A REVIEW OF ARTIFICIAL INTELLIGENCE TECHNIQUES USED WITH RENEWABLE ENERGY SYSTEMS

Purnaye Sonali Ramesh
Research Scholar
Department of Computer science Engineering
Sunrise University, Alwar, Rajasthan.
sonalirangdale1278@gmail.com

Dr. Rathod Sunil Damodar
Research Guide
Department of Computer science Engineering
Sunrise University, Alwar, Rajasthan.

Abstract:-

Renewable energy is gaining popularity as a reliable alternative energy source since it is safer and healthier than conventional energy and has made a significant contribution in this field. To keep up with this quickly developing technology, there are still a number of areas that need development. AI technology can assess the past, enhance the present, and forecast the future. AI will thus resolve the bulk of these problems. Although AI is complex, it decreases inaccuracy and strives for greater precision, making energies smarter. This article provides an overview of frequently used artificial intelligence (AI) approaches in applications using renewable energy sources. AI is used in almost every kind of energy (wind, solar, geothermal, hydro, oceanic, bio, hydrogen, and hybrid) for design, optimization, prediction, administration, transmission, and control. The goal of this research is to highlight the AI methods used in the renewable energy sector across this aspect.

Keywords:- *Artificial intelligence · Renewable energy · Solar energy*

Introduction

The enormous potential of renewable energy resources (RE) makes them capable of meeting the world's current energy demands. It may broaden the range of industries involved in energy generation, guarantee a long-term sustainable supply, and reduce emissions both locally and globally. It may in fact provide chances for local component manufacture as well as financially viable options for satisfying specific power service needs (mostly in developing countries and rural areas).

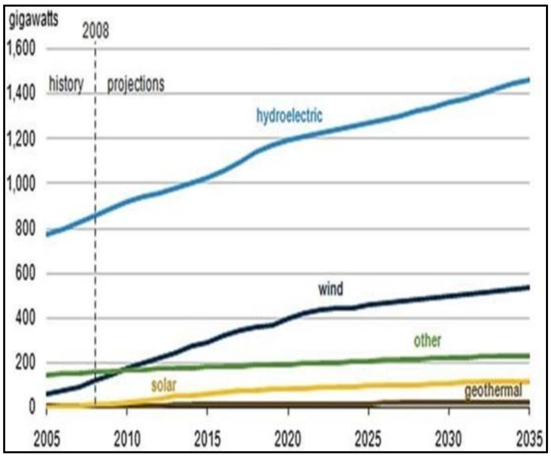

Fig. 1 Global installed power generation capacity by energy

Nearly all forms of renewable energy use AI for design, improvement, rating, operation, distribution, and law. The goal of this research is to highlight the AI methods used in the area of renewable energy throughout this scenario.

Existing hydroelectric power output is expected to increase more quickly than other renewable energy sources between 2008 and 2035. On the other hand, it is anticipated that implemented solar power generation would grow at the quickest pace over the projection period. Compared to the others, as shown in Fig. 1.

Artificial intelligence (AI) is proliferating in various areas of renewable energy systems (REs) as a result of increasing processing capability, tools, and data collecting. It has been shown that the design, control, and maintenance methods now used in the energy sector result in certain unfavorable effects. Additionally, the execution of these tasks using artificial intelligence (AI) has increased accuracy and precision and is presently at the forefront.

Due to its capacity to automate processes for higher levels of quality and productivity, artificial intelligence (AI) has become one of the most prominent study topics in recent years. They can learn, reason, and make decisions in the same manner that people do thanks to training methods and a complex set of instructions.

Additionally, it has been determined that the employment of AI in the digitization of energy systems significantly enhances the continuity, stability, dynamic responsiveness, and other crucial characteristics of the power system network. The power system's design, forecasting, control, optimization, maintenance, and security are now integrated using AI.

