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Artificial Intelligence Applications in Renewable Energy Systems

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Abstract: - Implementing clean energy sources into an electrical system provides a cost-effective alternative for limited energy usage while reducing carbon pollution. Renewable energies, which include photovoltaic panels and winds, are inconsistent in power output due to their reliance on meteorological conditions, including radiation from the sun, heat, and moisture. As a result, various prediction techniques have been established to increase the predictability of alternative energy sources. Recent knowledge, for example, AI [artificial intelligence] and ML [machine learning], provide several opportunities to deal with these issues. Artificial intelligence [AI] technology has increased in recent years, and its application in present manufacturing systems has expanded rapidly. The primary intention of this work remains to demonstrate how well AI artificial intelligence techniques may be used to model and predict renewable energy resources.

Keywords: Artificial intelligence, distribution power systems, fuzzy logic, machine learning, power systems, power system operation.

I. INTRODUCTION

The need for energy has increased due to human expansion and progress. The traditional energy source is fossil fuels such as coal, oil, and natural gases, which directly or indirectly impact the environment by causing difficulties such as greenhouse consequences, ozone exhaustion, etc. So, we need pollution-free, fresh, and green energy resources to protect the environment [1]. This may be done by incorporating green renewable energies such as solar (PV) output, wind energy, geothermal, biomass, and hydroelectric power, among others [2]. Depending on their benefits, drawbacks, economics, and feasibility, these resources can be used as an alternative source of electricity to meet demand [3]. The primary issue with sustainable power is supply interruption. Apart from the uncertainty of renewable energy production, the load is also unpredictable. Indecision is well-defined as the unpredictable control and amount of renewable output production compared to non-renewable power production [4]. Inconsistency is defined as constant power variation dependent on the availability of primary renewable fuels such as solar radiation, wind, and so on [5].

Inadequate renewable energy supplies can generate a discrepancy between power output and power requested by load, resulting in power outages and other problems. On the other hand, excessive renewable energy generation results in energy waste [6]. Since ancient times, humans have been fascinated by the notion of creating a machine that might "think." Rene Descartes, a French philosopher-mathematician, prophesied in 1637 that it would never be feasible to develop a computer that thinks like a person. However, in 1950, Alan Turing, a British mathematician and computer pioneer, stated that one day, a machine would be able to match human intellect in every aspect. AI technology [AI] refers to a collection of approaches that allow a computer to train from previous data to develop an intelligent machine capable of matching human-level intellect in a specified area [7]. AI (Artificial intelligence systems), ES (expert systems), and ANN (artificial neural networks) have represented a new frontier between power engineering and power electronics, presenting several opportunities to address these challenges.

The recreation of human intelligence in machines is known as “artificial intelligence,” with the ability to learn from experience and make decisions based on that experience. These procedures provide dominating mechanisms for smart grid estimates and hybrid renewable energy simulations, design, management, and defect inspections [8]. Artificial intelligence algorithms may be used to predict radiation from the sun and wind speed limit to get the most out of these resources. These methods offer the possibility of lowering the risk of system failure and ensuring the system's dependability [9-11].

The primary resolution of the study is to prove how AI [Artificial Intelligence] may be employed to handle particular challenges in each component of a renewable energy system. Figure-1 depicts the perception of the paper. The benefit of consuming such knowledge is that the optimum working point of not just each element but also the system as a whole may be attained, provided sufficient attention is taken throughout model creation and training.

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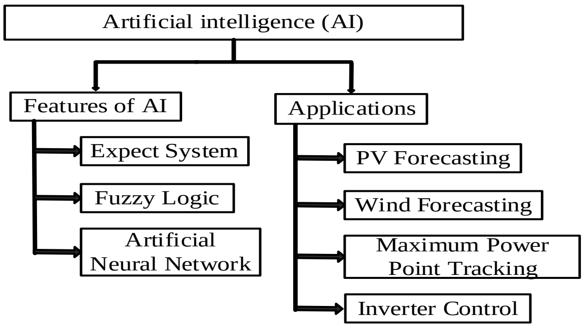

Figure 1: Perception of the Paper

This work's primary unit deals with the elementary topographies of AI(Artificial Intelligence) appropriate to renewable energy applications. The second portion is about forecasting as an AI-based application. This chapter discussed prediction strategies for solar and wind energy systems. Following that is the use of AI technology in MPP Tracking. Different machine learning algorithms implemented by different reviewers have also been described here. The following section is about inverters and how various AI systems have been created to handle various challenges with inverter topologies. The final part summarises the advantages and difficulties of artificial intelligence in renewable energy systems.

II. FEATURES

A. Expert System

The expected system is simply a "smart" software application built on logical operators that are considered to insert a human's knowledge in a specific field so it may resolve problems in favor of the human. According to the preceding description, it may be defined as "experience," which is the large amount of mission information transmitted from a human to a computer. An expert system typically includes a user interface, a knowledge base, and an inference machinery. A knowledge base usually has both a static and a dynamic database. Domain information is expressed in a specific formalism in the static database. It is built when the operator creates the structure, but that can be changed during runtime. The dynamic dataset might be enhanced throughout each program offered, but the data will be lost when the execution is finished. It stores all the information collected from the user and the intermediate results derived throughout the thought pattern. The knowledge base's core is arranged as a series of IF/THEN rules. The IF and THEN statements sections are often joined by and, or, not mean logical operations to form the conclusion.

The rules in the ES technology are generally described in abbreviated rule language (ARL), as well as variables (A, B, and C) that might be logical and numeric and also a mathematical representation or the processing of a command.

