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An Efficient Machine Learning Based Solutions for Renewable Energy System

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Abstract—The need for long-term energy solutions is growing in importance as the world continues to industrialise. Renewable energy sources, such as solar, wind, hydropower, geothermal, and biomass, are cleaner, inexhaustible alternatives to fossil fuels that contribute to the fight against climate change. This paper provides an overview of renewable energy (RE) sources and explores how machine learning (ML) techniques contribute to enhancing renewable energy systems' efficiency and sustainability. Renewable energy sources, including solar, wind, geothermal, and hydropower, offer environmentally friendly and inexhaustible energy solutions. Hybrid Renewable Energy Systems (HRES) combine multiple renewable sources to improve energy generation reliability and efficiency. Machine learning has emerged as a pivotal tool for optimising various aspects of renewable energy systems, such as energy generation forecasting, grid management, and energy demand prediction. This paper explores the role of key ML techniques—supervised, unsupervised, and reinforcement learning—in addressing complex challenges in renewable energy, including predicting weather-dependent energy generation, optimising storage systems, and integrating renewable sources into the grid. Through the application of ML algorithms can become more flexible, efficient, and reliable, supporting sustainable development goals. ML models also aid in fault detection, improving the overall lifespan and efficiency of energy systems. The potential of ML-driven solutions for renewable energy systems is vast, with significant implications for achieving a more sustainable and resilient energy future.

Keywords—Renewable energy (RE), Unsupervised learning, Energy demand forecasting, Electricity generation, Sustainability.

I. INTRODUCTION

As the world's industrialisation speed increases, it is clear that using too much fossil fuel would have detrimental effects on the environment and speed up the depletion of these resources. All of these things will make the health risks and difficulties caused by climate change even worse[1]. The energy source with the quickest rate of growth at the moment is renewable energy, followed by nuclear and fossil fuels. Power from the sun, wind, water, biomass, tidal waves, and geothermal heat are all examples of renewable energy sources[2]. Renewable energy has lately been the subject of a plethora of research due to its attractiveness as a sustainable energy source with little environmental impact. The next generation of energy supply is going to be a major obstacle for renewable energy sources. Energy supply systems that include renewable energy sources in their current or future configurations are known as renewable supply[3][4].

Also, renewable energy leads to decreased stress on the quality of the soil since it reduces the outflow of solid wastes[5]. By reducing the emissions of waste gas and waste liquid during usage, renewable energy may help achieve the goal of safeguarding water resources[6][7]. Therefore, renewable energy has been seeing explosive expansion in recent years. The 2017 report from REN21 states that in 2016, renewable energy accounted for 24.5% of the world's power production and 19.3% of the world's energy consumption. Solar energy has in the past received several legislative acts, incentives and subsidies in a bid to enhance its utilisation in many countries[8]. ML methods can complement these efforts in the renewable energy sector and enhance them considerably[9].

A more reliable energy supply and an end to regional power shortages are two of the most pressing concerns facing the energy industry today[10], and both may be addressed via the expansion of RE systems. However, this creation of different energy sources is uneventful and unpredictable because of the extreme instability and randomness of renewable energy. Therefore, there is still much to be accomplished in terms of effectively handling the inherent unpredictability of data pertaining to renewable energy sources[11] [12]. The energy system may be made more efficient with the use of very accurate energy metrics. Technology for energy forecasting is critical for energy system development, management, and policymaking. Technology for storing renewable energy is crucial as the number of methods for generating electricity from these sources grows[13][14].

However, ML has expanded to become a powerful means of improving renewable energy systems management and utilisation. Traditional approaches are finding it more difficult to provide accurate forecasts and optimisation tactics when it comes to renewable energy sources like hydro, wind, and solar, which are becoming more complicated and variable. ML algorithms are capable of processing a large set of data, identifying the existing patterns and modifying the power generation, storage and supply in real-time mode[15]. Finally, they stated that ML contributes to the development of more efficient and less costly energy system by improving the level of accuracy of forecasts and prediction of demand, as well as effectiveness of maintenance schedules of renewable systems[16].

