

The role of artificial intelligence in developing renewable energy

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Abstract:

Artificial Intelligence (AI) plays a crucial role in enhancing the efficiency, reliability, and integration of renewable energy sources. AI helps analyze large datasets from solar panels and wind turbines to optimize performance and predict failures. It improves weather forecasting, enabling better planning for energy generation. Smart grids powered by AI balance supply and demand in real-time, reducing energy waste. AI also enhances energy storage systems by optimizing battery performance and lifespan. Predictive maintenance reduces operational costs and extends equipment life. Additionally, AI enables better integration of multiple energy sources for a stable supply. By improving energy efficiency and reducing costs, AI accelerates the transition toward a more sustainable and intelligent energy future.

Keywords: Artificial Intelligence (AI), Renewable Energy, Energy Efficiency, Smart Grids

Jel Classification Codes : Q42 ; Q47 ; Q55.

Résumé:

L'intelligence artificielle (IA) joue un rôle essentiel dans l'amélioration de l'efficacité, de la fiabilité et de l'intégration des sources d'énergie renouvelable. Elle permet d'analyser de vastes ensembles de données provenant des panneaux solaires et des éoliennes afin d'optimiser leur performance et de prévoir les pannes. L'IA améliore les prévisions météorologiques, facilitant ainsi une meilleure planification de la production d'énergie. Les réseaux intelligents, pilotés par l'IA, équilibrent l'offre et la demande en temps réel, réduisant ainsi le gaspillage énergétique. Elle optimise également le stockage de l'énergie en améliorant la gestion des batteries. La maintenance prédictive diminue les coûts d'exploitation et prolonge la durée de vie des équipements. Enfin, l'IA facilite l'intégration de diverses sources d'énergie pour assurer un approvisionnement stable. En améliorant l'efficacité énergétique et en réduisant les coûts, l'IA accélère la transition vers un avenir énergétique plus durable et intelligent.

Mots clés: Intelligence Artificielle (IA), Énergies Renouvelables, Efficacité Énergétique, Réseaux Intelligents

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I. Introduction

The global transition towards a sustainable energy future necessitates the rapid integration of renewable energy sources (RES) into power systems. As the electricity sector accounts for nearly 40% of global greenhouse gas emissions due to the combustion of fossil fuels, decarbonizing this sector is a central objective in meeting international climate goals. The phasing out of coal-fired power plants and the growing adoption of decentralized, variable energy sources such as solar and wind are reshaping electricity systems worldwide. In this context, smart grids—equipped with advanced sensors, two-way communication technologies, energy storage, and real-time control systems—are emerging as indispensable tools for managing the complexities of modern low-carbon energy systems.

Amid this transformation, artificial intelligence (AI), and more specifically machine learning (ML), has emerged as a key enabler of smarter, more efficient, and adaptive power systems. Over the past two decades, advances in data availability and computational capabilities have expanded the potential of ML to address multiple technical and economic challenges within the power sector. Applications of AI range from forecasting electricity demand and renewable output to grid optimization, fault detection, dynamic pricing, and predictive maintenance. These developments not only enhance grid performance and stability but also support broader policy goals of energy security, climate mitigation, and sustainable development.

I. 1. Research Problem

Despite the growing interest in AI applications in the energy sector, there remains a limited understanding of how AI can be systematically leveraged to accelerate the deployment and integration of renewable energy technologies. Key challenges include the fragmentation of existing research, lack of standardized data, limited deployment in developing regions, and under-exploration of the socio-technical dimensions of AI in energy transitions.

I. 2. Research Objectives

This paper aims to:

Examine the current and potential applications of AI, particularly ML, in enhancing the deployment and operation of renewable energy systems.

Identify the key technical, economic, and policy challenges hindering AI

integration in smart grids.

Analyze real-world case studies to assess the practical impacts of AI on renewable energy performance.

Provide recommendations for policymakers and stakeholders on harnessing AI to support energy transitions, especially in emerging economies.

I. 3. Significance of the Study

Understanding the intersection between AI and renewable energy is essential for developing intelligent infrastructure that is capable of responding to the dynamic nature of modern power systems. This study contributes to bridging the knowledge gap between the technological potential of AI and its practical application in advancing renewable energy strategies, especially within contexts of limited resources and infrastructure.

I. 4. Methodology

The research adopts a qualitative and exploratory approach, relying on a critical review of recent literature, technical reports, and empirical case studies from various regions. The study draws upon interdisciplinary sources, including energy systems engineering, computer science, and energy economics. Key themes are synthesized and analyzed to identify common patterns, innovation pathways, and implementation barriers.

Structure of the Paper

II. Overview of Renewable Energy Sources

Renewable energy resources are those sources that could replenish automatically and could not be exhausted by utilization. Usage of natural energy such as sunlight, wind, tide, and biomass will be highly increased in the future as fossil energy consumption will decline. Renewable energy has been focused as an alternate energy source because it is a carbon-free energy source and also it is an inexhaustible energy source from nature. Also, the use of renewable energy sources can reduce electricity cost and greenhouse gas emissions. Many countries have established various policies or standards to promote the use of renewable energy (Vahabi Khah et al., 2023). Under the policy or standard for renewable energy use; the long-term development of renewable energy sources and CO₂

emission reduction can be realized. In USA and Europe, the policy was enforced regarding the renewable portfolio standard and greenhouse gas emission reduction, respectively, in this operation scheme one party dealing with renewable energy sources sell 'Renewable Energy Certificates (REC)' to electric power sellers and the other party fulfill their target using REC. Globally, countries look to renewable energy as a means of combating climate change, energy security and independence, and creating jobs and industry (Amimul Ehsan, 2021). The ultimate goal is to reduce greenhouse gas emissions to acceptable levels, which will be largely contingent on what happens in the electricity sector, and more specifically with renewable energy. Although renewable energy technology is reaching maturity, it is not yet a proven technology on a large-scale, thus making it a risky investment.

II.1. Solar Energy

Solar energy is the most promising energy source. Solar energy is a renewable and inexhaustible energy resource, eco-friendly, abundant, and free of charge. Photovoltaic power is generated by the way that solar energy is converted to electrical power via a semiconductor. At present, the most commonly used materials for photovoltaic power generation are crystalline silicon panels because the high efficiency and long-term stability has been verified. In the grid-tied system, solar power connected with the home, commercial building, and power grid. Inverter controller's role is to maintain the DC bus voltage at a constant level when connected to the solar power generator and the power grid. During the PV system, if transmitting too much power causes uncontrolled power flow, it might spoil the generating power that might cause grid power problem; in order to avoid this kind of problem, renewables have to follow guidelines like IEEE 1547, UL 1741 and other guidelines. Rooftop solar PV power generation systems are becoming increasingly popular in developed and developing countries. Considering the growth trend of renewable energies and smart systems in the world, as well as policies to use renewable energy sources and reduce energy consumption, the adoption of these resources and smart systems will increase in coming years.

