Artificial Intelligence Techniques Applied on Renewable Energy Systems: A Review

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Abstract Renewable energy is gaining traction as an efficient alternative source of energy; it is considerably safer and healthier than traditional energy, and it has greatly contributed to this area. However, there are still several areas that need improvement in order to meet this rapidly expanding technology. AI technology can evaluate the previous, improve the current, and predict what will happen. As a result, AI will fix the majority of these issues. AI is complicated, but it lowers error and aspires for better precision, making energies more intelligent. This paper presents an overview of commonly utilized artificial intelligence (AI) techniques in sustainable sources of energy applications. AI is applied in practically every form of energy for design, optimization, prediction, administration, transmission, and regulation (wind, solar, geothermal, hydro, ocean, bio, hydrogen, and hybrid). Throughout this aspect, the purpose of this study is to highlight the AI techniques utilized in the field of renewable energy.

Keywords Artificial intelligence · Renewable energy · Solar energy

1 Introduction

Renewable energy resources (RE) offer immense potential and can satisfy today's global energy needs. It could increase energy production industry variety, provide long-term sustainable supply, and lower local and global emissions. It can indeed give financially appealing choices for meeting specific power service requirements

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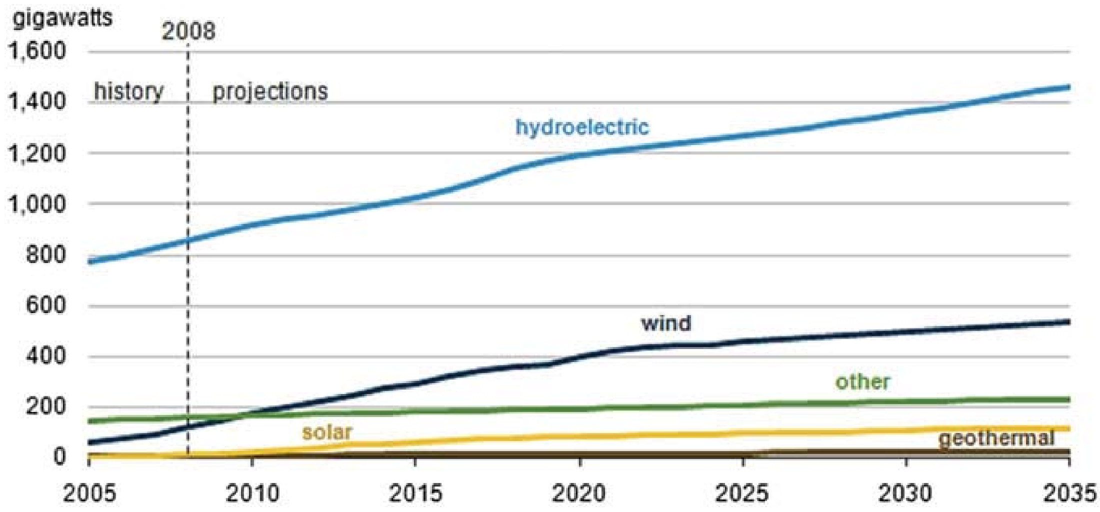

Fig. 1 Global installed power generation capacity by energy [2]

(mainly in developing nations and rustic regions), as well as opportunities for local component production. For design, improvement, rating, operation, distribution, and legislation, AI is employed in practically every kind of renewable energy. Throughout this scenario, the purpose of this study is to highlight the AI techniques utilized in the field of renewable energy [1].

Between 2008 and 2035, existing hydroelectric power generation is predicted to grow faster than other renewable energy sources. Implemented solar power generation, on the other hand, is expected to develop at the fastest rate over the forecast period. In comparison with the rest, as indicated in Fig. 1 [2].

Due to rising computational capacity, tools, and data collection, artificial intelligence (AI) is becoming more prevalent in many sectors of renewable energy systems (REs). The present approaches for design, control, and maintenance in the energy business have been shown to produce somewhat erroneous outcomes. Furthermore, the use of artificial intelligence (AI) to execute these activities has improved accuracy and precision, and it is currently at the forefront.