A. Motivation of the Study

Air pollution, climate change, and resource depletion are just a few of the environmental and health repercussions of fossil fuels, which is why our research is motivated by the growing global need to de-rely on them. RE sources such as wind, solar, and hydropower are cleaner and have low environmental impacts; however, they pose problems of intermittency and low reliability as systems of energy while being integrated into existing systems. To address these challenges, machine learning is viewed as promising as it improves energy forecasting, resource utilisation, as well as the system's overall efficiency. The overall purpose of this research is to contribute to existing global efforts towards enhancing energy security and a sustainable worldwide energy supply by exploring the capacity of ML in RE systems for more resilient, accessible and environment-friendly energy systems. Key points of the study are as follows below:

- The paper provides a comprehensive overview of renewable energy sources, including solar, wind, geothermal, and hydropower, highlighting their environmental benefits, endless supply, and potential applications in industries like housing, transportation, and more.
- The concept of HRES is introduced as a combination of multiple renewable energy sources or a mix of renewable and conventional energy systems, which enhances energy reliability, efficiency, and grid management through hybrid setups.
- Machine learning (ML) is identified as a transformative technology in renewable energy, particularly for predicting energy generation, optimising energy storage systems, and improving grid integration by leveraging historical and real-time data.
- The paper discusses major machine learning techniques applied in energy systems, such as supervised learning, unsupervised learning, and reinforcement learning, and how they are used for energy demand forecasting, wind and solar energy prediction, and optimising smart grids.
- The paper highlights practical applications of ML in the energy sector, such as forecasting energy demand, wind and solar energy prediction, optimising smart grids, and enabling smarter and more efficient renewable energy systems through data-driven insights and operational enhancements.

B. Structure of the Study

This paper is structured like thus: introducing renewable energy sources in Section II, Section III discussed the machine learning in renewable energy sources, then Section IV assesses how well machine learning tackles the challenges associated with renewable energy. Section V compiles pertinent literature with summary, and Section VI concludes the research and offers recommendations for future studies.

II. RENEWABLE ENERGY SOURCES: AN OVERVIEW

The phrase "renewable energy" describes power generated from a resource that is both naturally replenishable and has no finite supply. Wind, sun, biomass, and hydropower are all examples of renewable energy sources. Both the economy and pollution levels stand to benefit greatly from more effective use of RE sources [17]. Figure 1 shows the renewable energy sources.

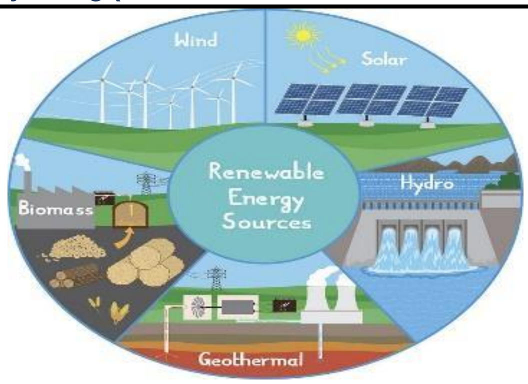

Figure 1: Renewable Energy Sources

RE systems are energy generation systems that utilise naturally replenishing sources of energy, like rain, sunlight, waves, wind, tides, and geothermal heat. Renewable energy sources include all forms of energy that can be endlessly renewed and can never run out. Numerous industries rely on them as an energy source, including housing, transportation, industry, and more. Figure 2 depicts the types of different renewable energy sources using ML given below:

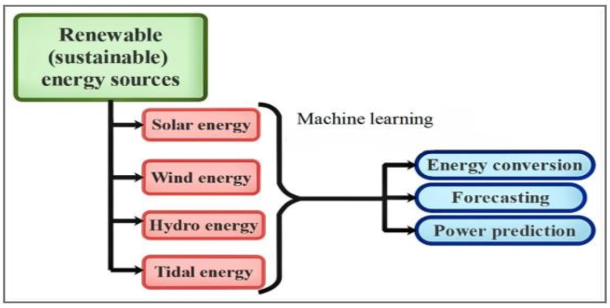

Figure 2: Renewable energy using ML

A. Type of different renewable energy sources

This section delves into the various renewable energy sources, offering a detailed analysis of each. The focus is on understanding their potential and impact.

