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Harnessing AI and IoT for Optimized Renewable Energy Integration and Resource Conservation

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ABSTRACT

This paper reviews various methods of integration of AI and IoT technologies in renewable energy (RE) systems. The reason of the integration is to optimise the energy production, distribution and consumption. With this current reported work, we intended to study many AI applications, including machine learning (ML) and Deep Learning (DL). The work also highlights the potential techniques to enhance the efficacy, reliability and sustainably of RE energy sources. The various challenges associated with this integration are also studied here. This work analyses the current research and industry trends, which further is useful in providing insights in the AI driven future for RE energy solutions. The RE sources that are focused here are solar, wind and its energy management. Integration of AI into this domain will enhance the modelling and other process such as RE generation, grid management and distribution of energy. Further, it is noticed that the integration of IoT will help in optimising the consumption of energy which is the need of the hour. This will lead in the reduction of electricity bills in household and commercial places. Additionally, when AI and IoT are used in conjunction, the resilience of power systems us enhanced.

Introduction

Energy is a vital part of contemporary civilisation, driving growth in the economy, facilitating growth in society, and powering technical developments [1]. The wide variety of energy uses, from manufacturing and transport to domestic power usage, indicates its ubiquitous effect throughout several industries [2]. Nonetheless, rising worldwide energy consumption, along with the urgent need to prevent global warming and pollution, has fuelled the search for renewable energy alternatives. This necessity has fuelled research into alternate sources of energy [3], efficiency improvements, and novel systems for managing energy to guarantee mankind's long-term viability [4]. The inexorable development of population, urbanisation, and industrialisation has significantly risen the use of energy (Khan, 2024), putting enormous demand on limited fossil fuel supplies and amplifying greenhouse gas pollutants, resulting in negative climatic effects [5]. To solve these difficulties, attention has switched to sources of clean energy like wind [6] hydroelectricity, solar energy [7] and geothermal electricity [8], which provide more environmentally friendly and environmentally friendly alternatives [9]. In addition, boosting efficiency in numerous industries is now critical to minimising unused energy and emissions of greenhouse gases [10].

Incorporating power-efficient technology, implementing Energy Management Systems (EMS), and encouraging lifestyle modifications are all critical stages towards reaching sustainable energy use habits. In the pursuit of Sustainable Energy Solutions (SES), the incorporation of sophisticated technology, notably Artificial Intelligence (AI), has been recognised as a possible path for revolutionising energy systems. AI is a collection of approaches that allow smarter choices and better EMS, include machine learning, optimisation computations, and data analytics. By using AI, electrical networks may improve grid activities, optimise the flow of energy, and enable demand-side response systems. AI technologies can analyse large volumes of energy data, detect usage trends, and generate accurate forecasts, allowing energy regulators, network managers, and customers to arrive at more educated decisions as shown in **Figure 1** [10]. Adopting AI in the energy sector has the ability to generate huge advantages in the areas of energy effectiveness, reduced expenses, improved reliability of the grid, and the incorporation of renewable energy (RE) sources, moving humanity forward an environmentally friendly and lucrative future [4]. The focus of this paper is to investigate the interface between AI and RE, emphasising the ability of AI to transform how humans manufacture, share, and use energies. AI has the ability to improve energy usage, decrease junk, and encourage sustainable behaviours by assessing massive volumes of information, optimising structures, and allowing smart choices to be made. This paper covers a variety of ideas and possibilities for using artificial intelligence to solve energy concerns while contributing to a healthier, greener tomorrow [11].

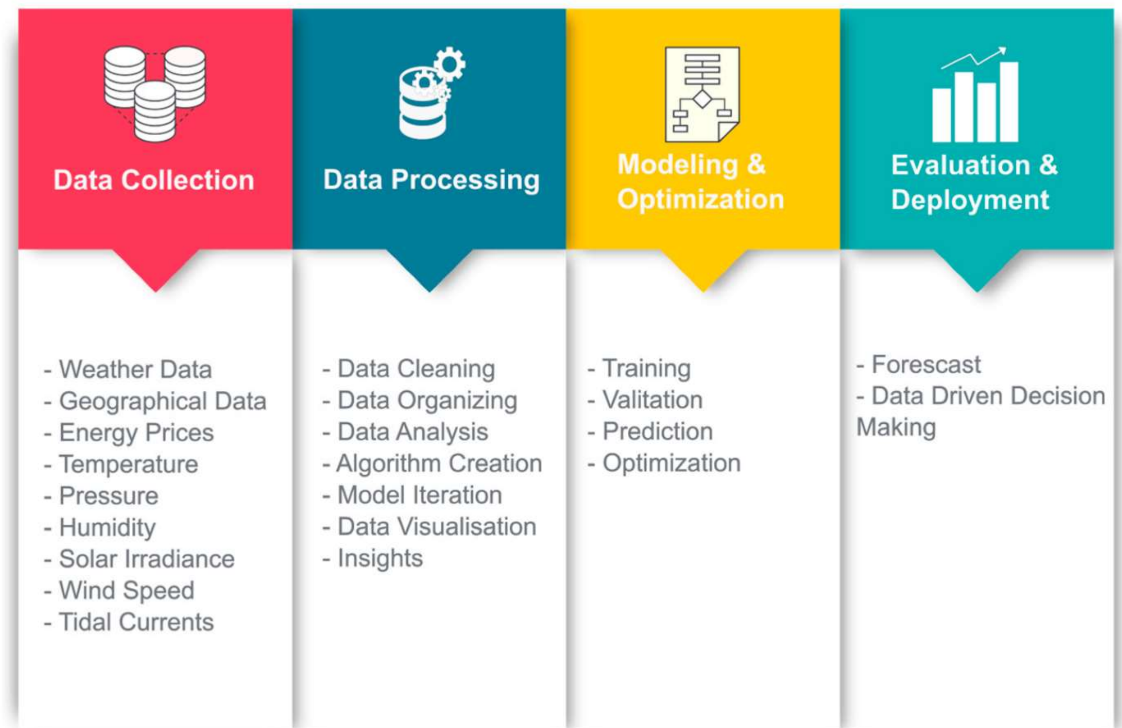

Figure 1: Stages in the creation of modelling and optimisation resources for energy forecasting. [10].