Renewable Energy Types

Solar Energy

Solar energy may be produced explicitly via the use of photovoltaic (PV) cells or implicitly through the collection and concentration of solar power (CSP), which produces steam that powers a turbine that produces electricity. It is possible to produce electricity directly from solar radiation by using the photovoltaic effect, which is based on the theory that photons of light force electrons into a higher energy state. Despite the fact that photovoltaics were first used to power spacecraft, there are various ways that PV power generation is employed in daily life, such as in grid-free houses, water use pumps, e-mobility, roadside emergency phones, and remote sensing.

Wind Energy

Wind is a clean, affordable, and readily available renewable energy source. Every day, wind turbines all around the world capture the energy of the air and convert it to power. When it comes to providing clean, sustainable energy for our planet, wind energy is becoming more important. Since ancient times, wind has been exploited as a major source of energy by transforming its kinetic energy into electricity via the use of windmills and wind turbines.

Hydroelectric Energy

When water flows through a dam, it creates hydroelectric energy (hydroelectric energy is produced when water flows through a dam; the dam may be opened or closed to various degrees to regulate water flow and produce the required quantity of power, depending on demand). Behind the dam, there is an intake where water enters and drives turbine blades. To produce electricity, a generator is spun by a turbine. The distance, the water droplets, and the volume of water that flows through the system all affect how much power is generated. Long electric cables may also be used to provide energy to homes, businesses, and industries. The majority of energy produced by renewable sources—nearly 16%—is produced using hydroelectric power, which is a renewable resource.

Ocean Energy

When we talk about sea energy, we're talking about a wide range of technological systems for applying a variety of transformation processes to generate power from the water. The first commercial units were deployed in this emerging market in 2008 and 2009. The ocean energy sector is crucial to making a significant impact in the supply of power to coastal nations and people, despite the fact that the enormous source of renewable energy has not yet been used on a broad scale.

Artificial Intelligence (AI)

A computer, robot, or other machine may simulate human cognitive activity thanks to artificial intelligence (AI). Enhancing computer processes that are involved in human cognition, such as thinking, learning, and problem-solving, is the fundamental aim of artificial intelligence. AI is often used for face recognition, which is especially effective for digitizing cognitive abilities. The use of artificial intelligence in electricity and renewable energy systems is now the subject of research. The most popular and efficient of these methods today are knowledge-based systems, fuzzy logic, and artificial neural networks. More accurate, quicker, and useful forecasts may be made using AI approaches than using any of the more conventional methodologies. On the other hand, data from renewable energy processes that are intrinsically noisy are a wonderful choice for processing with AI systems.

Even though it is a challenging subject to study, AI strives to grasp human cognition in order to develop intelligent entities who are capable of handling challenging challenges. The difficulty of manual calculation has lessened as AI has developed [15].

AI Techniques Applied in Renewable Energy

AI is used in almost every kind of renewable energy (wind, solar, hydro, ocean, and hybrid) for design, optimization, estimation, management, distribution, and policy. As the environment has become worse and traditional energy sources have run out, more people are becoming interested in renewable energy. In many regions, especially in Europe, wind power has been rapidly growing as a non-polluting renewable energy source. For instance, 4% of the world's energy consumption in Spain comes from the production of wind energy.

A simplified representation of several renewable energy sources and AI technology is shown in Figure 2.

Lalot used artificial neural networks to identify the temporal limitations of the solar detectors. A flat plate collector's static behavior may be explained by two elements, however its dynamic behavior needs the explanation of two more characteristics.