1) Solar energy

There are a number of environmentally safe ways to harness the sun's energy, including sunlight and solar thermal radiation. Solar radiation has all the makings of a perfect energy source: clean, cheap, and efficient. The two primary methods for harnessing solar energy are photovoltaic cells and solar thermal collectors. Sunlight may be used by devices called solar thermal collectors to heat a fluid in a mass flow system. Small-scale applications include heating water or areas, as well as large-scale electricity generation [18][19].

2) Wind Energy

A renewable energy source that is both free and pure is the wind. Pumping water, grinding grain, and moving ships are just a few of the many centuries-old uses on which it has relied. Wind energy has gained new societal uses with the advent of electric power, which can generate clean, endless electricity at various sizes and capacities. Nowadays, wind power production may be found in a range of sizes, from tiny residential units to large utility-sized systems. The modern utility-scale wind power industry is leading the global energy growth race. Nameplate capacity of wind power producers around the globe was 159.2 GW as of the end of 2009, accounting for about 2% of global energy consumption. The technology behind wind turbines has not settled on a single design despite all this expansion. In the realm of power conversion in particular, there is a plethora of designs both implemented and in the works[20][19].

3) Geothermal Energy

The term "geothermal energy" refers to heat that is both produced and retained by the Earth itself. Various people have utilised it for cooking, heating, and bathing. The Earth's core can reach temperatures of up to 4,000˚C, which is high enough to generate geothermal energy via radioactive decay. Although geothermal energy is available everywhere, the geothermal gradient is a critical factor that affects whether a region is a good place for development [21].

4) Hydropower

Hydroelectric power, sometimes simply referred to as hydropower, is a sustainable energy source that harnesses the kinetic energy of flowing water to generate electricity. Mills, sawmills, and other machinery that generate mechanical power from water have been in use for thousands of years. A reservoir and dam for water storage might be part of it or not. Equipment for hydropower primarily consists of three parts: generators, transformers, and turbines. A plethora of other parts, including valves and gates, electrical devices for managing the station's operations, power lines, a switchyard, and grid connections, will also be required [22].

B. Hybrid Renewable Energy Systems (HRES)

A term "Hybrid Renewable Energy System" (HRES) refers to a setup that combines two or more renewable energy sources, or at least one renewable source with a conventional one. Depending on the circumstances, these systems may either be run independently or linked to the grid. Power electronics converters, made possible by HRES, are a boon because they convert the unregulated power coming from renewable sources into energy that can be used at the load end. In addition to the previously mentioned applications, the main advantage of HRES nowadays is that it can harness the unique features of renewable power generation technologies to achieve efficiencies that would be unattainable with a single power source installed in a localised area.

Considering the location and load demand, grid-connected hybrid energy systems (Figure 3) assess and select parameters like the most appropriate components, their sizes, and power management (PM). Power generation from solar photovoltaic (PV) cells, energy storage, and wind turbines constitute an HRES.

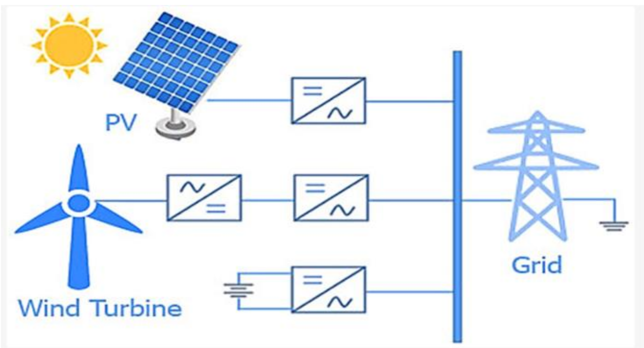

Figure 3: Grid-connected hybrid renewable-energy systems.

When the environment changes, a hybrid system may compensate for the weakness of one source by using the strength of the subordinate source. By analysing the local topography and other installation-specific factors, hybrid power systems combine two or more RE sources, like solar, wind, and others, to charge batteries and provide electricity to satisfy energy demands up to the required amount. In most cases, these renewable energy systems do not link up with the larger power grid. Also, they operate uniformly and independently in individual applications [23].

