World Journal of Advanced Research and Reviews
eISSN: 2581-9615 CODEN (USA): WJARAI
Cross Ref DOI: 10.30574/wjarr
Journal homepage: https://wjarr.com/

(REVIEW ARTICLE)

Check for updates

Applications of machine learning on machinery efficiency and reliability in clean energy projects

Bennett Ikechukwu Eziefula [1, 2], Darlington Eze Ekechukwu [3, 4, *] and Kenneth Ifeanyi Ibekwe [5, 6]

[1] *Oil & Gas with Energy Management Department, University of East London, United Kingdom.*
[2] *Chevron Nigeria LTD, Nigeria.*
[3] *Project and Maintenance Engineer MVV Energy, United Kingdom.*
[4] *Carbon Capture and Clean Hydrocarbon Energy Systems, African Centre of Excellence, Future Energies and Electrochemical Systems, Federal University of Technology, Owerri, Imo state, Nigeria.*
[5] *Electrical and Project Manager, Golden York Limited, United Kingdom.*
[6] *Solar Energy Systems, African Centre of Excellence, Future Energies and Electrochemical Systems, Federal University of Technology, Owerri, Imo state, Nigeria.*

World Journal of Advanced Research and Reviews, 2025, 25(03), 1226-1241

Publication history: Received on 08 February 2025; revised on 16 March 2025; accepted on 19 March 2025

Article DOI: https://doi.org/10.30574/wjarr.2025.25.3.0861

Abstract

Clean energy resources have been considered globally as the energy of the future due to its low or no carbon footprint. Clean energy is the energy that replenished itself after use. To get most of these energy resources, constant improvement in manufacturing and process is highly needed. One of the key technologies revolutionizing the clean energy power generation is machine learning. Machine learning is an algorithm that examine enormous volumes of data in order to spot trends, generate predictions, and improve decision-making. This article therefore, using descriptive approach explored the application of machine learning in clean energy machinery efficiency and reliability as well as clean energy projects. The energy systems and projects considered in the article include, solar, wind, tidal, geothermal, biomass and hydroelectric energy sources. Based on this article findings, machine learning algorithm can be utilized to initiate predictive maintenance, provide real-time data for decision-making, and optimize process and overall improve the efficiency and reliability of these energy machines. In terms of clean energy project delivery, machine learning can be utilized in project planning, site selection and resources allocation. Although, machine learning has quite a number of benefits, no doubt it has its own drawbacks. These drawbacks include the quality and availability of data, which might be irregular or scarce in some clean energy resource which will determine how accurate machine learning models can be developed. Widespread adoption may be hampered by computational complexity and the requirement for a strong hardware foundation.

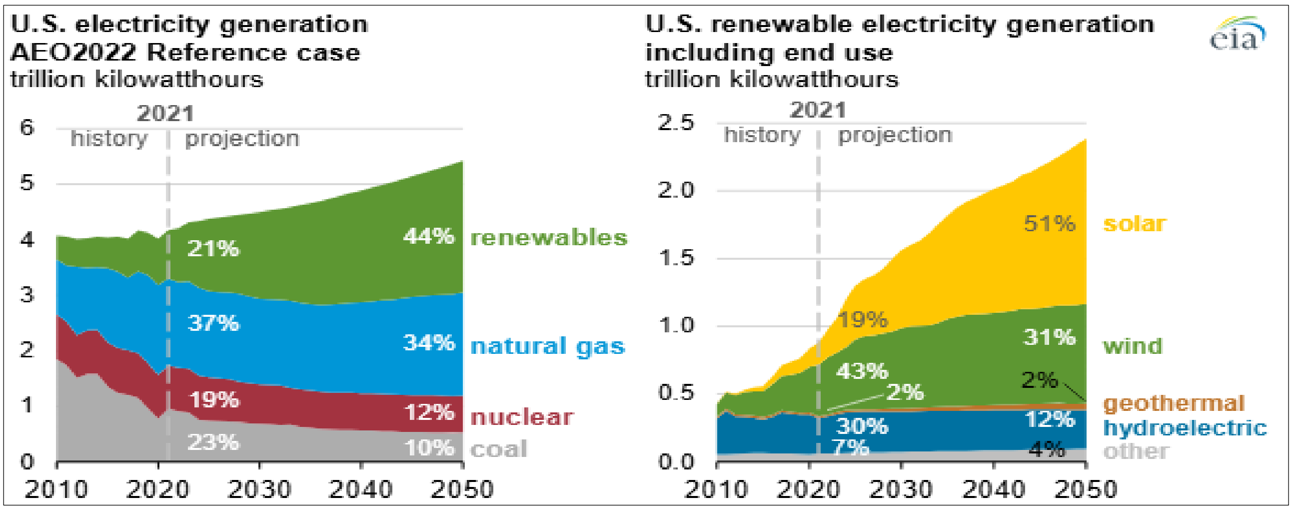
Keywords: Machine learning; Clean energy; Reliability; Efficiency; Solar; Wind; Tidal; Geothermal; Biomass; Hydroelectric

1. Introduction

The clean energy sector is quickly evolving, propelled by technological developments with an increasing demand for sustainable energy solutions to mitigate the changing climate [38]. In the UK for instance, the government's current plans call for at least 95% of electricity being generated from low-carbon sources by 2030, effectively aiming for clean power to meet 100% of its electricity demand by that time, with the majority of this coming from renewable sources like solar, offshore wind, and biomass etc. [55]. The UK is also committed to achieving net zero emissions by 2050, which would necessitate an even higher share of renewable energy [52]. Similarly, UK also plans to achieve 68% emissions cut

* Corresponding author: Darlington Eze Ekechukwu

by 2030, and achieve net zero by 2050 [36]. Additionally, United state projected to have 44% of its electricity from renewable energy such as solar, wind, geothermal, hydroelectric and other clean sources, while its clean energy source amount to only 3% of its total generation provided in the energy projection outlook from the year 2022 reference case as illustrated in Figure 1.



Source: [109].

Figure 1 Renewable energy projective target

United states also pledges to boost energy storage systems, like the battery energy storage system, solar hybrid systems, natural gas fired generators to provide energy when non-dispatchable energy source such as the solar, wind is unavailable [109].

Moreover, Germany is another country that pledges 100% of its electricity supply from clean energy by 2050. According to its updated Climate Change Act, Germany wants to reach net-zero emissions by 2045 and negative emissions after 2050, with intermediate goals of about 65% decrease from 1990 levels by 2030 and 88% reduction by 2040 [44]. In its overarching objective is to reach net-zero emissions by 2045, Germany's energy transition strategy calls for 80% of its electricity to come from renewable sources by 2030 and 100% by 2035 [43].

From the above, it can be concluded that these targets directly or indirectly translate into a number of innovations, developments in the adoption of clean energy systems and clean projects delivery. Therefore, in order to achieve these targets, and successfully deliver this renewable energy projects, crucial data such as weather data (wind speed, solar radiation), geographic data (terrain, land use), grid connection details, load profiles, environmental impact data, resource potential assessments, economic factors; installation, maintenance, incentives [32]. Others include regulatory frameworks unique to the project location and selected renewable energy source (solar, wind, hydro, geothermal) are all essential for developing a renewable energy project [42]. However, to guarantee optimal energy production and financial viability, the efficiency and reliability of the machinery utilized in clean energy projects continue to be a significant obstacle that need to be overcome [93]. Thus, by enhancing the functionality, upkeep, and durability of renewable energy infrastructure, machine learning (ML), a branch of artificial intelligence (AI), is significantly contributing to the resolution of these issues [4]. Creating algorithms that examine enormous volumes of data in order to spot trends, generate predictions, and improve decision-making is known as machine learning [14]. By incorporating machine learning into renewable energy machinery, operators may exploit real-time data analytics, automate procedures, and increase overall system efficiency. In order to decrease downtime and improve the dependability of clean energy generation systems, energy suppliers can shift from reactive to predictive maintenance with the use of machine learning-driven solutions [49]. Therefore, for the purpose of this article, applications of machine learning in clean energy machines/systems and clean energy projects delivery will be considered.

