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Artificial Intelligence-Driven Approaches for Renewable Energy Systems: Techniques, Applications, and Future Perspectives

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ABSTRACT

Renewable energy has emerged as a promising alternative to conventional energy sources due to its environmental benefits, improved safety, and potential to support sustainable development. Despite significant advancements, several challenges remain in enhancing the efficiency, reliability, and scalability of renewable energy technologies. Artificial intelligence (AI) offers substantial opportunities to address these challenges by analyzing historical data, optimizing current operations, and forecasting future energy trends. Through advanced computational techniques, AI can improve prediction accuracy, minimize operational errors, and facilitate the development of intelligent and efficient energy systems. This paper presents a comprehensive overview of widely used AI techniques and their applications in renewable energy systems. These techniques support various energy-related processes, including system design, performance optimization, energy generation forecasting, resource management, power transmission, and operational control. The study covers a broad range of renewable energy sources, including wind, solar, geothermal, hydropower, ocean, biomass, hydrogen, and hybrid energy systems. Furthermore, it highlights the role of AI in improving energy conversion efficiency, enhancing system reliability, and addressing emerging challenges in renewable energy integration and management. The objective of this review is to provide an overview of the principal AI techniques employed in renewable energy applications and to examine their potential contributions to the development of more sustainable, efficient, and intelligent energy systems.

Keywords: Artificial intelligence · Renewable energy, · Solar energy, cyber security, Ocean Energy.

1 Introduction

Renewable energy (RE) resources have considerable potential to meet the growing global demand for energy. Their widespread adoption can diversify energy production, ensure a sustainable long-term energy supply, and reduce both local and global emissions.

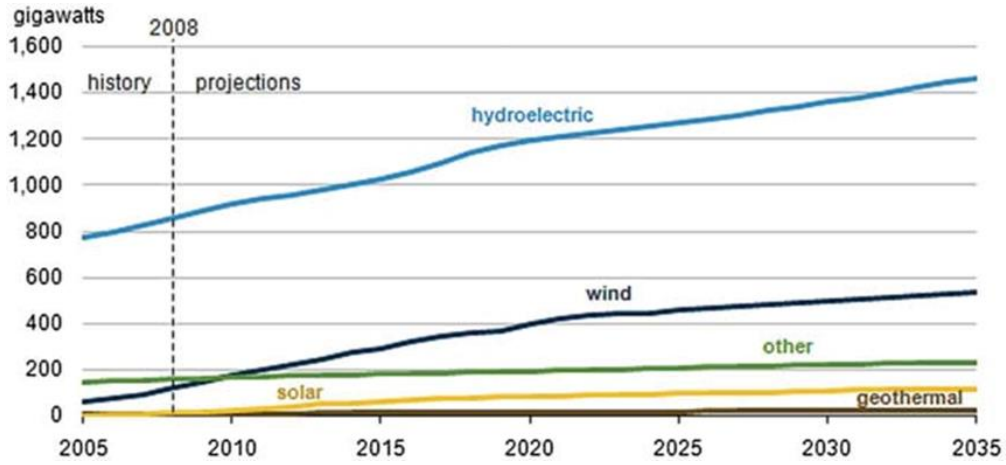


Fig. 1 Global installed power generation capacity by energy [2]

Furthermore, renewable energy technologies offer economically viable solutions for meeting specific electricity demands, particularly in developing countries and rural communities, while creating opportunities for local manufacturing and industrial development. Artificial intelligence (AI) has become an important tool across various renewable energy technologies, supporting system design, performance optimization, assessment, operation, power

distribution, and regulatory processes. In this context, the present study aims to review and discuss the AI techniques applied in the renewable energy sector [1].

Between 2008 and 2035, hydropower generation from existing facilities was projected to experience greater growth than other renewable energy sources. In contrast, solar power generation was expected to exhibit the highest growth rate over the same period. These trends illustrate the varying development trajectories of renewable energy technologies and their potential contributions to the global energy mix, as presented in Fig. 1 [2].