III. MACHINE LEARNING IN RENEWABLE ENERGY SYSTEMS

Machine learning has become one of the most promising approaches to enhancing renewable energy systems and bringing innovative changes in the improvement of forecasting, effectiveness, and management of these systems[24][25]. In renewable energy systems, machine learning models are utilised for tasks such as predicting energy generation from solar, wind, and hybrid sources, optimising energy storage systems, and improving an integration of RE into a grid. Combining the data of the past and the current information input, ML algorithms can predict the levels of weather-dependent energy generation, such as solar radiation or wind speed, which increases the dependability of energy systems. Also, ML is useful in increasing load control and energy usage making it easier to distribute power and avoid unnecessary use of electricity. While design for microrenewable energy systems is becoming complex with a hybrid system, reinforcement learning, supervised learning, and DL are vital to understanding and managing the system's dynamics and enhancing its efficiency of the system. This makes it possible to create a flexible and robust system of energy needed for sustainable development[26].

A. Key ML techniques used in the Energy Sector

In this section provide the techniques used in energy sector. The three major learning approaches applied by ML technologies include; Unsupervised Learning, Supervised Learning, And Reinforcement Learning.

1) Supervised Learning

Supervised learning methodology of ML involves comparing each input and output pair to a given repository of examples to arrive at a function that can accept an input and generate an output[27]. To deduce a function, the system leverages labelled training data and a set of training examples. ML algorithms that need human intervention are called supervised algorithms. The whole input dataset is split into two parts: the "train" and the "test" datasets. Predicting or classifying an output variable is required in the training dataset. Any algorithm may be trained on a training set and then used to predict or categorise data in a new dataset [28]. Figure 4 below shows the process of supervised ML algorithms.

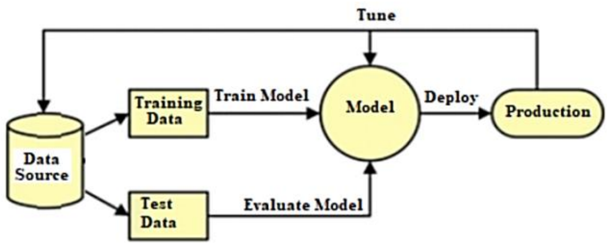

Figure 4: Supervised learning Workflow

2) Unsupervised Learning

Using supervised learning and tagged data, such as cat images classified as cats, data scientists may train systems to learn from examples. Unsupervised learning allows the system to independently assess the data and decide whether the photographs are of cats, with no intervention from a data scientist. In most cases, unsupervised ML requires a large quantity of data. Supervised learning is almost similar, except that it uses examples to improve the model's accuracy. The unsupervised learning procedure starts when data scientists put datasets to use in training algorithms. No data points have been tagged or classified in these datasets. The goal of training the algorithm is to identify dataset patterns and assign weights to data points based on those patterns [29]. The four categories of problems with unsupervised learning are auto-encoder, clustering, association, and anomaly detection (Figure 5).

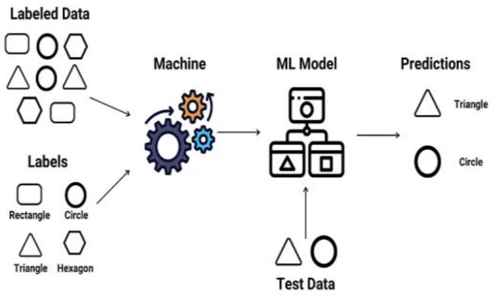

Figure 5: Unsupervised learning

3) Reinforcement Learning

Learning that determines how to improve outcomes is known as reinforcement learning. Until a scenario is presented to the learner, it is unaware of what steps to take. The learner's action may have an impact on future circumstances and their behaviour. Reinforcement learning relies just on two criteria: delayed results and trial-and-error search. Figure 6 shows the generic reinforcement learning paradigm.

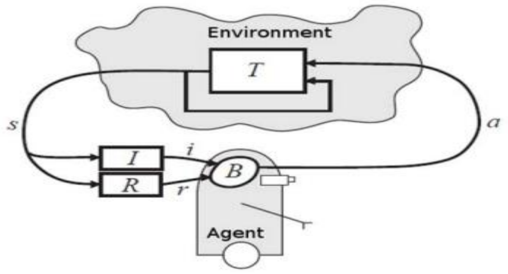

Figure 6: The Reinforcement Learning

In Figure 6, the environment provides the agent with input i, current states, a function to transition between states r, and input i itself. The inputs are used to develop behaviour B, and the agent then performs action at, which results in outcome[30].