1.1. Overview of Clean energy and their sources

The term clean energy describes energy that comes from renewable sources, such as solar, wind, hydropower, geothermal, and biomass, which emit few or no greenhouse gases [108]. As the name implies, clean energy is a form of energy that does not in any way contribute to air pollution. Because it originates from continuously replenishing sources, it is also known as renewable energy [8]. This basically means that, in comparison to fossil fuels like coal and fossils fuel, they have a smaller environmental impact. It also frequently includes energy that is saved through energy efficiency measures [39]. As illustrated in Fig. 2, there are various forms of clean energy based on their sources. Harvested from the sun is solar energy, which is the result of light and heat being transformed into energy [86]. Several technologies are used in this conversion. For various reasons, including low maintenance costs and cost-effective technologies, it is the most affordable energy source when compared to other sources [24]. According to [51], China is the world's top producer of solar energy, followed by the US, Germany, and Japan. The largest drawback of solar energy however, is that it depends on weather and takes a lot of area to erect solar panels [103].

Source: [86].

Figure 2 Forms of clean energy

1.1.1. Solar energy

One of the most widely utilized energies in the world is solar energy (SE), it is the radiant ionization energy that the Sun emits [5]. Solar energy uses photovoltaic (PV) energy one of the most popular and well-known solar energy technologies for a potential future energy source, currently PV energy accounts for about 2% of the world's electricity demand [23].

1.1.2. Wind energy

Another type of clean energy is wind energy, which uses wind to create electricity. The turbines transform the wind's kinetic energy into mechanical energy, which a generator subsequently transforms it into electrical energy [120]. India ranks fourth in terms of wind energy production, behind China, Germany, and the United States. Wind energy's primary drawback is its high land capacity requirements. They are frequently placed in isolated areas that are distant from the energy consumers; as a result, transportation expenses rise [56].

1.1.3. Hydro energy

According to [19], utilizing the force of flowing water to generate electricity is known as hydro energy. [98], noted that in this type of energy, the water's potential energy is transformed into kinetic energy, that powers the turbine and the generator, which generates electricity. The biggest drawback of hydro electricity generation is that, it needs a lot of area to store water, and building a dam facility costs a lot of money up front when compared to other kinds [13].

1.1.4. Tidal energy

Tidal energy generates electricity by harnessing the kinetic energy of tides and the rise and fall of seawater [64]. According to [29], although tidal turbines are constructed underwater, this is similar to wind energy in turbines. A major factor in the production of tides is gravity [96]. Since tides are more predictable than the sun and wind, this is more dependable. However, there is still much study and development to be done on this technology [65].

1.1.5. Geothermal energy

According to [71], the heat from the earth is used in boilers to create steam, which powers turbines, the form of energy generated via this process is known as geothermal energy. [95] reported that, for many years, this energy has been utilized for purposes other than electricity. The primary concerns with this form of energy are that in order to extract the heat, they must be constructed at precise locations, like tectonic plate borders [67].

1.1.6. Biomass energy

The only organic energy source is biomass energy, it is a form of energy that is extracted from either living or non-living things [107]. Microorganisms, plants, animals, etc. are all present in the source [16]. In this clean energy form, biomass feedstocks are utilized and transformed into power and various other uses, primarily biofuels [71].

From the foregoing, it can be observed that while none of the aforementioned energy sources are environmentally hazardous, each type has its own disadvantages. In place of non-renewable resources like petrol and diesel, biomass energy is currently being considered by numerous researchers and governments for the manufacture of different fuels like bioethanol, biodiesel, bio-butanol, etc. The application of machine learning on machinery efficiency and reliability in clean energy project delivery will also be considered in the subsequent section.

2. Clean energy projects delivery

The process of planning, creating, building, and running a project that uses renewable energy sources, such as solar, wind, hydro, geothermal, or biomass, to produce heat or electricity with emphasis on sustainability and minimizing environmental impact over the course of the project is known as clean energy project delivery [60]. Clean energy sources like wind and solar are inherently intermittent and far from consumer's demand. Supply chain techniques could be very beneficial in addressing these temporal and spatial disconnects [71]. Battery storage, for example, would provide as an inventory buffer for the grid when combining wind and solar power, which are less predictable [102]. Clean energy sources will not be financially viable without a strong supply network. The Clean Energy Delivery (CED) project works with important organizations in the renewable energy industry (such as generators, technology providers, and electric grid operators) to develop new supply chain methods for cost-effective clean energy delivery to end users [62]. The project's researchers hope to create insights and tools for problems ranging from daily operations management to strategic planning for the gradual implementation of clean energy generation and transmission [59]. Furthermore, the clean energy delivery project can assist businesses beyond the energy industry in aligning their environmental initiatives, such as carbon footprints, with commercial prospects from renewable energy procurement and, in some circumstances, generation [34].

2.1. Clean energy projects machineries

Basically, any technology that uses clean energy sources like sunlight, wind, water, geothermal heat, and organic matter to produce electricity or heat with little impact on the environment is used in clean energy projects [22]. Examples of such machines include solar panels, wind turbines, hydroelectric generators, geothermal heat pumps, biomass boilers, tidal turbines, and wave energy converters [73].

2.1.1. Solar photovoltaic panels

According to [84], to effectively turn sunlight into energy, solar power generation uses photovoltaic (PV) panels and other equipment. A solar power system's main component is its solar panels. Their components are photovoltaic cells, which use semiconductors, typically silicon to transform sunlight into direct current (DC) power. There are two primary varieties of solar panels, they are monocrystalline and polycrystalline [33]. Other machinery components include; solar panel, DC electricity is converted into alternating current (AC) for grid use via inverters. Common types include; power optimizers, microinverters, and string inverters [87]. Mounting structures which may be tracking or fixed systems that position panels to receive the most sunlight possible [47]. Charge controllers; control the flow of power in battery storage systems to avoid overcharging and the batteries systems store extra energy for use when there is little or no sunlight, lead-acid and lithium-ion batteries are frequently utilized [54]. Finally, grid-connected systems, transformers increase voltage for distribution and transmission. Figure 3 illustrate solar power plants showing the PV panels and their mounting structures inset for solar power generations.

Source: [99].

Figure 3 Solar power plant project

2.1.2. Wind energy generation machines

Wind energy is generated via wind turbines, that transforms the wind's kinetic energy into electrical power [37]. Onshore (land-based) and offshore (placed in oceans for stronger, more dependable wind resources) constitute the two main categories of wind turbines [21]. With continuous advancements, enhancing efficiency and grid integration, wind energy is a vital clean energy resource that provides a low-carbon, sustainable substitute for fossils fuel. The turbines are made up of various essential components including the Rotor Blades; that usually equipped with three aerodynamic blades for maximum efficiency, these blades capture wind energy and revolve [1]. Other parts including the generator, gearbox, and control systems are housed in the nacelle. The Gearbox boosts rotational speed to maximize the production of electricity. The generator transforms the revolving blades' mechanical energy into electrical energy [27]. The Tower raises the turbine to harness more powerful and steady winds while Yaw and Pitch Systems are used for optimal efficiency, modify the turbine's direction and blade angles [58]. Figure 4 exemplify one of the biggest global wind farms for power generation projects in Japan.