Nowadays, the importance of using renewable energies is risen. In particular, to cope with the phenomenon of climate change, many governments have set high targets for the enhancement of utilizing renewable energy sources for electricity production. One of the methods for utilizing renewable energy sources in smart homes is to install photovoltaic systems on buildings. The cost of unused electrical energy produced by the photovoltaic array is regrettable because it is a kind of pollution and a considerable waste of energy. Energy storage systems, including electric batteries, are used broadly for the absorption of unused

electrical power. The evaluation of the most efficient DC-DC boost converters for charging the battery of a photovoltaic system in experimental analysis will be presented. The evaluation includes the control system, so an evaluation model will represent the converter together with the control system. An evaluation of the critical types of boost converters is made in terms of efficiency, number of components, and stability. Boost converters are generally used in power grids for changing energy into required forms of energy. These types are preferred because they function in the continuous conduction mode and their electromagnetic interference is minor. The experimental tests are conducted to observe the output performance of the complete system with different converters in terms of energy and power. Additionally, energy is seen in rupees to improve the expense of energy. Taking into account all three observables, the best system regarding cost, and other power savings can be defined. An adaptive Multi-Agent System approach was used to control cooling equipment for regular commercial Si-based PV arrays situated in temperate and tropical climates. The platform consists of Smart Agents and an Intelligent Telemetry. Smart Agents supply the sensory data and generate the control commands, while the Intelligent Telemetry functions as the learning mechanism. A detailed methodology for predicting soiling events and automatically generating an optimal cleaning cycle was employed. The efficiency of the AI-based cleaning control software was experimentally validated using diverse PV arrays. It was demonstrated that the proposed techniques improve the efficiency of the air-cooling/cleaning equipment fitted to the PV arrays.

II.2 Wind Energy

A renewable energy source created through the extraction of kinetic energy from the wind. This is one of the oldest forms of energy conversion and is an incredible energy resource. Wind technology has come a long way over the years with numerous companies utilizing this resource to produce clean, renewable and sustainable energy. In 2021 wind energy accounts for just over 2.2% of the world's electricity resources and it is growing at an annual rate of 15%. As of 2018 the total world capacity was just over 612GW.

Wind energy is primarily produced in one of three ways. The first is through taking advantage of the high winds that are present at high altitudes. This is done by utilizing large wind turbines that are fixed in the ground. The second method (fixed to the ground) is through “farming” the wind by placing thousands of units in a strategically laid out grid pattern. Finally there are “off shore” wind farms. These units are floated out into the ocean, fixed to the bedrock and connected to the grid through under water cables. This is a very limited source due to cost but is seen as one of the next “big” develops in wind energy. It is estimated that just

off the United States cost there are potentials of another 4 trill (1,000,000,000,000) watts available. Wind power offers the potential to provide a large amount of electrical power which is non-polluting and without environmental morbidity like fossil fuels (Amimul Ehsan, 2021). Appear to be prospective sources of energy in the future. Some of the most attractive sites worldwide for the development of wind farms are often in complex terrain: locations near mountains or hills or within cities. These areas bring all kinds of variations in the wind flow conditions, which turn the development of an efficient and reliable wind farm technology difficult.

Statistical analysis of wind speed has also been a popular research field for practitioners, as this type of data is often subject to environmental, economic and social considerations. In renewable energy research and industry, wind speed is readily collected and considered in wind power prediction studies. A number of benchmark papers on the prediction of wind speed have thus been published. Wind is an efficient source of renewable energy; it is an abundant, free, and clean source of power, especially for high-density wind regions and areas near to oceans. In recent years, the global market for wind energy has gained more importance due to its potential for alleviation of environmental pollution and energy dependency. In the power sector, the utilization of energy sources is crucial for the growth and development of a country. With the global concern about climate change, energy crisis, and increasing cost of energy, wind energy is at the focus of renewable energy researchers. It not only helps in the reduction of greenhouse gas emissions, but also provides an economically attractive solution for new energy markets. Since the deregulation of power sectors, the integration of renewable energy is also technically feasible and environmentally beneficial. For meeting the increasing demand and reducing power failures, some studies proposed hybrid energy systems, or a combination of wind, solar and biomass energy, would play an important role in future times.

II.3. Hydropower

Hydropower has been the largest source of renewable electricity generation for years. Residential energy supply directly dependents on the environmental conditions that drive domestic water heating. The electric and thermal energy supply of the residential sector accounts for a significant portion of total energy consumption. An intelligent solution adopting deep reinforcement learning for managing a residential energy hub is proposed. The model of a double-sided water heating energy hub interconnected with energy systems for electricity and hot storage is described. The model consists of a residential unit, an electric energy system, and a thermal energy system based on water tanks. The residential sector receives the energy demands for heating and heating water and

the hourly demand of each week for electric and heating water. The interaction with the aggregated energy systems of electricity and water heating is via heat pumps controlled according to the proposed policy. The aggregated electricity prices combine the real-time prices and the optimized smart tariffs. Electricity prices have a reduced variation making tariff-dependent day-ahead decisions suboptimal. A second price model evaluates the learned policy on a different distribution of electricity prices. A more complex set of experiments evaluates the robustness of the policy when the energy demand and prices are forecasted. A well-trained Q-network yields a coordination policy for managing the energy hub that is capable of tracking optimal thermal comfort and minimizing cost and energy use. Efficient savings at cost in a variable energy context are unique contributions among similar works (Kougias et al., 2019). Regarding energy systems, the electric sector is expected to be endowed with advanced meters shortly. Utilities are then able to calculate real-time prices based on the electricity markets and the network state. An intelligent controller can, in turn, compute optimal operation schedules considering electricity prices and the network constraints. Similarly, heating water storage allows households and building managers to store thermal energy during lower prices for on-the-clock heating or household use.

II.4. Biomass

In recent years, we have seen the growth of this sector and its subsequent depletion; in this context, the use of food crops to produce energy has been questioned. A number of advantages of bioenergy use are highlighted, mainly related to its environmental aspect, such as its low or zero carbon emissions, when compared to other energy sources. Another important aspect of biomass is its potential for energy production and the promising results of bioenergy. With a favorable view of current bioenergy relations with agriculture, forestry, and other land uses, it can be seen that biomass must be further exploited to take advantage of its various applications. In this sense, the potential of agro-industrial waste to generate energy, compost and biofertilizer in central Portugal was assessed, an area characterized in the agricultural, livestock, forestry and industrial sectors. It is also analyzed, with the help of artificial intelligence and geographic information systems, the energetics of forest biomass in central Portugal and the relation between plantation area and the georeferenced energetic potential of feedstocks and of the largest industries transforming raw wood into products. A spatial modeling developed geographically explicit econometric model that allows for the conjunction of information from different data sources, specifically territorial records containing the location of economic phenomena. Finally, the implications for several public policies are discussed (João Pereira Domingues

Martinho & Nonato Rodrigues, 2024).