1. AI, ML, DL, and Sustainable Development Goals (SDGs)

AI and DL are novel technologies with great promise to help accomplish the Sustainable Development Goals (SDGs) [11-12]. Such technologies are fast evolving and have had significant implications in a variety of decision-making sectors, like medical care, commerce, farming, schooling, and banking. A thorough review of the influence of AI on every one of the 17 goals and 169 objectives of the 2030 Agenda for Sustainable Development (SD) revealed that AI might help accomplish 128 goals in all SDGs as shown in **Figure 2**.

Figure 2: SDG goals. [11]].

Yet, it has the potential to impede 58 targets, highlighting the importance of using these innovations with caution and ethics. AI has transformed areas such as farming, schooling, and banking as a component of Industry 4.0, helping to reduce poverty and boost economic development, especially in developing countries. In education, AI and DL have showed great potential in improving the learning processes and results. For example, the introduction of AI technologies such as ChatGPT has prompted a rethinking of established instructional assessment methods in higher learning. In addition, the use of DL methodologies has been shown to improve math skills and practical thinking in students at high schools. Particularly, in the context of linguistic acquisition, the importance of attentive listening, an often-overlooked ability, has been highlighted. Active listening is being shown to have a significant influence on numerous aspects of how languages are learnt, particularly phonetics, morphology, and pragmatics. Furthermore, the use of deep learning technology on physical education has allowed for continuous tracking and evaluation of students' activity movements and heart rates, providing important information into the efficacy of instructional strategies. These breakthroughs illustrate AI and deep learning's transformational capability of altering ways of teaching and improving the results of learning. In medical settings, AI has helped battle the COVID-19 epidemic and improve the delivery of healthcare. criteria for communicating medical AI studies to physicians were created, including the clinical artificial intelligence research checklists and particular performance measurement criteria for presenting and evaluating research that incorporates AI elements. The significance of comprehensible DL algorithms in the setting of building ethical AI systems and solutions based on data in accordance with the SDGs was highlighted. Visibility and comprehension in algorithms are critical for ensuring their moral and ethical usage. Outside medicine, AI and DL have showed success in plant biology, with conversations about the role of exascale computation and explainable AI in meeting the SDGs. Reliable testing and daily-resolution climate correlations are required to fine-tune ideotype creation to particular surroundings at varied granularities [12]. In the field of environmentally friendly facilities the significance of 3D concrete printing (3DCP) and AI-supported Digital Twin (DT) uses for fulfilling the relevant UN SDGs have been investigated. The subsequent studies will focus on developing a standardised theoretical structure for exploiting AI-supported DT associations. The effects of AI on the SDGs are being examined, yielding a few important insights for ESG (the environment, community, economy) in the face of rapid technological and societal development. The environmentally friendly, cultural and political policy perspectives on the implications of AI on sustainable development, with a focus on the advancement of the SDGs, were reinforced. Yet, the uncontrolled deployment of AI technology jeopardises progress towards the SDGs. Big Tech's unethical past implies it can't be entrusted to function without oversight from regulators. Appropriate preventive regulatory strategies have been offered to reduce the possibility of AI harming the SDGs. Recent breakthroughs have emphasised the relevance of the IoTs and ML in meeting the SDGs, with applications in health, energy, and cities. In addition, Deep Graph Learning (DGL) was offered as a solution to social difficulties and enhance people's everyday life. A knowledge graph-based DL system has also been created to scan SDG data for similarities in content efficiently. Rapid gains in AI and DL have been seen in a variety of industries, but a comparison review shows key differences. For example, Ukraine's machine-building business, an important sector for the economic development of the nation, has been struggling with digitalization's problems and prospects, particularly in terms of creativity generation. This demonstrates a gap between AI's promise and the real deployment in certain businesses. While poultry farming is increasing, pollution, soil degradation, and resource rivalry remain significant issues in agriculture [13].

The combination of big data and AI provides a chance to overcome these difficulties and optimise poultry farming. In addition, the oceans science industry has been using AI to recognise fish behaviour, which may have a substantial influence on fishing gear selectivity. Nevertheless, the data needed to evaluate fish interactions with fishing gear, particularly for temperate species, remains scarce. This highlights the requirement for larger datasets to adequately train DL systems [14]. All these applications are shown in Table 1.

Table 1: Popular AI uses in the SDGs [14]

SDG Goal	Application
No Poverty	Forecasting impoverished zones, optimising welfare settlements, and enhancing services for microfinance
Zero Hunger	Harvest forecasting, identification of diseases, and precision farming.
Good Health and Well-being	Illness epidemic forecasting, telemedicine, and AI-assisted diagnostics.
Quality Education	Personalised schooling and AI-assisted assessment
Gender Equality	Evaluation of prejudicial views regarding gender data
Clean Water and Sanitation	Water safety tracking, shortage forecasting, and optimisation of distribution networks for water
Decent Work and Economic Growth	Increasing productivity, creating jobs, anticipating economic trends.
Industry, Innovation, and Infrastructure	Optimising operations, lowering expenses for upkeep, and proactive upkeep.
Reduced Inequalities	Recognising and anticipating societal disparity, using AI in policy development, and specific efforts to reduce inequity
Climate Action	Development and refinement of climate scenarios, changing the climate forecasting, and ecological footprint monitoring

2. Role of AI, ML and DL in RE

The RE business is undergoing a major transition, thanks primarily to advances in AI and DL. These innovations have brought in an exciting age of productivity and long-term viability piquing the curiosity of scholars and business operators equally. The breakthroughs and uses of AI and DL in the RE sector may be divided into many basic areas. As shown in **Figure 3**, such fields include a broad variety of activities, from energy prediction and identifying anomalies in electrical systems to more complicated tasks like RE system development and reliability of the grid. The interaction of AI and deep learning across various disciplines highlights their critical significance in altering the present and prospective environment of RE [14].