Advances in computational capabilities, the availability of sophisticated analytical tools, and the increasing volume of collected data have accelerated the adoption of artificial intelligence (AI) across various renewable energy applications. Conventional approaches to energy system design, control, and maintenance may encounter limitations in accuracy, efficiency, and adaptability when addressing complex operational conditions. AI-based methods can help overcome these limitations by improving analytical accuracy, enhancing decision-making, and enabling more effective management of renewable energy systems. Consequently, AI is increasingly recognized as a valuable approach for improving the performance and reliability of modern energy infrastructure.

In recent decades, AI has attracted considerable research interest because of its ability to automate complex processes and improve system quality, efficiency, and productivity [3]. By utilizing data-driven learning algorithms and computational models, AI systems can identify patterns, learn from historical observations, perform logical inference, and support decision-making with limited human intervention. These capabilities make AI particularly suitable for addressing the dynamic and uncertain operating conditions associated with renewable energy systems.

Moreover, the integration of AI into the digitalization of energy infrastructure offers substantial potential to improve power system reliability, operational stability, dynamic response, and overall network performance [4]. AI techniques are increasingly being incorporated into multiple aspects of power system management, including system design [4], energy forecasting, operational control, performance optimization, predictive maintenance, and cyber security [5–7]. These applications can facilitate more intelligent energy management, improve the integration of renewable energy sources, and support the transition toward a reliable, efficient, and sustainable energy system.

2. Types of Renewable Energy

2.1 Solar Energy

Solar energy is harnessed primarily through two technologies: photovoltaic (PV) systems and concentrated solar power (CSP) systems. Photovoltaic technology converts sunlight directly into electricity through the photovoltaic effect, in which photons transfer energy to electrons within a semiconductor material, generating an electric current. In contrast, CSP systems use mirrors or other optical devices to concentrate solar radiation and produce heat. This thermal energy is then used to generate steam, which drives a turbine connected to an electrical generator. Although PV technology was initially developed for applications such as powering spacecraft, it is now widely used in various practical applications. These include residential electricity generation, off-grid power systems, water pumping, electric mobility, emergency communication devices, and remote monitoring and sensing systems [8, 9].

2.2 Wind Energy

Wind energy is a clean, renewable, and widely available source of power that contributes to reducing dependence on conventional fossil fuels. Wind turbines capture the kinetic energy of moving air and convert it into mechanical energy, which is subsequently transformed into electricity by a generator. Wind energy has been utilized for centuries, initially through traditional windmills for mechanical applications and later through modern wind turbines for electricity generation. With continuous advancements in turbine design, control technologies, and energy conversion systems, wind power has become an important component of the global transition toward sustainable energy. Its increasing deployment supports electricity generation while helping reduce greenhouse gas emissions and the environmental impacts associated with conventional energy production [10, 11].

2.3 Hydroelectric Energy

Hydroelectric energy is generated by converting the potential and kinetic energy of flowing or falling water into electricity. In a conventional hydropower plant, water stored in a reservoir behind a dam is directed through an intake and flows toward a turbine. The movement of water rotates the turbine, which drives an electrical generator to produce electricity. The output of a hydropower plant depends primarily on the water flow rate and the hydraulic head, which represents the effective vertical difference in water levels. In many facilities, water flow can be regulated to adjust electricity generation according to changing demand. The generated electricity is then transmitted through power networks to residential, commercial, and industrial consumers. Hydropower has historically been one of the largest sources of renewable electricity worldwide, accounting for a substantial share of renewable power generation [12].

2.4 Ocean Energy

Ocean energy encompasses a range of technologies that extract energy from marine resources, including tides, waves, ocean currents, and differences in water temperature or salinity. These technologies convert the energy available in ocean processes into electricity through different mechanical, hydraulic, or thermodynamic conversion systems. Although ocean energy has considerable potential as a renewable resource, its large-scale commercial deployment

remains limited compared with more established technologies such as solar and wind power. Early commercial ocean energy projects emerged during the late 2000s, marking an important step toward the development of this sector. Ocean energy could contribute to diversifying the renewable energy mix, particularly in coastal regions and island communities, where access to marine resources may provide additional opportunities for sustainable electricity generation. Continued research and technological development are essential to improve system efficiency, reliability, cost-effectiveness, and environmental compatibility [13].

