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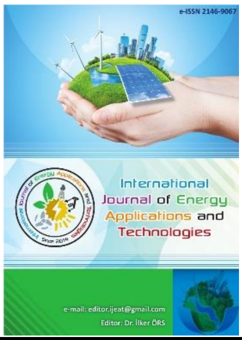

Review Article

Applications of artificial intelligence methods in renewable energy systems

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ABSTRACT

In order to reduce environmental problems caused by fossil fuels and to build a sustainable future, radical transformations are required in energy systems. In this transition process, energy sources characterized by environmental sustainability and renewability play a critical role. Renewable energy systems such as solar, wind and hydroelectric power are strategically important for reducing carbon emissions and ensuring energy security. This study comprehensively examines current applications of artificial intelligence (AI) techniques in these energy systems. In particular, it analyzes the contributions of AI-based solutions in key areas such as production forecasting, predictive maintenance strategies, system performance optimization and smart grid integration. Numerous studies have shown that machine learning methods, deep learning approaches and optimization algorithms enable accurate predictions and effective decision-making to address challenges such as intermittency, variability and uncertainty inherent in renewable energy sources. Moreover, the advantages offered by these technologies in enhancing operational efficiency, minimizing energy losses and supporting long-term environmental sustainability are emphasized. The findings suggest that AI-driven systems will significantly contribute to the digital transformation of the energy sector and play a decisive role in shaping the sustainable, flexible and intelligent energy infrastructures of the future.

Keywords: Artificial intelligence, Forecasting, Machine learning, Renewable energy systems, Smart grid.

1. Introduction

Renewable energy systems encompass alternative energy sources developed to reduce the environmental problems caused by fossil fuels and to build a sustainable future. Sources such as solar, wind, hydroelectric, biomass, and geothermal energy form the foundation of the renewable energy sector and play a significant role in meeting global energy demand. In this context, the present study aims to examine the applications of artificial intelligence (AI) in solar, wind, and hydroelectric energy systems, and to evaluate the contributions of these technologies to the integration of AI into renewable energy infrastructures.

Various technological methods have been developed to improve the efficiency of renewable energy systems and to maximize the benefits obtained from these resources. However, the intermittent and variable nature of these sources poses significant challenges for ensuring energy supply security. At this point, the use of AI techniques has become critically important.

AI offers effective solutions in the renewable energy field through its capabilities in big data analysis, predictive modeling, and system monitoring. In particular, machine learning and deep learning methods are widely applied in various areas such as forecasting energy production, early fault detection, optimization of maintenance processes, and smart grid applications. These technologies contribute to making energy systems more intelligent, efficient, and sustainable.

Considering the increasing energy demand and growing environmental concerns, the integration of AI-supported renewable energy systems is expected to play a strategic role in future energy management. This integrated approach is anticipated to accelerate the digital transformation of energy technologies and support environmental sustainability.

2. Overview of Renewable Energy Systems

Renewable energy systems aim to provide environmentally friendly and sustainable energy by utilizing naturally replenished sources. The main types of renewable energy include solar, wind, hydropower, biomass, and geothermal energy. Solar energy is harnessed through photovoltaic (PV) panels that convert sunlight directly into electricity, while wind energy is generated by converting kinetic energy from the wind using turbines. Hydropower systems rely on the conversion of water's potential energy into electricity via turbines and generators.

These systems are critical in reducing dependence on fossil fuels, thereby lowering greenhouse gas emissions and playing a vital role in combating climate change. Furthermore, they contribute to energy security and have the potential to reduce energy costs over the long term. However, the intermittent and variable nature of renewable energy resources poses significant challenges for reliable integration into national grids. To address these challenges, technologies such as energy storage systems, smart grid infrastructure, and advanced energy management systems are essential.

The integration of renewable energy systems is also crucial for diversifying national energy policies and achieving sustainable development goals. Additionally, the deployment of such systems supports local economic development through job creation and infrastructure expansion, particularly in rural or underdeveloped regions.

According to the International Energy Agency (IEA), the global share of electricity generation from renewable energy technologies is expected to change significantly between 2023 and 2030. As illustrated in Figure 1, hydropower holds the largest share among renewable sources in 2023. However, by 2030, both solar photovoltaic (PV) and wind power are projected to exhibit substantial growth, with solar PV surpassing all other sources to become the dominant contributor to clean electricity generation. This transition reflects the accelerated global investments in solar and wind technologies driven by falling costs and climate targets. The chart also shows relatively stable contributions from biomass and other renewables, while the combined share of solar and wind increases markedly, indicating a strategic shift in the global energy mix. [1].