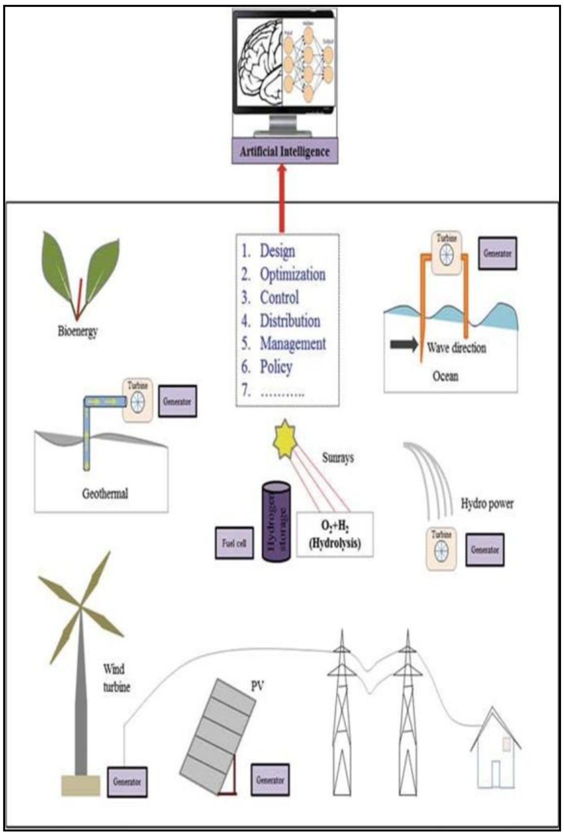

Fig. 2 Diagram depicting the use of artificial intelligence in various RE sources [18]

However, when a second-order process was examined, the network's discriminating power was not particularly strong. It has been established that collectors are third-order systems. A radial basis function (RBF) neural network is used to accurately identify pure third-order systems. To verify the neural network, the Euclidean distance between the collectors and their models was determined based on the number of learning steps. The recommended network found a difference of 2% for one parameter, demonstrating that neural networks are capable of differentiating collectors with comparable specifications.

An artificial neural network (ANN) was utilized by Veerachary and Yadaiah to determine the optimal operating point for a photovoltaic (PV) system. The maximum power point of a solar cell array and the integrated system's gross mechanical power operation are identified by the ANN controller after it has been trained using a gradient descent approach. The primary input for the neural network is solar insolation, and the output parameter is the converter chopping ratio that corresponds to the maximum power output of the PV cells or gross mechanical energy production of the complete PV system. The ANN projections exhibited errors of less than 2% and 7% for centrifugal and volumetric pump loads, respectively. In, a thorough analysis of NN's applications in power electronics is offered. There are several specific control and system identification examples provided. Fuzzy logic, metaheuristic methods, and other such AI technologies have not been discussed. Although it goes into further information about these tactics, it doesn't go into great length into AI algorithms; instead, it concentrates on illustrative instances. In his extensive discussion of metaheuristic methods for MPPT in photovoltaic (PV) systems, Bose provides several examples. [14], which only discusses the PV application, covers the AI methods used to PV systems.

Senjyu et al. designed the best arrangement of RE (GA) power producing systems on remote islands using a genetic algorithm. This method may be used to determine the ideal configurations for solar panels, wind turbine generators, and batteries. The generating system is made up of batteries, solar panels, diesel generators, and wind turbine generators. The suggested method may reduce operating expenses relative to diesel generators alone by around 10%.

A ground-breaking genetic algorithm-optimized technique for managing standalone hybrid renewable electricity systems with hydrogen storage is presented by Dufo-Lopez et al. The ideal hybrid system consists of RE resources (wind, PV, and hydro), batteries, fuel cells, an AC generator, and electrolyze.

The hybrid optimization by genetic algorithms (HOGAs) application, developed by Lopez and Agustin, uses a genetic algorithm (GA) to build a PV-diesel system and regulate its operation. The program was created in C ++. A stand-alone PV-only system dimensioned using a conventional design technique based on available energy under worst-case scenarios is contrasted with a HOGA-optimized PV-diesel system. The demand and solar exposure are same in both situations. The cost-effectiveness of the PV-hybrid system is shown by the computational results. A commercial software for hybrid system optimization is also contrasted with HOGA.

Mabel and Fernandez estimated wind power during a three-year period from seven wind farms using a neural network with feed-forward backpropagation. The

BPNN's prediction accuracy is excellent (the test set's RMSE was 0.0065, whereas the training set's was 0.0070). In order to calculate wind velocity data from two different sites, the performance of three different ANN techniques (BPNN, RBFNN, and adaptive linear element network (ADALINE)) has been examined.