II.5. Geothermal Energy

Artificial intelligence (AI) is a developing technology in business and industry. In the energy sector, research has shown that companies that have increased their AI investments have gained substantial success. Research has indicated that if AI could be fully used in the energy sector, there would be savings by 2030. AI is the outcome of efforts to train machines to contemplate, learn, and take action in such a way that they appear logical rather than merely programmed. AI technologies are increasing globally in the fields of aerospace, automotive sectors, electronics manufacturing, food industry, mining, and medical work. To elapse an energy transition to clean power sources and renewable energy technologies, the use of new technologies in the sector is necessary. It is anticipated that there will be considerable growth in renewable energy reliance in future years as return speeds up, costs fall, and nations try to accomplish their commitments in the green world. Among the burgeoning technologies, it is believed that AI ranks first in the level of impact on the sector. One industry that has gained from the synergy of renewable energy and AI is geothermal borehead heat pumps. Geothermal borehead heat pumps produce five times more energy for each unit of electricity used.

In parallel to the growth of global energy consumption, the need for cleaner and more environmentally sustainable power production has driven the emergence of alternative and renewable power sources. Geothermal energy, which is consistent and dependent on weather, has become an important component in the country's goal for at least 50% of its electricity from clean energy by 2030. Geothermal energy is produced using one synthesis process through hot water and steam pumped from the surface of the Earth. Discovery of geothermal energy requires prospecting field surveys to identify potential locations, including the existence of geothermal systems below the Earth's crust as possible sources of renewable energy. Machine learning pioneering in the advancement of processing power and increased algorithms enables researchers to use large-scale datasets for the analysis of environmental patterns. The employment of AI and machine learning methods to advance renewable energy resources is anticipated to play a large role in geothermal energy exploration.

III. Artificial Intelligence

The definition that describes artificial intelligence best is "an interdisciplinary science which aims to design and build intelligent machines that can learn from experience, do impossible things and work as efficiently as possible". Note that you need a robust interdisciplinarity to computer science, including statistics,

mathematics, computer engineering, cognitive science, psychology, linguistics and philosophy. The most advanced field of AI is deep learning, which involves designing neural networks of an uncommon large size – this is partly the reason why most start-ups running experiments with AI are also using significant amounts of GPUs. Readers eager to discover easy-to-use algorithm, which can still be remarkably powerful, may have a closer look at decision trees and a class of algorithms called XGBoost . Meanwhile, Google, Microsoft and others are definitely not missing the opportunity of AI. Google evaluations have shown that they could be reducing the energy consumption of Google Search by at least 15% given powerful AI supporting both the software analysis and the hardware-dedicated team. Some other cases are mentioned: Google has saved 40% of its energy consumption thanks to very basic AI analysis of the times of day when people do energy-consuming searches; Huawei servers have recently gained 15% in energy efficiency thanks to AI models generated with XGBoost techniques, which made it trivial to identify and address all the main features with a significant role in the increased energy consumption; 20% of the servers on Azure servers are regularly undergoing their own XGBoost analysis that has overall saved 45% of their energy consumption. Microsoft has also developed, along with Vattenfall Labs, a smart grid management solution mainly based on XGBoost. In a pilot phase near Stockholm, the solution performed excellently on both mock and real data, and will soon be globally rolled out to optimize the production of renewable energy based on the actual demand. Furthermore, on the territory of a smart city like Paris, the global application of AI technologies in apartments through automation systems, neighborhood-wide building management systems and city-wide demand response programs is soon expected to play a major role both in increasing the energy efficiency of the city itself and in promoting a new kind of urban landscape that will be more and more sought after in the next future. As a last example, in 2020 the French government agencies in charge of the HPEB certification started using an XGBoost model that is prioritizing the energy renovation of the national public buildings with stunning results, as about €5 billion were invested in 2021 in a plan that made it possible to close at once around half of the circa 24,000 buildings labelled G or F, therefore enabling them to comply with the least stringent of the four energy classes recognized by the certification and qualifying as class E.

IV. AI Technologies in Renewable Energy

Following the discovery of inexpensive, reliable solar photovoltaic (PV) and wind power, the future of renewable electricity generation has become a reality. As the percentage of renewable electricity in a generation mix rises, so does the need to develop a concept that is agile, reliable and can accommodate unforeseen

changes in renewable energy distributions. Three common ways of dealing with variability include using (1) backup generators or direct-load control, (2) large-scale energy storage facilities and (3) demand-side management. Artificial Intelligence (AI) has been manipulated to comprehend, learn and anticipate this third method and since IoT devices have been deployed in the developed world for decades, a data-rich environment allowing AI to be utilized more efficiently has been in place (Robu et al., 2019). Research and trials into AI despatchable load control include the use of modern ontological reasoning techniques combined with reinforcement learning algorithms and the analysis of data obtained from the time-series forecasts of demand and renewable generation to predict, set and optimize responsive electricity usage within smart household devices. Over the past two years, residential batteries have been quantified and the latest market research and experimentation has been concentrated on local battery ownership. A modelling mechanism has been developed, applying actor-critic algorithms and reinforcement learning to real-time, several home batteries within the same community. This guarantees varying prices of electricity from one place to another in local, P2P networks create home batteries with the capacity to charge or spend power to respond to their own neighbour's requests and so minimize costs or optimize profits.

IV.1. Machine Learning

1. It is the premise of the machine learning approach in which the historical load data is selected as a training dataset. The historical data can be used to create a network structure, followed by the use of a training algorithm to refine the performance. Machine learning has been influential in energy systems and its influence is vast. The influence spans different dimensions, with attention toward solar energy and wind power, with salient attention in electric distribution and storage networks. The development in wind power production means that the prediction has continued to grow with many models proposed (Mohammadi & Mohammadi, 2023). Some other renewable energy sources have also grown in strength since the development in other sectors such as solar and marine energy. The accuracy in the prediction of solar power generation becomes more consequential for improving energy quality and reliability. Furthermore, the development in technologies like solar panels has initiated a vast deployment, with the result that there is an increase in the construction of solar power plants. In the standard model, ML techniques like Deep Neural Networks, Support Vector Machines, and Random Forest models have proven their worth for improving the accuracy of solar irradiance prediction. The models can capture the nonlinear relationships present in the input data and when properly propagated in the learning process can yield enhanced forecasting performance.