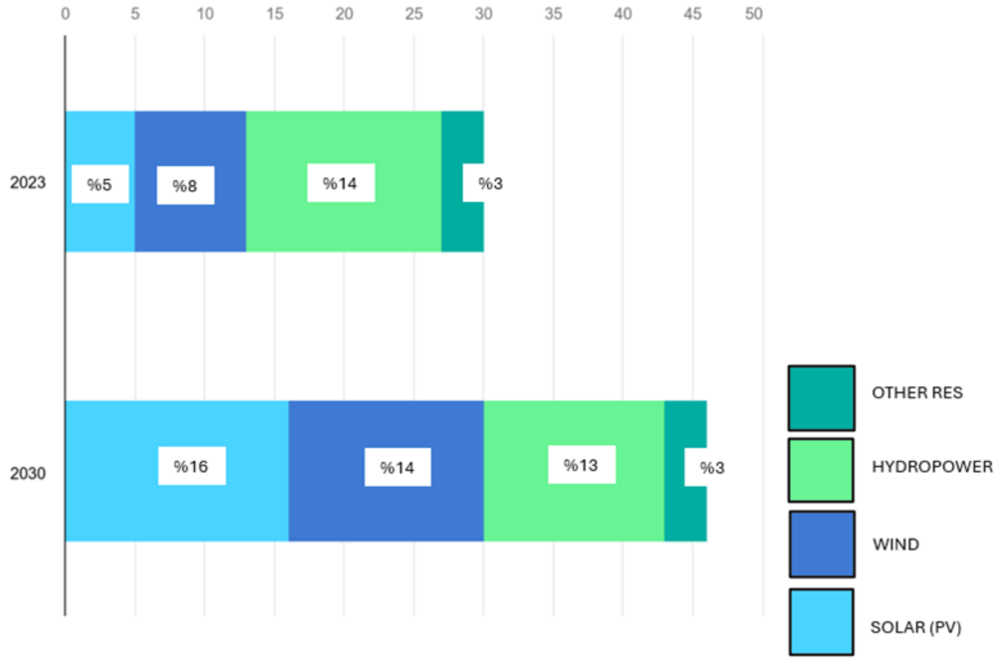

Fig. 1. Global electricity generation by renewable energy technology, 2023 and 2030. (International Energy Agency (IEA), [1]

2.1. Solar energy

Solar energy is one of the most widely used renewable energy sources. According to the Renewable Energy Policy Network, the total installed solar energy capacity is projected to exceed 8,000 GW by 2050 [2]. Solar energy is harnessed through photovoltaic (PV) panels that convert sunlight directly into electricity via semiconducting materials, which absorb photons and generate an electric current.

Solar energy utilization is generally categorized as either passive or active. In passive systems, solar PV energy is used directly or indirectly. For example, direct usage involves converting the DC (direct current) electricity from PV panels into AC (alternating current) for consumption in buildings. However, fluctuations in solar irradiance can lead to energy production variability. Indirect usage, on the other hand, includes concentrating sunlight using mirrors or lenses to

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generate thermal energy, which is then used to produce electricity via steam turbines. This approach is known as Concentrated Solar Power (CSP). CSP systems, which offer both heat and electricity generation, have attracted substantial global investments in recent years.

CSP technologies typically use two focusing principles: line-focus and point-focus. In line-focus systems, solar radiation is concentrated along a focal line using parabolic trough collectors or linear Fresnel reflectors. In point-focus systems, sunlight is concentrated to a single point to reach higher temperatures, commonly seen in solar tower and parabolic dish systems. Examples of these technologies are presented in Figure 2 [3].

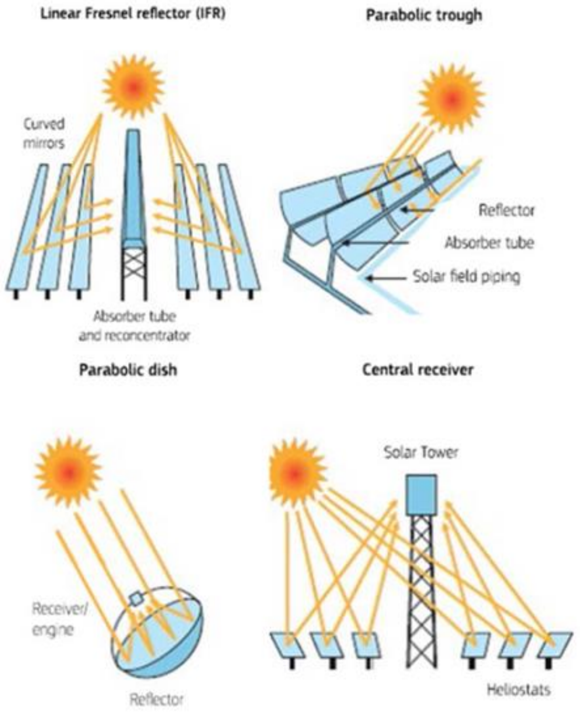

Fig. 2. Line – focus and point – focus CSP Technologies [3]

Advancements in solar tracking systems also play a vital role in enhancing energy production by ensuring panels remain optimally angled toward the sun throughout the day. Although solar energy is highly effective in regions with abundant sunlight, its efficiency depends on various factors such as irradiance, ambient temperature, and panel orientation.

The versatility of solar energy allows for applications ranging from small residential rooftops to large-scale solar farms [4]. With advantages such as zero emissions, low operational costs, and energy independence, solar energy stands out as a key solution in the global shift toward sustainability. Moreover, declining costs of PV panels and technological advancements have accelerated global adoption. However, the intermittency of solar energy remains a significant challenge, necessitating the integration of energy storage systems to ensure a stable and continuous power supply.

2.2. Wind energy

Wind energy is a rapidly growing renewable energy source with significant global importance. Wind turbines convert the kinetic energy of wind into electricity, providing a clean and cost-effective solution for energy generation. The potential of wind energy depends on variables such as wind speed, direction, and consistency. It is especially prevalent in coastal and open-field regions, where wind conditions are favorable for localized power generation.

Figure 3 shows the cumulative growth in global wind energy capacity over the past decade. Total capacity reached approximately 1,136 GW by the end of 2024, with 117 GW of new capacity added in 2024 alone. The dark blue bars show expected annual capacity additions, while the gray segments highlight the shortfall required to meet net-zero scenarios by 2050. The green line indicates cumulative capacity needed to stay aligned with a 1.5°C climate pathway. The trend line suggests that the 2,000 GW barrier could be surpassed by 2030. This growth is supported by technological advances, rising fossil fuel prices, and international efforts to combat climate change.[5]. Compared to conventional energy generation, wind farms generate significantly lower environmental impact and contribute to substantial reductions in greenhouse gas emissions.

Wind energy systems are generally divided into onshore and offshore wind farms. Offshore wind farms, which benefit from higher wind speeds and fewer obstacles, tend to be more efficient and are often equipped with turbines ranging from 6 to 8 MW in capacity [6]. Onshore wind farms, typically located in rural or agricultural areas, usually have smaller capacities around 2.1 MW per turbine [7]. As wind energy technologies continue to evolve, turbine capacities are also increasing accordingly.