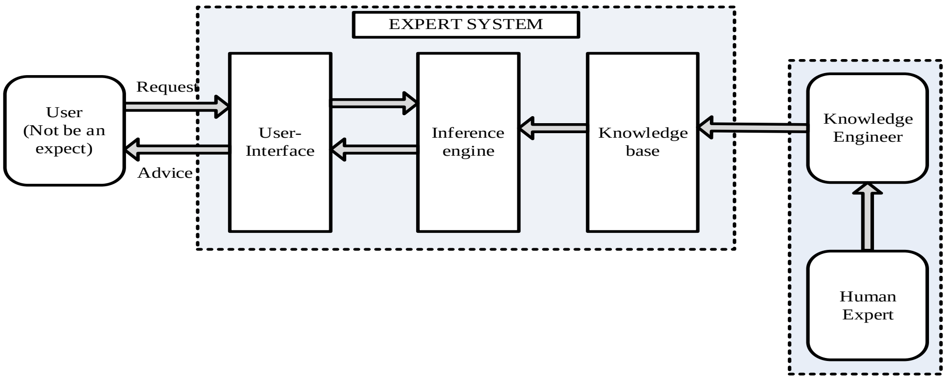

Figure 2: Basic Components of Expect System

The inference engine in Figure-2 The user interface connects with the KB (knowledge base) and a user. It systematically compares the If–Then rules in the knowledge base to the knowledge given by the user before deciding on the situation. If the rules of the if-segment are valid, the rules are triggered or validated, and the controller's performance indicated by the then statement is carried out. The customer is generally a semi-skilled person who connects with the processer in daily English in a friendly way. Text editors can expand on the user's help and why and how commands. The ES system is dependent on user education. The user interface informs the user about the system's performance, collects input from the user that the system requires to function, and presents the results of the reasoning process. Expert controls, algorithms, artificial neural networks, and intelligent search algorithms may all be built using various techniques.

To design an expert control system, we must not only understand the dynamic functioning of the system but also predict the control reaction to each of the various possible situations. The more system variables are evaluated, the more information is accessible for decision-making, resulting in a better system and higher power generation outputs. That's why an expert management system is predicated on human experience and knowledge. It provides a technique to find solutions through appropriately managing its parameters and acceptable control of requirements to change recorded data. In other terms, it is a strategy for controlling the experience of specialists in this field.

B. Fuzzy Logic (FLC)

FLC is an intellectual process that is similar to human thinking. The Fuzzy logic technique replicates how people conclude, consisting of entirely transitional options between YES and NO, which means digital values. The standard logic block, which a processer can grasp, receives exact input sources and offers an outcome as TRUE or FALSE, comparable with YES or NO in human terms. It may be used in schemes varying in extent and ability, from minor microcontrollers to vast networked compute cluster regulator systems. It can also be executed in software, hardware, or a combination. Figure 3 depicts the fuzzy logic block diagram.

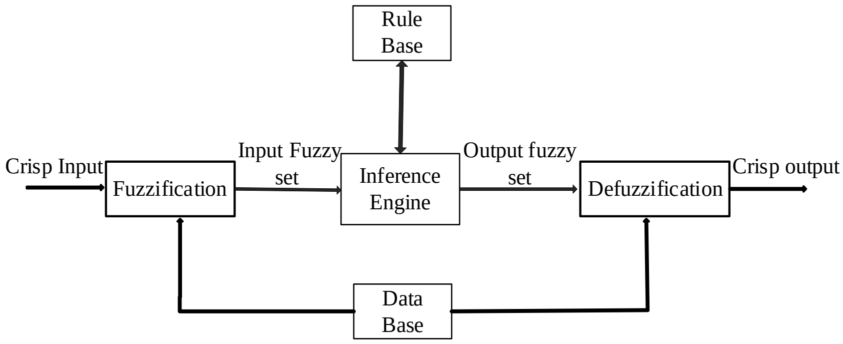

Figure 3: Basic Construction Of The Fuzzy Logic System

It primarily contains four mechanisms. Firstly, the Fuzzification Module turns crisp integers into fuzzy sets. Crisp data is the accurate inputs restrained by sensors and supplied to the control system for more processing, such as pressure, temperature, rpm, etc. The next one is the Knowledge Base: It comprises the collection of rules and IF-THEN conditions offered by specialists to manage the decision-making system based on linguistic data. Recent advances in fuzzy set theory provide various viable strategies for designing and adjusting fuzzy systems. The majority of these advancements lower the level of the rule base. The third one is the Inference Engine: It calculates the degree of correspondence between the current fuzzy contribution and each rule and selects which rules are to be stimulated based on the input area. The control actions are designed by merging the fired rules. The final one is the defuzzification module, which turns the fuzzy sets produced by the inference engine into crisp values. Numerous defuzzification strategies are available, and the most appropriate one is employed in conjunction with a certain expert system to decrease errors. The membership functions work on variable sets that are uncertain. Membership functionality allows you to measure linguistic terms and graphically depict a fuzzy collection. Easy membership functions are chosen since complicated functions do not improve output accuracy. The triangle membership function shape is the most popular among the different membership function designs. The MF explanation of the fuzzy terms and the matrix rules constitute the knowledge base of a fuzzy interface system. FIS was constructed with the support of MATLAB–based fuzzy Toolbox [12] and tuned by MATLAB/Simulink simulation of the structure.

C. Artificial Neural Network

The terminology "Artificial Neural Network" comes after artificial neural systems that create a model of human intelligence. Convolutional neural networks, like the human brain, include nerve cells that are coupled to each other at various levels of the network systems. These neurons are referred to as nodes. In convolution neural networks, dendrites from biological neural networks indicate the inputs, the cell nucleus provides nodes, the synapse defines weights, and the axon is the output.

