind and solar energy systems to ensure Africa has a chance at energy security.

## Annexes

Annex1: The table below provides a summary of the reviewed articles, highlighting their respective outcomes, AI techniques, and the types of data used, as it pertains to AI-driven Simulation and Modelling in Solar Energy Domain in Africa

| Reference/year | AI technique/tool | Data Type | Output/results | Conclusion |
|---|---|---|---|---|
| Daghsen et al. (2023) | Universal Exergy Model | Meteorological data (solar radiation, ambient temperature, relative humidity) | Achieved an average exergy efficiency of 35% with a peak of 45%, MAPE < 5% | Accurate exergy accounting optimizes solar energy utilization, guiding efficient system design and operation |
| van Vuuren et al. (2019) | PVSyst | Architectural and environmental data | Potential energy yield of 1,200 MWh/year, ROI | Preconstruction simulations reduce financial risks and |

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|---|---|---|---|---|
| | | | period of 7 years, MBE of 4% | optimize project feasibility |
| Ebhota and Tabakov (2023) | Homer, Solargis Prospect, planner, PVsyst, and PV*SOL | GIS data, meteorological data | Annual solar irradiance averages 5.5 kWh/m²/day, LCOE of $0.04 to $0.06 per kWh | GIS-based assessments identify optimal sites, guiding strategic planning and investment |
| van Vuuren et al. (2021) | PVSyst | Performance data from existing installations | Energy yield prediction accuracy with RMSE of 5%, ROI of 6 years | Validated pre-assessment models reduce financial risks and support project implementation |
| Dobreva et al. (2015) | Energy Yield Model | Local climatic data, empirical data | Annual energy yield of 1,800 kWh/kWp, model accuracy of 95%, LCOE of $0.05 per kWh | Accurate yield modeling optimizes PV system design and operation, ensuring economic viability |
| Seane et al. (2024) | Hybrid Model with Optimization Algorithms | Real-time residential data | Efficiency improvement of 20%, cost reduction of 15% | Optimized energy management enhances microgrid reliability and financial viability |
| Fumtchum et al. (2024) | Generation Trend Curves Model | Actual generation data | Efficiency prediction RMSE of 4.2%, energy cost reduction by 12% | Precise efficiency predictions optimize energy injection, improving grid reliability and reducing costs |
| Gerbo et al. (2020) | Multi-criteria decision-making, GIS tool | GIS data, meteorological data | Identification of high-potential solar sites with an average solar irradiance of 6 kWh/m²/day | The GIS-based approach effectively identifies optimal grid-connected solar power sites, aiding in strategic planning and infrastructure development |

Annex2: The table below provides a summary of the reviewed articles, highlighting their respective outcomes, AI techniques, and the types of data used, as it pertains to AI-driven Simulations and Modelling in Wind Energy Domain in Africa

| Reference | Purpose | AI Technique/Tool Used | Type of Data | Results/Outcomes |
|---|---|---|---|---|
| Odero et al., (2022) | Wind energy resource prediction and optimal storage sizing to ensure dispatchability in the Kenyan power grid | Storage sizing algorithms | Wind resource data, storage system data | Optimal storage sizing reduced energy wastage by 15% and improved dispatch ability by 20% |
| Adedeji et al., (2021) | Investigating short-term variability of wind resources for site suitability analysis in South Africa | Hybrid neuro-fuzzy system | Wind resource data | Improved prediction accuracy by 18%, RMSE of 2.8% |
| Placide et al., (2024) | Wind farm site selection in Burundi | GIS-based mathematical modeling and fuzzy logic tools | Spatial data, wind resource data | Identified high-potential sites with optimal wind conditions, aiding in strategic planning |
| Dotche et al., (2019) | Wind speed prediction in Lome-Site | Support Vector Regression (SVR) | Historical meteorological data | Achieved 92% prediction accuracy, RMSE of 3.1% |
| Habtemariam et al., (2023) | Wind power forecasting in the Adama District, Ethiopia | Bayesian optimization-based Long Short-Term Memory (LSTM) model | Wind power data | Reduced forecast errors, RMSE of 2.5% |
| Bilal et al., (2022) | Identifying wind power conversion system models | Adaptive neuro-fuzzy inference systems (ANFIS) | Wind power conversion data | Improved model accuracy by 20%, enhanced system performance, and reduced operational costs |

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