However, the integration of wind energy into the electricity grid presents several technical challenges due to its intermittent nature. Variability in wind speed leads to fluctuations in energy production, potentially disrupting grid stability. Therefore, integrating energy storage systems and advanced forecasting algorithms becomes essential [8].

Artificial intelligence (AI) techniques are increasingly being applied in wind energy systems to enhance forecasting, performance analysis, and fault detection. Machine learning algorithms can process complex meteorological variables such as wind speed and direction to provide accurate production forecasts, thereby increasing the reliability and efficiency of wind farms. Predictive maintenance supported by AI can reduce downtime, improve performance, and significantly lower operational costs. With continuous technological improvements, wind energy will play an even more prominent role in meeting clean energy demands in the near future.

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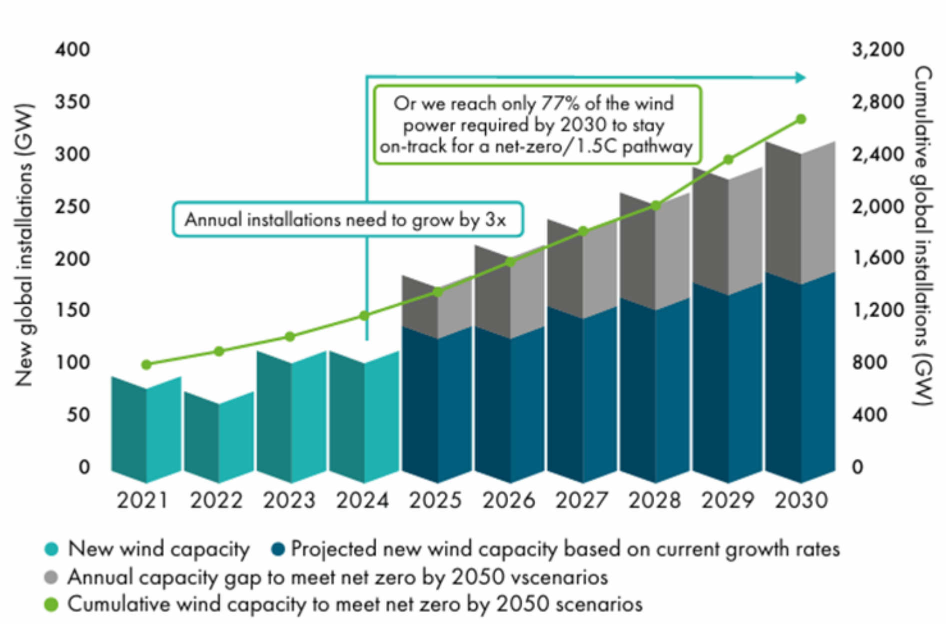

Fig. 3. Projected global wind power capacity growth and gap analysis for meeting net-zero targets by 2030 and 2050 [6]

2.3. Hydropower energy

Hydropower is based on the conversion of water's potential energy into electricity using turbines and generators. As shown in Figure 4, this process typically involves releasing water from a height via a dam, channeling it through penstocks, and turning turbines to produce electricity, which is then transmitted to the grid. Hydropower systems form the backbone of global renewable energy production, accounting for approximately 78% of total renewable output [10].

One of the most significant advantages of hydropower is its low carbon emissions. For instance, hydropower plants emit approximately 97.7% less carbon compared to coal-fired power plants [10], making them a critical component in climate change mitigation strategies. However, large-scale dam construction can have adverse environmental impacts, including ecosystem disruption, altered water flow, and displacement of local communities [11].

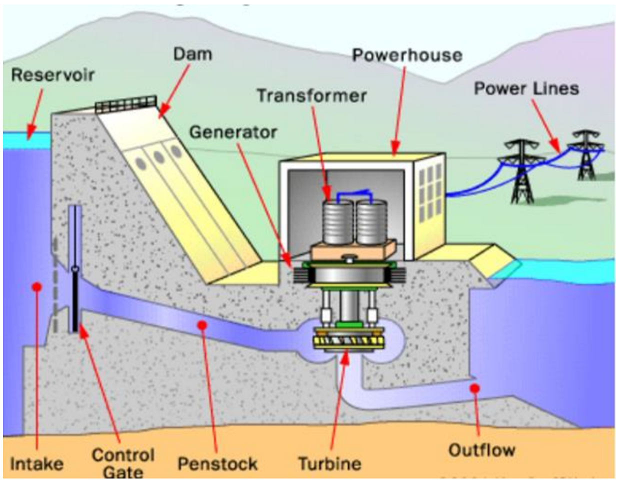

Fig.4. Components of hydropower plant [12]

Although the initial investment cost of hydropower projects can be high, they tend to have long operational lifespans. The average annual operation and maintenance cost is typically around 2% of the initial investment, indicating strong long-term economic sustainability [13].

In recent years, the integration of artificial intelligence into hydropower systems has significantly improved operational efficiency. AI techniques are used to forecast water inflow, analyze energy demand, and optimize maintenance scheduling [14]. These innovations enhance system performance and facilitate integration with energy storage technologies.

Modern hydropower systems benefit from AI in areas such as condition monitoring, fault diagnosis, and predictive maintenance. With the help of machine learning, operators can assess the health of equipment in real time, detect anomalies early, and prevent costly failures [15]. As a result, these methods support improved reliability, reduced downtime, and lower maintenance expenses.

In summary, the future of hydropower is closely linked to innovations in AI. These technologies will continue to strengthen the role of hydropower as a reliable, sustainable, and efficient energy source in the global renewable energy landscape.