AI has been one of the most popular areas of research in recent decades, owing to its ability to automate systems for improved quality and productivity [3]. Through training techniques with a set of sophisticated instructions, it allows them to learn, reasoning, and decide in the same way that humans do.

Additionally, the use of AI in the digitalization of energy systems has been classified as having significant capability to improve in power system network continuity, stability, dynamic responsiveness, and other critical developments [4]. Nowadays, AI is being used to integrate components of the power system such as design [4], forecasting, control, optimization, maintenance, and security [5–7].

2 Renewable Energy Types

2.1 Solar Energy

Solar power can be generated physically using photovoltaic (PV) cells or implicitly by gathering and concentrating solar power (CSP) to generate steam, which will be used to operate a turbine to generate electricity. The photovoltaic effect, which leads to the idea that photons of light push electrons into a higher energy state, is used to directly generate electricity from solar radiation. Although photovoltaics were first used to power spacecrafts, there are several PV power generating usage in ordinary living, including grid-independent homes, water utilization pumps, e-mobility, wayside emergency phones, and remote sensing [8, 9].

2.2 Wind Energy

Wind is a renewable energy source that is pure, cheap, and easily accessible. Wind turbines collect the air's energy and turn it into electricity every day across the globe. Wind energy is becoming more essential in terms of how we power our world—in a clean, sustainable way. Wind as a key source of energy has been used for ages by converting its dynamic power into electricity using windmills and wind turbines. [10, 11].

2.3 Hydroelectric Energy

Hydroelectric energy is generated when water is coming thru a dam (hydroelectric electricity is created while water is coming through with a dam) (the dam can be opened or closed to varying degrees to control water flow and to produce the amount of electricity needed, based on demand). Water goes into an intake behind the dam, where it powers turbine blades. A turbine spins a generator to generate electricity. The amount of electricity produced is proportional to the distance, and the water drops as well as the volume of water that flows through the system. Energy can also be supplied to households, industries, and companies via lengthy electric wires. Hydroelectric power is the most frequently used renewable resource, responsible for nearly 16% of electricity generated by renewable use [12].

2.4 Ocean Energy

Sea energy refers to a broad variety of technical systems for using a number of transformation techniques to create electricity from the ocean. It is a new industry, with the first commercial units being installed in 2008 and 2009. Although the huge source of renewable energy has yet to be used on a large scale, the ocean energy sector plays an important role to make a big difference to the supply of electricity to coastal countries and people [13].

3 Artificial Intelligence (AI)

Artificial intelligence (AI) allows a computer, robot, or device to mimic human cognitive behavior. The basic goal of artificial intelligence is to improve computer functions that are involved in human cognition, such as thinking, learning, and problem-solving. AI is particularly useful for digitizing cognitive capacities; and a common use of AI is facial recognition. Research on the application of artificial intelligence approaches to power and renewable energy systems is now underway. Artificial neural networks, fuzzy logic, and knowledge-based systems are now the most widely utilized and effective of these techniques. The AI techniques can make predictions better, faster, and more practical than any of the traditional methods. On the other side, inherently, noisy data from renewable energy procedures are a great candidate for handling with AI systems [14].

Even if comprehending the intricate thought of a human mind is a difficult topic to tackle, AI aspires to understand human thought in order to create intelligent beings capable of solving complex problems. The advancement of AI has decreased the strain of manual computation [15].

4 AI Techniques Applied in Renewable Energy

For design, optimization, estimate, management, distribution, and policy, AI is employed in practically every type of renewable energy (wind, solar, hydro, ocean, and hybrid). People's attention has been drawn to renewable energy as the environment has deteriorated, and conventional supplies have been depleted. Wind power has been quickly expanding in many locations, particularly in Europe, as a non-polluting renewable energy source. In Spain, for example, wind power generation accounts for 4% of global energy consumption.

Figure 2 shows a simplified display of several sorts of renewable power sources and AI technologies [16–18].