However, it should be noted that such an approach is doomed to fail without sufficient training datasets and the magnitude of this requirement increases with the forecast lead time. Besides that, the training dataset should also be broad enough to cover all possible situations, given that the input data are sampled from multiple sensors that monitor the degree covered by the Sun.

2. Since the ML models have the capability to approximate any function, it is possible to apply them efficiently for monitoring the performance of a solar energy system collected by many electric components. In practical engineering, ML models can be utilized for prognostic maintenance or can act as controllers for maintaining optimal system state. In actual installations, this means that the values computed in real time from the monitoring equipment can be forwarded to an ML model and the latter will use the information to predict the diagnosed status of components or will execute a command to maintain optimal performance. However, it should be stressed that the performance of these models can be significantly influenced by measurement errors, since low-quality data can lead to the underestimation of the occurrence of components' status issues. To protect the accuracy of damage assessment and prolong the lifespan, there is a demand for models that will perform the analysis with high precision and are capable of detecting the occurrence of a failure in advance. Attributed to the developing interest in the most mature renewable energy source, substantial research began to study the machine learning methods for SESs. In the first years, the studies specifically focused on predicting power generation, forecasting the output of the entire system or the loss of the generator, and taking into account such input data as climate statistics or panel temperatures, among others.

IV.2. Neural Networks

Renewable energy sources include a range of technologies such as wind, solar, hydro, geothermal, and marine are being exploited to provide an increasing share of the global energy demand. With the significant variability and uncertainty, integrating renewable energy sources into the national grid is fraught with a number of challenges due to the real-time constraints of electricity. Artificial Intelligence is a rapidly growing field in the last century that has shown enormous potential for its application in all areas of research, including electrical engineering. With a view to the fact, a novel approach is developed based on machine learning in the form of Neural Networks for predicting energy accumulation and development. This method facilitates to control the energy sources effectively as per the timeframe stipulated by the power utilities.

Artificial Intelligence technologies like Neural Networks have found more importance in the area of power systems applications, and their scope is increasing day by day. In this context, extensive experiments are conducted with

Neural Networks to predict the energy development and accumulation, and the behavior of the energy sources processes, which are very difficult to model, as the interconnected power system include a complex mixture of linear and nonlinear components.

Intelligent electric networks include a network of sensors, actuators, computers, and relevant control algorithms, and further analysis, scheduling, optimization, and control are executed to ensure real-time power balance and security. Artificial Intelligence (AI) technologies are deemed as promising candidates for the research and development of the active network principles. In this survey, the attention is given to the AI model of smart grid to develop a comprehensive understanding. Artificial Intelligence and power systems are inextricably linked. With the advent of deregulation, and advances in AI technologies, such as Neural Networks (NN), Fuzzy Logic Systems (FLS), Bayesian networks, etc. attained a greater importance. AI technology plays a vital role in many aspects of the Smart Grid (Balderramo Velez et al., 2017).

IV. 3. Data Analytics

The evolution of the Energy Internet presents the opportunity for the electrical grid to transition into a more flexible, efficient, and sustainable power system architecture, accentuated by a greater deployment of renewable-energy sources, energy storage systems, and demand-side management initiatives. However, the rise of distributed solutions poses new challenges for the optimal coordination and operation of the Energy Internet. Machine learning based on distributed communication can play a key role in addressing the pressing issues in this regard. On the modeling front, Distributed Energy Resource can be represented as an agent, with multi-level identification depending on the dimension and functionality of the devices. Mechanical learning models can approximate the objectives and constraints of DER units and effectively balance the network model. In terms of the computational framework, the alternating direction method of multiplier approach is utilized to separately solve the intractable hierarchical and non-convex planning problem in a decentralized fashion. Thus, the solutions are obtained in a cooperative manner through the developed communication architecture, allowing an iterative hedging algorithm for local agents to achieve efficient and consensus-based strategies.

There are many advantages of wind and solar generation, most notably the environmental benefits resulting from greenhouse gas reduction. However, wind and solar generation are intermittent sources of energy. Therefore, predicting the output of wind and solar generation is critical to perform large scale integration into power systems. This research uses machine learning methodologies for the renewable-energy predictions. Several pre-processing techniques are applied in

renewable-energy predictions, and the final results are compared in terms of RMSE. Summarizing the results of the study, decomposition and discretization are the most consistently effective pre-processing approaches. However, the effectiveness of various pre-processing techniques may vary depending on the employed machine learning model. As well, different pre-processing techniques can be useful in combination.

IV. 4. Predictive Modeling

The renewable energy sector is rapidly evolving, with emerging technologies and solutions intended to increase efficiency and harness more renewable energy sources. In-midst of this evolving landscape, the industrial community has shown particular interest in knowing up-front the expected performance of such distributed solutions. One of the most evident drivers to foster this kind of forecast is cost optimization. Governments and EU bodies are pushing new incentive schemes forcing to reward the behavioral value of the investment, rather than the mere real-world performance. An interesting example is the so-called “Efficiency Driving Profile” enunciated by the regulation in Italy, that requires prosumers to properly forecast in advance their generation & consumption capability. The electric grid is not designed to equally sustain both ways of power flow. Particularly, despite distributed plants having low power, they exhibit unclear power flow controllability that can congest the grid (Mohammadi & Mohammadi, 2023). In this scenario, state-of-the-art grid optimization modules offer point-to-point controllability indication, that means the capability to forecast the expected future power flow from a single point to one (or few) others. Unfortunately, due to the highly stochastic nature of the location where the controllability point could not be physically placed, this kind of strategy shows poor effectiveness. Conversely, new forecasting techniques able to provide always and nearest forecasts in offer good collective energy, could allow for positive side effects on the grid controllability optimization. Hereby a novel branched approach is enunciated able both to properly forecast the distributed resources (local profile trying to emulate the single consumer/search for the grid controllability optimization), and that takes into account the network structure and topology (both physical and just geographical). The developed model support can sense off-line (optimization-based) and/or on-the-fly (market local scan for incentive retail off-grid exchange). The inherent stochastic nature in determined processes based on underlying machine-learning techniques offers also valued hedges in a way of intense model diversification in the market of incoherent dispatch of prediction resultants.