3 Artificial Intelligence (AI)

Artificial intelligence (AI) refers to the ability of computers, robots, and other computational systems to perform tasks that typically require human intelligence. Its primary objective is to develop systems capable of executing cognitive functions, including reasoning, learning, pattern recognition, and problem-solving. AI facilitates the automation of complex analytical processes and has found applications in numerous fields, including facial recognition, data analysis, and intelligent decision-making. In recent years, considerable research has focused on applying AI techniques to power systems and renewable energy technologies. Among the commonly employed approaches are artificial neural networks (ANNs), fuzzy logic systems, and knowledge-based systems. These techniques can improve prediction accuracy, computational efficiency, and operational performance compared with conventional methods in many applications. Furthermore, renewable energy systems often involve uncertain, nonlinear, and noisy data, making AI-based approaches particularly suitable for modeling complex relationships and extracting meaningful information from energy-related measurements [14].

Although replicating the complexity of human cognition remains a significant scientific challenge, AI research aims to develop intelligent systems capable of learning, reasoning, and solving complex problems. By automating computationally intensive tasks and reducing dependence on manual calculations, AI can improve productivity, accelerate data processing, and support more efficient decision-making across engineering and scientific applications [15].

4. AI Techniques Applied in Renewable Energy

Artificial intelligence has been applied extensively to renewable energy systems to support design, optimization, forecasting, energy management, power distribution, and operational control. These applications span several renewable energy sources, including solar, wind, hydropower, ocean energy, and hybrid energy systems. Growing concerns regarding environmental degradation, fossil fuel depletion, and increasing energy demand have accelerated interest in renewable energy technologies. Wind power, in particular, has expanded considerably in several regions, including Europe, because of its potential to generate electricity with relatively low operational emissions. For example, Spain has developed substantial wind energy capacity as part of its transition toward cleaner electricity generation. Figure 2 presents a simplified overview of different renewable energy sources and the AI techniques associated with their applications [16–18].

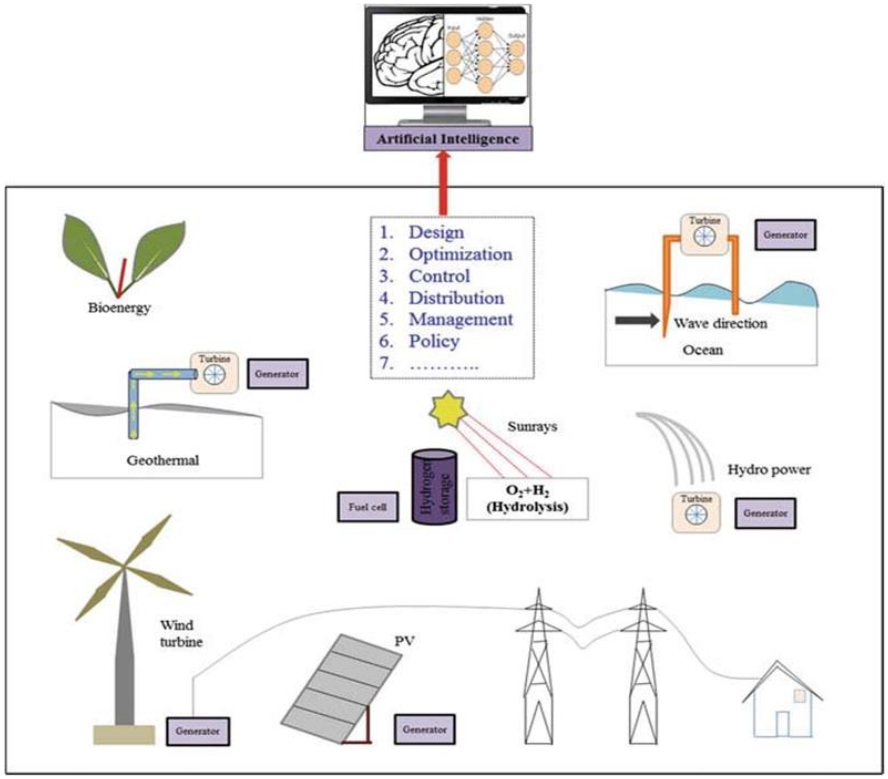


Fig. 2 Diagram depicting the use of artificial intelligence in various RE sources [18]