A more sophisticated version of ANN (recurrent high-order neural networks) was used for wind power prediction by Kariniotakis et al. The performance of the ANN model and the Naive Bayes (NB) method are contrasted. The ANN has the lowest RMSE when measured against the NB. The BPNN technique was used to forecast wind speed in the Marmara during the years 1993–1997.

Fuzzy methods for estimating wind speed and power using real coded GA and binary coded GA were suggested by Damousis and Dokopoulos. Wireless modems were used to download wind energy data from a remote location, which was then processed using fuzzy methodology, yielding findings that were 29.7% and 39.8% more accurate than the permanent approach for the next hour and long, respectively.

Numerous evolutionary AI techniques have also been used to solar energy applications. Mashohor et al. recommended GA in solar tracking for improved PV system performance. The population size of the ideal GA-solar system is initially 100, there are 50 epochs, and the mutation and crossover probabilities are 0.7 and 0.001, respectively. The system's effectiveness is further shown by the production yield's low standard deviation (1.55). A solar water heating system that is as effective as feasible is designed using GA. A solar component value of 98% was achieved by developing the plate collection area with the GA set at 63 m.

In order to monitor the peak power of a PV array connected to a battery, Kumar et al. used GA. The efficiency of the perturb and observe (PO) algorithm is contrasted with that of the GA. A 400 V line voltage is produced by the boost converter.

The use of GA by Monteiro et al. to modify the hidden layer's parameters enhanced prediction accuracy (RMS 0.0432). The BPNN (RMSE 286.11) and traditional persistence (RMSE 445.48) approaches are contrasted with the GA HISIMI model (RMSE 283.89) strategy.

In order to maximize the size of a hybrid RE system and increase its efficiency, O'Sullivan et al. used PSO. An enhanced GA is used in the operation optimization of a hybrid RE system, outperforming the traditional GA approach [35]. The net present cost (NPC), cost of energy (COE), and generation cost (GC) of a hybrid RE system are improved using the bee technique.

The majority of the literature review's work is summarized in Table 1 along with the techniques used and results obtained.

Comparative Analysis

Each of the models covered above stands out for something special and functions well in a number of situations. In the field of photovoltaics (PV), artificial neural network (ANN) models are effective and may provide better long-term prediction results. They are widely used as input to time-series models because ARMA enables them to provide better results.

The simplest time-series algorithms are the tenacity models. They can outperform a number of other algorithms for fairly straightforward prediction. They are often used in practice despite their inconsistent predictability. Academics have conducted the most of the time-series modeling method research during the last thirty years.

New models built on artificial intelligence, such fuzzy logic and neural network models, have been created. Fuzzy logic systems and wind energy consumption algorithms are two examples of algorithms that employ a large quantity of historical data as modeling input to make accurate short-term forecasts.

Table 1 Summary of AI techniques applied in renewable energy

References	Methods	Description	Achievement
Lalot	ANNs/ RBF	A radial basis function was used to identify temporal characteristics of solar collectors using ANNs (RBF)	For one parameter, the suggested network identified a difference of 2%
Veeracharry and Yadaiah	ANN	An artificial neural network (ANN) was used to find the best operating point for a photovoltaic (PV) system	For centrifugal and volumetric pump loads, the ANN forecasts had an error of less than 2% and 7%, respectively
Senjyu et al.	Genetic algorithm (GA)	Using a genetic algorithm, developed an optimal configuration of power generating systems in isolated islands with RE (GA)	In comparison with diesel generators alone, the proposed technique can cut operation costs by around 10%
Dufo-Lopez et al.	Hybrid optimization by genetic algorithms (GAs)	Produced hybrid optimization by genetic algorithms (HOGAs), a tool for designing a PV-diesel system using a genetic algorithm (GA) (sizing and operation control of a PV-diesel system)	The PV-hybrid system's economic benefits are demonstrated by the computational findings
Mabel and Fernandez	Feed-forward backpropagation neural network (BPNN)	BPNN is used to evaluate wind power from seven wind farms during a three-year timeframe	The BPNN has a respectable prediction accuracy (RMSE 0.0070 for the training set and 0.0065 for the test set)
Kariniotakis et al.	Advanced version of ANN	For wind power estimation, an upgraded form of ANN was implemented	In comparison with the NB, the ANN has the smallest RMSE
Damousis and Dokopoulos	Fuzzy methods using the two GA algorithms	For wind speed and power estimate, developed fuzzy approaches employing the multiple GA algorithms (real coded GA and	The fuzzy method outperforms the persistent method by 29.7% and 39.8% for the next hour and long-term predictions,