3. Artificial Intelligence Methods

Renewable energy systems are inherently uncertain and dynamic and require advanced techniques for accurate prediction, diagnosis, and optimization. In this section, we review how machine learning, deep learning, and metaheuristic optimization methods have been effectively integrated into renewable energy applications by recent literature. [16]

3.1. Machine learning

Among various supervised learning techniques, tree-based ensemble models such as Random Forest (RF) and XGBoost are consistently recognized for their accuracy in solar PV forecasting. For instance, Asiedu et al. (2024) compared single and hybrid ML models on a 180 kWp PV system, finding that RF performed best for 2-week and month-ahead predictions, while a stacked hybrid of XGBoost and RF excelled in week-ahead forecasts. [17] Similarly, Theocharides et al. (2024) developed an XGBoost classifier for day-ahead PV generation that achieved nRMSE 8.20% and MAPE 6.91% over a year-long validation, proving robustness across clear and cloudy conditions[18].

A comparative study by Soleymani & Mohammadzadeh (2023) evaluated the performance of Random Forest, XGBoost, LightGBM, CatBoost, and MLP-ANN for solar irradiance forecasting using MAE, RMSE, and R^2 metrics. The results demonstrated that Random Forest achieved the highest accuracy (RMSE: 87.18, MAE: 34.82, R^2: 0.95), outperforming XGBoost and LightGBM. Notably, the performance of MLP-ANN improved significantly when Pearson Correlation Coefficient (PCC)-based feature selection was applied, increasing R^2 from 0.83 to 0.91. These findings, summarized in Table 1, underscore the robustness and reliability of ensemble-based ML models, particularly RF, in capturing the nonlinear and dynamic behavior of solar power systems [19].

Table 1. Performance comparison of different machine learning algorithms on solar radiation prediction [19].

Algorithm	RMSE	MAE	R^2
MLP-ANN (no feature selection)	124.5	55.41	0.83
MLP-ANN (with PCC)	95.16	41.45	0.91
Random Forest	87.18	34.82	0.95
LightGBM	111.49	50.16	0.87
XGBoost	114.01	51.57	0.86
CatBoost	130.42	60.12	0.79

3.2. Deep learning

Deep learning (DL) methods have demonstrated exceptional capabilities in handling the complexity and variability of renewable energy systems. These techniques are particularly effective in learning nonlinear relationships and temporal patterns from large volumes of data, making them highly suitable for applications in solar, wind, and hydropower systems.

In photovoltaic (PV) forecasting, deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have been widely adopted for their ability to model sequential data. For instance, hybrid architecture combining LSTM and gradient boosting methods have achieved impressive results in day-ahead PV power generation predictions [18]. Moreover, convolutional neural networks (CNNs) are often employed to extract spatial features from satellite or sky camera imagery, enabling enhanced solar irradiance forecasting.

In wind energy systems, deep learning plays a key role in wind speed forecasting, power output estimation, and fault detection. RNN-based models can learn temporal dependencies from meteorological data, while hybrid approaches incorporating CNN and attention mechanisms have shown promise in capturing spatial-temporal wind field variations. Accurate wind forecasting directly contributes to improved grid integration and load balancing in smart energy systems.

Similarly, in hydropower applications, DL models are applied to predict water inflow, reservoir levels, and turbine performance. These models enhance predictive maintenance and operational scheduling by analyzing patterns from historical inflow and climate data. LSTM models, for example, have been used to anticipate water levels and flow rates with high accuracy, aiding in efficient plant management and reducing unplanned downtimes [21].

Overall, the adoption of DL methods across various renewable energy systems supports intelligent decision-making, minimizes forecasting errors, and enhances system reliability. Their integration into AI-based energy frameworks continues to evolve, enabling next-generation solutions for clean and sustainable energy infrastructures.

3.3. Metaheuristic optimization

In renewable energy system planning, metaheuristic algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and NSGA-II are widely utilized to solve complex, nonlinear, and multi-objective problems. These algorithms are particularly useful for component sizing, operational planning, and performance optimization in hybrid renewable energy systems (HRES).

Güven and Yörükeren [22] conducted a comparative study analyzing the effectiveness of GA, PSO, and their hybrid GA–PSO approach for optimizing stand-alone HRES configurations. Their results showed that PSO outperformed the other methods in terms of lower Levelized Cost of Energy (LCOE) and Loss of Power Supply Probability (LPSP), indicating a more efficient system configuration with better reliability.

Similarly, Bade et al. [23] applied PSO to the design of a hybrid microgrid comprising PV, wind, and biomass sources. Their study emphasized that PSO could effectively minimize the Net Present Cost (NPC) and COE, while ensuring high renewable energy penetration. The results demonstrated

PSO's superior performance over GA and NSGA-II in terms of solution convergence, reliability, and economic feasibility. These studies confirm that metaheuristic techniques, particularly PSO-based algorithms, provide significant improvements in both technical and economic metrics when applied to complex renewable energy system design problems.

4. AI Based Applications in Solar Energy Systems

Solar energy plays a strategic role in energy transformation due to its clean and renewable features. Artificial intelligence (AI) techniques are widely used to make these systems more reliable, predictable and efficient. In this section, the applications of AI methods integrated into solar energy systems in production forecasting, maintenance and monitoring, and efficiency optimization are discussed.

4.1. AI Approaches in production forecasting

Production estimation in solar energy systems is a critical process in order to increase the integration of renewable resources into the grid and to ensure system reliability. In particular, the reduction of production uncertainties caused by variable meteorological conditions necessitates the use of accurate prediction models. Artificial intelligence-based methods are widely applied in this field in both short-term and long-term production planning.

Forecast models are generally built on time series analysis and regression-based approaches. In production estimations based on environmental factors such as solar radiation, temperature, relative humidity, wind speed and cloudiness, many machine learning and deep learning algorithms are used.

One of the most common methods in studies in this field, Artificial Neural Networks (ANN), offers high-accuracy predictions with multi-layer perceptrons (MLP) and long-short-term memory (LSTM) structures. LSTM models stand out especially due to their ability to model long-term dependencies in time series data [24].

Another effective method, Support Vector Machines (SVM), is preferred due to its ability to work with nonlinear data structures, especially in short-term production forecasts. The SVR (Support Vector Regression) sub-model provides successful results in regression-based forecasting problems [24].