Lalot investigated the application of artificial neural networks (ANNs) to identify the dynamic characteristics of solar collectors. The study examined the parameters required to characterize the behavior of flat-plate collectors under both steady-state and transient operating conditions. Two parameters were sufficient to describe the static behavior, whereas additional parameters were necessary to represent the dynamic response accurately. However, the network demonstrated limited discrimination capability when applied to second-order processes. Since solar collectors were found to exhibit third-order system behavior, a radial basis function (RBF) neural network was employed to identify these characteristics. The Euclidean distance between the measured collector behavior and the corresponding model predictions was calculated at different stages of training to evaluate network performance. The results indicated that the neural network could distinguish between collectors with similar characteristics, identifying a difference of approximately 2% in one of the parameters [19].

Veerachary and Yadaiah employed an artificial neural network (ANN) to determine the optimal operating point of a photovoltaic (PV) system. The ANN controller was trained using a gradient-descent algorithm to identify the maximum power point of a PV array and optimize the power output of the integrated system. Solar irradiance was used as the primary input to the neural network, while the corresponding converter duty cycle associated with maximum PV power or optimal system operation served as the output. The proposed approach was evaluated under centrifugal and positive-displacement pump loads. The prediction errors were reported to be below 2% for centrifugal pump loads and 7% for positive-displacement pump loads [20]. Reference [21] provides a comprehensive review of neural network applications in power electronics, including examples related to system identification and control. However, other AI approaches, such as fuzzy logic and metaheuristic optimization algorithms, are not covered extensively in that study. Although reference [22] discusses these techniques in greater detail, its emphasis is primarily on illustrative applications rather than a comprehensive analysis of the underlying algorithms. Bose [22] presents an extensive discussion of metaheuristic techniques for maximum power point tracking (MPPT) in photovoltaic systems, while reference [14] focuses specifically on AI applications in PV technology.

Senjyu et al. developed a genetic algorithm (GA)-based optimization approach to determine the optimal configuration of renewable energy generation systems for isolated islands. The method was designed to identify suitable combinations and capacities of photovoltaic panels, wind turbine generators, and battery storage systems. The overall configuration included diesel generators, wind turbines, PV systems, and batteries. By optimizing the system configuration and operation, the proposed approach reduced operating costs by approximately 10% compared with a system relying exclusively on diesel generators [23].

Dufo-López et al. [24] proposed a genetic algorithm-based optimization method for the management of stand-alone hybrid renewable energy systems incorporating hydrogen storage. The hybrid configuration considered renewable energy sources, including wind, photovoltaic, and hydropower systems, together with batteries, fuel cells, an AC generator, and an electrolyzer. The optimization framework aimed to identify an effective system configuration and operating strategy while improving the utilization of renewable resources and energy storage technologies.

López and Agustín developed a software tool known as hybrid optimization by genetic algorithms (HOGA) for the design and operational optimization of PV-diesel hybrid energy systems. Implemented in C++, the program uses genetic algorithms to determine appropriate system sizing and operating control strategies. The authors compared a HOGA-optimized PV-diesel configuration with a stand-alone PV system designed using a conventional method based on worst-case energy availability. Both systems were evaluated under equivalent energy demand and solar irradiation conditions. The computational results demonstrated the economic advantages of the optimized hybrid configuration. The performance of HOGA was also compared with that of a commercially available hybrid system optimization program [25].

Mabel and Fernandez [26] applied a feed-forward neural network trained using backpropagation to estimate wind power generation across seven wind farms over a three-year period. The reported results indicated satisfactory prediction performance, with root mean square error (RMSE) values of 0.0065 for the testing dataset and 0.0070 for the training dataset. In a related investigation, three artificial neural network architectures—backpropagation neural networks (BPNNs), radial basis function neural networks (RBFNNs), and adaptive linear element (ADALINE) networks—were evaluated for estimating wind speed using data collected from two different locations [27].

Kariniotakis et al. [28] investigated a more advanced ANN architecture based on recurrent high-order neural networks for wind power forecasting. The predictive performance of the ANN model was compared with that of the Naive Bayes (NB) method. The ANN approach achieved a lower RMSE than the NB technique, indicating improved forecasting accuracy under the conditions considered. In another study, a backpropagation neural network was used to predict wind speed in the Marmara region using data covering the period from 1993 to 1997 [29].