Source: [20].

Figure 4 Wind power projects

2.1.3. Hydro energy generation machines

The kinetic energy of falling or flowing water is transformed into electrical power via hydroelectric energy machines [98]. The hydroelectric turbine, that is powered by water flow, is the main part. Generators that transform mechanical energy into electrical energy are attached to these turbines [11]. Hydroelectric plants employ a variety of turbine types.

Reaction turbines, like Francis and Kaplan turbines, are appropriate for lower-head, high-flow situations, whereas impulse turbines, like Pelton wheels, are utilized for high-head, low-flow water sources [12]. The water pressure and flow rate at the location determine the choice of the turbine to be use. There are three types of hydroelectric plants; pumped-storage, run-of-river, and dam-based [80]. When energy is needed, dam-based facilities discharge the water that has been stored in reservoirs. With little storage, run-of-river plants use the natural flow of rivers to produce power [120]. As energy storage devices, pumped-storage facilities release water through turbines during periods of high electricity demand and pump it to an upper reservoir during periods of low demand. Hydroelectric power plants generate electricity in an efficient, low-carbon, and renewable manner [83]. Nevertheless, they can affect regional ecosystems and necessitate substantial infrastructure. Innovations in small-scale hydro systems and fish-friendly turbines are enhancing sustainability while preserving energy efficiency [88].

2.1.4. Tidal energy generation machines

Tidal energy can be generated by transforming the kinetic energy of the tidal stream into electrical energy [83]. Different heads between two bodies of water can theoretically provide tidal energy [116]. Like other clean energy resources like wind and solar, tidal currents and tides waves are predictable, although they are sporadic, resulting from semi-diurnal and spring-neap variability [111]. Tidal energy was commonly used as tidal mills centuries ago in Europe and around the Atlantic coast of North America [53]. The hydrokinetic system and oscillating water column are the two Tidal energy technologies that are currently in use. By 2020, tidal power is anticipated to improved and more economical with increased technology [10]. Figure 5 shows a tidal or subsea power generation system.

Source: [61].

Figure 5 Tidal or subsea power generation system

2.1.5. Geothermal energy generation machines

Geothermal energy producing devices generate power by using heat from the Earth's core. These systems draw steam or hot water from subterranean reservoirs using geothermal wells. Turbines attached to electric generators are then used to transform the thermal energy into mechanical power [85]. Geothermal power plants come in three primary varieties; binary cycle, flash steam, and dry steam. Turbines in dry steam plants are directly powered by subterranean steam. High-pressure hot water is extracted in flash steam facilities, where it quickly transforms into steam to power turbines [70]. Binary cycle plants transfer heat without directly producing steam by using a secondary working fluid that has a lower boiling point than water. For geothermal sources with moderate temperatures, this technique works well. [72] noted that continuous operation of geothermal energy devices produces dependable, renewable, and low-emission electricity. To maximize performance, they need specialized equipment such as cooling systems, heat exchangers, and steam separators [13]. By intentionally fracturing rock to boost heat extraction, enhanced geothermal systems (EGS) are being created to increase the availability of resources [63]. Geothermal machines provide long-term, sustainable energy solutions, despite their high initial price and geographic restrictions. Geothermal power is becoming more widely available and effective for meeting the world's energy needs [28].

2.1.6. Biomass energy generation machines

Biomass energy generation machine produces heat or power from organic resources like wood, agricultural waste, and biodegradable trash [94]. To break down biomass and release energy, these systems use pyrolysis, gasification, anaerobic digestion, or combustion. [15], reported that burning biomass creates steam in direct combustion systems, which powers a steam turbine that is coupled to an energy generator [71]. Biomass is transformed by gasification into syngas, or synthetic gas, which fuels gas turbines and internal combustion engines. By using bacteria to break down organic waste, anaerobic digestion produces biogas, primarily methane, which powers petrol engines and microturbines [87]. Biomass is thermally broken down by pyrolysis to produce syngas, charcoal, and bio-oil, which can then be converted into fuels [105]. Large industrial facilities and small-scale home digesters are examples of biomass power plants. Boilers, turbines, digesters, gasifiers, and emission control systems are essential parts that maximize efficiency and minimize pollution [81]. Improved feedstock processing, carbon capture, and high-efficiency boilers are the main topics of recent developments [90]. By using waste materials, biomass energy machines provide renewable, carbon-neutral energy; but, in order to avoid emissions and deforestation, they need sustainable source [76]. Despite advancements in waste-to-energy and sophisticated biofuels, biomass continues to play a significant role in the world's renewable energy mix [77].

3. Efficiency and reliability in clean energy generating machines

The transition to a sustainable energy future depends on the efficiency and reliability of renewable energy generating equipment or machine [50]. Clean energy technologies, such as geothermal systems, hydroelectric generators, wind turbines, and solar panels, are made to transform renewable resources into usable power with as little negative influence on the environment as possible [75]. The ability of a system to efficiently transform available energy into electrical power is referred to as efficiency in clean energy generation [30]. For example, depending on the technology employed, solar panels' efficiency ratings usually range from 15% to 22% [110]. This efficiency is being increased by developments in photovoltaic materials, such as perovskite cells. With advancements in aerodynamics and blade design, wind turbines may increase their output while operating at 35% to 50% efficiency [28]. Because hydroelectric and geothermal power plants can capture continuous natural energy flows, their efficiency frequently surpasses 80% [97].

Consistent energy generation over time is guaranteed by reliability, clean energy sources can produce intermittently, in contrast to fossil fuel facilities that produce continuously [2]. Because solar and wind power are weather-dependent, energy storage devices like batteries are crucial for reliability. However, more reliable generation is provided by geothermal and hydroelectric electricity [74]. Grid integration, maintenance requirements, and machine durability all have an impact on reliability. Therefore, to increase longevity and performance, contemporary wind turbines and solar farms should include predictive maintenance technology and intelligent monitoring systems [112]. Efficiency and reliability are continuously improved by technological developments in materials, energy storage, and system integration [15]. AI-driven energy management, smart grids, and advancements in battery storage all contribute to the optimization of renewable energy consumption, lowering downtime and enhancing efficiency [48]. Clean energy technologies are essential to a sustainable energy future because they are becoming increasingly competitive with conventional fossil fuels [77]. In the subsequent section, the application of machine learning on the efficiency and reliability of clean energy machines will be the main focus of the article.

3.1. Machine learning and efficiency and reliability of clean energy machineries

According to [100], the optimization of clean energy machines' efficiency and reliability has emerged as a critical concern as the world moves towards sustainable energy solutions. A subset of artificial intelligence (AI), machine learning (ML) is crucial for improving the efficiency of several renewable energy machines components, such as hydroelectric power generation systems, geothermal, biomass, wind, solar, and tidal power [16]. Machine learning algorithms examine enormous volumes of data, spot trends, and make forecasted choices that enhance resource usage, maintenance planning, and energy production [50]. The function of machine learning (ML) in improving clean energy machine reliability and efficiency is covered in this study.