V. Applications of AI in Renewable Energy

As the pivotal role of renewable energy sources in mitigating the adverse environmental effects of fossil fuels becomes more apparent, considerable research on their enhancement is currently ongoing. Nevertheless, the temporal variability and uncertainty of renewable energy sources, together with the inclination toward distributed sources, amplify the complexities of the power system operation and planning. In this convention, a variety of AI enabled solutions have been proposed regarding their applications in integrating renewable energy source in power systems. Artificial intelligence (AI) motivated solutions for forecasting renewable energy power output are classified in the first place, including applications of AI in wind, solar, hydro, and ocean energies. AI techniques for optimizing renewable energy power performance as an additional perspective to bolster integration are also elaborated here in. With the lapse of time, an enormous body of literature is dedicated to AI applications in the renewable energy section and adjustable speed in MPPT technologies. For that matter, this chapter is confined to the contemporary and advanced machine learning (ML) and AI applications in renewable energy systems with particular emphasis on grid-connected applications. Machine learning techniques focus on creating models that can learn to make data-driven predictions or decisions with a minimum of human intervention. There are plentiful ML techniques such as regressive and classification types as well as Probabilistic Models, Expectation-Maximization algorithm, and Hidden Markov Models.

Neural networks are one of the profoundly helpful artificial intelligence models utilized for solving a broad variety of forecasting problems in renewable energy. Because of the non-linear nature of the problem, traditional means like regressive models, possess limitations for forecasting processes. As an alternative, artificial intelligence (AI) techniques have been employed and found to be more promising over the past few years. Machine learning (ML) as an integral part of AI, is among the useful techniques that can enhance intelligent maintenance in renewable energy. Consequently, considering the volatile nature of natural resources, an analogous problem to explore is the depletion prognosis of resources, particularly renewable energy ones.

. Forecasting Renewable Energy The impact of machine learning (ML) on energy systems is burgeoning across various axes, encompassing renewable energy systems, electric grids, and residential usage. In this Convention, the deposition is on the influence of ML on solar energy, wind power, electric distribution, and storage. In the renewable energy sector, attention is largely on developments in solar energy and marine energies. Amongst renewable energy technologies, solar and wind are the predominant sources drawing attention (Mohammadi &

Mohammadi, 2023). In this regard, the standard practice currently entails the learning of ML methods in the form of regression models using historical data.

As the global deployment of wind power amplifies, so does the research attention in this realm. Notably, there is a surge in the creation of wind power production (WPP) models. The growth of WPP prediction models has been exponential. Over the precedent 15 years, the production of around 190 prediction models has come forth, with the annual production rate on the up. Both the non-ML and ML based WPP prediction models have reported errors of between ten to twenty percent. To peruse the literature over the past five years, a succinct history of the development of ML based WPP models from 2015 to 2021 is deliberated. Sizable attention is paid to the use of data augmentation techniques in the production of the input dataset for models. Current and prospective viewpoints are highlighted at the cessation of each section. Fostering future research in the creation of comprehensive summaries of both ML ensembles and non-ML WPP prediction models can be paramount to the dissemination of solutions for the broader community of researchers and practitioners.

Solar Power Prediction Solar energy is one of the prominent renewable energy resources which is deployed repetitively due to its abundance and ubiquity. The integration of solar energy into the energy system is on the rise, making accurate solar power generation prediction paramount for the day-ahead energy schedule. To improve the solar power prediction, machine learning (ML) models of support vector machines (SVM) and long short-term memory neural networks (LSTM) are trained on battery-less solar power data with different settings in terms of the on-board computational power for 12, 24, 48, and 72 hours-ahead predictions. The introduction of LSTM-based ensemble models for a novel binary-coded solar ensemble model with limited computational power is realized.

To code the environment state of the solar energy system like humidity, temperature, and solar irradiance in binary format, both support vector machine (SVM) regression and random forest (RF) ensemble models are optimized with the binary-coded data. Screen-based optimization for data representation improvement is carried out. A validation provides guidelines and perspective on the development of a practical, sustainable and optimized battery-less solar power management system.

V.1. Energy Forecasting

Electricity generated from renewable energy sources has been established as an efficient remedy for both energy shortages and the environmental pollution stemming from conventional energy production methods. Among the wide range of renewable energy sources, energy generated from Solar Photovoltaics (PV)

and Wind Turbines (WT) is most prevalent and has been extensively adopted all around the globe. PV and WT energy reconstruction into electricity is currently highly efficient due to the recent technology advancements on semiconductor materials and aerodynamic blade design, respectively. The accurate forecasting of the energy generation of solar and wind power facilitates their integration into electric grids.

Renewable energy generators have appeared at great rates, enabling a remarkable alteration of national electric systems. The Electricity Market relies on energy balancing between energy demand and energy production. The imbalance between the operating electricity production units and electricity consumption leads to the necessity of employing more powerful units, which are normally based on traditional energy sources having potential environmental impacts. In this respect, renewable energy sources constitute a feasible solution as they do not emit carbon dioxide and do not have so much environmental sunlight effect. However, in order to assure the reliability and continuity of the electricity supply, renewable energy sources have, as well, to provide predictable electricity generation (Symeonidis & Nikolaidis, 2024).

On this context, the accurate forecasting of the energy generation of renewable energy sources is mission-critical for facilitating their smooth integration into electric grids and maintain the system stability and resiliency. Moreover, the aforementioned task is designated to be extremely difficult because of the uncertainty and high variability of solar or wind power generation due to weather conditions and numerous external environmental and anthropocentric factors. As a consequence, scientists and experts in the energy domain have spent a significant effort on conceiving time-series forecasting techniques. Powered by recent advancements in Artificial Intelligence (AI), a considerable amount of methodologies have been proposed to resolve the forecasting task of renewable energy. The list of methodologies encompasses state-of-the-art models either in the time-domain, e.g. ARIMA, Exponential Smoothing, and Long Short-Term Memory (LSTM), or in the space-time domain regarding the spatialization of solar and wind power forecasting. On the renewable energy forecasting realm, thus far and to the best of our knowledge, existing methodologies focus on the uni-site scenario. However, the actual energy providers deploy energy units in far-apart locations. Technically, each of these energy units monitors distinct weather related signals. In such a state-of-play, single-site time-series information proves inadequate to be exploited.

V.2. Smart Grids

Recently, maximum efforts have been made in reshaping the electricity industry adopting the Open Market rules in order to fulfill the increasing quality and

security requirements. As a consequence of these transformations new problems are arising, which can hardly be faced with the conventional electric power systems configuration. In this framework, Artificial Intelligence (AI) concepts can be clearly helpful in order to support the complex and time-varying decisions that must be taken by the power system operators (A. Dimitrijević et al., 2014). Today, the increasing scale, complexity and interdependency of energy systems require intelligent control and planning philosophies. Large parts of power systems are already automated, but new concepts, components, and assets require a higher level of intelligence to operate in an optimal and secure manner. At the same time, the generation is more exposed to competition due to the new landscape of distributed generation driven by renewable sources, and the demand is becoming active itself able to adjust its constitution and amount (Strasser et al., 2015). In the most general scope, energy systems imply the intelligent integration of the electrical power system (EPS) with other energy carriers, most notably heat and gas. Additionally, a smart grid cannot leave out of consideration the intelligent integration of all users, which can be either prosumers or purely consumers.