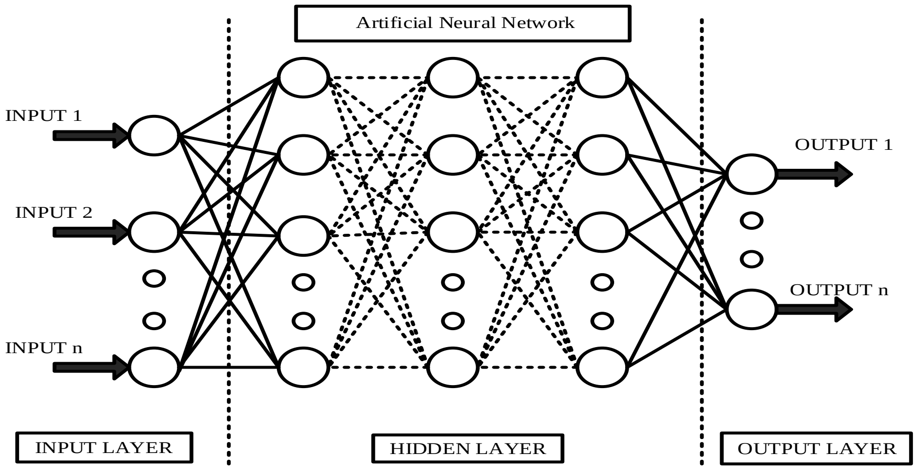

Figure 4: Elementary structure of the neural network

To understand the principle of an ANN (artificial neural network) design, we first understand what a neural network is. Many neurons, referred to as units, are placed in a series of layers to pronounce a neural system. The architecture of the artificial neural system is depicted in Figure 4. It is made up of three layers in total. [a] Input Layer: This layer receives inputs in various of forms that the systems analyst specifies. The hidden layer appears in the middle of the input layer and the outcome layer. It does all of the calculations to identify the hidden characteristics and designs. [c] Output Layer: The input undergoes a sequence of modifications utilizing the hidden layer, resulting in an output transmitted with this layer. The ANN receives data and calculates the weighted total of the source data and a bias. This calculation is depicted in the arrangement of a transfer function.

$$\sum_{i=1}^{n} Wi * Xi + b$$

The thing calculates the weighted sum, which is then fed into an activation function to generate the result. Activation functions [AF]regulate whether a node would fire or not. Those who are terminated that person only make it to the outcome units. Numerous activation functions are available that might be used depending on the type of work we are conducting. Neural Networks [ANN] are classified into several varieties constructed on the roles of human mind cells& networks. An artificial neuron accomplishes tasks in the same way that a human brain neuron and network do. Most ANN (neural networks) will have some commonalities with their more complicated genetic counterparts and will be extremely competent at their specific activities. Feedback ANN is one of them; in this model, the output returns to the network to get the greatest outcomes organically. Feedback networks provide information back into themselves and are particularly matched to solving optimization problems. Core system mistakes are fixed by making use of feedback networks. Feed-Forward ANN: it is a simple and common neural system consisting of a source and output layer and must have one neuron layer. The system's intensity may be detected based on the behavior of the linked neurons by assessing its output by evaluating its input, and finally, the output is concluded. The key benefit of this system is that it learns how to assess and also detect input outlines.

D. Machine Learning

Machine learning algorithms have already been utilized in various disciplines related to data-driven challenges throughout the last few decades. Statistical data, mathematics, ANN, data analysis, optimization, and machine intelligence are all examples of machine-learning approaches. Machine-learning approaches attempt to discover relationships between source data and outcome data through and without mathematical representations of complications. Later, the training data has sufficiently trained the machine-learning systems; decision-makers may acquire pleasing predicting output standards by giving the forecasted input information into the best-trained configurations. The data or information pre-processing step is critical in learning algorithms and may significantly increase machine learning performance [13]. ML technology primarily employs three learning techniques: supervised, unsupervised learning, and reinforcement learning, which is clearly shown in figure-5.

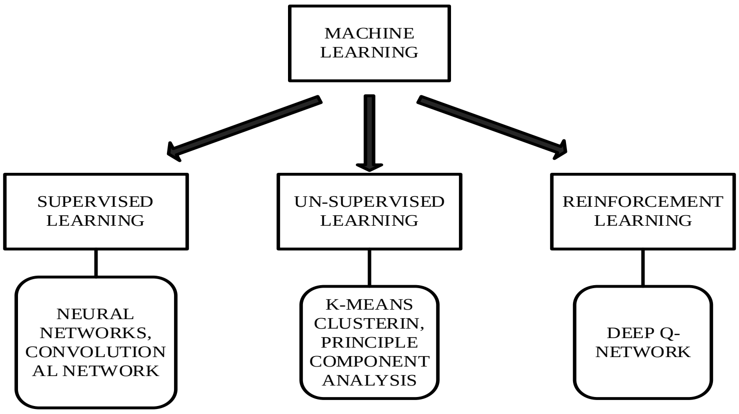

Figure 5: Categories of machine learning

During the training phase, supervised learning makes use of labeled data. Unsupervised learning is the process of independently categorizing incoming data into clusters based on specific criteria for training material that has not been labeled ahead of time. As a result, the number of clusters is often determined by the clustering criterion utilized. Reinforcement learning refers to understanding through interacting with the surrounding situation to get feedback and enhance the predicted benefits. Many conceptual processes and implementations have been developed using three fundamental learning concepts [14]. DP (Deep learning model) is a subfield of ML [machine learning] and has lately developed cause of the fast growth of computer models in hardware and software. DP (Deep learning) can realize distinct nonlinear properties and advanced invariant information arrangements. It has thus been used in numerous domains to achieve satisfactory results [15].