Lalot employed artificial neural networks to detect the solar detectors' timing constraints. Two factors properly explain the static behavior of a flat plate collector,

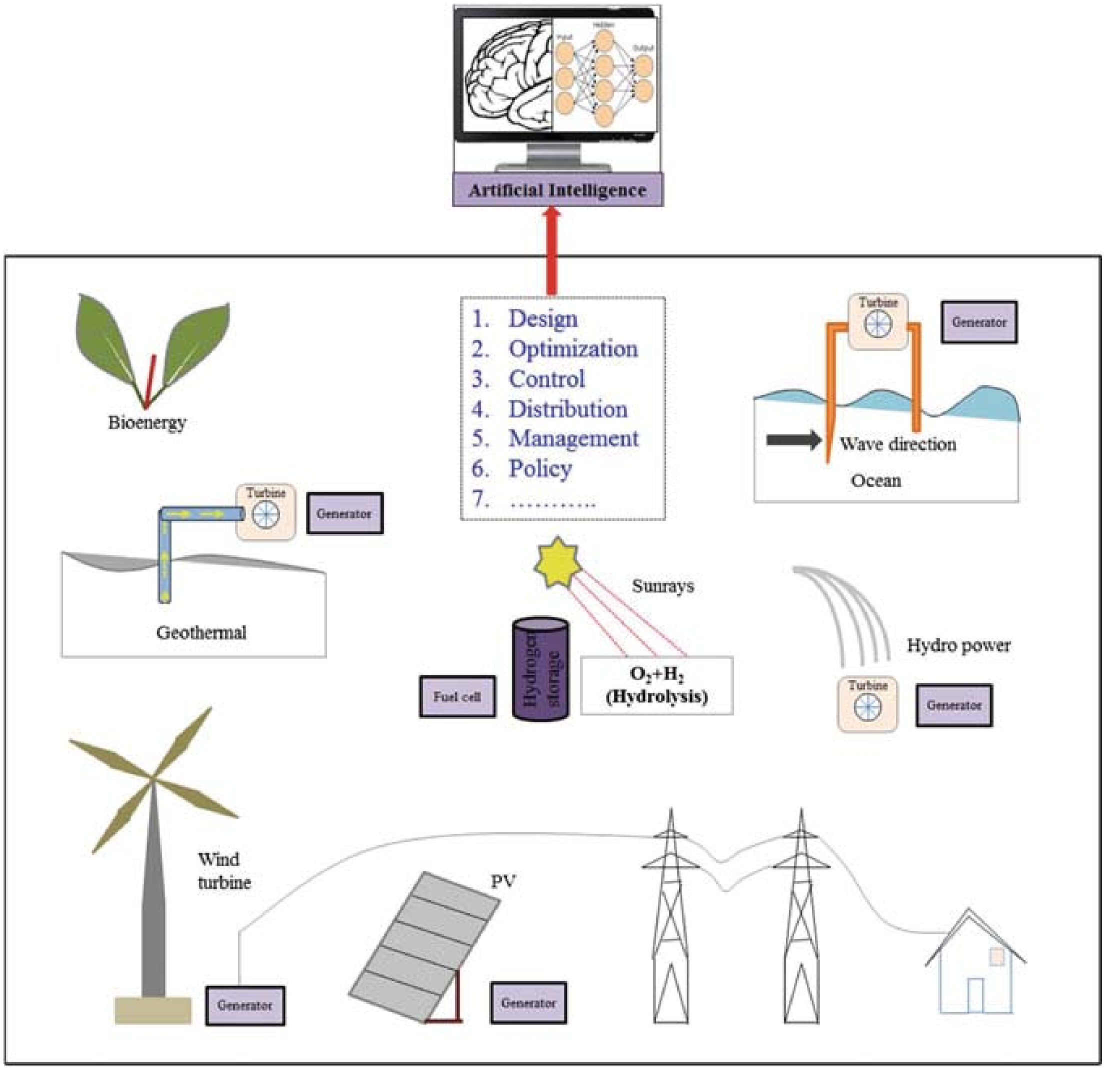

Fig. 2 Diagram depicting the use of artificial intelligence in various RE sources [18]

whereas two additional parameters are required to clearly explain the dynamic behavior. When a second-order process was investigated, however, the network's discrimination ability was not very great. Collectors have been demonstrated to be regarded third-order systems. To correctly determine pure third-order systems, a radial basis function (RBF) neural network is used. Based on number of learning steps, the Euclidean distance between the collectors and their models was computed to validate the neural network. Finally, neural networks were proven to be capable of discriminating collectors with similar parameters: the suggested network identified a difference of 2% for one parameter [19].

