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Emerging Trends in Renewable Energy: An Application of Machine Learning (ML) Model

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ABSTRACT

Climate change is dominantly caused by greenhouse gas emissions from fossil fuels and this necessitates an urgent shift toward alternative energy sources. Renewable energy sources such as solar, wind, tidal, and geothermal energy offer sustainable alternatives and are often considered replacing fossil fuel in future. While renewable energy systems offer great alternative, their intermittent and variable nature introduces operational challenges, particularly with regard to system reliability and grid integration. One of the most pressing concerns is the unexpected failures that may arise and impose severe burden. This study investigates how machine learning (ML) models can be leveraged as advance research topic to predict system failures in renewable energy infrastructures. Through a structured critical review, this paper examine ML's role in enhancing system reliability, improving predictive maintenance, and optimizing operational performance. The study further identifies emerging trends, and evaluates their potential in large-scale deployment. This work contributes to the advancement of predictive maintenance and positions ML as a potential tool to achieve sustainable development goal 7, a cleaner, reliable, and accessible energy

Keywords: Predictive Maintenance, Renewable Energy, Machine Learning, Failure Prediction, Reliability, Sustainability

INTRODUCTION

The world has been confronting an unprecedented climate crisis and efforts have been discussed years upon years for decades now. The yearly Conference of parties conferences (COP) gives a credence but many researchers and analyst have begun to ask question on 'how far are we from the so called target of bringing global warming to 1.5 °C before crossing critical tipping points'. (Carrington, *2025*), in his work said exactly two years, underscoring the urgency of accelerated actions even five times more than what has been previously done.

Fossil fuel based energy production is and will remain a dominant source of greenhouse gas for years to come and it contribute over 75% of global emissions and approximately 90% of CO_2 emitted into the atmosphere (UN, 2025). Despite renewable energy (RE) current supplying 29% of the global electricity and with increasingly cost-competitive nature of some RE especially solar and wind energy, the migration is not fast enough to meet the Paris agreement targets (Climate Facts, 2025). To meet the Paris agreement targets, we must reduce emission by about 45% by 2030 and reach net zero by 2050 else, we are welcoming the worst climate impact. Recorded climate disasters have surpassed five folds from that of fifty years ago. The Dubai 2024 rainfall disaster speaks more about the impact of climate change and what is yet to come.

Despite the rapid growth of renewable energy (RE), the intermittent nature of wind, tidal, wave, solar, and geothermal systems presents important challenges for reliability of RE energy systems and their integration into the grid. Sudden rise or drops in power generation can overload the grid or cause grid collapse, leading to unplanned maintenance which may in turn cause component failures, increase cost, and disruption of energy supply (Alam et al.,2006). Improving operational resilience and minimizing faults are therefore essential for a stable and clean energy future.

Recent advances in machine learning (ML) are a promising solution for predictive maintenance in renewable energy systems. ML algorithms such as random forest, neural networks, decision trees, federated learning etc. have already excel in anticipating failures in wind turbine, and solar systems. Thus, helping to reduce unplanned maintenance and outage. Additionally, integrating ML into smart grid system enable near real time forecasting and reliability of renewable energy systems (Rashid, et al, 2024).

Statement of the Problem

The world is facing an unprecedented energy crisis, driven by increasing global demand, depleting fossil fuel reserves, and escalating environmental concerns. Renewable energy sources, such as solar, wind, and hydro power, have emerged as promising alternatives to traditional fossil fuels. However, their integration into the existing energy grid poses significant challenges, including intermittency, variability, and uncertainty. The inherent unpredictability of renewable energy sources makes it challenging to ensure a stable and reliable energy supply, leading to grid instability, energy storage issues, and reduced efficiency.

Machine learning (ML) techniques have been increasingly applied to address these challenges, enabling predictive analytics, optimization, and decision-making in renewable energy systems. However, the application of ML models in renewable energy is still in its nascent stages, and several research gaps and challenges need to be addressed. Thus this study is carried out to investigate the emerging trends in renewable energy with a focus on the application of Machine Learning (ML) Model.

Research Objectives

The main aim of this study is to examine the emerging trends in renewable energy with a focus on the application of Machine Learning (ML) Model. Specifically the study addresses four key objectives:

1. Examine the ML models and frameworks that are emerging in renewable energy.
2. Investigate the challenges in applying machine learning models in renewable energy.
3. Assess the innovations and advance research in renewable energy
4. Explore the impact of renewable energy and its role in addressing global challenges.