The data used in solar energy forecasting is mostly obtained from meteorological stations, satellite images and numerical weather forecast models. These data are subjected to pre-processing steps such as data cleaning, elimination of missing values and normalization before modeling; thus, the accuracy of the model is increased.

In addition, regular updating of production forecast models is important, especially in terms of reflecting the effect of sudden weather changes on production more accurately. In this way, models become more flexible to environmental variability and contribute to the stability of the energy system.

Artificial intelligence-based forecasting approaches are not limited to short-term forecasts; they are also effectively used in longer-scale strategic planning such as seasonal fluctuations and annual production trends. The effectiveness of these techniques depends largely on model architecture and data quality. In this context, it has been shown in many studies that methods such as LSTM and SVR can be used with high accuracy in solar energy forecasting [24].

4.2. Use of AI in failure prediction and condition monitoring systems

Solar energy systems may encounter problems such as contamination, wear and failure over time due to environmental conditions. In this context, artificial intelligence-supported maintenance and monitoring systems play an effective role in increasing operational reliability.

Convolutional neural networks (CNN) can detect contamination, cracks or physical deterioration on panel surfaces through images obtained with drones or fixed cameras [25]. In addition, unsupervised learning algorithms (e.g. Isolation Forest) are used for anomaly detection in sensor data. Early diagnosis of hardware failures is possible with time series modeling and supervised learning techniques (Random Forest, XGBoost, LSTM) [26].

These systems reduce unplanned outages by predicting maintenance needs in advance, optimizing maintenance costs and ensuring energy production continuity. System performance is evaluated with indicators such as failure prediction accuracy, early warning rate and false alarm frequency.

4.3 AI-Based optimization techniques for increasing energy efficiency

Artificial intelligence-based methods enable the development of multi-dimensional strategies that provide both the effective use of physical hardware and the optimization of production processes in order to increase efficiency in solar energy systems. In this context, smart inverter and microgrid management, production forecasting, panel control systems and demand side optimization are among the main areas where artificial intelligence is effectively applied.

Machine learning-based models evaluate historical production data together with meteorological variables (radiance, temperature, humidity, etc.) to ensure more efficient operation of panel placement, angle optimization and monitoring systems. In such systems, artificial intelligence algorithms can optimize panel movements by making real-time decisions according to environmental feedback, thus increasing energy production and increasing system efficiency.

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Artificial intelligence-based solutions stand out especially in Maximum Power Point Tracking (MPPT) processes. Artificial Neural Network (ANN) and fuzzy logic-based MPPT algorithms provide faster responses compared to classical methods and provide high tracking accuracy. It has been shown in the literature that these methods exhibit higher performance than classical systems in multi-condition environments [27].

The integration of physical simulation models with artificial intelligence algorithms increases the system's ability to adapt to different environmental conditions. Hybrid control strategies can predict how panel movement mechanisms will behave in various scenarios, thus achieving a more stable production profile. Comparative studies with numerical models show that these hybrid structures provide significant energy savings compared to traditional methods [28].

Artificial intelligence also plays an effective role in real-time energy management systems. Energy flow is optimized by instantly monitoring, predicting and evaluating production-consumption data, and energy losses are reduced by working together with demand-side management and storage systems. These systems reduce maintenance times and improve the return on investment by extending the system life [29].

As a result, artificial intelligence-supported optimization techniques stand out as an innovative solution in terms of increasing production efficiency in solar energy systems, making system performance sustainable and providing economic benefits.

5. Artificial Intelligence Based Modeling in Wind Energy Systems

Wind energy is becoming increasingly important among renewable energy sources; however, its management is complicated due to its variable and unpredictable nature. In this context, artificial intelligence (AI) technologies offer various solutions to increase the efficiency and reliability of wind energy systems. AI algorithms are used in many critical application areas such as predicting wind speed, monitoring turbine performance and dynamically managing energy networks. These applications enable wind energy production to be realized in a more flexible, sustainable and cost-effective way.

5.1 Data-Driven forecasting models for wind energy production forecasting

Wind energy resources pose great challenges in terms of production planning due to their discontinuous and difficult to predict structures. While traditional statistical models cannot fully meet this need, AI-based approaches provide higher accuracy in short- and medium-term production estimates.

Machine learning techniques, especially algorithms such as support vector regression (SVR), random forests and XGBoost; can predict future production with high accuracy by analyzing past wind data (speed, direction, temperature, pressure) [30]. Deep learning models, especially long short-term memory (LSTM) and convolutional neural networks (CNN), exhibit high performance in predicting production levels on an hourly and daily basis by learning temporal patterns [31].

The integration of these models with real-time data updates provides flexibility and accuracy in operational planning processes. Thus, grid management can be carried out more effectively; energy losses are reduced and economic and environmental contributions are made.

5.2 Turbine performance monitoring and predictive fault detection approaches

The performance of wind turbines is critical for the continuity of energy production and the economic efficiency of the system. Mechanical wear, environmental stress factors and maintenance delays that may occur in turbines over time can cause performance losses.

AI-supported systems can analyze sensor data (e.g. temperature, vibration, rotational speed, power generation) received from turbine components and perform failure prediction and performance evaluation [32]. Decision trees, k-nearest neighbor (k-NN) and gradient boosting algorithms are widely used in this context.

Deep learning-based approaches offer more effective feature extraction on large and complex data sets. For example, CNN models can identify structural problems such as bearing damage or rotor imbalance from vibration signals; LSTM models can detect slowly developing failures early by following performance changes over time [33-34].

In addition, turbine simulations are performed in a virtual environment with digital twin applications and system efficiency is increased by optimizing parameters such as blade angle and rotational speed.

5.3 AI-Assisted network management and optimization strategies in smart grid integration

AI-based network management systems facilitate the integration of intermittent generation sources such as wind energy into electrical grids and strengthen grid stability. These systems play a critical role in ensuring energy supply-demand balance, optimizing energy storage strategies, and managing loads on transmission lines.