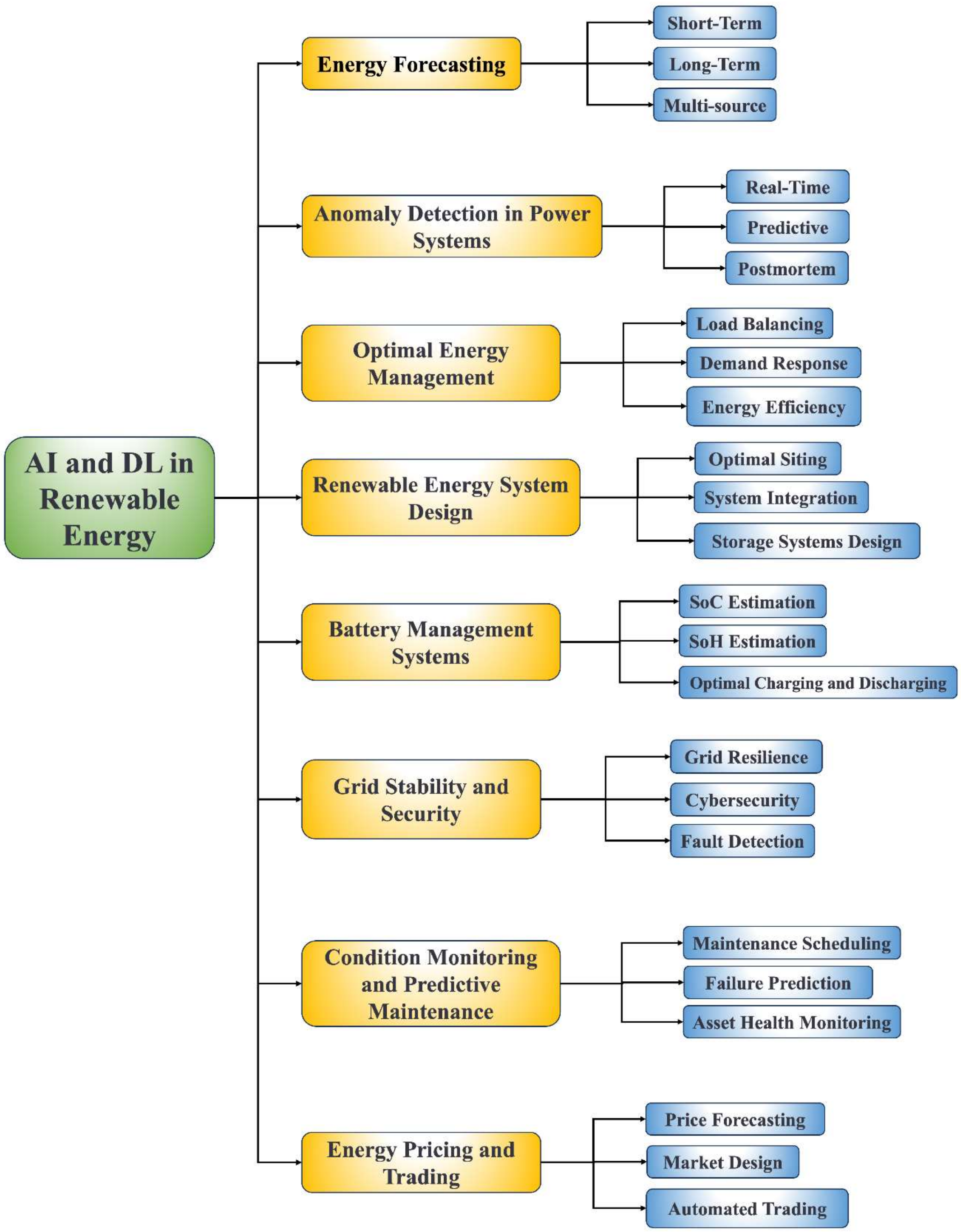

Figure 3: The use of AI and DL in RE [14]

3. Artificial Intelligence Applied to Variable Renewable Energy Systems

Variable renewable energy (VRE) assets, especially those regulated by weather, are projected to play key roles in worldwide decarbonisation initiatives and the transition to RE [10]. To obtain the greatest efficiency in their utilisation, VRE devices must be deployed using optimisation approaches. AI approaches are extensively employed in VRE function prediction systems to predict, management, and make decisions.

3.1. Solar Power Forecasting

Several evaluations of the application of artificial intelligence for solar energy forecasting are currently undertaken. A precise projection of solar irradiance is critical for electrical system developers and utility companies to efficiently operate solar energy installations. Studies of Solar Power Forecasting (SPF) using

Photovoltaic (PV) systems give perspectives on present approaches and potential developments. Along with temperature, the amount of Global Horizontal Irradiance (GHI) has a significant impact on the effectiveness of the PV module. The effective architecture of a PV forecast systems is also reliant on aspects such as forecasts horizons, input choice using correlational analysis, preliminary and final processing of data, climate categorisation [11], networking optimisation, and estimation of uncertainty. GHI forecasting is typically carried out using two techniques: the first uses cloud photography with physical representations, and the subsequent methods use ML approaches for mathematical models of statistics [12-13]. Physical representations include weather conditions which are closely connected to sunlight production, which complicates the process owing to the unpredictability of the weather information utilised as input. On the other hand, statistical methods use historical data to establish a link between climatic factors and PV power output, which is then used to construct the energy forecasting framework Amongst the physical, mathematical, AI, ensemble, and hybrid algorithms, significant evaluations have revealed that ANNs, particularly convolutional neural networks (CNNs) [14-15], are particularly promise for short-term accuracy in forecasting and have received the greatest amount of attention. Research on ML approaches for solar energy forecasting predicted the adoption of SVM, regression trees, and RF in the next years owing to their positive outcomes in competition with ANN [16-17]. A proposal was made to employ ensemble predictions instead of straightforward ones. **Figure 4** depicts the process of using AI for solar power predictions [10].