Veerachary and Yadaiah used an artificial neural network (ANN) to find the best operating point for a photovoltaic (PV) system. The ANN controller is trained using a gradient descent technique to identify the maximum power point of a solar cell array and the integrated system's gross mechanical power operation. Solar insolation is the essential input to the neural network, and the converter chopping ratio corresponding to the maximum power output of the PV cells or gross mechanical energy production of the integrated PV system is the output parameter. For centrifugal and volumetric pump loads, the ANN forecasts had an error of less than 2% and 7%, respectively [20]. A full survey of the uses of NN in power electronics is presented in [21]. Many particular control and system identification examples are given. Additional AI technologies, such as fuzzy logic, metaheuristic approaches, and so on, have not been touched on. Although [22] goes into greater detail about these strategies, it focuses on illustrative examples instead of an in-depth study of AI algorithms. Bose [22] presents a comprehensive explanation of metaheuristic approaches for MPPT in photovoltaic (PV) systems. The AI techniques utilized to PV systems are covered in [14], which is focused solely on the PV application.

Using a genetic algorithm, Senjyu et al. created an ideal configuration of power generating systems in isolated islands with RE (GA). This technique can be used to figure out how many solar panels, wind turbine generators, and battery configurations are best. Diesel generators, wind turbine generators, a photovoltaic system, and batteries make up the generating system. In compared to diesel generators alone, the proposed technique can minimize operation costs by around 10% [23].

Dufo-Lopez et al. [24] present a revolutionary genetic algorithm-optimized technique for controlling stand-alone hybrid renewable electrical systems with hydrogen storage. RE resources (wind, PV, and hydro), batteries, fuel cells, an AC generator, and electrolyze make up the optimal hybrid system.

Lopez and Agustin created the hybrid optimization by genetic algorithms (HOGAs), a program that designs a PV-diesel system using a genetic algorithm (GA) (sizing and operation control of a PV-diesel system). C ++ was used to create the software. A HOGA-optimized PV-diesel system is compared to a stand-alone PV-only system dimensioned using a traditional design method based on available energy under worst-case scenarios. The need and sun irradiation are the same in both circumstances. The computational findings demonstrate the PV-hybrid system's cost-effectiveness. HOGA is also compared to a commercial program for hybrid system optimization [25].

Mabel and Fernandez [26] used a neural network with feed-forward backpropagation to estimate wind power over a three-year period from seven wind farms. The prediction accuracy of the BPNN is commendable (the test set had an RMSE of 0.0065, and the training set had an RMSE of 0.0070.). The performance of three distinct forms of ANN approaches (BPNN, RBFNN, and adaptive linear element network (ADALINE)) has been investigated in the calculation of wind velocity data from two separate locations [27].

For wind power estimation, Kariniotakis et al. [28] ANN (recurrent high-order neural networks) was employed in a more advanced form. The ANN model's performance is compared to that of the Naive Bayes (NB) technique. When compared to the NB, the ANN has the lowest RMSE. For the years 1993–1997, the BPNN approach was employed to anticipate wind speed in the Marmara [29].

Damousis and Dokopoulos proposed fuzzy approaches for wind speed and power estimates utilizing multiple GA algorithms (real coded GA and binary coded GA). Data about wind energy from a faraway site were obtained utilizing wireless modems and analyzed using the fuzzy methodology, which produced 29.7% and 39.8% accurate accuracy results than the permanent technique for the following hour and lengthy, accordingly [30].

Solar energy applications have also used several evolutionary AI approaches [31, 32]. GA in solar tracking was suggested by Mashohor et al. [31] for increased PV system performance. The best GA-solar system has an initial size of the population of 100, 50 epochs, and mutation and crossover chances of 0.7 and 0.001, accordingly. The low-standard deviation (1.55) in production yield also demonstrates the system's efficiency. GA is used to design a solar water heating system that is as efficient as possible. The plate gathering area has been actually developed with the GA set to 63 m, resulting in a solar portion value of 98% [31].