Multi-agent systems and reinforcement learning algorithms create decision support systems in dynamic energy networks, enabling the safe and efficient transfer of wind generation to the grid [35]. Real-time control systems analyze data obtained from wind turbines to optimize energy flow; and increase system reliability by providing rapid intervention in case of emergency.

AI-supported forecasting systems work in integration with short-term generation forecasts, increasing the flexibility of

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the system against demand fluctuations. In addition, these systems integrated with microgrid structures can autonomously perform functions such as energy routing, load transfer, and local production-consumption management. Microgrids are supported by energy storage systems (ESS) to both increase power quality and enable energy exchange with neighboring microgrids. This structure enables more efficient management of decentralized energy production.

A typical microgrid architecture is schematically presented in Figure 5. This structure reflects the multi-faceted data and energy interaction established between the central control unit, renewable energy sources (e.g. wind and solar), energy storage systems, and consumer loads. The image exemplifies the operating logic of distributed energy management systems and their integration with AI-supported decision mechanisms.

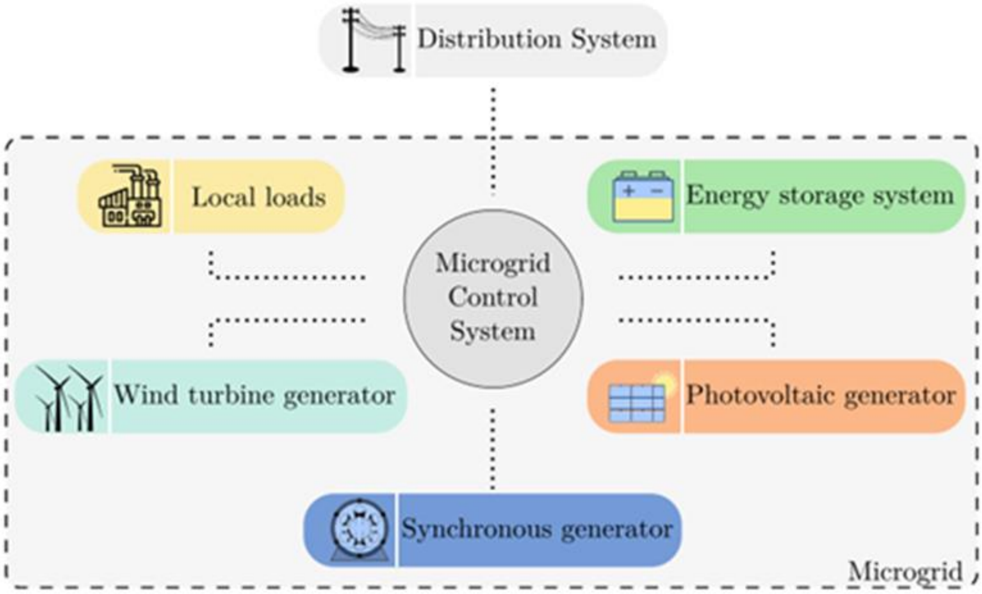

Fig. 5. Microgrid schematic

6. Artificial Intelligence Based Applications in Hydroelectric Energy Systems

Artificial intelligence (AI) has become a critical technology in terms of strengthening decision support mechanisms, increasing operational efficiency and ensuring sustainability in hydroelectric energy systems. In particular, machine learning (ML) and deep learning (DL) techniques offer significant advantages in processing hydrological data, enabling more accurate and efficient management of energy production processes [36].

6.1 AI-Aided water flow forecast and management

Water flow management is one of the most fundamental determinants of the production performance of hydroelectric power plants. Artificial intelligence algorithms provide high accuracy in future water flow predictions by analyzing hydro-meteorological data such as past stream flows, rainfall amounts, soil moisture and temperature [37]. In this context, successful deep learning approaches, especially in time series modeling such as RNN and LSTM, enable adaptation to sudden changes [38].

In addition, data-driven decision support systems developed for the regulation of water levels, reservoir management and reduction of environmental impacts gain multivariate analysis capability with algorithms such as Decision Tree, Random Forest and XGBoost [39]. In a study in the literature, it was observed that the model created with the LSTM architecture made successful predictions with lower error rates compared to ARIMA. In addition, these models contribute to the development of early warning systems against extreme situations such as floods and droughts [40]. Thus, not only energy production processes but also river ecology and environmental balance are protected.

6.2 Estimating hydroelectric production capacity with AI

Energy production estimation in hydroelectric power plants is of strategic importance in terms of production planning and grid stability. AI-based estimation models can predict production capacity by analyzing parameters such as precipitation, evaporation, snow melt and soil moisture. For this purpose, methods such as SVR, GBM and ANN are frequently used [41].

In a study conducted by Galvao Filho et al. [41], 1350-day data from the Jirau Hydroelectric Power Plant in Brazil were analyzed with the LSTM model and high estimation accuracy was obtained with low error rates. It was stated that this model is also suitable for practical use by operating teams. The study in question is remarkable in terms of providing more efficient and sustainable use of water resources.

6.3 Predictive maintenance and failure prevention methods

In hydroelectric power plants, timely and effective execution of maintenance activities is of critical importance in terms of both operational continuity and economic sustainability. At this point, AI-supported predictive maintenance systems offer more effective solutions compared to traditional time-based maintenance approaches. It becomes possible to predict failures in advance by analyzing temperature, vibration, sound and pressure data obtained from components such as turbines, generators and valves [42].

For example, in the study conducted by Velasquez and Flores, different classification algorithms were compared and it was determined that the Random Forest algorithm showed superior success. In addition, it was emphasized that the applied data pre-processing and feature selection steps significantly increased the model performance. These systems not only detect failures in advance; they also contribute to the optimization of maintenance scheduling and resource planning. Thus, maintenance can be performed without stopping the system, equipment life is extended and interruptions in energy production are minimized.

