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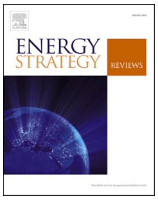

Artificial intelligence and data-driven approaches in renewable energy: A review of achievements and challenges

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ABSTRACT

As the global shift to sustainable energy accelerates, renewable energy systems (RES) increasingly depend on artificial intelligence (AI) and data-driven methods to improve predictive modeling, optimize operations, and integrate with power grids. This review looks at how AI and data methods help solve key renewable energy problems like unreliable supply, uncertainty, and difficult optimization. A clear review process was used. It focused on studies from 2020 to 2025 found in databases such as ScienceDirect, Scopus, and IEEE Xplore. Following PRISMA guidelines, about 150 core studies were chosen from many thousands for detailed review. Results show that neural networks, like CNNs, RNNs, LSTMs, and GNNs, are commonly used for forecasting and fault detection. Hybrid models that mix deep learning with optimization algorithms, such as genetic algorithms, work well for system design and energy management. Reinforcement learning and methods like random forests also help with real-time decisions for microgrids and energy storage. Also, physics-informed machine learning is accurate for studying battery aging, controlling load frequency, and improving electrolyzer cells. This review introduces a new multidimensional taxonomy that organizes AI applications by algorithm type, integration approach, system use, and policy considerations—addressing a gap in earlier reviews. Current trends highlight AI-enabled coordination across multiple energy systems and resilience planning enhanced by metaheuristics. While these technologies show strong potential, their widespread adoption faces obstacles such as inconsistent data quality, limited real-world testing, and adaptability across domains. To advance this field, the development of standardized benchmarks and advanced hybrid algorithms is recommended. This study maps a practical route for using AI and data-driven innovation to support the worldwide transition to renewable energy.

Nomenclature		GNN	Graph Neural Networks
		RL	Reinforcement Learning
Abbreviations		RF	Random Forest
AI	Artificial Intelligence	GBT	Gradient Boosting Trees
RES	Renewable Energy Systems	EMS	Energy Management System
ML	Machine Learning	ANFIS	Adaptive Neuro-Fuzzy Inference System
DT	Decision Tree	LFC	Load Frequency Control
KNN	k-Nearest Neighbors	CFD	Computational Fluid Dynamics
ANN	Artificial Neural Networks	MLP	Multilayer Perceptron
SVM	Support Vector Machine	PV	Photovoltaic
BP	Back-Propagation	DRO	Distributionally Robust Optimization
PSO	Particle Swarm Optimization	SOEC	Solid Oxide Electrolysis Cell
DNN	Deep Neural Network	DE	Differential Evolution
MG	Microgrid	GA	Genetic Algorithm
CNN	Convolutional Neural Networks	HS	Harmony Search
RNN	Recurrent Neural Networks	OCO	Online Convex Optimization
LR	Linear Regression	OPF	Optimal Power Flow
LSTM	Long Short-Term Memory	P2P	Power-to-Power

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1. Introduction

Accompanying the growth of the global population, the progression of urbanization, and the development of the economy, the demand for energy in human daily life has risen dramatically [1]. Non-renewable energy sources (i.e., traditional energy sources, including coal, natural gas, oil, etc.) have long been exploited and utilized, and still play a key role in many fields to meet the growing energy consumption and huge demand for electricity supply [2]. The continued consumption of non-renewable energy sources has brought many adverse effects and seriously affected the concept of sustainable development [3]. In order to be able to solve a series of pollution problems caused by traditional energy without affecting social and economic development. In addition, renewable energy has received widespread attention, and its proportion in the global energy mix is rising, becoming a force in promoting the energy transition [4]. However, the intermittent, fluctuating, and uneven geographical distribution of renewable energy have brought many challenges to its efficient development and utilization [5]. In this context, AI and data-driven methods have emerged, injecting new vitality into the research field of renewable energy, with great application potential and research value, and attracting increasing attention and significant interest from both academia and industry.

The application of RES includes solar power generation, wind power generation [6], geothermal energy recovery, photovoltaic cells, hydrogen energy system [7] and various micro grid integration [8]. Renewable energy technology involves complex physical processes and many influencing factors. For example, solar power generation is affected by meteorological conditions such as light intensity, temperature change and cloud cover, while wind power generation is closely related to wind speed [9], wind direction and landform [10]. Traditional methods based on experience and simplified models are difficult to achieve accurate prediction and optimal control in the face of these complex and changeable scenarios. AI technology, with its powerful data processing and pattern recognition capabilities, can dig out hidden rules and correlations from a large number of historical data and real-time monitoring data, and build more accurate prediction models. For example, the deep learning algorithm can be used to fuse and analyze multi-source data such as meteorological data and power generation equipment operation data, which can realize high-precision short-term and ultra-short-term prediction of solar and wind power generation power, provide key decision-making basis for power grid dispatching [11] and energy storage configuration, and effectively reduce the intermittent impact of renewable energy on the stable operation of the power grid to increase the absorption rate of renewable energy [12].Data-driven approaches also play a crucial role in simplifying models, improving prediction accuracy, and optimizing algorithms for renewable energy technologies. For example, the planning and location of offshore wind turbines are difficult to decide, so by building a data-driven model to integrate sample data, and then using random forest and other algorithms for analysis and processing, the scale and location of offshore wind power facilities can be predicted more accurately, which provides a scientific basis for the location of renewable energy facilities and reduces the uncertainty of renewable energy technology. It also ensures the stable operation of the renewable energy system and improves its return on investment [13]. At the same time, in the design of synergistic and complementary systems for renewable energy and other energy forms, such as wind-solar-storage integrated systems [14], hybrid energy source complementary microgrids, etc., with the help of AI optimization algorithms, the optimal configuration and collaborative operation control of different energy forms can be realized, giving full play to the advantages of each energy source, and improving the overall performance and energy utilization efficiency of the system.