IV. MACHINE LEARNING TO ADDRESS SUSTAINABLE RENEWABLE ENERGY SYSTEM

Machine learning is highly effective in promoting sustainable renewable energy by optimising various processes. It can predict energy production from sources like solar and wind, improving planning and efficiency. ML algorithms analyse large data sets to identify patterns, allowing for better energy management and reduced waste. They also enhance grid management by forecasting demand and adjusting supply in real-time. Additionally, ML aids in maintaining renewable energy systems by detecting faults early, which minimises downtime. The overall future of RE sources is brightened by ML's role in building a more reliable, efficient, and sustainable energy system. Hydropower, wind, and solar power all rely significantly on previous weather patterns for their effectiveness, making climatological data from the past essential for their growth. As a common factor affecting the efficiency of renewable energy, weather forecasting is often included first in scenarios including SVM, DT, RF, and regression models.

Renewable energy sources need further research into the fundamental processes that govern system dynamics. One other cutting-edge element that may boost model quality is an extension of sensing techniques for data collection, such as using photos, text, or time series[31]. CNNs [32] and RNNs, which are extensively used in image analysis and NLP, are examples of DNNs that may extract information from these kinds of inputs. One limitation of these models is the massive quantities of data included in the data sets used in these kinds of designs. The computing effort may be reduced, however, by approaches that can gather the needed information, like kernel procedures [18].

A. Applications of Machine Learning in Renewable Energy Systems

ML has transformative potential in renewable energy systems, helping optimise operations, enhance efficiency, and support sustainability efforts. Below are some of the chief realisations of ML in renewable energy systems.

1) Energy Demand Forecasting

Forecasting energy demand is an essential component of business decision-making procedures in the energy sector, as it is essential for predicting prices, generation, and capacity. These forecasts are employed by all industry segments to plan and operate electricity systems and business entities [33][25]. Machine learning predictive models including LSTM, Random Forest, Neural Networks are important to predict the energy demand with high accuracy levels to help the operators of the grid to balance supply and demand of energy. This is important as it holds for integrating RE sources which are largely unpredictable, thus the need to build a stable and more reliable energy system [34].

2) Wind Energy Forecasting

WTs are among the least pollutive power generation solutions, which means wind energy is cleaner. Nevertheless, the economic operations of power systems are greatly affected by the unpredictability and variability of wind energy output, which is induced by different weather conditions[35]. Such problems are combated by machine learning models in that the models are capable of estimating the wind speed and direction and position the turbines correspondingly and also the energy output estimation that will make the utilisation of wind power more effective and dependable.

3) Solar Energy Forecasting

With the population increase, demand for electricity also increases and the greenhouse effect occurs which has pushed human and corporate entities to embrace solar energy. Machine learning techniques are employed to predict solar power generation using historical data, weather patterns, and satellite images. These predictions improve the reliability of solar energy, enabling better planning and integration into the power grid[36].

4) Smart Grids Optimization

Machine learning can enhance the performance of smart grids by optimising the flow of electricity, managing energy storage, and reducing losses in energy transmission. This guarantees the stability of systems that have a significant penetration of renewable energy [37][38]. Smart grid's superior communication infrastructure allows for constant monitoring of system components and data exchange between them, making the system more intelligent and dependable [39].

V. LITERATURE REVIEW

Previous studies primarily employed statistical methods for renewable energy systems. However, these approaches are inadequate for addressing complex and dynamic scenarios, highlighting a necessity for ML and DL solutions.

This paper, Fanglei et al., (2020) to find out how the system's frequency reacts as the percentage of RE sources, like synchronous and renewable power producers, varies. Using data collected during a power outage, this model aggregates the governor system characteristics of several synchronous generators to determine the system's inertia-constant and damping-constant. The model has been verified using a model of the power system. Utilising the comprehensive model, a method is proposed for ascertaining the upper limit of RE penetration within the constraints of frequency stability[40].