3.1.1. Machine learning in solar energy

Photovoltaic (PV) panels and concentrated solar power (CSP) plants are two examples of solar energy systems that greatly benefit from machine learning (ML) applications [112]. Machine learning models can be utilized to improve the efficiency and reliability by forecast solar irradiance based on temperature fluctuations, cloud cover, and weather patterns, thereby maximizing energy output [25]. By means of predicting changes in energy production and energy demands, forecasting algorithms like deep learning models and artificial neural networks (ANNs) facilitate improved grid integration [45]. Additionally, by identifying issues with solar panels like shadowing, dust buildup, or cell deterioration, ML-driven predictive maintenance lowers downtime and boosts overall efficiency and reliability of the entire solar clean energy system [68].

3.1.2. Machine learning in wind energy

Due to their reliance on fluctuating wind conditions, wind turbine efficiency optimization is a difficult task [101]. Dynamic blade angle adjustments and power production maximization are made possible by machine learning algorithms that use historical and meteorological data to anticipate wind direction and speed [35]. Turbine control systems are improved using reinforcement learning (RL) algorithms, which discover the best operational practices to lower mechanical stress and increase lifespan at the same improving the efficiency and reliability of the system [7]. Furthermore, predictive maintenance and fault detection systems based on machine learning (ML) find early indications of wear and tear in turbine parts, lowering the chance of unplanned breakdowns and maintenance expenses [35]. Additionally, machine learning algorithm for instance, regression, (Supervisory Control and Data Acquisition) SCADA and simulated data can be utilized to monitor wind blades faults and temperature in the generator components of the wind energy system [101]. Several kinds of datasets may be used by a wind farm condition monitoring system. SCADA and other operational and event datasets serve as the foundation for the majority of condition monitoring models that have been described in [104]. By delivering time-series signals at regular intervals, SCADA systems have been integrated into turbines to regulate the production of electricity [117]. Sensors mounted on important wind turbine components, such as bearing vibration, temperature, phase currents, wind speed, etc. are used in this kind of system to gather basic data for use in condition monitoring in order to increase system efficiency and reliability [119].

3.1.3. Machine learning in tidal energy

Ocean currents and tidal movements, which are impacted by weather patterns, sea level fluctuations, and lunar cycles, are used to generate energy in tidal power plants [56]. In order to maximize turbine positioning and energy extraction efficiency and reliability, machine learning algorithms examine hydrodynamic patterns for example, the feed-forward neural networks (FFNN), recurrent neural networks (RNN), back-propagation neural networks (BPNN), and cascade-correlation neural networks (CCNN) demonstrated good results in predicting the wave height [113, 6]. Forecasting variations in tidal currents, predictive analytics enhance turbine scheduling and guarantee steady energy production which subsequently improves efficiency and reliability [46]. Also, through identifying anomalies like biofouling or structural deterioration in submerged turbines, machine learning (ML) also improves real-time monitoring systems, increasing operating longevity and dependability [80].

3.1.4. Machine learning in geothermal energy

According to [115], in order to produce energy, geothermal power plants use heat from the Earth's interior. Real-time performance monitoring, drilling optimization, and reservoir characterization are some of the geothermal energy uses of machine learning [85]. Machine learning models find the best drilling locations by evaluating seismic and geological data, which lowers exploration expenses and increases extraction effectiveness [40]. Furthermore, well integrity is monitored by ML-powered predictive maintenance systems, which identify early indicators of scaling, corrosion, or equipment failure to guarantee uninterrupted power generation [113]. Artificial neural network (ANN) and Levenberg–Marguardt algorithm are important ML algorithm utilized in operation optimization and bottom-hole-temperature prediction for geothermal power stations [78]. Additionally, Shallow machine learning (ML) models, like the XGBoost model based on the decision tree, random forest model, and support vector machine (SVM), frequently outperformed the ANN in predicting influencing parameters, like the reservoir temperature and drill speed [115]. More notably, deep learning (DL) models performed better than shallow ML models like ANN and SVM in reservoir temperature prediction, productivity prediction, and geological logging [106].

3.1.5. Machine learning in biomass energy

Biomass power plants use anaerobic digestion, gasification, or combustion to turn organic resources into energy [77]. According to [114], maximizing process efficiency, feedstock selection, and combustion conditions, machine learning improves the generation of biomass energy. In order to identify the optimal fuel mix, which maximizes energy output while minimizing emissions, advanced machine learning algorithms examine the attributes of the feedstock [122]. Additionally, identifying abnormalities in biomass boilers, turbines, and gasifiers, ML-driven predictive maintenance systems lower operating expenses and downtime [79]. Biomass plants can achieve real-time monitoring and adaptive control for enhanced performance and sustainability by combining machine learning (ML) with Internet of Things (IoT) sensors [91].

3.1.6. Machine learning in hydroelectric power

In order to generate electricity, hydroelectric power plants depend on reservoir levels and water flow [31]. [18] reported that forecasting inflow rates, reservoir levels, and seasonal fluctuations, machine learning models improve the management of water resources. Machine learning assists hydropower operators in modifying turbine operations to ensure maximum efficiency, reliability and avoid water waste by evaluating meteorological data [9]. In order to identify early indications of wear or possible breakdowns, predictive maintenance systems employ machine learning algorithms to monitor turbines, generators, and dam structures [92]. This proactive strategy prolongs the life of hydroelectric infrastructure, improves efficiency, reliability, and lowers maintenance costs [41].

3.2. Machine learning in clean energy project delivery

The implementation of sustainable energy projects is being revolutionized by machine learning (ML), which maximizes efficiency, lowers costs, and increases dependability [48]. Machine learning improves decision-making, automation, and predictive analytics in a variety of renewable energy industries, such as solar, wind, tidal, geothermal, hydropower, and biomass energy using huge datasets [68]. Clean energy solutions become more economical and sustainable as a result of this technology's ability to manage resource distribution, expedite project development, and enhance overall system performance [8]. In sites selection for sustainable energy projects for instance, machine learning algorithms examine enormous datasets that include environmental, meteorological, and topographical data. ML assesses the impacts of terrain, shade, and sunshine exposure on solar energy [3]. It evaluates turbulence, land elevation, and wind patterns in wind energy. ML is used to assess water flow rates, depth, and ecosystem impact in tidal and hydroelectric projects. ML's capacity to analyze geological data and identify regions with high subsurface heat potential is advantageous for geothermal energy. Biomass site selection uses ML to optimize proximity to organic waste sources and minimize transportation costs [82].

[118] state that machine learning improves feasibility studies through modelling energy output, environmental impact, and economic viability. [72] also state that simulating possible hazards like equipment deterioration or resource fluctuations, it guarantees well-informed decision-making. In hydroelectric and tidal projects, ML predicts seasonal water level variations to determine long-term viability [59]. ML forecasts project timeframes by examining past project data, which aids stakeholders in anticipating delays. Construction phases for wind turbine installations, biomass plants, and solar farms are optimized by ML-driven scheduling, which reduces interruptions [60]. According to [14], forecasting material requirements, allocating workers, and optimizing budgets, machine learning simplifies resource allocation. Machine learning predicts the amount of drilling equipment needed for geothermal projects, and it maximizes the efficiency of wind and solar energy by optimizing the distribution of panels or turbines [93].

4. Challenges and future directions

Despite its many advantages, there are a number of difficulties in integrating machine learning into renewable energy devices and clean energy projects delivery [63]. The quality and availability of data, which might be irregular or scarce in some renewable energy sectors, determine how accurate machine learning models can be developed [81]. Widespread adoption may be hampered by computational complexity and the requirement for a strong hardware foundation [26]. To avoid any cyberthreats, cybersecurity issues pertaining to ML-driven energy management systems also need to be resolved. It is anticipated that future developments in machine learning (ML), such as explainable AI (XAI), federated learning, and quantum computing, would further improve the dependability and efficiency of renewable energy equipment [8]. Innovations in machine learning applications will be fueled by cooperative research and industry partnerships, guaranteeing that renewable energy systems run as efficiently as possible while having the least possible negative environmental impact and cost [89].