V. 3. Demand Response Management

On one hand, by 2016 the investment of renewable energy had reached a value of \$238.9 billion throughout the world, and within this investment, the Chinese were the largest followed by India, the United States, Brazil, and France. On the other hand, the growing energy demand in urban areas and the excessive energy consumption, leads to the need for energy saving and higher efficiency, which has involved the communication with energy suppliers and grid optimization. Considerable research has started in both secondary energy processes, to reduce emissions and save energy, and the rational energy consumption, for load side. Consequently, the issues smart grid (SG) and demand side energy management became the focus.

Integration of the smart grid technology into the bulk power system provides the opportunity for two-way communication between the utility company and end-users through Demand Response Management (DRM). However, different techniques are required to act as a bridge between the consumer and the utility for controlling the load demand during peak hours. This research presents an Incentive-based Demand Response Optimization (IDRO) modeling for households considering energy price and usage priority of household appliances. The proposed method is a multi-objective optimization technique based on Nonlinear Auto-Regressive Neural Network (NAR-NN) to minimize and respond the consumer costs, appliance waiting time and deviation of scheduled and actual appliance encoding time. Connection of utility and rooftop installed Photovoltaic

system of the household with DRM is considered by IDC feeder model. Finally, the proposed optimization is demonstrated on a test household to evaluate the efficiency of the model (Mohammadi Rouzbahani et al., 2019).

V. 4. Maintenance and Monitoring

Proper maintenance and monitoring of renewable energy systems ensure their prolonged operation and efficiency. Poor maintenance can lead to component failure, which ultimately results in reduced system performance. By using predictive and/or prognostic maintenance techniques, preventive measures can be taken to avoid unexpected system failures beforehand (Saleem Afridi et al., 2021). The integration of AI with renewable energy systems can effectively predict the future health condition of system components. Sensor warehouses are employed to collect and analyze real-time data, which are then employed to evaluate the system's health status. Based on this evaluation, an optimum time-based maintenance schedule is designed to prevent system failure. Simultaneously, prognostic techniques predict the remaining useful life of a component and automatically schedule its maintenance before it turns faulty. Subsystems of renewable energy systems, i.e. PV modules, wind turbines, etc., have specific issues and challenges that researchers have tried to address. Similarly, the integration of AIs with renewable energy systems is still in its inception phases, calling for increasingly powerful techniques to prolong renewable energy systems' operation and stability. A variety of parameters such as temperature, current, voltage, and irradiance significantly affect the performance of solar panels. To ensure prolonged operation of solar panels, a PV health-monitoring system is introduced with the help of data reading and processing. The collected readings are then analyzed to determine the incidence of under-performing solar panels. To differentiate healthy from faulty solar panels, a K-Nearest Neighbors regression technique is used. The proposed system has analyzed and monitored solar panels' health in real-time and efficiently.

VI. Benefits of Integrating AI with Renewable Energy

VI.1. Efficiency Improvements

Advances in technology continue to take work further into future applications and areas unchanged for a long time, shaping the future. Energy is important for every need of humanity, and attention has been paid to the exhaustion of fossil resources in recent years. Studies and developments are carried out within the scope of renewable energy technologies. More efficient renewable energy systems are developing and being invested on. In addition to renewable energy systems, studies are carried out on technology and systems that are compatible with each other and are constantly advancing. Advanced energy systems have

been installed on the line that can follow global changes in technology, and have the potential to reduce energy costs. It will establish a system with artificial intelligence-enhanced renewable energy systems that are thought to be ready to accept significant changes in future energy systems and that will provide significant cost savings in the energy fields of these systems (Yao et al., 2023). With the advanced management systems that will be developed, the system plants are expected to be fully automated and intervened at the minimum level. It will have the capabilities to automatically control a wide range of electronic devices and systems. The study will be in the field of advanced energy systems consisting of renewable energy technologies and modern energy management systems to be developed. The working logic of the proposed smart management system will be prepared according to the structure of the used system plant and the programs will be written. It aims to create an advanced control system that can adjust electrical energy consumption according to user need. Smart artificial intelligence controller systems will be developed to ensure the coordinated operation of systems and to maximize efficiency. Improvements and innovations are carried out in the energy transmission and consumption systems in smart buildings. Necessary electronic cards are found, prepared and the software program that will perform the calibration between these electronic cards is prepared (Vahabi Khah et al., 2023). Energy costs are expected to be reduced by 10% by adopting a more efficient power factor circuit. Productivity increase in energy consumption is expected to be around 20% thanks to smart lighting technology.

VI.2.Enhanced Reliability

With the passage of time, renewable energy sources have gained much attention. The reasons include growth in global warming, cost of production, and unprecedented transition in technological era. Wind and solar energy systems are two handsome choices among renewable energies due to their clean nature. However, they exhibit reliability issues and unscheduled shutdowns due to high maintenance and cost. Predictive maintenance can be a solution to overcome these issues. Recently, artificial intelligence (AI) has emerged as a promising tool to deal with predictive maintenance in renewable energy systems. In this work, AI research on predictive maintenance in wind turbines and solar energy systems is reviewed. This study covers AI-based approaches for the prediction of faults in multiple components of wind and solar systems, online monitoring, and prognosis of remaining useful life (RUL). General techniques, advantages, and limitations of AI are also discussed. The existing challenges, open issues, and potential research directions are identified. Moreover, a taxonomy of AI-based predictive maintenance is presented to better understand the study.

VI.3. Enhanced Reliability

Renewable energy systems (RES) have gained much attention and are widely integrated into main power grids. RES are abundant, sustainable, and eco-friendly sources of energy gained from earth, such as wind, solar, and biomass. Wind and solar energy systems are two pervasive choices due to global availability, cost-effective solutions, and maximum conversion efficiency. However, reliability of RES is the major threat to the economy because of a raising trend in maintenance, failure, and unscheduled shutdowns, and unscheduled maintenance issues (Saleem Afridi et al., 2021).

The common techniques used for monitoring wind and solar farms are categorized as either condition monitoring systems or periodic manual inspection approaches. However, they possess some limitations, e.g., the necessity of a wind turbine stays off during inspection. To rectify these issues, the latest research in the context of predictive and prognostic maintenance (PPM) is proposed.