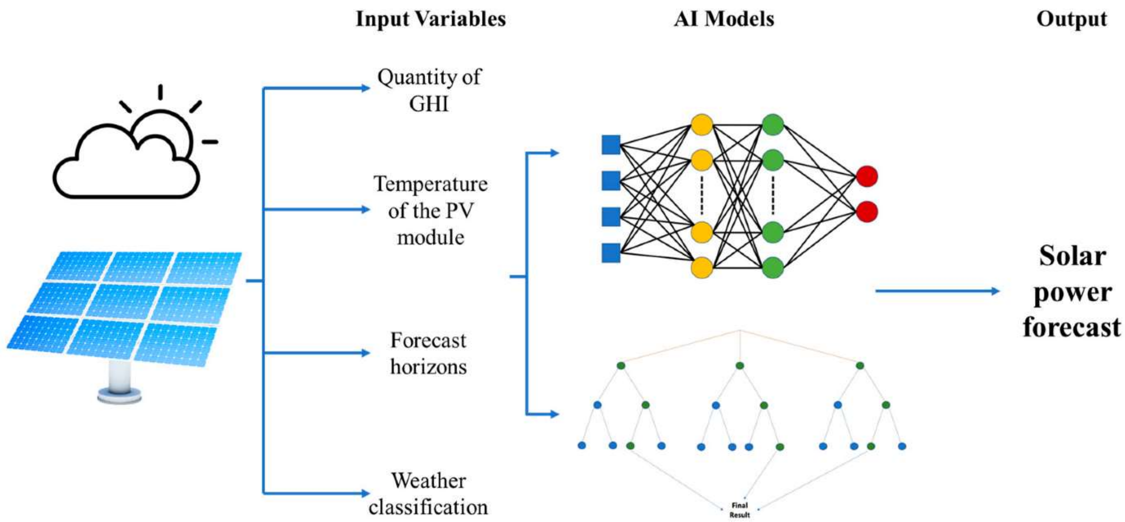

Figure 4: Diagram depicting the procedure of inputting parameters into AI algorithms to generate solar power estimates [10]

The calculation of prediction intervals (PIs) for spot predictions of solar power, as well as their enhancement, has recently attracted attention in the field of research. The application of optimisation approaches combined with ANNs may be utilised to customise PIs to various periods of the day instead of intervals. For example, the amount of electricity generated throughout the nighttime is nil, therefore the interval of PIs throughout those times can be smaller than throughout the daytime. Research on solar installations in Australia computed intervals for prediction utilising a multifaceted PSO combined with ANN [17-19]. The forecasting ranges were shown to be enhanced whenever actual solar energy was combined with climatic projections for short forecasting timeframes of 1-2 hours, lowering ambiguity [20]. The effects of varying weather conditions in various areas complicate the generalisation idea. Climate variables have been demonstrated to impact the efficacy of several machine learning systems for predicting solar irradiance. An instance is solar power projection research done in Kuwait's Shagaya Renewable Energy Park [21] an arid desert environment with mostly bright and clear skies. The usage of a regime-dependent technique, in which k-means clustering was employed to separately identify regimes prior using an ANN, resulted in lower results. The prevalence of clear sky circumstances in Kuwait's weather patterns causes regime-identification algorithms to perform poorly, since there are few occurrences of overcast sky situations, and these methods may be well suitable for climatic regimens that have more diversified cloud situations [22]. Another example is the Nordic climate, that is distinguished by prolonged days in the summer and short winters days, considerable snowfall, and very varied weather patterns caused by rapidly changing clouds. Such cloud motions may have serious consequences for PV systems connected to low-voltage networks. In addition, the snow-caused soiling impact throughout the winter is a crucial consideration. The complicated optical properties of snow make it difficult to estimate the drop in power output caused by soiling. An assessment of ML techniques to forecasting revealed that the ML algorithm used was determined by the research area's weather circumstances. During steady meteorological circumstances, the predictable part dominates the stochastic part, giving traditional ML methods like SVM and Random Forest (RF) feasible options. In uncertain meteorological situations, when the stochastic element is as significant as the predictable, standard algorithms frequently fail badly, and DL approaches are discovered to better reflect the intricate framework of the procedures.

PV power production has an underlying issue of interruption, which reduces power system dependability. As a result, it is critical to develop trustworthy forecasting models for these systems. The work in [21] provides an organised and thorough summary of SPF strategies. The study highlighted five essential topics: learning approaches, analysing data, forecasting approach categorisation, significant variables influencing forecast efficiency, and forecast uncertainty estimate. It was discovered that supervised methods were utilised more often than unsupervised approaches, as well as that most forecasting algorithms included a data cleaning and normalisation procedure to decrease predicting mistakes. Various extracted feature approaches were utilised, notably the most popular techniques, Wavelet Decomposition and Empirical Mode Decomposition. Particularly interesting is the fact that many ML models that utilise optimum procedures have gotten increased attention, including PSO, GA, and WOA among the most frequently utilised optimum algorithm. Solar irradiation, velocity of the wind, and temperatures were found as the key parameters influencing predicting outcomes, and as such, they are the most widely utilised input variables. While predictive models containing uncertain data are particularly valuable for system performance, deterministic predictions are still the major approaches employed; nonetheless, the relevance of both of them is likely to rise.

To assess the performance of the suggested deep approach, we conducted the following tests using gathered PV power datasets. The work in [22] was trained and evaluated via the Python 3.8-based Pytorch DL structure, which was combined with an AMD Ryzen 5 5600X CPU running at 3.70 GHz, an NVIDIA RTX 2070 GPU, and a 16 GB RAM physical setup. The suggested dual CNN-LSTM system forecasts PV power production, as seen in **Figure 5**. In step 1, power production data collected from a PV generator is divided into bright and overcast days data. In step 2, the acquired data is pre-processed to eliminate any noise components, such as values that are absent or anomalies, that might disrupt the procedure. The data is subsequently normalised for use as a network input. In step three, the CNN and LSTM are trained on the training data. Every model solely considers power production data. Step 4 involves testing and verifying a forecast model's output using different matrices.