III. FORECASTING METHODS IN PHOTOVOLTAIC AND WIND SYSTEMS

A. PV Forecasting

Solar radiation is the primary factor from which photovoltaic systems generate power. A precise estimate of solar radiation is critical in calculating photovoltaic system generation, and it must be considered throughout the design process to minimize misalignment within the generation of power storage. Prediction in ML is split into 2 parts. Offline modeling, in which scientific information is utilized to train the models, and real-time prediction, in which current time data is utilized to estimate required parameters, are two approaches. PV system forecasting has used ANN (artificial neural networks), FL (fuzzy logic), (ARIMA), and other methodologies. The features of neural network models over traditional models are that they do not require any system parameters, offer fewer processing demands, and enable compact solutions for problems with numerous variables. A neural system can study relatively complicated nonlinearities, making it well-suited for real-world applications [16]. Some research has concentrated on projecting renewable sources using a one ML model [17]. However, it is challenging to increase prediction accuracy using a single machine-learning algorithm because of the variety of data, clock cycles, prediction limits, parameters, and performance measures. As a result, several research studies have established hybrid machine-learning model approaches in sustainable projections to increase predictive accuracy. Support vector and deep learning algorithms have recently gained popularity in the field of ML (machine learning) [18].

Recent research studies explore the use of machine-learning algorithms to anticipate renewable power. In [19], a thorough examination of dual renewable-energy systems was provided. This research includes integrating renewable system feasibility studies, optimal size, modeling, control and dependability, and evolutionary approach applications. [20] examines the use of neural networks in energy and reliability predictions. Photovoltaic, hydro, and wind energy sources were investigated in this study. Many examples were offered to show the advantages of ANN (neural networks) in energy and consistency predictions. In [21], they investigated the uses and categorization of machine-learning algorithms in power systems. The writers demonstrated hybrid models outperform standard machine-learning algorithms in energy system applications. In [22], renewable generation system forecasting models from the perspectives of power forecasting structures, storage devices, environmental rules and economics, dependability, and optimum sustainability efforts. This assessment benefited the power division by providing recent trends and forecasted power system design and operation advances. In [23], claims of SVM techniques to predict PV and wind power were examined, and it was found that the proposed methods beat further prediction schemes in terms of estimate precision. Furthermore, the writers established that hybrid means combination SVM models accomplish well single support-vector machine models in predicting. In [24] analysis of the use of ML methods in estimating solar radiation was conducted. According to the authors, convolutional neural networks, support vector regression, regression trees, random forest, and gradient boosting are potential tools for energy from the sun estimation, and combinational model techniques are viable strategies to increase predicting precision.

In [25] the authors conducted an evaluation and performance study of prediction strategies in PV power generation. According to this work, using neural systems [ANN] and an SVM means support vector machine approach has become prevalent in the prediction sector. The authors noted fluctuations in meteorological circumstances caused by large predicted faults in solar prediction since PV radiation is a primary input of the PV system. In[26] evaluated categorization methods for renewable energy challenges and provided useful understandings to scholars and practitioners. In [27] they conducted a literature study on solar power prediction utilizing AI algorithms, machine-learning approaches, deep-learning approaches, and hybrid methodologies. According to the article writer, people were able to calculate data information in solar photovoltaic weather prediction by combining mathematical weather reports with the extraction of features and deep learning models to help long-term PV system estimation, long short-term memory networks, and convolutional neural network [CNN], also recurrent neural network [RNN].

Solar irradiance in the PV energy prediction system may be modeled as a time series through multiple time scales. The ARMA, which means autoregressive moving average, was the most often applied time series estimating style[28][29]. Deep-learning techniques, machine-learning models, and support-vector machines [30–33]. Regarding SVM implementations for photovoltaic forecasting, variable selection is essential to SVM predicting accuracy. As a result, several research has employed optimization approaches to identify SVM model parameters [34–36], including genetic algorithm [GA], grid search, particle swarm optimization [PSO], firefly algorithm model[FFA], neural networks [ANN][37–39]was successful data-driven forecasting schemes. Deep learning encompasses CNN [40], deep neural networks [41, 42], long short-term memory [43–46], and the additional combination models used in dual-step solar energy calculations. Another approach to forecasting solar irradiance is the Basic Perceptron Method, which is a supervised learning in which masses are updated based on the development of unfavorable responses at the output. MADLINEs have various applications in solar forecasting and domains other than solar irradiance forecasting and modeling [47, 48]. Figure 6 depicts the fundamental block diagram of the solar and wind forecasting models.

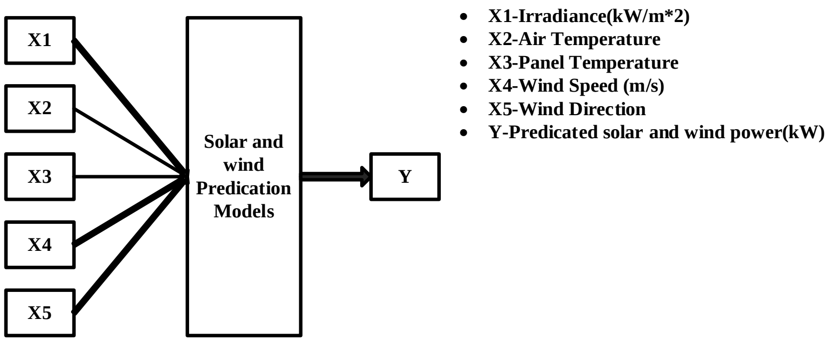

Figure 6: Basic Model Of Solar And Wind Forecasting

Table1.Summary of Solar & Wind Forecast Models and Techniques

Ref.No	Year	Source of Energy	Model	Techniques
[28][29]	2019	Solar	Statistical	ARIMA
[30–33]	2020,2019	Solar	Artificial intelligence	RF [30], SVR, RF [31]; RF [32]; RF, gradient boosted regression, extreme GB [33]
[34][36]	2020	Solar	Hybrid	moth-flame optimization algorithm-SVM[34]; SVM-PSO [36];
[35]	2020	Solar	Artificial intelligence	Copula-base nonlinear quantile regression
[37]	2020	Solar	Artificial intelligence	Artificial neural networks
[38]	2019	Solar	Artificial intelligence	Artificial neural networks
[39]	2018	Solar	Artificial intelligence	Artificial neural networks
[40][41][42]	2019	Solar	Artificial intelligence	CNN[40];DNN[41][42]
[43]	2020	Solar	Artificial intelligence	DNN, RNN, LSTM
[44][45]	2019	Solar	Artificial intelligence	ML and statistical hybrid model [44]; LSTM, GRU [45]