5. Conclusions

In the era of energy transition to clean energy, mainly driven by climate change and its related environmental concerns. There is global pledge to cut down emissions especially from energy use which can be achieved through clean energy resources such as solar, wind, tidal, geothermal, biomass and hydroelectric energy systems. The development of this energy resources also necessitate transition in both operational and manufacturing process of these energy machines. This article therefore, using descriptive approach provide an insight on how machine learning as an AI component can be utilized to improve machinery efficiency and reliability in clean energy systems and clean energy projects. The article showed that machine learning can be utilized to improve machine efficiency and reliability in clean energy systems as well as clean energy project delivery in a number of ways. In solar energy for instance, machine learning algorithm can utilize weather data to predict the amount of irradiant energy needed for solar PV farm in energy project delivery.

Machine learning can also be used to maximize efficiency, enhance dependability, and lower operating costs, thereby transforming the renewable energy industry. Optimization algorithms, real-time monitoring systems, and machine learning (ML)-driven predictive analytics improve the efficiency of renewable energy systems utilized in solar, wind, tidal, geothermal, biomass, and hydroelectric power. As technology develops, machine learning will become increasingly more important in hastening the world's shift to sustainable energy, helping to create a cleaner and more resilient energy landscape. Machine learning also significantly enhances site selection, feasibility, duration estimation, and resource allocation in clean energy projects, driving efficiency and sustainability.

Recommendations

Although this article effectively highlights the transformative role of machine learning in enhancing machinery efficiency and reliability in clean energy systems and clean energy projects delivery. However, it recommends that:

- The discussion on predictive maintenance could be expanded with specific examples of how machine learning algorithms reduce downtime and maintenance costs.
- Integrating comparisons between traditional maintenance approaches and machine learning-driven solutions would strengthen the paper’s argument.
- More emphasis on challenges, such as data quality, computational costs, and implementation barriers, would provide a balanced perspective.

Compliance with ethical standards

Disclosure of conflict of interest

Authors declared that there is no conflict of interest.

References

[1] Abdelateef Mostafa, M., El-Hay, E.A. and ELkholy, M.M. (2023) Recent trends in wind energy conversion system with grid integration based on soft computing methods: comprehensive review, comparisons and insights. *Archives of Computational Methods in Engineering*, *30*(3), pp.1439-1478.

[2] Adefarati, T. and Bansal, R.C. (2019) Reliability, economic and environmental analysis of a microgrid system in the presence of renewable energy resources. *Applied energy*, *236*, pp.1089-1114.

[3] Alabi, T.M., Aghimien, E.I., Agbajor, F.D., Yang, Z., Lu, L., Adeoye, A.R. and Gopaluni, B. (2022). A review on the integrated optimization techniques and machine learning approaches for modeling, prediction, and decision making on integrated energy systems. *Renewable Energy*, *194*, pp.822-849.

[4] Alcácer, V. and Cruz-Machado, V. (2019) Scanning the industry 4.0: A literature review on technologies for manufacturing systems. *Engineering science and technology, an international journal*, *22*(3), pp.899-919.

[5] Alhafadhi, L., Teh, J., Lai, C.M. and Salem, M. (2020) Predictive adaptive filter for reducing total harmonics distortion in PV systems. *Energies*, *13*(12), p.3286.

[6] Aljeddani, S.M.A. (2023) Forecasting temperature of the Saudi Arabian Province of Makkah using a discrete state–space modeling approach. *Journal of Umm Al-Qura University for Engineering and Architecture*, *14*(2), pp.79-94.

[7] Alkesaiberi, A., Harrou, F. and Sun, Y. (2022) Efficient wind power prediction using machine learning methods: A comparative study. *Energies*, *15*(7), p.2327.

[8] Allal, Z., Noura, H.N., Salman, O. and Chahine, K. (2024) Machine learning solutions for renewable energy systems: Applications, challenges, limitations, and future directions. *Journal of Environmental Management*, *354*, p.120392.

[9] Alrayess, H., Gharbia, S., Beden, N. and Keskin, A.U. (2018) Using machine learning techniques and deep learning in forecasting the hydroelectric power generation in almus dam, turkey. *Safety*, *72*.

[10] Altawell, N. (2021) 12-Energy technologies and energy storage systems for sustainable development. *Rural Electrification. Academic Press*, pp.231-48.

[11] Anaza, S.O., Abdulazeez, M.S., Yisah, Y.A., Yusuf, Y.O., Salawu, B.U. and Momoh, S.U. (2017) Micro hydro-electric energy generation-An overview. *American Journal of Engineering Research (AJER)*, *6*(2), pp.5-12.

[12] Ang, T.Z., Salem, M., Kamarol, M., Das, H.S., Nazari, M.A. and Prabaharan, N. (2022) A comprehensive study of renewable energy sources: Classifications, challenges and suggestions. Energy strategy reviews, 43, p.100939.

[13] Arora, D. and Arora, R.K. (2024) Hydro power generation-growth story, challenges & solutions. Water and Energy International, 67(4), pp.28-32.

[14] Badillo, S., Banfai, B., Birzele, F., Davydov, I.I., Hutchinson, L., Kam-Thong, T., Siebourg-Polster, J., Steiert, B. and Zhang, J.D. (2020) An introduction to machine learning. Clinical pharmacology & therapeutics, 107(4), pp.871-885.

[15] Balakrishnan, D., Sharma, P., Bora, B.J. and Dizge, N. (2024) Harnessing biomass energy: Advancements through machine learning and AI applications for sustainability and efficiency. Process Safety and Environmental Protection.

[16] Benti, N.E., Chaka, M.D. and Semie, A.G. (2023) Forecasting renewable energy generation with machine learning and deep learning: Current advances and future prospects. Sustainability, 15(9), p.7087.

[17] Benti, N.E., Gurmesa, G.S., Argaw, T., Aneseyee, A.B., Gunta, S., Kassahun, G.B., Aga, G.S. and Asfaw, A.A. (2021) The current status, challenges and prospects of using biomass energy in Ethiopia. Biotechnology for Biofuels, 14, pp.1-24.

[18] Bernardes Jr, J., Santos, M., Abreu, T., Prado Jr, L., Miranda, D., Julio, R., Viana, P., Fonseca, M., Bortoni, E. and Bastos, G.S. (2022) Hydropower operation optimization using machine learning: A systematic review. AI, 3(1), pp.78-99.

[19] Blakers, A., Stocks, M., Lu, B. and Cheng, C. (2021) A review of pumped hydro energy storage. Progress in Energy, 3(2), p.022003.

[20] Bloomberg (2023) World's biggest wind power projects are in crisis just when world needs them most. https://energy.economictimes.indiatimes.com/news/renewable/worlds-biggest-wind-power-projects-are-in-crisis-just-when-world-needs-them-most/102160151

[21] Bosnjakovic, M., Katinić, M., Santa, R. and Marić, D. (2022) Wind turbine technology trends. Applied Sciences, 12(17), p.8653.

[22] Brekken, T.K., Hapke, H.M., Stillinger, C. and Prudell, J. (2010) Machines and drives comparison for low-power renewable energy and oscillating applications. IEEE Transactions on Energy Conversion, 25(4), pp.1162-1170.