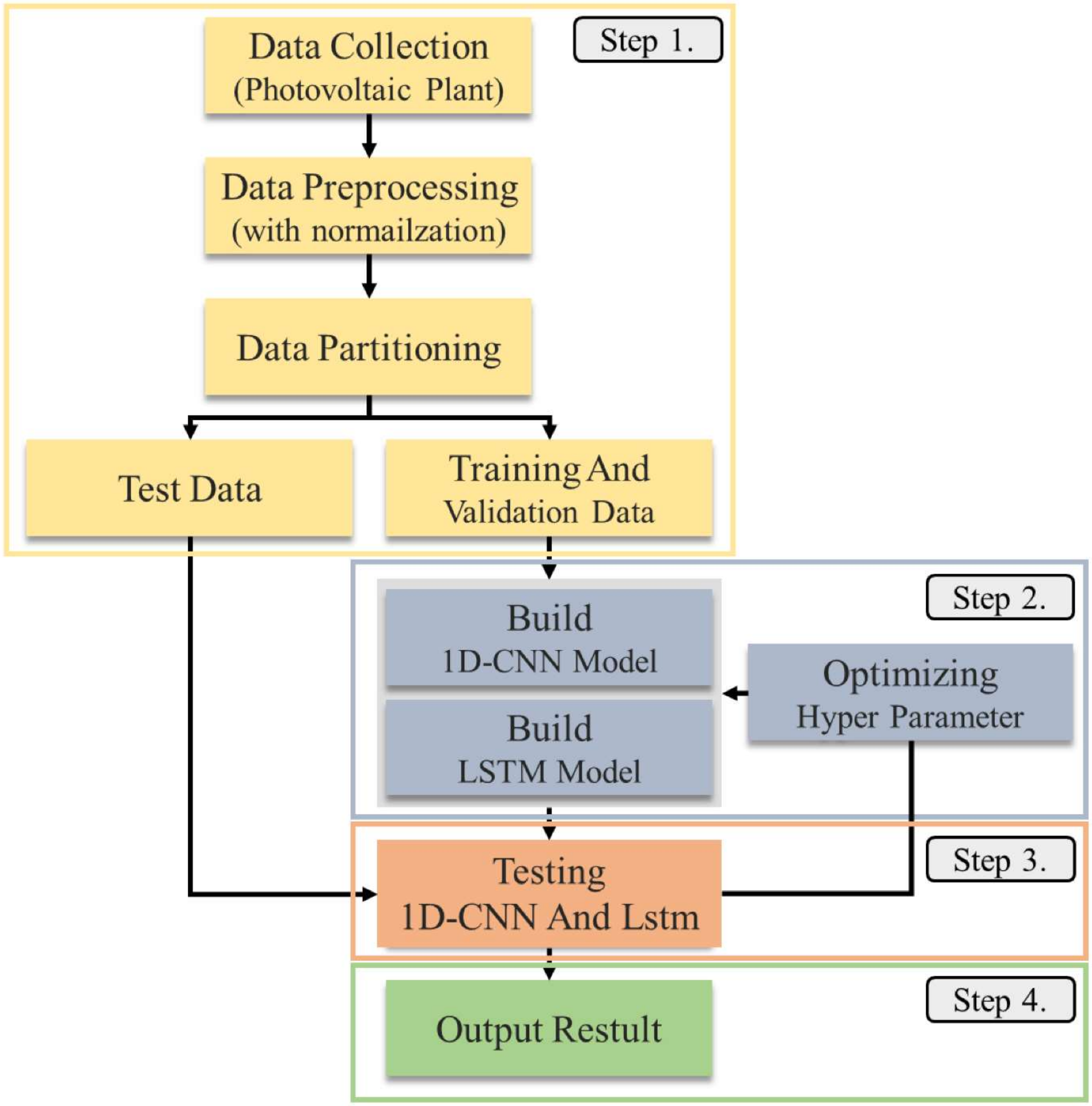

Figure 5: Illustration for the suggested PV energy production forecasting system [22]

3.2. Wind Power Forecasting (WPF)

The instability and randomness in the speed of the wind is the fundamental contribution to the difficulty of generating a consistent supply of electricity from wind sources. Wind velocity is influenced by many meteorological variables like the direction of the wind and pressure in the atmosphere [23-26]. Power production in wind farms swings dramatically with variations in wind speed owing to the non-linear connection between power output and the speed of the wind. Improved WPF skills are thus crucial for windmill choice, generation organising, and grid reliability. A search for research revealed a variety of evaluations on the application of AI for WPF, with AI methodologies resulting in advancements in the method of forecasting [27-29]. AI approaches such as ANNs and SVMs have been used for wind speed forecasting, particularly to provide point predictions. Because wind speed and power conversions are stochastic, uncertain predictions using a probabilistic structure are an important topic of study in WPF. PIs thus make use of to measure ambiguity using limits that are higher and lower on the anticipated quantity [30-32]. To improve accuracy, it is advised to employ several ANNs to anticipate wind speed, as well as suitable initial and final processing approaches. Ensemble approaches have also shown potential for future applications.

The work in [9] offer a WPF system and a demand control technique. To participate in the weekly marketplace that governs both demand and supply in the Maine a microgrid a novel demand control system is suggested that employs big based on data wind energy forecasts. A precise forecast is required for successful demand administration [33-34]. A DL algorithm called EDCNN is used to successfully estimate day-ahead hour windy output on Maine wind farm data. The numerical findings support the suggested algorithm's effectiveness in WPF. The suggested DSM algorithms typically spread the burden. The findings show that the suggested DSM approach effectively distributes the load, resulting in a load profile that is virtually equally distributed. Furthermore, the suggested DSM method significantly cuts costs related to consumption as shown in **Figure 6**.

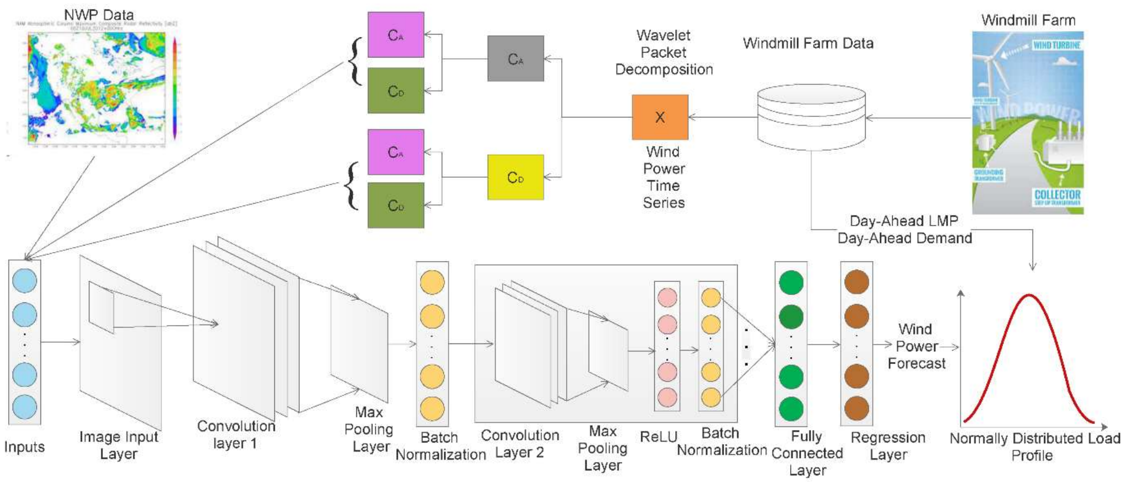

Figure 6: WPF model. [9]