Research Questions

The following research questions are essential for this study:

1. What are the ML models and frameworks that are emerging in renewable energy?
2. What are the challenges in applying machine learning model in renewable energy?
3. What are the innovations and advance research in renewable energy?
4. What is the impact of renewable energy and its role in addressing global challenges?

Significance of the Study

Over the past decade, the world has realized that renewable holds a great potential to address climate change impact, strengthens energy security and enhance achievement of energy sustainability. This paper contributes to the growing body of knowledge in the quest towards advancing renewable energy technologies by assessing and evaluating the various levels of advancement and sustainability issue inhibiting wide scale deployment of those technologies.

Limitations

While this study aims to provide a robust analysis of ML-based predictive maintenance of renewable energy as an advanced research topic in renewable energy, the following limitations exist:

1. Primary focus is limited to English-language based publications and may omit region-specific studies
2. Much emphasis is on smart grid-connected and sensor-equipped renewable energy installations
3. Project performance metrics may vary due to inconsistent reporting standards and test conditions.
4. ML is a branch of artificial Intelligence that is rapidly evolving and new developments may emerge that are not covered in this study.

Despite these limitations, this research provides a valuable framework for understanding Machine learning based predictive maintenance as an advance research topic in renewable energy. This study will it contributes to ongoing efforts to easily to combat climate change and increase the portion of renewable energy in the global energy mix.

Literature Review

Machine Learning (ML) Models and Frameworks

ML is a subset of AI that is shaping how distributed energy resources (DERs) are integrated into the grid and managed at the grid. At the fore front of the ML models used in this area is the Model-free Reinforcement Learning (RL) and federated multi-agent deep RL (F-MADRL)

1. **Model-free Reinforcement Learning (RL):** The accessibility of microgrid operators to massive microgrid data creates an opportunity to achieve a data driven control. This is where MFRL comes in. It is goal-oriented, data-driven, and model-free characteristics (She, et al, 2023). Model-free reinforcement

learning (MFRL) is a subset of artificial intelligence techniques that enable systems to learn optimal behaviors by directly interacting with their environment and without needing a predefined model of the system dynamics. Unlike model-based methods that rely on known equations or simulations, model-free algorithms learn from experience, adjusting their strategies based on reward feedback over time. MFRL is increasingly applied to optimize control strategies in complex, dynamic, and uncertain settings. Examples of MFRL used in renewable energy include Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Soft Actor-Critic (SAC) (Wang, et al, 2022).

2. Federated Multi-Agent Deep Reinforcement Learning (F-MADRL) Algorithm: It is a framework that merge the concept of federated learning (FL) and multi-agent reinforcement learning (MARL) to train a system of agents while ensuring self-sufficiency and improved communication. In F-MADRL, multiple agents with their own local data are allowed to cooperate and make informed decisions through a central server, but without directly sharing their raw data file. Data Privacy issue and data security is key advantage of F-MADRL(Li, et al, 2024). The two main component of F-MADRL are the participant and the collaborator. The participant being denoted by the Neural network model trains the data and share the parametric experiences with the collaborator periodically. Studies have affirmed that Deep reinforced learning (DRL) is superior at managing flexible demand, spot pricing, and diverse distributed energy resources (DER) control.

3. Federated Learning & Privacy-Preserving AI: Distributed renewable assets often face barriers when we try to adopt machine learning and it often have to do with data privacy concern and data silos. Federated learning (FL) allows local model training while protecting sensitive data and has been of practical use but heterogeneity and bottlenecks in communication persist. On the other hand, Federated multi-agent RL strategies balance local autonomy, collective knowledge, and data security for cross-grid learning.

Emerging Frontier: Multi-Agent and Graph-Based Reinforcement Learning: Several attempts and research work to integrate ML and AI in renewable energy resulted in many challenges and that have paved way for new frontiers. The new research direction are now focusing on:

1. Graph-based RL uses topological and relational data inherent to power networks, to enhance load frequency control under complex conditions.
2. Multi-agent RL (MARL) frameworks enable synchronized decision-making across DER units in smart communities.
3. Fractalgrid concepts propose multilayer self-similar microgrid hierarchies, necessitating multi-agent coordination.