[46]	2018	Solar	Artificial intelligence	LSTM
[49]	2019	Wind	Statistical	Physics-informed statistical
[51]	2019	Wind	Artificial intelligence	Gaussian process regression [GPR], Support vector [SVR], ANN
[55]	2017	Wind	Artificial intelligence	RF
[57]	2019	Wind	Artificial intelligence	Improved LSTM-enhanced forget-gate network
[61]	2019	Wind	Artificial intelligence	Multi-layer perceptron [MLP]
[72]	2018	Wind	Hybrid	Type-2 fuzzy neural network-PSO
[74]	2018	Wind	Hybrid	ELM-Improved complementary ensemble EMD with Adaptive noise- [ARIMA]
[78]	2018	Wind	Hybrid	VMD-singular spectrum analysis-LSTM-ELM
[80]	2019	Wind	Hybrid	Sparse Bayesian-based functional regression
	2018	Wind	Hybrid	Wavelet packet decomposition-LSTM
	2018	Wind	Hybrid	Empirical wavelet transformation, Recurrent neural network [RNN]

B. Wind Forecasting

Due to the obvious unpredictable nature of wind supply, electricity production through wind power generation differs from traditional thermal power generation. Modeling in wind power generation technologies is concerned with the problems of supply and consumption in the power source and resolving imbalances between the pair. Among several research, the neural network, which comprises the typical multi-layer perceptron, is the most commonly used approach for wind forecasting. The most popular forms of neural networks recommended for estimating wind rapidity in the short term utilize multi-layer perceptrons.

Statistical approaches were utilized in the early stages of the wind energy forecast. [49, 50]. Recent research used AI and machine learning approaches, which include support-vector systems, in wind-energy forecasting. [51, 52], gradient boosting decision trees [53], random forest algorithms[54, 55].The combination technique means both ANN and also fuzzy logic models are created by combining two artificial intelligence technologies, and it is known as an adaptive neural fuzzy system approach [ANFIS]. Fuzzy logic designs are applied when determining variables is complicated and developing a particular model is time-consuming. The Bayesian approach is also used to anticipate wind speed limits. A FL design system is also being used at the wind park for predicting wind speed and electricity generation. [56], long and short-term memory systems [57–60], and also ANN systems [61–69].

Machine-learning approaches are used to detect data patterns in wind energy forecasting. Furthermore, hybrid techniques have been created to quickly and successfully improve prediction models by merging data processing methodologies and optimization techniques into machine-learning systems [70–72]. Ensemble empirical mode decomposition [EEMD], wavelet packet decomposition [WPD], and Wavelet decomposition [WD] were used to remove noise impacts from original information and can significantly enhance wind-speed forecast accuracy[73,74]. ELM means Extreme-learning machines were employed in wind generation predictions [75–78]. The Bayesian constructed strategy was used to forecast hybrid wind power in [79, 80]. The geometric findings showed that the Bayesian design technique exceeded the other prediction model in predicting hybrid wind energy. To forecast wind speed, a hybrid system consisting of the convolutional neural network [CNN] and also WPD, long short-term memory [LSTM]has been created and may produce good predictive accuracy [81]. In wind power forecasts, the combinational model means hybrid consisting of a long short-term memory network, empirical wavelet transform, and Elman neural networks[ENN] better than the remaining forecasting methods[82]. Table 1 depicts the summary of various solar and wind energy-based techniques.

IV. MAXIMUM POWER POINT TRACKING

It comprises a control scheme provided by an appropriate algorithm and is used to create an ideal duty cycle. Next, it is sent into a DC/DC power converter that is employed to harvest the high energy from the PV panel. Some concerns arise during the implementing of a practical MPPT approach for a Photovoltaic network, such as efficiency issues, a rise in overall cost, wasted energy, execution, and layout issues. Many MPPT techniques for PV programs have been designed, involving perturbation and observation [P&O][83], hill climbing [84], incremental conductance [85] Others.

These approaches are commonly employed because of the simplicity with which they may be implemented. These may, meanwhile, have limitations, such as instability due to reactivity to rapid changes in meteorological conditions. [86] as well as fluctuations around the operating point [87, 88].In addition, fuzzy logic-based methods provide good characteristics such as response rapidity and small oscillations at MPP. However, there are difficulties with changing irradiation information. [89]. Methods based on artificial neural networks [ANNs][90, 91] were some of the ways used to overcome the challenge. The fundamental concept of the MPPT technique based on ANN is shown in figure-7.