This paper, Ahmed et al., (2020) uses both ML and GPR inside the EMM. To begin training the ML-based GPR model, an optimisation model is first built to ascertain the fundamental performance parameters (PES, PEC, and GR). We may say that these metrics represent PES, PEC, and GR. Secondly, to account for the stochasticity of RE sources, load, and energy price, a GPR model is created to predict PES, PEC, and GR. This model shares the same input variables as the optimisation model based on Genetic Algorithm (GA) for PES, PEC, and GR. The variations of PES, PEC, and GR are taken into account to smooth out the seasonal dynamics of prosumers' energy production and consumption[41].

This study, Colak and Ahmed, (2021) provides a concise overview of the energy management processes, control schemes, and capacity sizing methods used in hybrid renewable energy systems. The practical results pertaining to the potential difficulties have been presented in addition to the elaboration and comparison of the current approaches[42].

In this study, Li et al., (2019) examination of the power system's sufficiency and adaptability, including examination of resource characteristics, simulation of production, and reliability study. Analysis of power flow and stability, power quality, connections, and gearbox design are all part of the electrical system design's overall examination of connection mode and stability. Future efforts should prioritise the technical aspects of integration planning and assessment, including modelling, techniques, and evaluation indices[43].

This paper, Alankrita and Srivastava, (2020) examines an use of ML in various renewable energy system domains, such as forecasting (by creating precise models), maximum power point tracking (by providing control that is robust and smooth and not easily perturbed by input noise), and inverters (by supplying high-quality power that is stable regardless of input fluctuations). Even if ML offers several opportunities to handle various problems related to renewable energy systems, whether or not to utilise it as an efficient solution for a particular system relies on a number of criteria[44].

Table 1: Presents the summary of related work based on Renewable energy system

Reference	Area of Focus	Techniques	Key Findings/ Contribution	Future work	Limitations
[40]	Frequency response in renewable energy systems	System modelling with inertia and damping constants	Method to estimate maximum renewable energy penetration considering frequency stability	Study varying renewable energy types and levels	Limited validation with real systems
[41]	Prosumer energy management and grid optimisation	ML, GPR, and GA optimisation	Optimised energy surplus, cost, and grid revenue; predicted seasonal variations.	Expand model with real-world scenarios	Complex model formulation and assumptions
[42]	Hybrid renewable energy systems	Capacity sizing, control strategies	Comprehensive review of existing hybrid systems and challenges	Explore new control strategies and frameworks	Lacks real-world experimental validation
[43]	Power system adequacy and flexibility	Resource analysis, power flow, and stability	Analysed power system adequacy, production simulation, and stability	Develop new integration models with emerging technologies	Limited focus on renewable grid reliability
[44]	Machine learning in renewable energy	ML for forecasting, power tracking, inverter control	Demonstrated ML applications in forecasting and control	Investigate new ML applications in renewable energy	Input data quality and noise limit ML effectiveness

VI. CONCLUSION AND FUTURE WORK

Machine learning has become an indispensable technology in advancing the efficiency, reliability, and sustainability of renewable energy systems. The integration of ML techniques into RE systems enables better forecasting, optimisation of energy storage, and improved energy management. By leveraging data-driven insights, ML algorithms help mitigate the inherent variability and unpredictability of renewable energy sources like wind and solar power. Moreover, machine learning enhances the performance of hybrid energy systems, grid management, and smart grids, making energy systems more flexible and robust. The application of ML models in renewable energy forecasting, demand prediction, and system optimisation holds great promise for advancing sustainable energy practices and reducing carbon emissions. As the demand for clean energy grows, the continued development of ML-based solutions will play a crucial role in creating a more reliable, efficient, and sustainable global energy landscape.

The study's limitations include difficulties in integrating diverse renewable energy sources, managing the variability of energy output (e.g., from solar and wind), and challenges in accurately forecasting energy demand due to data availability and quality. For future work, the authors propose using advanced machine learning techniques, such as deep learning and reinforcement learning, to enhance energy forecasting and hybrid system optimisation. Additionally, integrating real-time data analytics and further exploring AI in energy storage and distribution are suggested avenues for improvement.

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