These innovations and research are central to developing resilient, predictive and self-regulating renewable energy systems. The key research directions identified in this study are highlighted in the table below

Table 1: Research directions

Research Topic	Aim
Predictive Maintenance	To achieve earlier failure detection and cost savings via ML/PdM.
Smart Microgrid Control	To enable decentralized, real-time energy management using RL framework.
Explainable AI	To enhances user trust and regulatory compliance in predictive systems.
Federated Learning	To ensures collaborative model training without compromising data privacy.
Graph & Multi-Agent RL	To support complex, nested network behavior and emergent control.

Challenges in Applying Machine Learning Models in Renewable Energy

Machine learning (ML) has been increasingly applied in renewable energy to improve efficiency, predict energy output, and optimize system performance. However, several challenges hinder the widespread adoption of ML models in this field. Some of the key challenges include:

1. Data Quality and Availability: ML models require high-quality, diverse, and extensive datasets, which are often difficult to obtain in renewable energy applications (Zhang et al., 2020).

2. Complexity of Renewable Energy Systems: Renewable energy systems involve complex interactions between multiple components, making it challenging to develop accurate ML models (Wang et al., 2019).
3. Uncertainty and Variability: Renewable energy sources are inherently variable and uncertain, making it difficult to predict energy output and optimize system performance (Kaur et al., 2020).
4. Interpretability and Explainability: ML models can be difficult to interpret and explain, making it challenging to understand the underlying relationships between variables (Rahman et al., 2020).
5. Scalability and Generalizability: ML models may not generalize well to new, unseen data or scale to larger systems (Zhang et al., 2020).
6. Integration with Existing Infrastructure: Integrating ML models with existing renewable energy infrastructure can be challenging (Wang et al., 2019).
7. Cybersecurity: ML models can be vulnerable to cyber-attacks, which can compromise the security of renewable energy systems (Kaur et al., 2020).

Impact of Challenges

These challenges can lead to:

1. Reduced Efficiency: Inaccurate or inefficient ML models can reduce the overall efficiency of renewable energy systems (Zhang et al., 2020).
2. Increased Costs: Developing and implementing ML models can be costly, and the challenges mentioned above can increase these costs (Wang et al., 2019).
3. Decreased Reliability: ML models that are not robust or reliable can decrease the overall reliability of renewable energy systems (Kaur et al., 2020).

Initiatives to Address Challenges

1. Data-Driven Approaches: Developing data-driven approaches to improve data quality and availability (Zhang et al., 2020).
2. Transfer Learning: Using transfer learning to adapt ML models to new, unseen data (Rahman et al., 2020).
3. Explainable AI: Developing explainable AI techniques to improve interpretability and explainability (Rahman et al., 2020).
4. Cybersecurity Measures: Implementing robust cybersecurity measures to protect ML models and renewable energy systems (Kaur et al., 2020).

Innovations and Advance Research in Renewable Energy

The present moment in the energy sector is a pivotal one as the global energy sector is witnessing a transformative shift: a migration from the so called dirty fuel to renewable energy. As renewable resources become crucial in today's energy discussion surrounding the global energy mix, embedding smartness and intelligence into the system, especially through machine learning (ML) and artificial intelligence (AI) is very essential. In this study we explore how emerging research trends in ML-powered innovations is being used in renewable energy especially in predictive maintenance, smart microgrid control.

Machine Learning(ML) **for Predictive Maintenance**

The application of ML-based predictive maintenance (PdM) has gained wide recognition among renewable energy expert especially as it has to do with offering accurate failure forecasts and cost-effective upkeep. The commonly used method of monitoring a system performance is by the set of various activities done by it and this is referred to as Condition Based Monitoring (CBM) or System Health Monitoring (SHM) which is focused on observation of the current operational states of the system but when SHM is coupled with prediction of future failure states, it is termed 'Predictive maintenance or simply Prognostic (Afridi et al, 2021). When ML algorithm is applied to SHM data, it can be used to decide when to carry out the maintenance to reduce unwanted breakdown. In short, SHM is a reactive method or diagnostic approach and prognostic is a proactive approach. In Renewable energy system, where reducing shutdown period is key, prognostic outperform diagnostic systems.