In [34] , the authors suggested a day-ahead WPF model using numerous ML methods, a precise small-area NWP approach, and hourly data series containing electricity generated by wind turbines which may be used on a national scale in Poland as well as in nations that have comparable climatological limitations. The authors showed that every model (RF, XGB, ANN, and DNN) generated predictions with comparable, excellent accuracy. The XGB method was particularly reliable for hourly projections, achieving a mean absolute percentage error (MAPE) of 26.7%, whereas the ANN technique was most effective for daily totals of generated energy, with a MAPE of 13.6%. While the contrast of ML approaches wasn't the primary focus of this study, there were a disparity between results across times of year, hours of the day, and if the machine produces a lot or little actual energy. The outcomes, which are shown in a variety of error measurements, scatter plots, rows, and Taylor sketches, reveal that all of the offered approaches can estimate day-ahead wind output with excellent precision, despite modest score discrepancies. Two decision tree-based approaches (XGB and RF) outperformed ANN and DNN in circumstances with very high hourly production of energy. On the contrary hand, the findings of two neural network-based approaches (ANN and DNN) show decreased MAPE variation on an everyday and month scale. For all methodologies, June had the greatest MAPE and January had the least, whereas wintertime had the least variances and summer has the largest. Special examples were investigated, including both highly precise production of energy projections and those with significant inaccuracies. In steady weather circumstances with medium winds, every model projected wind energy generation with excellent accuracy; however, when weather conditions are severely unstable or the wind velocity is exceptionally high, errors in forecasting will rise. With the suggested strategy, NWP prediction accuracy has a significant influence on scores. In a case study dated August 27, 2020, while the convection storm existed in a region of Poland with a large concentration of deployed wind turbines, the ALARO model's exaggeration of the wind speed led to a significant positive bias in energy output, particularly in the late hours. A study conducted on December 27, 2020, highlighted a circumstance in which the ALARO model accurately forecasted extremely high wind speeds in Poland; nevertheless, owing to acknowledged limits of ML models, extreme circumstances were often overestimated. Another cause could be that a few wind turbines were turned down owing to excessive energy output. The third category of case studies includes instances such as the one shown on February 5, 2020, featuring modest winds and steady situations, in which the suggested technique functions effectively.

4. IoT in RE predication

Fossil fuels are still the backbone of the energy industry and provide around 80% of the world's total energy output. There are many negative effects on the environment, human health, and the economy that result from burning fossil fuels too much. These include, but are not limited to, air pollution and global warming. Two major possibilities to reduce the negative consequences of fossil fuel consumption are energy conservation, which is using less power to provide the equivalent assistance, and the introduction of RE sources. Energy losses and carbon dioxide emissions may be significantly mitigated with the help of the Internet of Things. At each point in the production chain, an IoT-based EMS may keep tabs on actual energy use and raise consciousness regarding energy efficiency [28].

In the 1990s, software for controlling and acquiring data from supervision controls as well as automating various other operations gained popularity in the electrical industry. In the early phases of the IoT, the power industry benefited from its ability to track and control machinery and procedures, which reduced the likelihood of output loss or outage. Outdated power plants primarily face problems with effectiveness, dependability, impact on the environment, and upkeep. High levels of electrical loss and instability may be caused by the electrical sector's old technology and issues with inadequate upkeep. Certain possessions are over 40 years old, very costly, and difficult to replace. The IoT has the potential to alleviate a number of these difficulties associated with energy plant administration. IoT sensors allow gadgets connected to the internet to detect anomalous drops in energy use or operational failures and notify the user when repair is required. The system's efficiency and dependability are enhanced, and servicing expenses are decreased, as a result of this. If a current electricity plant of the same scale were to be fitted on the IoT platform, it could save fifty million dollars over the lifespan, while a brand-new power plant centred on the IoT could save two hundred and thirty million dollars, according to [29]. Many nations are encouraging RESs as a means to lessen their reliance on fossil fuels and increase their use of alternative power sources. The electrical power system is faced with additional issues, referred to as "the intermittency challenge," when it comes to RE sources like wind and solar that are weather-related or unpredictable. Because of supply as well as demand being unpredictable and causing an imbalance on different time frames, it is very challenging for a power system with a significant percentage of VRE to correlate the production of energy with demand. More incorporation shares of renewable energy and lower GHG emissions may be achieved via the use of IoT systems, which provide an opportunity to balance production with consumption. This, in consequently, may reduce the obstacles associated with adopting VRE [30]. With the aid of ML algorithms, which are made possible by the IoT, it is possible to find the sweet spot between various consumption and supply methods, leading to more effective energy usage [31-34]. One example is the use of AI procedures to alternate thermal plant generation with internally power-producing sources, such as a collection of a smaller scale PV panels.

Because of their vitality capacity and the advanced state of these methods, RE sources like wind and PVs are getting a lot of focus in the effort to lower releases of greenhouse gases and increases in the rate of adoption of RE sources. Electricity for self-consumers and rural areas may be sourced from these other sources of energy, which can replace more traditional methods. Devices might be set up to operate in either a grid-dependent or independent mode depending on the energy arrangement. The short-term nature of RE sources makes it difficult to incorporate a large number of them into the power system. Integrating distributed energy resources (DERs) and allowing for bidirectional energy and data movement in the electrical distribution network are made possible by the connectivity facilities becoming the fundamental component and primary foundation for potential intelligent grids. A graphical picture illustrating the grid's incorporation of hybrid renewable energy systems (HRES) could be seen in **Figure 7**. By bolstering various services like demand handling and demand-side leadership, HRES will offer energy companies with a plethora of benefits during times of high consumption. In order to integrate DERs with enhanced resiliency, dependability, and effectiveness, a foundational communications system is crucial [30].