VII. Challenges and Limitations

Discussed work begets challenges in the future, identifying directions for further research and emerging problems yet to be addressed by the IA Smart Grid community. Energy delivery systems are going through an era of massive transformation, re-engineering and sophisticated control. This involves growing interdependencies within power, gas and heat networks and also coupling to other critical infrastructures. The integration of various renewable generation and storage units is on the rise, whilst at the same time the energy markets start to open up in many countries (Robu et al., 2019). These changes are driving development of the smart grid concept.

To date, the majority of smart grid research has been directed at understanding large-scale phenomena, like energy market dynamics, power system stability or large-scale grid co-ordination. Nevertheless, increasingly complex energy trading and local energy schemes emerging at the local grid level. Here, AI applications for managing smart grids have to deal with a wide range of unresolved challenges and issues which include the increased need for explainability of AI-generated suggestions, the integration of renewed social and ethic studies within the broader context of ongoing development, and the difficulty of formally aggregating or describing a wide variety of common sense or expert knowledge.

Consistency in deliveries Abstract guidelines, citations, formatting, references. All authors must read the abstract PDF. There are two types of conference paper submissions: the full paper length, and the short paper length. The guidelines herein pertain to both lengths, but the types of content that may be included will necessarily vary between the two formats. Authors may choose the full paper

length which permits up to eight pages of content and up to two additional pages containing only references. Alternatively, it may choose the short paper length, which must adhere to the three-page limitation and may contain an additional fourth page of references.

By a significant margin, the most common approach to AI in the Energy domain pertains to managing energy supplies for energy neutralization maximization and peak shaving. The development of renewable storage and embedded generation technologies has caused their broad adoption by private customers and communities, making them an essential building block of local energy schemes. In such settings, communities have limited access to the bulk energy market and have to rely on local embedded micro-generation and storage for their energy needs. Peer-to-peer energy trading mechanisms are a natural-fit extension of these developments. On one hand, they can be used for surplus energy selling or distributed resources organization, which can further stimulate the adoption of micro-generation. On the other hand, it can be used to buy the missing energy from a neighbor or from a different owned source of storage or production. Here it comes to the fore a set of research issues aimed at tackling this broad challenge by the Smart Grid community.

VIII.1. Data Privacy Concerns

While distributed artificial solutions are emerging to address all these issues, new challenges must be considered. For example, as robust decision-making is a key performance indicator in complex domains, a key concern is that it may be obtained due to unintended biases in the output of the learning algorithms, thereby negatively affecting the welfare of third parties. The researchers observe that when artificial intelligence (AI) systems are tasked with learning robust solutions, unexpected behaviours may emerge during the learning process as an unintended consequence of the optimization algorithm. In electricity markets, for example, an executable optimization algorithm governing energy production, trading and distribution across a diverse array of devices can be easily engineered to maximize welfare for a specific set of devices, leading the other participants subject to gradients or competitive pressures. If the learning process resulting in the implementation of the algorithm is shielded or opaque to third-party developers, stakeholders, or decision-makers, countermeasures could be out of the topic's scope, and the intelligent system could operate and optimize in ways that disadvantage large portions of the market (Robu et al., 2019). In related examples, the work of these researchers has shown that intent to maximize robustness and an honourable behaviour on the part of the trained AI system can lead to results that are suboptimal in statistical or interactive performance. These findings underscore the complexity of the agent-environment interaction,

particularly when human behavioural dynamics are involved.

VII.2. Technological Barriers

The transformation of electricity networks worldwide is driven by a necessity for a more sustainable and efficient use of energy. This is being achieved through extensive development of renewable energy sources and the adoption of varied distributed generation setups. These changes bring both opportunity and increased complexity to the networks served. An increased reliance on renewable energy systems is raising concerns regarding the stability and controllability of modern grids. There are, however, significant technological, social, and economic challenges currently hindering the transition to a fully renewable energy mix. An AI driven solution is inherently uncertain boundary conditions. Therefore, a major interest in first identifying and modeling the bounds on each boundary condition to ensure the robustness of any AI that is subsequently employed. There is a great urgency to overcome these barriers given the timeframe which truly impactful action must be taken to mitigate the worst effects of climate change. Nevertheless, the transition towards low-carbon energy markets and economies is not an easy task, and the change of paradigm has brought about new challenges to the electricity industry. It faces numerous challenges including an ageing infrastructure, the assimilation of novel grid-scale technologies, and an ever changing demand profile. A substantial body of research has focused on the use of AI techniques to help alleviate these challenges. Works have examined the use of AI to maximize conventional plant efficiency and to predict individual load demands based on end user behaviour. Due to the size of the task and the technical challenges that transformation poses, many distribution companies have been slow to invest in the redesign of their existing networks. As a result, the AI community has only just begun to consider how best to accommodate the likely changes to the distribution grid. An analysis highlights the key barriers, which must be overcome before the expected changes to the distribution network can be fully realized.

VII.3. Regulatory Issues

In December 2015, the Paris Agreement aimed to strengthen the global response to the threat of climate change by keeping a global temperature rise this century well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase even further to 1.5 °C. However, the current commitment of only 90 countries is predicted to warm the earth by 2.7 °C. Energy systems are central to this issue as they are responsible for 73% of global greenhouse gas (GHG) emissions. The transition of energy system from fossil fuel-centered to carbon neutral is one of the keys to realizing the climate goals set by the

international community. Electric grids are one of the most critical infrastructures affected by climate change, and their reliability and security play a crucial role in society. Today's electric grids are complex systems driven by endless dynamics of electricity and market. The operation of such systems are heavily regulated and comply with numerous technical requirements and market rules. Recent advances in the digital grid with AI and intelligent energy management systems increased the heterogeneity of the already complex ecosystem, including diversified data and applications. One major problem that arises is the currently available laws and regulations are mostly rigid while the technology evolves at an accelerated pace leading to unintended consequences. Thus, it is timely and imperative to comprehensively study the problem of energy system digitization in the era of AI by proposing an innovative three-layered approach to mitigating the unintended consequences in power systems (Xie et al., 2022).

VIII. Future Trends in AI and Renewable Energy

Renewable energy sources are steadily becoming more prevalent and economically effective. This means that the demand for services related to renewable energy will increase. In turn, understanding the potential of new technology applications in renewable energy provision will be necessary. For instance, the increase in renewable electricity generation due to advances in solar and wind technology creates a considerable storage challenge. This has benefited from increased artificial intelligence (AI) applications already, with the rise of energy transition markets. The interaction between renewable energy and AI beyond just predictive algorithms is gaining momentum and is expected to be a very active and relevant field of global research in the upcoming years. Relevant directions include learning-based control strategies for energy-efficient cooling in data centers, reinforcement learning for green wave scheduling, the design of adaptive AI schemes for the control of Distributed Energy Resources in smart grids, uncertainty quantification and boost learning for more accurate probabilistic forecasts of wind energy production, forecast updating strategies for renewable energy virtual power plants, and the development of interpretable AI models for socio-technological energy forecasting applications.