		binary coded GA)	respectively
Mashohor et al.	Genetic algorithm (GA)	GA in solar tracking is recommended for increased PV system performance	The system's efficiency is also demonstrated by the low standard deviation (1.55) in generation gain
Atia et al.	Genetic algorithm (GA)	GA is used to develop a solar water heating system that is as efficient as possible	With the GA set to 63 m, the plate catcher region has been improved, resulting in a solar fraction value of 98 percent
O'Sullivan et al.	Particle swarm optimization (PSO)	PSO is used to optimize the size of a hybrid RE system	Improve the cost-effectiveness of the hybrid RE system
Lalot	ANNs/ RBF	The identification was done using a radial basis function. Temporal characteristics of solar collectors using ANNs (RBF)	For one parameter, the suggested network showed a difference of 2%
Veeracharry and Yadaiah	ANN	An artificial neural network (ANN) was used to determine the best operating point of a photovoltaic (PV) system	For centrifugal and volumetric pump loads, the ANN predictions had an error of less than 2% and 7%, respectively
Senjyu et al.	Genetic algorithm (GA)	Using a genetic algorithm, produced an optimal configuration of power generating systems in isolated islands with RE (GA)	In comparison with diesel generators alone, the proposed technique can cut operation costs by around 10%
Dufo-Lopez et al.	Hybrid optimization by genetic algorithms (GAs)	Produced hybrid optimization by genetic algorithms (HOGAs), a tool that designs a PV-diesel system using a GA (sizing and operation control of a PV-diesel system)	The computational findings demonstrate the PV-hybrid system's cost-effectiveness

Neural networks are effective at handling raw data input and have strong learning and training capabilities. Fuzzy logic models are superior than others when it comes to reasoning challenges, but they have poor learning and adaptability capabilities. In order to get excellent outcomes, fuzzy logic and neural networks were combined in novel methods. Because these tactics rely on several conditions, it is difficult to meaningfully compare them all, and gathering data is a challenging task. The artificial-based method, however, performs better than other techniques in terms of short-term prediction, according to several comparisons and related research.

Challenges

Based on current AI developments, the use of AI technology in RE is anticipated to run into the following major challenges:

It is necessary to improve reliability even further. While applying AI to energy systems has resulted in a high rate of problem and defect identification, it still falls short of the demands of the application. AI may currently only be used to enhance established working practices.

Infrastructure improvement is required. The usage of AI requires a lot of data samples, powerful computers, and interconnected worldwide networks. Big data, for example, is a crucial component of infrastructure, therefore its degree and supporting capacity must be taken into account.

Conclusion and Future Directions

Through the previous evaluation of all technologies utilized in the sectors of renewable energy, it is extremely necessary to develop these techniques and try to disseminate these tech- niques because of a large benefit in providing electric power without environmental detrimental. Artificial intelligence approaches' significant contributions to the development of renewable energy-based power generating methods. In order to further work in renewable energy and the generation of electricity, it is crucial to concentrate on deep learning and machine learning approaches after examining the majority of the techniques used in these fields.

Advances in presently available AI techniques are quite likely to be noticed in the following years. There seems to be a data huge gap in the economy right now, but with the advent of IOT's solutions, the adoption of a broad variety of sensors, adaptive streaming given by drones for monitoring purpose, and NLP approaches, the issue of a shortage of data is likely to fade away.

It is important to note that neural networks (NNWs) are now gaining the most attention for potential applications among all AI methodologies.

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