In today's world, many countries are now utilizing a multisource power generation systems that can seamlessly integrate with the distribution and transmission system, Hence the global clamor for smart grid. Predictive maintenance being a key part of smart grid has been a new frontier to many researchers. While several research has been done in this area, the application of machine learning and artificial intelligence in predictive maintenance is a hot cake among researchers and it keeps evolving rapidly.

Deep learning on Supervisory Control and Data Acquisition (SCADA) data

Deep learning on SCADA data has been explored by researchers. In the work of (Gigoni, et al, 2019), predictive maintenance model predicting failures in wind turbine parts was demonstrated by coupling machine learning and statistical process in SCADA data. The result shows that the method was able to predict failures at main bearing, gearbox, and generator up to 1-2 months. Unified ML prognostics reviews also reveal that XGBoost, SVMs, random forests, LSTMs, and CNNs usually achieve higher fault detection accuracy and significantly reduce unplanned outages. Similarly, Remaining Useful Life (RUL) forecasting, employs deep learning, forecasts potential failure well in advance with very low error (She et al, 2023). All these enable data-driven maintenance strategies that optimize component lifespan, operation costs, and energy availability which is pivotal for making renewable energy resilient.

Renewable Energy and Global Challenges

Renewable energy refers to energy derived from source that can be replenished naturally such as solar, wind, hydro, geothermal, and biomass. Renewables have advantage of offering a clean, sustainable, and increasingly affordable energy alternative compared to fossil fuels, which are finite and dangerous to the environment. According to the International Renewable Energy Agency (2024), as of 2022, renewables accounted for nearly 40% of global installed power capacity. Each renewable source operates on distinct principles and these technologies varies in scale and application including smart grid, and off-grid rural electrification.

1. **Solar Energy**: It deals with the conversion of sunlight into electricity via photovoltaic (PV) panels or solar thermal collectors.
2. **Wind energy**: Tide technology utilizes wind turbines to generate mechanical power or electricity
3. **Hydropower**: Generates electricity by capturing kinetic energy from flowing water
4. **Geothermal**: Taps into the Earth's internal heat for heating and electricity
5. **Biomass**: Uses organic materials for heat, electricity, or fuel production

Maintenance and System Failures: Another technical limitations of renewable energy have to do with failure of components and downtime. All components are subjected to degradation over time and result in faults. These components include but not limited to wind turbines, solar inverters, and battery systems. Unexpected failures often result in increased cost, increased downtime and eventually energy loss. Machine learning based predictive maintenance has emerged as frontier and promising solution to anticipate and prevent such unexpected failures ahead of time.

4.Economic and Investment Risks: Although renewable energy costs are increasingly dropping, the initial capital investments (CAPEX) are always very huge, especially for offshore wind, geothermal, large-scale photovoltaic and large-scale storage. As a result, not many individuals can afford it. Most of the large scale renewable energy are often funded by the government or international agency. In regions where there are no strong and good policy frameworks or currency stability, private investment are always very limited.

Role of Renewable Energy in Addressing Global Challenges

Energy security and climate change are interrelated and renewable energy plays a critical role in mitigating these two interrelated global crises. These two interrelated but complex problem are what led to the renewed interest in renewable energy especially solar energy. Many advance research are ongoing on improvement of solar panel efficiencies and even in the area of materials such as perovskite cells. It is widely believed that renewable energy will contest with fossil fuel in the future and can help counter the problem that depleting fossil fuel resources will pose in future and further guarantee energy security.

1. **Climate Change Mitigation**

Burning fossil fuels accounts for 75% of global greenhouse gas emissions, precisely C2O (World Energy Outlook 2022). Renewables, on the other hand emit little to no direct greenhouse gases during operation and hence forms a pivotal mitigation strategy to replace the carbon-intensive power sources in order to achieve the 1.5°C global warming target set under the Paris Agreement.

As reported in (AR6 Synthesis Report, 2023), rapid deployment of renewables combined with electrification, energy efficiency, and carbon capture technology will cut emissions by over 50% by 2030. Technologies like solar PV and onshore wind are already cheaper than new coal or gas plants in many regions and their cost keeps getting economically feasible year on year, thereby, making climate change mitigation efforts through renewable energy an economically viable concept (IRENA, 2024).