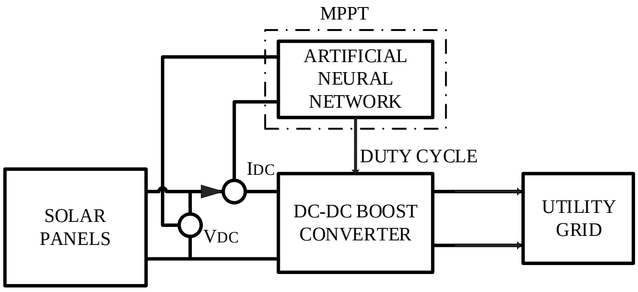

Figure 7: The fundamental concept of the MPPT technique based on ANN

In a constructed Maximum power point approach in a Photovoltaic system, input variables such as SC current, OC voltage, apparent power, voltage level, and atmospheric characteristics such as heating rate, percentage of solar irradiation impact on panel, and wind velocity are chosen as attributes. The consistency and effectiveness of the NN-based Maximum PowerPoint are determined by the algorithm creation and evaluation in the hidden units.[92]. Several suggested MPPT controllers based on artificial neural networks employ a feed-forward-back propagational approach to train the model. Information is communicated forward or backward in this weight correlation alteration. Although neural network machine learning algorithms are well-known, their capability to model non-linear functions allowed for the accurate prediction of Photovoltaic panel reference voltage equivalent to maximum power output. Besides accuracy in determining the MPP, ANN-centered techniques demonstrated a quick response time throughout the testing process. The quantity of weights is utilized to apply distinct inputs to the hidden neurons, and the outcome is sent to the output nodes. To reduce the difference between the actual and anticipated outcome of ANNs, the backpropagation neural approach is utilized to train utilizing the gradient decent algorithm for weight fluctuations of each level.[93, 94].In [95] proposes an innovative approach for increasing the outcome voltage of a solar panel when linked to a DC/DC power converter with varying load circumstances. A major part of this paper is to forecast the maximum reference voltage of the Solar cells under every climate circumstance using ML approaches and also to utilize as a reference for a PID control system that helps ensure the dc/dc step-up power converter offers a steady outcome voltage and extreme power level with a variety of meteorological conditions and loads. It also demonstrates that the system performs better when utilizing SVM, which means supporting vector machines as the ML technique than when applying convolutional neural networks.

The based P&O maximum power tracking regulator scheme also performs well in the constructed PV scheme. The Energy generated by the photovoltaic panels is delivered to load through a DC/DC power converter. The calculated solar plate voltage standards and current given to FL constructed a maximum power tracking controller network to predict MPP. FL control network is utilized to fix the extent of change in voltage, which is mandatory for corresponding MP on voltage source and current values through the PV panel. The MPPT control tracking [MPPT] system in Fuzzy Control P&O will determine the solar modules' operational voltage by controlling the power converter's duty series [96]. The FL maximum power tracking regulator depends on the inference instruction, and It may be assessed using the trial-and-error method[97]. Changes in energy and power about potential variation are used as inputs, and FL is programmed with such rules data to build perturbation voltage. The primary advantages of employing an FL-based MPP approach are that it eliminates the need for exact knowledge of PV module characteristics and it is an accurate system modeling. [98]. Compared with conventional FL-constructed maximum power tracking, the fractional order FL was developed to regulate the accelerated power tracking and evade deviation from MPP [99].

V. INVERTER

The result of a PV model is direct current energy that must be converted to AC via a converter. Its nonlinearity and changes in the production of power and voltage create a problem when constructing grid-connected solar inverters. The author developed a Neural modulation technique for grid-linked converters, which performs well in detecting reference signals. A FL-based inverter control network is utilized to reduce PV generation disturbance. Power fluctuations may cause converter difficulties, such as poor power factor, distortions, wastage, and control issues. As a nonlinear signaling processor, NN generates extracted features of the fundamental switching sequence comparable to the standard switching frequency value kept on the model's input.[100]. Linear programming is generally used in NNs, and networks are trained using the back-propagation algorithm via time strategy. To improve performance and reliability in the presence of faults, NN employs the integral of fault as the network's intake and the voltages caused by the interruption in the grid as the network's output. [101]. In the case of a multi-level inverter-based propulsion system, a fault detection strategy depends on NN, which could provide a better knowledge of fault behavior patterns, suspected cases, and fault diagnosis. [102]. The output of an AFNNC system may be conveniently delivered through switched pules in a step-up inverter, with no limits on regulating item analysis, just like in the scenario of the control scheme. In several publications, the advantages of AFNNC are explored compared to the classic double-loop propagation integral control technique. [103].

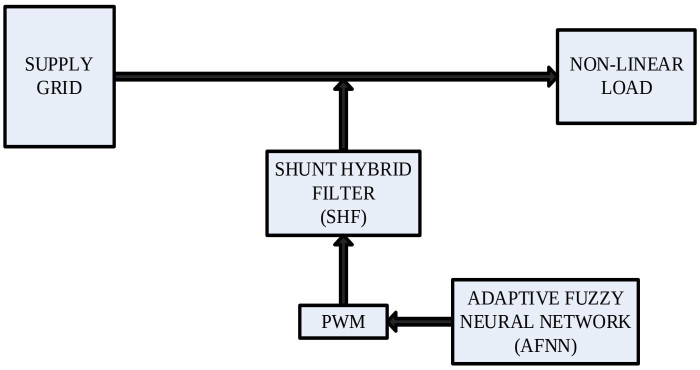

Figure 8: The fundamental paradigm of artificial intelligence-based inverter control

NN is also used in multilevel inverters. Multiple approaches for selective harmonic suppression have been presented. [104]. In this, direct current input connected to the inverter is taken to be time-changeable; it arises in solar energy as solar insolation fluctuates the entire day. These would be intended to change the phase angle dependent on the grid voltage. Among the most common methods is to utilize a genetic technique to create several switching angles offline for fluctuations in system voltage and to use AN to estimate genuine phase angles at various periods based on available data. The fundamental paradigm of artificial intelligence-based inverter control systems is shown in figure-8.