Damousis and Dokopoulos investigated fuzzy logic-based approaches for forecasting wind speed and wind power, incorporating genetic algorithms with both real-coded and binary-coded representations. Wind energy data collected from a remote location were transmitted using wireless modems and subsequently processed using the proposed fuzzy methodology. The reported results indicated improvements in forecasting performance over a persistence-based reference method, with accuracy improvements of 29.7% for short-term forecasting and 39.8% for longer forecasting horizons, respectively [30].

Several evolutionary AI techniques have also been investigated for solar energy applications [31, 32]. Mashohor et al. [31] proposed a genetic algorithm-based approach for solar tracking to improve the performance of photovoltaic systems. The optimization process used a population size of 100 individuals, 50 generations, a crossover probability of 0.7, and a mutation probability of 0.001. The reported standard deviation of 1.55 in the energy yield indicated relatively consistent system performance under the investigated conditions. The study also considered GA-based optimization of a solar water-heating system. The collector plate area was optimized to approximately 63 m^2, producing a reported solar fraction of 98% [31].

Kumar et al. [32] applied a genetic algorithm to identify the maximum power point of a photovoltaic array connected to a battery storage system. The performance of the proposed GA-based method was compared with that of the perturb-and-observe (P&O) algorithm. The system incorporated a boost converter designed to provide a DC-link voltage of 400 V. This comparison was intended to assess the effectiveness of GA-based optimization for PV power extraction and system operation.

Monteiro et al. [33] employed a genetic algorithm to optimize the parameters of the hidden layer in a neural network, with the objective of improving prediction performance. The optimized model achieved an RMSE of 0.0432, as reported in the study. In a separate comparison involving wind power forecasting, the GA-HISIMI model produced an RMSE of 283.89, outperforming the backpropagation neural network (BPNN), which achieved an RMSE of 286.11, and the conventional persistence method, which recorded an RMSE of 445.48. These results illustrate the potential benefits of combining evolutionary optimization with predictive modeling.

O'Sullivan et al. [34] applied particle swarm optimization (PSO) to determine the optimal sizing of hybrid renewable energy systems, with the primary objective of reducing overall system costs. In another investigation, an improved genetic algorithm was employed to optimize the operation of a hybrid renewable energy system, demonstrating better performance than the conventional GA approach [35]. Additionally, a bee-inspired optimization algorithm was used to improve the performance of hybrid energy systems based on several economic indicators, including net present cost (NPC), cost of energy (COE), and generation cost (GC) [36].

Table 1 summarizes the major contributions reported in the literature, highlighting the AI methods employed, their respective renewable energy applications, and the principal findings of each study. Collectively, these investigations demonstrate the potential of AI techniques—including neural networks, fuzzy logic, genetic algorithms, particle swarm optimization, and other bio-inspired methods—to improve forecasting accuracy, optimize system configurations, enhance operational control, and reduce costs across renewable energy technologies.

5. Comparative Analysis

The models discussed above exhibit distinct characteristics and demonstrate varying levels of effectiveness depending on the application and operating conditions. Artificial neural network (ANN) models have shown considerable potential in photovoltaic (PV) systems, particularly for improving prediction accuracy and supporting long-term forecasting. Their ability to capture complex nonlinear relationships makes them suitable for modeling the behavior of renewable energy systems. Furthermore, integrating ANNs with time-series forecasting techniques, such as autoregressive moving average (ARMA) models, can enhance predictive performance by combining the learning capabilities of neural networks with the statistical characteristics of time-dependent data.

Persistence models represent some of the simplest approaches to time-series forecasting. These models assume that future values will remain close to the most recently observed values and can provide reasonable predictions under relatively stable operating conditions. Despite their simplicity, persistence models can perform competitively against more sophisticated forecasting techniques over short prediction horizons. However, their accuracy may deteriorate when environmental conditions or energy generation patterns change significantly. Nevertheless, their computational simplicity and ease of implementation have made them widely used as baseline methods for evaluating the performance of more advanced forecasting models. Over the past three decades, considerable research has been devoted to the development and evaluation of time-series modeling and forecasting techniques.