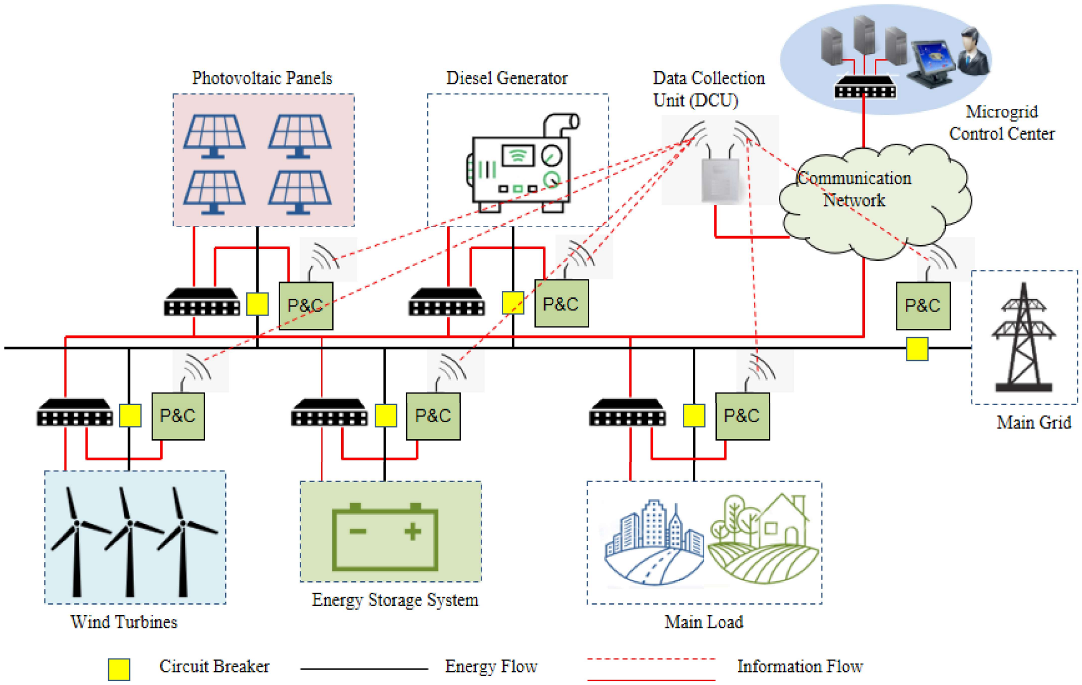

Figure 7: HRES [30]

Both the electrical network and the network's communication tiers make up the HRES, which is a cyber-physical system **(Figure 7).** The Transformers, the feeders, conversion devices, and electrical lines make up the electrical network layer, which also includes different forms of energy including battery packs, PVs, wind turbines, and diesel engines. An underpinning network of communications connecting nodes in the physical framework with actuators and sensor arrays is supported by the communications architecture level. The local control centre may then oversee the system's functioning thanks to this. Information and communication technologies (ICTs) are crucial to this incorporation because they facilitate the incorporation of HRES, which is necessary for the migration from the current, antiquated electrical system to a future-proof connected grid. From various angles, a number of studies have examined HRES. These include EMS, response to demand, financial cost, greenhouse gas pollutants and impact on the environment, optimised origin size, communication system, IoT-enabled smart grid, HRES optimisation, modelling according to international norms, optimal setting, planning of capacity, and many more [38].

A HEMS monitors and manages the house's consumption of energy as well as the scheduling and functioning of various devices [39]. With the help of demand-side management, that encourages people to move appliance usage away from peak hours and towards off-peak ones, one can achieve this goal and reduce home power bills. It is critical to alter the appliance use pattern by scheduling them in a manner that meets all of the optimisation criteria set by the RASP. For many years, scientists have been trying to find ways to provide renewable energy sources (RES) that are not only cheap, simple to create, and good for the environment (Rabah et al., 2023). RE integration offers the most economical options, based to many research. In order to maximise customer satisfaction, minimise peak-to-average power consumption, and minimise energy costs, home device timing is defined as an optimisation issue. This challenge seeks to arrange intelligent home equipment in the most efficient manner possible. Scheduling strategies that make use of optimisation techniques are therefore able to address this issue [32]. The method for scheduling home appliances in [32] is the bald eagle search optimisation algorithm (BES). **Figure 8** depicts a recommended intelligent grid infrastructure that incorporates energy internet connection, burdens, the public power grid, and RE sources [40].

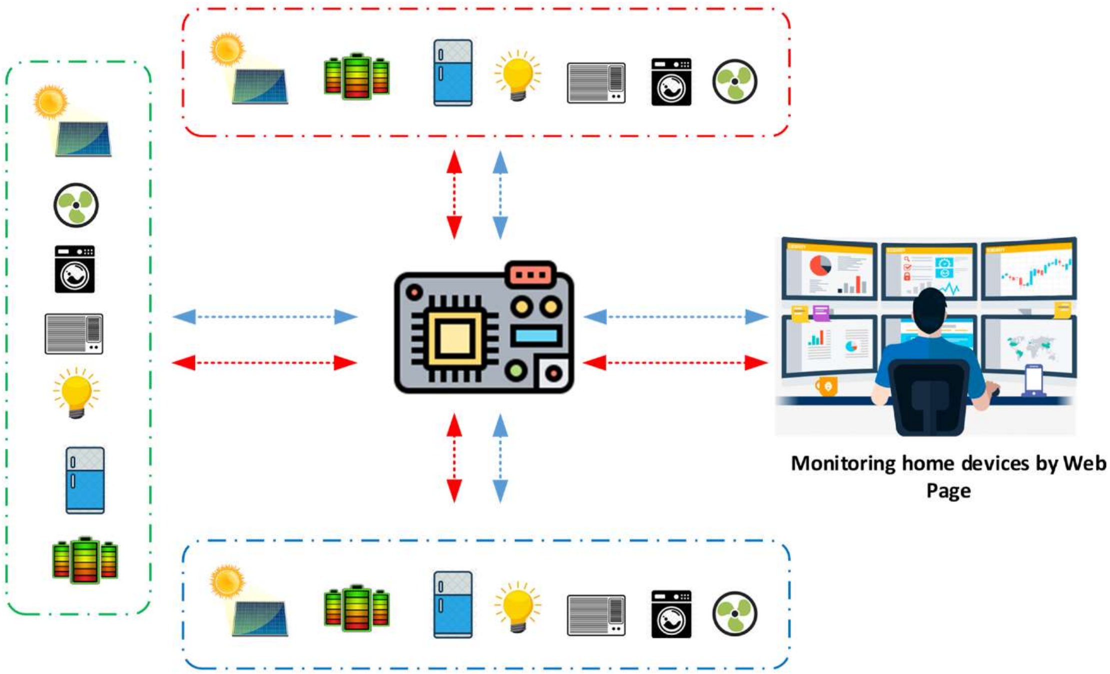

Figure 8: Smart Grid parts [32]