Reactive volt/ampere control is also possible using neural networks [ANN]. This technique creates a dynamic typical of the model, and an ANN is built on top of it. The advantage of ANN is that it supplied little sound in weight modification, essentially making the arrangement more resilient and designed for real-time input. [105]. Furthermore, ANN makes it very easy to apply a one-phase inverter regulator to the network [106]. Unlike previous approaches, neural networks enable minimal sampler rates, frequency switching, and stable performance even when system parameters vary.

Data Description

The dataset had vast data about different renewable energy systems: investment, storage, consumption, energy production, installed capacity, and environmental impact. This description has to provide an extensive review of renewable energy and help in the research and analysis of sustainable energy. The dataset description shows that 13 variables were extracted in this paper. Some of the variables are different Types of Renewable Energy (Solar, Wind, Hydroelectric, Geothermal, etc), Installed capacity in megawatts (MW), Energy storage capacity in megawatt-hours (MWh), Initial investment costs in USD, Air pollution reduction index and so on.

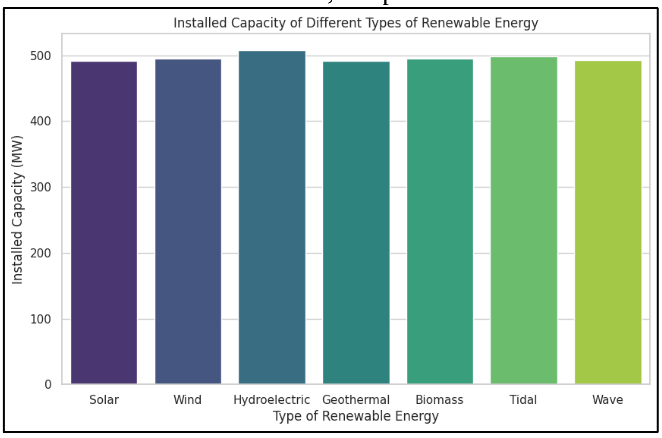

Figure-9 Installed Capacity of Different Renewable Energy Systems

Installed Capacity has several types of Renewable energy sources, similar to every installed capacity over 500 MV, and this capacity does not have individual dominant energy sources. The installation capacity analysis result of each renewable energy system is shown in Figure 9.

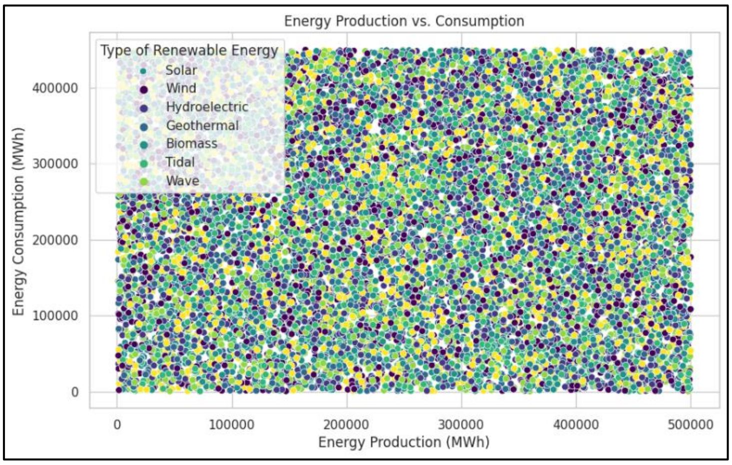

Figure-10 Energy Production Vs Energy Consumption Of Different Renewable Energy Systems

The scatter plot shown in Figure 10 produces a very thick and extensive distribution of points. This process will show the variation in the value of energy consumption and energy production with several renewable energy sources, and there is no clear tendency between these two-energy production and energy consumption, including different types of renewable energy, are not directly linked in the dataset.

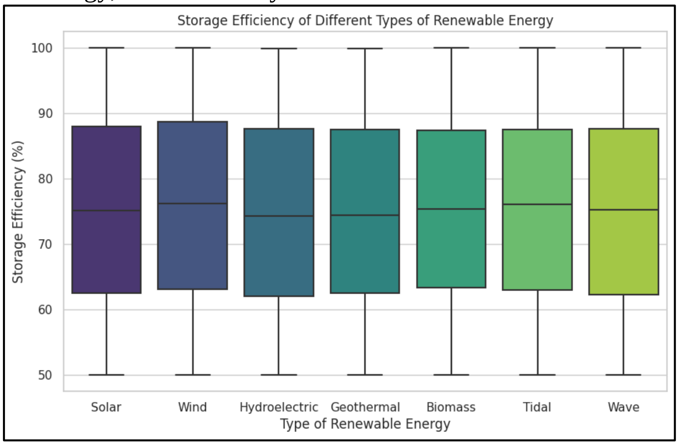

Figure-11 Storage Capacity of Renewable Energy System

The box plot of Fgure-11 shows the percentage of storage efficiency with various types of renewable energy that are quietly consonant between the falling range of 60% and 90%. Solar power has efficiency with a low level of median storage compared with others, and Tidal and Wave energy has a wide range of efficiency.