AI-supported maintenance systems improve decision-making processes in multivariable and complex hydroelectric power plants, increase system reliability and reduce total maintenance costs.

7. Integration of RES with Administrative Challenges and Smart System Approaches

Effective management of renewable energy systems is critical for optimizing energy resources and establishing a sustainable energy infrastructure. According to the International Energy Agency (IEA) 2023 Electricity Market Report, renewable resources, together with nuclear energy, are expected to meet more than 90% of the global electricity demand increase by 2025 [43]. However, the fact that the current energy infrastructure is designed in line with traditional power generation systems brings with it various technical and structural obstacles in the integration of renewable energy resources into these networks.

The most important of these obstacles is the unpredictability of production levels due to the intermittent nature of renewable energy resources and the difficulties experienced in maintaining grid balance [44]. In this context, energy storage systems (e.g. battery systems, pumped hydroelectric power plants) play an important role in balancing these fluctuations.

Artificial intelligence-based control systems have the potential to optimize not only production processes but also supply-demand management, energy market pricing and policy development processes [45]. Machine learning and deep learning algorithms support two-way communication infrastructure in smart grids, increasing grid security and energy distribution efficiency [46]. These technologies also form the basis of operational decision support systems, can develop adaptive responses to unforeseen situations and maximize system performance.

7.1 Architectural structure and functional components of smart grids

Smart grids (Smart Grids) aim to optimize energy flow and increase grid reliability by working in integration with energy management systems (EMS). These structures are equipped with advanced measurement, analysis and automation technologies to support data-driven decision-making processes. The foundations of smart grid technology were laid in the 1990s with the widespread use of electronic meters and advanced communication systems.

Over time, the implementation of Advanced Meter Management (AMM) systems has paved the way for the use of data-driven analysis and automatic control mechanisms in energy management [47]. These structures, which work integrated with real-time control systems such as SCADA, can monitor energy consumption instantly, detect problems quickly and intervene [48].

The basic components within the smart grid structure are as follows: [54]

- Advanced Measurement Infrastructure (AMI): Provides detailed consumption monitoring, dynamic billing and participation in demand response programs with meters that collect real-time data [49–50].
- Secure Communication Networks: Provides bidirectional data flow between network components, enabling network monitoring and control [51–52].
- Smart Distribution Systems: Equipped with systems that provide voltage and frequency control and automatically isolate problems [53].
- Consumer Participation and Smart Devices: User contribution to energy management is increasing through systems that adjust the behavior of devices according to energy consumption patterns.
- Cyber Security: Advanced encryption and access control systems are vital to ensure data security.

In this context, in order to better understand the architecture of smart grids, Figure 6 shows both electrical and communication structures together. [54] Figure 6-a presents the electrical infrastructure where renewable and fossil-based energy sources reach final consumers via smart meters and microgrids via transmission lines and transformer centers. This structure visually reveals the central and local components of the process from energy production to distribution.

Figure 6-b details the communication networks of smart grid systems. Starting from the control center, data flow is provided via wide area network (WAN), neighborhood and

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home area networks (NAN and HAN); thus, energy consumption data can be monitored, analyzed and made open to real-time intervention. This structure increases grid flexibility and efficiency by providing secure and dynamic two-way data communication between smart meters, sensors and control systems.

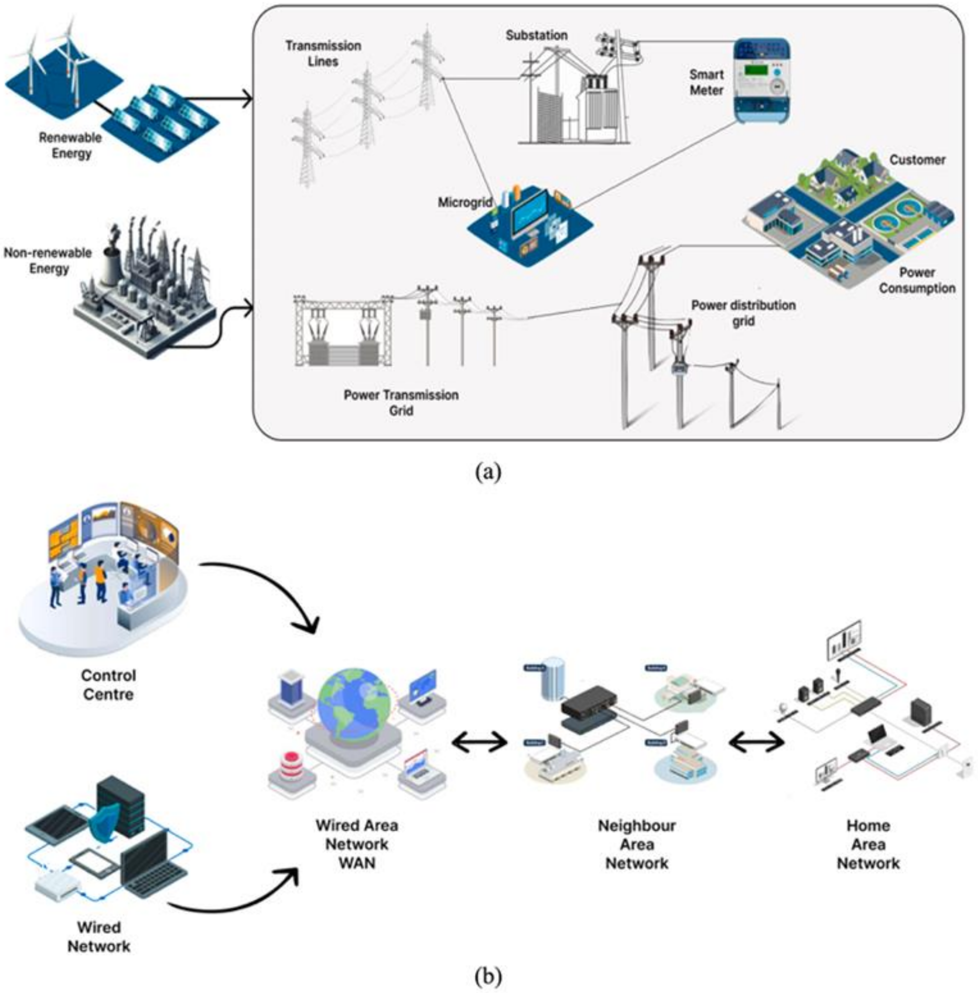

Fig. 6. Smart grid structure: (a) Electrical Network of Smart Grid, (b) Communication Network of Smart Grid [54]