[23] Bughneda, A., Salem, M., Richelli, A., Ishak, D, and Alatai, S. (2021). Review of Multilevel Inverters for PV Energy System Applications. Energies, 14(6), pp. 1585.

[24] Carley, S. and Konisky, D.M., 2020. The justice and equity implications of the clean energy transition. Nature Energy, 5(8), pp.569-577.

[25] Chauhan, V.S., Sharma, R. and Shah, H. (2024) Exploring Sustainability Through Clean Energy, Artificial Intelligence, and Machine Learning: Ethical Perspectives. In AI Applications for Clean Energy and Sustainability (pp. 119-138). IGI Global.

[26] Cheng, M. and Zhu, Y. (2014) The state of the art of wind energy conversion systems and technologies: A review. Energy conversion and management, 88, pp.332-347.

[27] Chitgar, N., Hemmati, A. and Sadrzadeh, M. (2023) A comparative performance analysis, working fluid selection, and machine learning optimization of ORC systems driven by geothermal energy. Energy Conversion and Management, 286, p.117072.

[28] Chowdhury, M.S., Rahman, K.S., Selvanathan, V., Nuthammachot, N., Suklueng, M., Mostafaeipour, A., Habib, A., Akhtaruzzaman, M., Amin, N. and Techato, K. (2021) Current trends and prospects of tidal energy technology. Environment, development and sustainability, 23, pp.8179-8194.

[29] Chu, S., Cui, Y. and Liu, N. (2017) The path towards sustainable energy. Nature materials, 16(1), pp.16-22.

[30] Condemi, C., Casillas-Perez, D., Mastroeni, L., Jiménez-Fernández, S. and Salcedo-Sanz, S. (2021). Hydro-power production capacity prediction based on machine learning regression techniques. Knowledge-Based Systems, 222, p.107012.

[31] Cox, S.L., Lopez, A.J., Watson, A.C., Grue, N.W. and Leisch, J.E. (2018) Renewable energy data, analysis, and decisions: a guide for practitioners (No. NREL/TP-6A20-68913). National Renewable Energy Lab. (NREL), Golden, CO (United States).

[32] Dambhare, M.V., Butey, B. and Moharil, S.V. (2021) Solar photovoltaic technology: A review of different types of solar cells and its future trends. In Journal of Physics: Conference Series (Vol. 1913, No. 1, p. 012053). IOP Publishing.

[33] Dean, N. (2022) Collaborating on clean energy action. Nature Energy, 7(9), pp.785-787.

[34] Demolli, H., Dokuz, A.S., Ecemis, A. and Gokcek, M. (2019) Wind power forecasting based on daily wind speed data using machine learning algorithms. Energy Conversion and Management, 198, p.111823.

[35] Department for Business, Energy and Industrial Strategy (2020) Modelling 2050: Electricity Systems Analysis. Available at: https://www.gov.uk/government/publications/modelling-2050-electricity-system-analysis.

[36] Desalegn, B., Gebeyehu, D. and Tamrat, B. (2022). Wind energy conversion technologies and engineering approaches to enhancing wind power generation: A review. *Heliyon*, *8*(11).

[37] Diez-Olivan, A., Del Ser, J., Galar, D. and Sierra, B. (2019) Data fusion and machine learning for industrial prognosis: Trends and perspectives towards Industry 4.0. *Information Fusion*, *50*, pp.92-111.

[38] Dincer, I. and Acar, C. (2015) A review on clean energy solutions for better sustainability. *International journal of energy research*, *39*(5), pp.585-606.

[39] Duplyakin, D., Beckers, K.F., Siler, D.L., Martin, M.J. and Johnston, H.E. (2022) Modeling subsurface performance of a geothermal reservoir using machine learning. *Energies*, *15*(3), p.967.

[40] Ekanayake, P., Wickramasinghe, L., Jayasinghe, J.J.W. and Rathnayake, U. (2021) Regression-Based Prediction of Power Generation at Samanalawewa Hydropower Plant in Sri Lanka Using Machine Learning. Mathematical Problems in Engineering, 2021(1), p.4913824.

[41] Fadlallah, S.O. and Serradj, D.E.B. (2020) Determination of the optimal solar photovoltaic (PV) system for Sudan. Solar Energy, 208, pp.800-813.

[42] Federal environment Agency (2010) 2050:100% energy target: 100% renewable electricity supply. Available at: https://www.umweltbundesamt.de/sites/default/files/medien/378/publikationen/energieziel_2050_kurz.pdf .

[43] Federal Ministry for Environment, Nature Conservation, Building and Nuclear Safety (2020) Climate Action Plan, 2050. Available at: https://climate-laws.org/documents/climate-action-plan-2050_b6ce?id=climate-action-plan-2050_37a5.

[44] Forootan, M.M., Larki, I., Zahedi, R. and Ahmadi, A. (2022) Machine learning and deep learning in energy systems: A review. Sustainability, 14(8), p.4832.

[45] Gaber, I.M. and Ibrahim, R.A. (2023) Hourly electricity price prediction applying deep learning for electricity market management. In 2023 IEEE international conference on environment and electrical engineering and 2023 IEEE industrial and commercial power systems Europe (EEEIC/I&CPS Europe) (pp. 1-5). IEEE.

[46] Gajbhiye, T.S., Nikam, K.C., Kaliappan, S., Patil, P.P., Dhal, P.K. and Pandian, C.K. (2023) Sustainable renewable energy sources and solar mounting systems for PV panels: A critical review. In AIP Conference Proceedings (Vol. 2800, No. 1). AIP Publishing.

[47] Gandoman, F.H., Ahmadi, A., Sharaf, A.M., Siano, P., Pou, J., Hredzak, B. and Agelidis, V.G. (2018) Review of FACTS technologies and applications for power quality in smart grids with renewable energy systems. *Renewable and sustainable energy reviews*, *82*, pp.502-514.

[48] Geng, Z., Bai, J., Jiang, D. and Han, Y. (2018) Energy structure analysis and energy saving of complex chemical industries: a novel fuzzy interpretative structural model. *Applied Thermal Engineering*, *142*, pp.433-443.

[49] Ghandehariun, S., Ghandehariun, A.M. and Ziabari, N.B. (2023) Performance prediction and optimization of a hybrid renewable-energy-based multigeneration system using machine learning. *Energy*, *282*, p.128908.

[50] Gielen, D., Boshell, F., Saygin, D., Bazilian, M.D., Wagner, N. and Gorini, R. (2019) The role of renewable energy in the global energy transformation. *Energy strategy reviews*, *24*, pp.38-50.

[51] Grams, C.M., Beerli, R., Pfenninger, S., Staffell, I. and Wernli, H. (2017) Balancing Europe's wind-power output through spatial deployment informed by weather regimes. *Nature climate change*, *7*(8), pp.557-562.

[52] Greaves, D., Iglesias, G. and Wiley, J. (2018). *Wave and tidal energy*. John Wiley & Sons Limited.

[53] Grebenchikov, N.P., Varlamov, D.O., Zuev, S.M., Maleev, R.A., Skvortsov, A.A. and Grebenchikov, A.P. (2020) Study of solar panel charge controllers. *Journal of Communications Technology and Electronics*, *65*, pp.1053-1061.

[54] Gupta, R. and Gregg, M. (2018) Assessing energy use and overheating risk in net zero energy dwellings in UK. *Energy and Buildings*, *158*, pp.897-905.