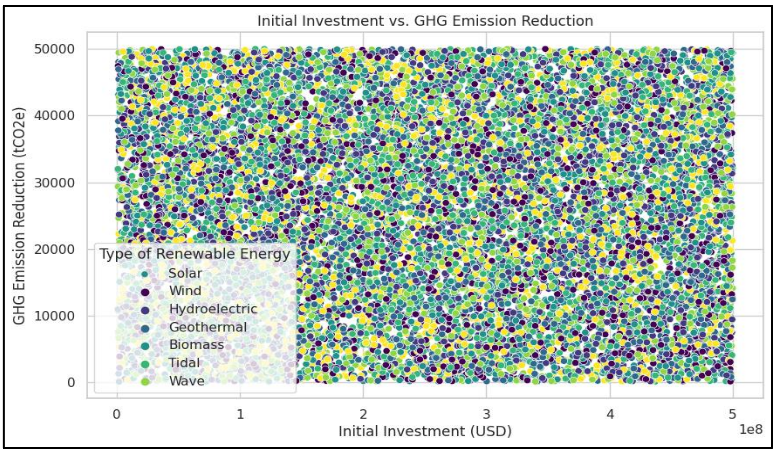

Figure-12 Initial Investment Vs. Emission Reduction

The Initial investment Versus Emission reduction ratio of various types of renewable energy systems is shown in figure-12. The figure shows that it is impossible to predict the accurate result of evaluating initial investment and

GHG emission reduction. This is because reducing GHG emissions is not directly correlated with initial investment. In some cases, an advanced renewable energy system or equipment is required to reduce the high level of GHG emissions or to control emissions during climatic change. To implement advanced techniques, a high amount of investment is required; at this time, indirect investment is correlated with GHG emission reduction. Due to this indirect correlation between initial investment and GHG emission, it is difficult to predict a direct relationship among various renewable energy systems.

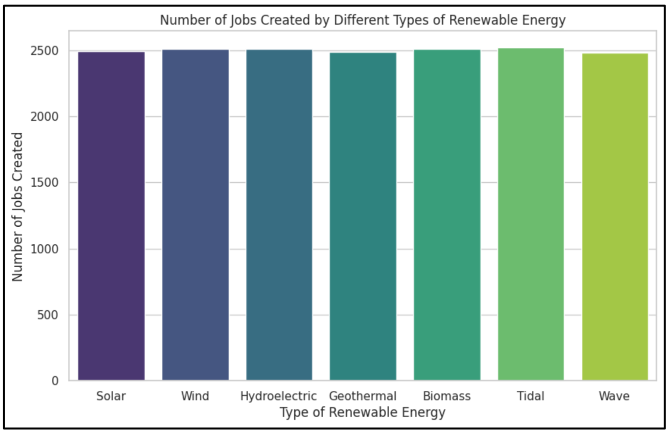

Figure-13. Renewable Energy Systems Vs. No. Jobs Created

The total number of jobs created by implementing various renewable energy systems is shown in Figure-13. The overall analysis depicts that almost all types of renewable energy systems have provided a greater number of jobs, equivalent to 2500. The tidal renewable energy system has provided 5% of jobs higher than other types. It is clear from the graph that renewable energy systems have a greater impact on job creation.

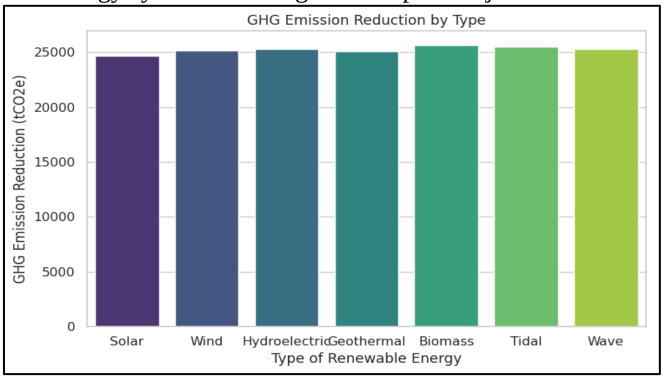

Figure-14. Renewable Energy System Vs. GHG Emission Reduction

Figure-14 depicts the efficiency of the different types of renewable energy in reducing GHG emissions. The analysis shows that all renewable energy systems have reduced greenhouse gas emissions simultaneously. The biomass-based system has reduced GHS emissions by 2% compared to other systems. From the overall analysis, the renewable energy system is more suitable for emission control, job creation, energy management, power production, storage efficiency, and cost consumption. Each feature in the input dataset has a unique function and performs well to create a more suitable, sustainable, and robust renewable energy system.

VI. CONCLUSION

Artificial intelligence technologies have become crucial tools for renewable energy development. In the beginning, the article briefly discusses ES, FL, and ANN, key branches of artificial intelligence. It is then followed by examining the application of machine learning in various aspects of renewable sources, including the potential it provides and the difficulties it presents. Due to various current concerns about climate change and global warming, focusing on renewable technology is booming. As a result, reliable forecasting of sustainable energy generation has become critical, and several relevant research have been done. As a result, implementations of machine-learning methodologies in sustainable predicting have risen in importance. This work also reviewed and graded machine-learning methods employed in recent energy projects. Machine-learning techniques are increasingly used for renewable energy, with the bulk of solar and wind energy estimates based on artificial intelligence approaches and hybrid models. Recent studies have reported that with an appropriate prediction, power control for renewable

energies may be enhanced, resulting in a greater use of renewable energy in energy systems, which will be highly helpful.
ML may similarly be utilized in MPPT systems; its key benefit is less sensitivity to input sound and quicker performance. Nearly all approaches for MPP tracking have additionally been proposed, employing a hybrid system that combines ML [machine learning] and classical methods. Besides this, machine learning may handle various challenges in inverters and deliver stable power production even when renewable energies are unpredictable. The expense of highly specialized computer equipment is a major concern with machine learning systems. Data pre-processing and data clearing operations might be time-consuming. Furthermore, ML is identical subject to partiality, making an entire system unusable. As a result, ML [machine learning] necessitates cautious proposal and execution, and through the correct machine knowledge algorithms, various challenges linked with renewable power systems may be solved. The study's main value is that it gives an overview of multiple parts where artificial intelligence has been used and provides a clear picture of how artificial intelligence benefits many areas.

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