Recent advances in artificial intelligence have facilitated the development of more sophisticated predictive models, particularly artificial neural networks and fuzzy logic systems. These approaches can learn complex patterns from historical data and accommodate the nonlinearities and uncertainties commonly encountered in renewable energy applications. When trained using sufficient and representative historical data, neural network and fuzzy logic models can provide accurate short-term forecasts of wind power generation, energy demand, and other renewable energy parameters. Their predictive performance depends on factors such as data quality, model architecture, parameter selection, and the variability of operating conditions.

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	For one parameter, the suggested network identified a difference of
Veerachary and Yadaiah [20]	ANN	An artificial neural network (ANN) was used to find the best operating point for a photovoltaic	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	In comparison with diesel generators alone, the proposed technique can cut operation costs by around 10%

References	**Methods**	**Description**	**Achievement**
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	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
Kariniotakis et al. [28]	Advanced version of ANN	For wind power estimation, an upgraded form of ANN was	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	The fuzzy method outperforms the persistent method by 29.7% and 39.8% for the next hour and long-term predictions
Mashohor et al. [31]	Genetic algorithm (GA)	GA in solar tracking is recommended for increased PV	The system's efficiency is also demonstrated by the low standard
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
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	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

Despite recent advancements in artificial intelligence (AI), the integration of AI technologies into renewable energy (RE) systems continues to face several significant challenges.

Reliability and accuracy: The reliability of AI-based techniques requires further improvement before they can be deployed extensively in practical renewable energy applications. Although AI systems have demonstrated considerable potential for detecting faults, identifying operational anomalies, and predicting system performance, their accuracy and robustness may still be insufficient under certain real-world operating conditions. Consequently, AI is often used alongside conventional analytical and control methods rather than as a complete replacement. Further research is needed to improve model generalization, reliability, interpretability, and performance under uncertain and changing environmental conditions.

Infrastructure and data requirements: The successful implementation of AI in renewable energy systems depends on the availability of high-quality datasets, adequate computational resources, and reliable communication networks. Many AI algorithms require substantial historical data and processing capacity for effective training, validation, and deployment. However, limitations in data availability, computing infrastructure, and network connectivity can restrict their adoption, particularly in remote areas and developing regions. Therefore, investment in advanced data management systems, computational infrastructure, sensor networks, and communication technologies is essential to support the broader integration of AI into renewable energy applications.

7. Conclusion and Future Directions

The review of AI techniques applied to renewable energy technologies highlights their considerable potential to improve electricity generation, system efficiency, operational reliability, and energy management while supporting environmental sustainability. The application of AI methods across solar, wind, hydropower, ocean, and hybrid energy systems demonstrates their importance in addressing challenges related to forecasting, optimization, control, and predictive maintenance. Continued development and wider adoption of these techniques are essential to maximize the benefits of renewable energy and facilitate the transition toward cleaner and more sustainable electricity generation. In particular, greater attention should be directed toward machine learning and deep learning approaches because of their ability to analyze complex datasets, identify nonlinear relationships, and improve the predictive and operational performance of renewable energy systems.

Future advancements in AI are expected to create additional opportunities for renewable energy applications. Although limited data availability remains a major challenge, emerging technologies may help overcome this constraint. The integration of the Internet of Things (IoT), advanced sensor networks, drone-assisted monitoring, and adaptive data acquisition systems can facilitate continuous data collection and real-time monitoring of energy infrastructure. Furthermore, natural language processing (NLP) and other advanced data analytics techniques may support more effective information extraction, knowledge management, and decision-making in energy systems. These developments could improve the availability, quality, and accessibility of data required for training and deploying AI models.

Among the various AI approaches, artificial neural networks (ANNs) continue to attract considerable research interest because of their capacity to model complex nonlinear systems and learn from historical observations. Future research should explore their integration with deep learning architectures, hybrid optimization algorithms, and physics-informed models to enhance prediction accuracy, computational efficiency, and interpretability. Additional priorities include developing robust AI models capable of operating under uncertain environmental conditions, improving cybersecurity and data privacy, reducing computational and implementation costs, and validating AI-based solutions through real-world applications. Addressing these research challenges will be crucial to establishing reliable, scalable, and intelligent renewable energy systems capable of meeting future global energy demands.

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