[55] Hassan, M.K., Youssef, H., Gaber, I.M., Shehata, A.S., Khairy, Y. and El-Bary, A.A. (2024) A predictive machine learning model for estimating wave energy based on wave conditions relevant to coastal regions. *Results in Engineering*, *21*, p.101734.

[56] Hassan, Q., Viktor, P., Al-Musawi, T.J., Ali, B.M., Algburi, S., Alzoubi, H.M., Al-Jiboory, A.K., Sameen, A.Z., Salman, H.M. and Jaszczur, M. (2024) The renewable energy role in the global energy Transformations. *Renewable Energy Focus*, *48*, p.100545.

[57] Hemanth Kumar, M.B., Saravanan, B., Sanjeevikumar, P. and Blaabjerg, F. (2018) Review on control techniques and methodologies for maximum power extraction from wind energy systems. *IET Renewable power generation*, *12*(14), pp.1609-1622.

[58] Hilmarsson, H.Þ. (2017) Scaling up funding for clean energy projects in developing and emerging countries via ppps: Costs, benefits, challenges and some cases. *Taikomoji ekonomika: sisteminiai tyrimai*, *11*(2), pp.105-122.

[59] Jaiswal, K.K., Chowdhury, C.R., Yadav, D., Verma, R., Dutta, S., Jaiswal, K.S., Sangmesh, B. and Karuppasamy, K.S.K. (2022) Renewable and sustainable clean energy development and impact on social, economic, and environmental health. Energy Nexus, 7, pp. 100118.

[60] Japan Sustainability (2012) Japanese Firm Begins Development of Tidal Power Generation System. Available at: https://www.japanfs.org/en/news/archives/news_id031523.html.

[61] Jones, A.W., 2015. Perceived barriers and policy solutions in clean energy infrastructure investment. Journal of Cleaner Production, 104, pp.297-304.

[62] Kabeyi, M.J.B. (2019) Geothermal electricity generation, challenges, opportunities and recommendations. International Journal of Advances in Scientific Research and Engineering (ijasre), 5(8), pp.53-95.

[63] Khare, V. and Bhuiyan, M.A. (2022) Tidal energy-path towards sustainable energy: A technical review. Cleaner Energy Systems, 3, p.100041.

[64] Khojasteh, D., Khojasteh, D., Kamali, R., Beyene, A. and Iglesias, G. (2018) Assessment of renewable energy resources in Iran; with a focus on wave and tidal energy. Renewable and Sustainable Energy Reviews, 81, pp.2992-3005.

[65] Kiasari, M., Ghaffari, M. and Aly, H.H. (2024) A comprehensive review of the current status of smart grid technologies for renewable energies integration and future trends: The role of machine learning and energy storage systems. Energies, 17(16), p.4128.

[66] Korucan, A., Derin-Gure, P., Celebi, B., Baker, D. and Vander Velde, M. (2024) Opportunities and challenges of geothermal energy in Turkiye. Energy for Sustainable Development, 79, p.101417.

[67] Krechowicz, A., Krechowicz, M. and Poczeta, K. (2022) Machine learning approaches to predict electricity production from renewable energy sources. Energies, 15(23), p.9146.

[68] Krechowicz, M. and Krechowicz, A. (2021) Risk assessment in energy infrastructure installations by horizontal directional drilling using machine learning. *Energies*, *14*(2), p.289.

[69] Kulasekara, H. and Seynulabdeen, V. (2019) A review of geothermal energy for future power generation. In *2019 5th international conference on advances in electrical engineering (ICAEE)* (pp. 223-228). IEEE.

[70] Li, Y., Ali, G. and Akbar, A.R. (2023) Advances in geothermal energy prospectivity mapping research based on machine learning in the age of big data. *Sustainable Energy Technologies and Assessments*, *60*, p.103550.

[71] Li, Y., Wang, C., Li, G., Wang, J., Zhao, D. and Chen, C. (2020) Improving operational flexibility of integrated energy system with uncertain renewable generations considering thermal inertia of buildings. *Energy Conversion and Management*, *207*, p.112526.

[72] Lian, J., Zhang, Y., Ma, C., Yang, Y. and Chaima, E. (2019) A review on recent sizing methodologies of hybrid renewable energy systems. *Energy Conversion and Management*, *199*, p.112027.

[73] Markard, J. (2018) The next phase of the energy transition and its implications for research and policy. *Nature Energy*, *3*(8), pp.628-633.

[74] Miao, Z., Grift, T.E., Hansen, A.C. and Ting, K.C. (2011) Energy requirement for comminution of biomass in relation to particle physical properties. *Industrial crops and products*, *33*(2), pp.504-513.

[75] Mokarram, M., Ronizi, S.R.A. and Negahban, S., 2024. Optimizing biomass energy production in the southern region of Iran: A deterministic MCDM and machine learning approach in GIS. *Energy Policy*, *195*, p.114350.

[76] Moraga, J., Duzgun, H.S., Cavur, M. and Soydan, H. (2022) The geothermal artificial intelligence for geothermal exploration. *Renewable Energy*, *192*, pp.134-149.

[77] Morris, J.D., Daood, S.S. and Nimmo, W. (2022) Machine learning prediction and analysis of commercial wood fuel blends used in a typical biomass power station. *Fuel*, *316*, p.123364.

[78] Mousavi, S.M., Ghasemi, M., Dehghan Manshadi, M. and Mosavi, A. (2021) Deep learning for wave energy converter modeling using long short-term memory. *Mathematics*, *9*(8), p.871.

[79] Munir, M.T., Li, B. and Naqvi, M. (2023) Revolutionizing municipal solid waste management (MSWM) with machine learning as a clean resource: Opportunities, challenges and solutions. *Fuel*, *348*, p.128548.

[80] Narvaez, G., Giraldo, L.F., Bressan, M. and Pantoja, A. (2021) Machine learning for site-adaptation and solar radiation forecasting. *Renewable Energy*, *167*, pp.333-342.

[81] Neill, S.P., Hashemi, M.R. and Lewis, M.J. (2016) Tidal energy leasing and tidal phasing. *Renewable Energy*, *85*, pp.580-587.

[82] Obaideen, K., Olabi, A.G., Al Swailmeen, Y., Shehata, N., Abdelkareem, M.A., Alami, A.H., Rodriguez, C. and Sayed, E.T. (2023) Solar energy: Applications, trends analysis, bibliometric analysis and research contribution to sustainable development goals (SDGs). *Sustainability*, *15*(2), p.1418.

[83] Okoroafor, E.R., Smith, C.M., Ochie, K.I., Nwosu, C.J., Gudmundsdottir, H. and Aljubran, M.J. (2022) Machine learning in subsurface geothermal energy: Two decades in review. *Geothermics*, *102*, p.102401.

[84] Patil, P.B., Sarkar, D. and Sarkar, A. (2023) Clean energy production by microorganisms: A sustainable approach. Microbial Tools for Sustainable Ecosystem Services, 3, pp. 1 – 14.

[85] Rabbani, M.A. (2020) Solar power systems and dc to ac inverters. Acta Technica Corviniensis-Bulletin of Engineering, 13(2), pp.19-28.

[86] Rahman, A., Farrok, O. and Haque, M.M. (2022) Environmental impact of renewable energy source based electrical power plants: Solar, wind, hydroelectric, biomass, geothermal, tidal, ocean, and osmotic. Renewable and sustainable energy reviews, 161, p.112279.

[87] Rane, N.L., Choudhary, S.P. and Rane, J. (2024) Artificial Intelligence and machine learning in renewable and sustainable energy strategies: A critical review and future perspectives. Partners Universal International Innovation Journal, 2(3), pp.80-102.