Current and recent advances in AI have had a strong and lasting effect on a multitude of industries including financial services, healthcare, transportation, and marketing. Renewable energy is no exception. Taken together with advancements in energy technology and policy, these novel methods of AI are being used to better understand and control renewable systems. Machine learning has had a particularly profound effect on renewable energy systems, with scientists discovering and predicting complicated patterns and phenomena that would have otherwise been extremely difficult or impossible to find. The rapid

growth and adoption of renewable energy sources have arisen rapidly. However, the efficiency and conversion of renewable energy sources usually depend on the input parameters, which may be complex and changing. In contrast, AI can handle any type and volume of data.

In recent years, there has been a surge in research in which AI is applied to various aspects of renewable energy. This connubial is there to research including but not limited to: forecasting, control, and energy markets. Such research is encompassed within the backdrop of the smart grid, the electrical variant of Industry 4.0. Ethical and social challenges are considered by (i) learning from shared, renewable, sources, and (ii) a shared understanding of privacy. The theoretical analysis demonstrates novel ethical, economic, and social implications of the interactions with the findings naturally suggesting directions for future research. Open challenges in the smart grid domain are also outlined (Robu et al., 2019).

VIII.1. Emerging Technologies

The integration of renewable energy sources is constrained by several technical requirements, notably grid stability. In contrast with conventional centralized energy sources, many renewable systems involve distributed and inherently uncontrollable sources, in the form of solar panels, wind turbines or wave generators. A promising solution involves the digitization of the energy system, to create the so-called smart grids. In Europe, the promotion of smart grid research has led since 2011 to a sustained increase in the related funding, especially in the development of smart protection systems and storage technologies. The smart grid, allowing a decentralised and adaptive control of energy distribution, is seen as a disruptive technology that will heavily impact the energy system over the next decades. It is a complex sociotechnical system composed of distributed sensors, communication and automation equipment, as well as centralized analytics and decision making processes. The AI community is involved in several aspects of this transformation, including the design of secure and reliable communication systems, the development of active network management procedures, and, through the use of multi-agent systems, the restructuring of the market at the distribution level (Robu et al., 2019). One of the most studied components of the smart grid is the active management of distribution systems. This includes techniques to accurately forecast the generation and consumption of a multitude of independent agents, such as individual power consumption of households uniformly equipped with solar panels and electric vehicles; the design of economically efficient, decentralized strategies for voltage and frequency control; and the development of seamless reconfiguration mechanisms to adapt to the continuous variation of the network

due to the connection and disconnection of microgeneration stations. Notably, small and medium villages constitute complex rural distribution systems where electricity losses can reach up to 40%.

VIII.2. Global Policy Implications

The recent policy document of the Indian government, Electricity Amendment Bill 2021, strives to initiate healthier markets and enhanced service quality by guaranteeing consumer choice and competition. Furthermore, it promotes the swapping of aggregate demand between distribution businesses (DBs). But industrial users have objections against it: it will operate to the detriment of SMEs and farmers; rather than market yardstick competition, monopoly will arise; and it contradicts the Electricity Act, 2003, that allows neighborhood areas to establish their own distribution services. Both Environment and Health contribute to the extensive improvement of renewable energy sources (RES). But Large Green-led Industrial Units (LGIs) are consuming much energy. This concern can be neutralized by the concept of ‘green power’ and the set-up of RPPs, CTS and WTCs for LGIs. The building of RPP in a green belt will exclude a cluster of villages. Thus, specifying mini RPP models of different capacities will examine the optimized capacity of a mini one that, if satisfied, may be mounted in villages in proximity to LGIs (Xie et al., 2022). Thereon, this paper will discuss and analyze the corresponding legalized power technologies and renewable energy sources from the policy viewpoint of the economy, environment, and health. The blockchain permitted IoT and D2D decentralized architecture and reciprocal power swapping among neighboring industrial solo RES Prosumers. Such disruptive measures are foreseen to be even more persuasive and tackle the main difficulties: (i) maintenance of system integrity in unusual situation transactions because of distributed algorithm and non-cooperation constraints; and (ii) reduction of overall system resources and computational intricacies because of a scalable and distributed digital system (Robu et al., 2019). More concentration on representing dispersed automatic entities and constructing chaincode transactors ascribed to power trading.

IX. Conclusion

For most of its history, the literature on modeling wind speed using machine learning (ML) focused on the prediction of single points in time, with relatively little attention paid to associating temporal characteristics of the prediction or exploration of the cross-dependence of the spatio-temporal prediction variable (Amimul Ehsan, 2021). This latter is typically done using multivariate statistical models, which often have limitations in adapting to spatio-temporal dynamics or in simulating a large number of surfaces. Using copula functions, which can

separately describe the marginal distributions and their dependencies, allows for the flexible modeling of the conditional dependence structure of random variables.

In the emerging field of renewable energy storage, techniques like power to power algorithms can be significantly improving efficiency, increasing energy densities, and equalizing timescales between storage media and energy buses. (Yao et al., 2023). The Renewable Energy Exchange (REeX) platform, based on accelerating Particle Swarm Optimization (PSO), is then used to compare and evaluate a broad array of the efficacy of the power to power algorithm suite. Elections, carried out systematically through a high-fidelity domain-specific framework, apply to both solar and wind energy storage notable.

IX. 1.Key findings of the research include:

AI can improve the efficiency of renewable energy systems by up to 20% through optimized scheduling and demand forecasting.

Predictive maintenance powered by AI effectively reduces unplanned downtimes in solar and wind energy systems.

AI-driven control systems enable seamless integration of renewable energy sources into existing grids, reducing reliance on conventional energy.

IX.2. Recommendations:

- Invest in smart and secure digital infrastructure to support AI deployment in energy systems.
- Develop and update regulatory frameworks to ensure ethical, transparent, and fair use of AI technologies in the energy sector.
- Promote the creation of national AI strategies that include renewable energy as a key focus area.:
- Encourage interdisciplinary research to develop interpretable and adaptive AI models for renewable energy applications.
- Focus on creating AI solutions suitable for regions with limited data availability, especially in developing countries.
- Investigate the socio-technical and ethical dimensions of AI integration into energy systems.
- Integrate AI tools for predictive maintenance, energy forecasting, and demand-side management to improve operational efficiency.
- Invest in AI-powered optimization solutions to reduce operational costs and increase system reliability.
- Partner with research institutions to pilot advanced AI models in real-world energy infrastructure.:

- Promote cross-border knowledge exchange and open-access platforms for renewable energy and AI data.
- Support international standardization efforts for AI applications in energy systems.
- Encourage joint funding

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