5. Challenges

When AI is added to RES, it creates both exciting possibilities and big problems. AI has the potential to improve the efficiency, effectiveness, and dependability of RE sources, but there are some problems that need to be fixed before they can be fully integrated. A lot of excellent information is needed for AI systems to learn and make decisions. It can be hard to get complete and precise data on winds, sun rays, weather trends, and various other crucial variables that affect green energy. AI models and estimates may not work as well as they could if they have incomplete or wrong data. RES are usually complicated and not linear, with many factors and relationships that change over time. Making AI models that correctly show how complicated these systems work can be hard. Adding different types of sustainable energy, like wind, solar, and water, to a single infrastructure makes it more complicated. RE sources, like solar and wind, aren't always reliable, which makes it hard for AI-based forecast controls to work. For AI to work well with RE, it needs to be able to deal with unpredictable and quick changes in how energy is generated. Various kinds of green energy don't all use the same data forms, connection methods, or management interactions, which makes it harder for AI to work with them all.188 Standardising systems and standards is important for making it easier for different parts of RES to work together and interact with each other. A lot of computing power is often needed for AI systems, especially DL models. Due to the need for strong computer facilities, it can be hard to use these methods in real-time uses for RE sources, particularly in places that are far away or don't have a lot of resources. Most people think of AI models, especially complicated ones like ANNs, as "black boxes," which makes it hard to figure out how they make decisions. Explicitness and openness are important for building trust and knowing why AI-driven choices are made in important systems like green energy. RES are affected by changes in the climate, malfunctioning equipment, and new technologies.18 It's hard to make sure that AI models are strong and flexible enough to deal with changes and problems that come up out of the blue. For long-term stability, it is important that model update and modification procedures work all the time. Adding AI to RE sources (RES) could mean paying a lot of money up front for gear, programs, and competent employees. Small sites or ones with limited resources may have trouble designating assets to AI integrating, which makes it harder for these innovations to be widely used. As AI becomes more important to RES, the risk of hacking dangers rises. To make sure that green energy infrastructure can operate safely and reliably, it is important to keep algorithms, controls, and internet connections safe from hackers. Laws and rules that govern AI may not be able to keep up with how quickly it changes. Regulations that aren't clear or are too strict could make it harder for AI to be used in RES. To make responsible and broad adoption easier, there needs to be clear guidance and help from regulators. To solve these problems, experts, people who have a stake in the business, and lawmakers need to work together. As technology improves and recommendations become clear, these problems will be solved, making it easier to combine AI with RES and creating a more stable and long-lasting energy future. This part does a great job of explaining the problems that come up when you try to combine AI and RES and the possible solutions. It narrows the conversation to specific, doable ways to deal with these problems, maybe with the help of cases from new studies or pilot programs [33-38]. Putting AI to use in RES can have big effects on society and the world, both good and bad. AI can help make RES work better and cut down on carbon pollution, but it leaves its own mark on the world. It takes a lot of computing power to train AI models, which means a lot of energy is used and carbon is released. So, the ecological impact of AI processes needs to be carefully controlled to make sure that the beneficial effects of AI in green energy are greater than its environmental prices. AI could make accessibility to energy through making green energy easier for more people to get and cheaper for more of them. EMS that use AI can improve the way energy is distributed and allow for decentralised energy production. This lets groups make their own renewable energy and depend less on centralised power lines. AI programs may pick up prejudices from the data that was used to teach them. This could lead to unfair or unjust results, like not everyone having the same utilisation of renewable energies. It is very important to get rid of these flaws and make certain AI systems are built and used in a fair way. Concerns have been raised about data security and confidentiality because AI systems used in alternative energies may gather and analyse private data. Protecting personal information and making sure data is safe are important for keeping people's trust in AI apps. The use of AI to automate work in RES could mean the loss of jobs in some areas, like the usual production and transfer of energy. It is essential to come up with and use policies and programs that help people change and improve their skills for new jobs in the green energy sector. The use of AI in RES could have big positive effects on the climate and society, like lowering carbon pollution and making energy access more equal. But it's important to think about how AI operations affect the environment, make sure AI usage is fair and equal, and deal with ethics issues like anonymity, security of information, and job loss. By handling these factors correctly, AI can change the energy environment and speed up the move to a fair and safe power era.

6. Conclusion and Future Work

As AI and IoT technologies come together in RE systems, it becomes a good platform for solving many unsolved problems. This will also lead in the development of advanced sustainable deployments. This paper has focussed on significant developments of AI in RE which will improve the system efficiency. The RE sources that are focused here are solar, wind and its energy management. Integration of AI into this domain will enhance the modelling and other process such as RE generation, grid management and distribution of energy. Further, it is noticed that the integration of IoT will help in optimising the consumption of energy which is the need of the hour. This will lead in the reduction of electricity bills in household and commercial places. Additionally, when AI and IoT are used in conjunction, the resilience of power systems us enhanced. With this, there are challenges that should be tackled to make this process a success. There is a need for standardisation of protocols for various RE systems. There are also computational requirements that needs to keep in mind and suitable models are to be designed. Ethical concern that is related with data security is very crucial to bee considered during the development of such systems.

There is need for more robust and explainable AI models which will assist in more positive effects on sustainability. Hybrid AI techniques can be employed so that unique features of carious models can be used in enhancing the overall system and its efficiency. Edge computing may also be used in the future to optimise the system. This may give a path to solve the ethical concerns that are discussed here. AI models should also look into the energy storage optimisation and also in grid stability. There is also a need for educating students about the environmental and socio-economic effects of AI integration in RE systems to have sustainable implementations. These solutions may result in better AI integration of RE sources along with IoT. This also leads to a low-carbon energy future, which in turn will bring about drastic changes in the climate and provide a cleaner energy ecosystem.

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