7.2 Demand side management and AI-Powered response systems

Effective management of energy demand plays a key role in grid security and sustainability. Demand management aims to reduce energy costs by analyzing consumer behavior and optimizing energy consumption. Such solutions are critical for grid reliability, especially during peak energy consumption hours.

Thanks to Demand Response Programs (DRP) used in smart grids, consumers are encouraged to flexibly adapt their energy use to grid conditions. This reduces the load on the grid, improves power quality and reduces investment costs [54].

Artificial intelligence has played an important role in the development of these systems. In particular:

- Reinforcement learning algorithms enable modeling of consumer behavior and more precise control of demand-response relationships.
- Predictive algorithms facilitate operational planning by predicting future energy demand [55–56].

AI-supported demand management not only increases system efficiency; it also contributes to the democratization of energy systems by increasing consumer participation.

8. AI-Assisted Energy Efficiency Applications

Artificial intelligence (AI) plays an important role in the energy sector thanks to its ability to process large data sets and optimize complex systems. Especially in the field of renewable energy, AI applications are becoming increasingly widespread in order to ensure more effective management of production and consumption processes. In areas such as energy monitoring, control, maintenance, storage management and system optimization, AI solutions not only increase energy efficiency but also provide economic and environmental benefits. AI-supported systems are expected to create an economic value of $1.3 trillion by 2030 [57].

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8.1 AI-Based strategies for energy savings

Energy saving strategies are methods developed to reduce consumption and increase system efficiency. In this context, artificial intelligence offers multi-dimensional solutions through machine learning and data analytics techniques. AI algorithms can analyze energy consumption data, model user behavior, detect energy waste and optimize system performance [58].

These technologies are also integrated into smart building energy management systems (BEMS) to provide significant energy savings in areas such as HVAC, lighting and device management. These systems play a critical role in reducing inefficiencies called energy performance gaps, which cause buildings to deviate from the values predicted during the design phase [59].

8.2 AI Approaches for sustainable energy management

Sustainability-focused energy applications aim to ensure long-term efficient use of resources and minimize environmental impacts. Artificial intelligence can optimize the energy supply-demand balance by predicting the production level of intermittent renewable resources such as solar and wind. In this way, it helps grid operators implement more stable and reliable strategies in production planning.

AI-supported smart grids integrate distribution and storage systems, enabling the use of energy obtained from renewable sources with maximum efficiency. In addition, these systems contribute to environmental sustainability with decision support structures based on data analysis [58].

9. Future Trends in AI and Renewable Energy

The dynamic structure of renewable energy systems and the increasing energy demand increase the need for more flexible, reliable and intelligent solutions in the energy infrastructure. In this context, artificial intelligence (AI) and machine learning (ML) techniques play a strategic role in increasing the efficiency of all processes from energy production to distribution.

In the future, it is expected that AI will be integrated with new generation digital technologies such as edge computing, 5G technologies and quantum computing. This integration will play a decisive role especially in the development of decentralized energy production models and autonomous energy networks. Real-time decision-making and rapid response capabilities will enable energy systems to become agile and resilient.

The proliferation of distributed energy resources such as microgrids and virtual power plants can be managed more efficiently thanks to the advanced prediction, control and optimization capabilities of artificial intelligence algorithms. These systems have the capacity to operate without being dependent on the central grid and allow local energy needs to be met in a sustainable way [60].

However, this transformation process also brings with it some important challenges. Data privacy and cybersecurity issues come to the fore in these systems that require large data processing capacity. In addition, preventing biases in AI algorithms, ensuring transparent decision-making processes, and designing in line with ethical principles are also important issues to be emphasized [61–62].

Finally, in order for these technologies to be integrated into existing energy infrastructures, qualified human resources, legislative regulations, and public-private sector collaborations need to be strengthened. In this context, state-supported incentives, university-industry collaborations, and strategic investments will play a key role in accelerating the AI-supported energy transformation.

10. Conclusion and Evaluation

The inherent challenges of renewable energy systems, such as discontinuity, variability, and uncertainty, reveal the need for advanced technologies to increase the reliability and operational efficiency of these systems. In this context, data-driven approaches such as artificial intelligence (AI) and machine learning (ML) offer innovative solutions in many critical areas such as energy production estimation, development of pre-failure maintenance strategies, management of energy storage systems, and smart grid applications.

AI-based models integrated into major renewable energy sources such as solar, wind, and hydroelectric power provide significant contributions to reducing environmental impacts and efficient use of resources, as well as ensuring production continuity by optimizing system performance. In addition, AI-supported decision support systems play a critical role not only in short-term operational processes but also in long-term strategic energy planning.

In the future, the integration of artificial intelligence with advanced technologies such as 5G, quantum computing, and edge computing will enable the construction of decentralized, autonomous, and adaptive energy systems. However, this transformation process is not limited to technical development alone; It also requires a multidimensional approach such as data security, compliance with ethical principles, legal regulations and transformation of institutional structures.

As a result, AI-supported renewable energy systems are considered a fundamental building block in achieving sustainability goals and the digital transformation of the energy sector. The effective and ethical use of these technologies will contribute to the creation of more flexible, environmentally friendly and resilient energy infrastructures in the future.

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Conflict of interest

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