Kumar et al. employed GA to track the highest point of power of a PV array coupled to a battery. The GA's effectiveness is compared to that of the perturb and observe (PO) algorithm. The boost converter produces a 400 V line voltage [32].

The employment of GA in parameter adjustment of the hidden layer by Monteiro et al. resulted in improved prediction efficiency (RMS 0.0432). The GA + HISIMI model (RMSE 283.89) approach is compared to the BPNN (RMSE 286.11) and conventional persistence (RMSE 445.48) methods [33].

O'Sullivan et al. employed PSO to optimize the size of a hybrid RE system in order to make it more cost effective [34]. In the operation optimization of a hybrid RE system, an upgraded GA is applied, which outperforms the classic GA method [35]. The bee method is used to improve the performance characteristics of a hybrid RE system (net present cost (NPC), cost of energy (COE), and generation cost (GC)) [36].

Table 1 shows the summary of most work in literature review with the used methods and its achievements.

5 Comparative Analysis

The models discussed above each have their own unique qualities and can behave effectively in a variety of settings. Artificial neural network (ANN) models are effective in the photovoltaic (PV) field and can provide improved long-term prediction outcomes. They are frequently utilized as feed to time-series models, since ARMA helps them get improved result.

The tenacity models are the most straightforward time-series algorithms. In terms of very simple prediction, they can outperform several other algorithms. Despite their inconsistency in prediction accuracy, they are commonly employed in practice. In the last thirty years, the majority of research on time-series modeling techniques has been done by academics.

New artificial intelligence-based models such as neural network models and fuzzy logic models have been developed. Algorithms that use a vast amount of historical data for modeling input, such as wind energy consumption algorithms and fuzzy logic systems, can produce precise short-term predictions.

Table 1 Summary of AI techniques applied in renewable energy

References	Methods	Description	Achievement
Lalot [19]	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%
Veerachary and Yadaiah [20]	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. [23]	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. [25]	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 [26]	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. [28]	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 [30]	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 binary coded GA)	The fuzzy method outperforms the persistent method by 29.7% and 39.8% for the next hour and long-term predictions, respectively
Mashohor et al. [31]	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

(continued)

Table 1 (continued)

References	Methods	Description	Achievement
Atia et al. [37]	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. [34]	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 [19]	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%
Veerachary and Yadaiah [20]	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. [23]	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. [25]	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

Raw data input is handled well by neural networks, which also have significant learning and training capabilities. When it comes to reasoning difficulties, fuzzy logic models surpass others, but their learning and adapting abilities are subpar. Fuzzy logic and neural networks were merged in new approaches to get good results. Because these strategies are dependent on varied settings, meaningful comparisons of all of them are difficult, and data collecting is a difficult undertaking. However, there are some comparisons and similar studies that prove that artificial-based algorithm outperforms other approaches in terms of short-term prediction.

6 Challenges

Based on existing AI advances, the implementation of AI technology in RE is projected to encounter the following significant obstacles:

Reliability needs to be enhanced even more. While AI technology implemented to energy systems has achieved a high rate of issue and defect detection, it still falls short of actual application requirements. At this time, AI can only be utilized as a supplement to traditional methods of work.

There is a need to upgrade infrastructure. The use of AI is dependent on a large number of data samples, high-computer power, and global network interaction. The supporting capability and degree of necessary infrastructure assets, such as big data, are, however, important considerations.

7 Conclusion and Future Directions

Through the previous review of all technologies used in the fields of renewable energy, it is very important to develop these techniques and work to spread these techniques because of a great benefit in producing electric power without environmental harmful. The important role of artificial intelligence techniques and their effective role in developing electricity production using renewable energy techniques. After reviewing most of the techniques used in these areas, it is very important to focus on the deep learning and machine learning techniques to improve work in renewable energy and production electricity.

Advances in currently accessible AI approaches are extremely likely to be seen in the coming years. There appears to be a data large disparity in the economy right now, but with the rise of IOT's solutions, the implementation of a wide range of sensors, adaptive streaming supplied by drones for monitoring purpose, and NLP techniques, the problem of a lack of data is likely to fade away.

It is worth noting that, among all AI techniques, neural networks (NNWs) are now receiving the most attention for future applications.

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