[88] Roman, K., Barwicki, J., Hryniewicz, M., Szadkowska, D. and Szadkowski, J. (2021) Production of electricity and heat from biomass wastes using a converted aircraft turbine AI-20. Processes, 9(2), p.364.

[89] Ross-Veitía, B.D., Palma-Ramírez, D., Arias-Gilart, R., Conde-García, R.E., Espinel-Hernández, A., Nuñez-Alvarez, J.R., Hernández-Herrera, H. and Llosas-Albuerne, Y.E. (2024) Machine learning regression algorithms to predict emissions from steam boilers. Heliyon, 10(5).

[90] Sapitang, M., M. Ridwan, W., Faizal Kushiar, K., Najah Ahmed, A. and El-Shafie, A. (2020) Machine learning application in reservoir water level forecasting for sustainable hydropower generation strategy. Sustainability, 12(15), p.6121.

[91] Shang, C. and You, F. (2019) Data analytics and machine learning for smart process manufacturing: Recent advances and perspectives in the big data era. Engineering, 5(6), pp.1010-1016.

[92] Sharma, S., Khanra, P. and Ramkumar, K.R. (2021) Performance analysis of biomass energy using machine and deep learning approaches. In Journal of Physics: Conference Series (Vol. 2089, No. 1, p. 012003). IOP Publishing.

[93] Sharmin, T., Khan, N.R., Akram, M.S. and Ehsan, M.M. (2023) A state-of-the-art review on geothermal energy extraction, utilization, and improvement strategies: conventional, hybridized, and enhanced geothermal systems. International Journal of Thermofluids, 18, p.100323.

[94] Shetty, C. and Priyam, A. (2022) A review on tidal energy technologies. Materials Today: Proceedings, 56, pp.2774-2779.

[95] Siecker, J., Kusakana, K. and Numbi, E.B. (2017) A review of solar photovoltaic systems cooling technologies. Renewable and Sustainable Energy Reviews, 79, pp.192-203.

[96] Singh, V.K. and Singal, S.K. (2017) Operation of hydro power plants-a review. Renewable and Sustainable Energy Reviews, 69, pp.610-619.

[97] Sinomach (2024). l Dhafra PV2 solar power plant recognized as an international green energy pioneer project. Available at: https://www.sinomach.com.cn/en/MediaCenter/News/202410/t20241030_441406.html.

[98] Sohani, A., Sayyaadi, H., Cornaro, C., Shahverdian, M.H., Pierro, M., Moser, D., Karimi, N., Doranehgard, M.H. and Li, L.K. (2022) Using machine learning in photovoltaics to create smarter and cleaner energy generation systems: A comprehensive review. Journal of Cleaner Production, 364, p.132701.

[99] Stetco, A., Dinmohammadi, F., Zhao, X., Robu, V., Flynn, D., Barnes, M., Keane, J. and Nenadic, G. (2019) Machine learning methods for wind turbine condition monitoring: A review. Renewable energy, 133, pp.620-635.

[100] Stritzke, S. (2018) Clean energy for all': the implementation of Scaling Solar in Zambia. World Journal of Science, Technology and Sustainable Development, 15(3), pp.214-225.

[101] Tabassum, S., Rahman, T., Islam, A.U., Rahman, S., Dipta, D.R., Roy, S., Mohammad, N., Nawar, N. and Hossain, E. (2021) Solar energy in the United States: Development, challenges and future prospects. Energies, 14(23), p.8142.

[102] Tautz-Weinert, J. and Watson, S.J. (2016) Using SCADA Data for Wind Turbine Condition Monitoring—A Review. IET Renew. Power Gener. 2017, 11, 382–394 [online]

[103] Thakur, A., Canter, C.E. and Kumar, A. (2014) Life-cycle energy and emission analysis of power generation from forest biomass. Applied energy, 128, pp.246-253.

[104] Topór, T., Słota-Valim, M. and Kudrewicz, R. (2023) Assessing the geothermal potential of selected depleted oil and gas reservoirs based on geological modeling and machine learning tools. Energies, 16(13), p.5211.

[105] Tun, M.M., Juchelkova, D., Win, M.M., Thu, A.M. and Puchor, T. (2019) Biomass energy: An overview of biomass sources, energy potential, and management in Southeast Asian countries. Resources, 8(2), p.81.

[106] Turner, J.M. (2022) The matter of a clean energy future. Science, 376(6600), pp.1361-1361.

[107] U.S Energy Information Administration, Annual energy outlook (2022) EIA projects that renewable generation will supply 44% of U.S. electricity by 2050. Available at: https://www.eia.gov/todayinenergy/detail.php?id=51698.

[108] Venkateswari, R. and Sreejith, S. (2019) Factors influencing the efficiency of photovoltaic system. Renewable and Sustainable Energy Reviews, 101, pp.376-394.

[109] Vlachogiannis, J.G. (2014) Marine-current power generation model for smart grids. Journal of Power Sources, 249, pp.172-174.

[110] Voyant, C., Notton, G., Kalogirou, S., Nivet, M.L., Paoli, C., Motte, F. and Fouilloy, A. (2017) Machine learning methods for solar radiation forecasting: A review. Renewable energy, 105, pp.569-582.

[111] Wang, D., Cao, R., Hao, S., Liang, C., Chen, G., Chen, P., Li, Y. and Zou, X. (2023) Accelerated prediction of Cu-based single-atom alloy catalysts for CO2 reduction by machine learning. *Green Energy & Environment*, *8*(3), pp.820-830.

[112] Wang, H.S.H. and Yao, Y. (2023) Machine learning for sustainable development and applications of biomass and biomass-derived carbonaceous materials in water and agricultural systems: A review. *Resources, Conservation and Recycling*, *190*, p.106847.

[113] Wang, L., Yu, Z., Zhang, Y. and Yao, P. (2023) Review of machine learning methods applied to enhanced geothermal systems. *Environmental Earth Sciences*, *82*(3), p.69.

[114] Waters, S. and Aggidis, G. (2016) Tidal range technologies and state of the art in review. *Renewable and Sustainable Energy Reviews*, *59*, pp.514-529.

[115] Wymore, M.L., Van Dam, J.E., Ceylan, H. and Qiao, D. (2015) A survey of health monitoring systems for wind turbines. *Renewable and Sustainable Energy Reviews*, *52*, pp.976-990.

[116] Xu, W. and Matzner, S. (2018) Underwater fish detection using deep learning for water power applications. In *2018 International conference on computational science and computational intelligence (CSCI)* (pp. 313-318). IEEE.

[117] Yang, W., Court, R. and Jiang, J. (2013) Wind turbine condition monitoring by the approach of SCADA data analysis. *Renewable energy*, *53*, pp.365-376.

[118] Zhang, F., Tang, T., Su, J. and Huang, K. (2020) Inter-sector network and clean energy innovation: Evidence from the wind power sector. *Journal of Cleaner Production*, *263*, p.121287.

[119] Zhang, Z., Li, X., Yin, J., Xu, Y., Fei, W., Xue, M., Wang, Q., Zhou, J. and Guo, W. (2018) Emerging hydrovoltaic technology. *Nature nanotechnology*, *13*(12), pp.1109-1119.

[120] Zhu, S., Preuss, N. and You, F. (2023) Advancing sustainable development goals with machine learning and optimization for wet waste biomass to renewable energy conversion. *Journal of Cleaner Production*, *422*, p.138606.