2. **Energy Access and Security**

The world is still off the track to achieving SDG 7 by 2030. Over 733 million have no energy access and billions are still cooking with detrimental fuel (The Energy Progress Report ,2022). Considering decentralization and scalability, renewable energy is a great options to reduce energy poverty especially where grid extension is expensive and in island areas.

3. **Need for Advanced Research**

To achieve the trio of climate change mitigation, energy security, and economic growth, one cannot ignore the importance of advance research in overcoming the challenges of renewable energy system. Advanced research is essential in the area of Energy storage, forecasting models to improve solar irradiance and wind speed prediction, enhancing material efficiency and recyclability, digitization and Automation of energy systems. Of the aforementioned, Advanced machine learning-based predictive maintenance is particularly promising because it helps to reduce unplanned downtime, reduce maintenance cost and eventually extend lifespan of the system. For instance, deep learning models trained on real-time turbine sensor data have achieved training accuracy of about 80.23% and test accuracy of 76.01%.(Walker, 2022). Similarly, in solar systems, AI models can identify inverter and panel anomalies with less false alarms (Berghout, et al, 2021).

Summary of the Findings

This study examines the emerging trends and applications of machine learning (ML) models in renewable energy, investigating the challenges, innovations, and impacts of ML in this field.

1. ML Models and Frameworks in Renewable Energy

The study reviews various ML models and frameworks used in renewable energy, including:

- i. Model-free Reinforcement Learning (RL)
- ii. Federated Multi-Agent Deep Reinforcement Learning (F-MADRL) Algorithm
- iii. Federated Learning & Privacy-Preserving AI

2. The study identifies several challenges in applying ML models in renewable energy, including:

- ✓ Data quality and availability
- ✓ Complexity of renewable energy systems
- ✓ Uncertainty and variability of renewable energy sources
- ✓ Interpretability and explainability of ML models
- ✓ Integration with existing infrastructure

3. The study highlights several innovations and advanced research in renewable energy, including:

- ✓ Machine Learning(ML) for Predictive Maintenance
- ✓ Deep learning on Supervisory Control and Data Acquisition (SCADA) data

4. The study discusses the impacts of renewable energy on addressing global challenges, including:

- ✓ Climate Change Mitigation
- ✓ Energy Access and Security
- ✓ Need for Advanced Research

CONCLUSION

The migration to toward renewable energy and the diversification of the global energy mix is a techno-environmental challenge prompting nations to aim at meeting carbon neutrality. As many countries of the world now aim to meet their nationally determined contributions (NDCs), the dire need for deploying clean, reliable and cost-effective renewable energy systems is clearly undeniable. However, these renewable energy systems are inherently complex, multifaceted, often decentralized, and vulnerable to operational inefficiencies due to intermittency, variability, and mechanical wear.

Machine learning models, especially deep learning, reinforcement learning, and federated learning are at the forefront of enabling smarter, predictive and autonomous energy systems. Additionally, a concept called explainable AI (XAI) and privacy-preserving learning mechanisms are now being integrated to ensure trust, and data security concerns.

As with many other advancement and concept, challenges abounds including data quality and availability, complexity of renewable energy systems, uncertainty and variability, interpretability and explainability, scalability and generalizability, integration with existing infrastructure, cybersecurity. Addressing these issues requires sustained advance multidisciplinary research and collaboration across engineering, computer science, energy policy, and industry stakeholders.

RECOMMENDATIONS

Sequel to the findings of this study and current trend, the following recommendations:

- **Investment in Data Infrastructure and Open Datasets:** Data is very crucial in driving renewable energy forward. It is therefore recommended that the participants in the energy sector maintain a standardised publicly labeled datasets especially on wind and solar to accelerate the development of a robust and generalizable machine learning model for renewable energy systems.
- **Hybrid Approaches to Predictive Maintenance:** It is very imperative to be considering ML models that combine physics-based simulations with data-driven techniques to improve model accuracy and generalizability. Similarly, adoption of federated learning framework should be developed and tested in real life for data privacy and predictive maintenance of renewable energy systems.
- **Pilot Multi-Agent Systems and RL in Smart Grids:** Many field trials are required to properly test multi-agent reinforcement learning for distributed energy management in real-world microgrids. This will give researchers opportunity to validate the safety, coordination and scalability of the system. .

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