In the field of RES, a variety of models were widely used to address the intermittency and uncertainty of renewable energy, including persistence models, physics-based numerical weather prediction (NWP) models, regression [15], and statistical models [16]. Each of these models has its own advantages and disadvantages: for example, persistence models excel in short-term forecasting, while physical models are better suited for medium- and long-term forecasting [17]. However, these models need to be further developed and optimized for optimal planning, estimation, integration, and operation [18]. In recent years, significant progress has been made in the application of AI technology in RES, mainly focusing on the following aspects: first, predicting the volatility of renewable energy to improve the stability and reliability of the system; The second is to optimize the maximum power point tracking (MPPT) to improve the energy conversion efficiency [19]; The third is to optimize the configuration and operation of hybrid RES. Researchers have widely used a variety of AI methods to predict the volatility of renewable energy [20],including artificial neural networks (ANNs) and support vector machines (SVMs).), least squares support vector machine (LS-SVM), and fuzzy inference system. In recent years, deep learning methods such as recurrent neural networks (RNNs), long short-term memory networks (LSTMs) [21] and convolutional neural networks (CNNs) have emerged) has also been thoroughly studied. In addition, ensemble learning models, including random forests, CatBoost, and XGBoost, as well as hybrid methods combining traditional machine learning with reinforcement learning, are now widely applied in RES [22]. These AI techniques have substantially increased prediction accuracy and operational efficiency, delivering robust data-driven support for practical decision-making. The growing availability of meteorological and system performance data has further enhanced the predictive power of AI in this field. Studies indicate that AI will maintain its leading role in renewable energy forecasting for decades to come [16].

In recent years, the application of AI and data-driven methods in RES has experienced exponential growth. According to a 2024 report by the International Energy Agency (IEA), the market penetration rate of AI in energy management has been increasing at an annual rate of 34.7% over the past five years. The number of related research publications has surged by over 260% since 2020, with more than 1800 articles indexed in the Web of Science Core Collection in 2024 alone [23]. Meanwhile, global investment in R&D for AI-driven energy systems has also risen significantly. For instance, the European Union's "Horizon Europe" program allocated over €2.1 billion for AI and energy integration projects between 2021 and 2025, with 37% explicitly targeting the optimization and intelligent dispatch of renewable energy. Many AI and data-driven approaches to renewable energy have been proposed, as well as challenges, solutions, and future opportunities in the renewable energy sector. These investigations have contributed valuable insights for the modeling, forecasting, planning, and operation of RES. However, while individual studies provide useful references, there is a notable lack of synthesis that integrates this diverse research into a unified, multi-dimensional framework. Existing reviews tend to be limited—either focusing narrowly on algorithmic classifications or summarizing findings by energy type in isolation. They often fail to connect methodological advances with tangible system-level performance and real-world operational viability. This article presents a comprehensive overview of various AI and data-driven techniques applicable to the modeling, prediction, and optimization of RES. By reviewing vital literature from the past five years, the study aims to map how these methods can be effectively deployed. Its central goal is to outline a forward-looking vision for applying machine learning across all segments of the energy system, offering clear guidance for researchers, engineers, and policymakers—including those new to AI concepts in the energy sector. Selecting appropriate data-driven approaches is essential to accelerating the global development of efficient and sustainable energy systems.

To achieve these objectives, the study is organized into three main parts. First, the Methods section introduces crucial AI and data-driven approaches, offering foundational knowledge to support their understanding and implementation. Next, the Applications section systematically categorizes and examines the use of these methods across RES. Finally, the Results and Discussion section provides a synthesized summary of the findings and proposes directions for future research. This study employs a multi-dimensional framework to assess current research across four main categories: algorithm types, application areas, integration strategies, and policy and reproducibility factors. This structured review identifies dominant research trends and exposes significant gaps in the literature. For instance, while hybrid models like CNN-LSTM are widely applied to short-term forecasting, far less attention is given to critical system-level issues—such as ensuring grid stability during extreme weather or establishing standardized validation protocols for AI-managed grid operations. This analytical method clarifies both well-developed research themes and urgent priorities for future work, aiding the effective integration of RES. Table 1 compares this paper with the most recent research articles to demonstrate the research gaps addressed by this work.

2. Review methodology

2.1. Search strategy and selection process

AI has been used to predict how much renewable energy will be needed since the 1990s. Between 1990 and 2010, the first steps were taken in the use of neural network models to predict wind energy. These models were slightly better than earlier methods, as shown by real-world tests. Artificial Neural Networks (ANNs) and Support Vector Machines (SVMs) emerged as primary tools for point forecasting of wind and solar power [17]. From 2010 until around 2018, we saw a big change in how deep learning worked. Convolutional networks were used to track cloud spatiotemporally, and LSTM-based constructs were applied to anemometric patterns that were important examples in this area. They did much better than previous models by more than 30%. Since 2018, the focus has been on hybrid systems. These combine different tools: graph networks to understand spatial connections, transformers to model time-based patterns, and federated learning to allow different operators to work together. Modern systems can now analyze very large datasets while keeping data private. This represents a shift from single models to connected forecasting networks [24]. The trajectory of neural network (NN) applications vividly illustrates this three-phase evolution. In the Empirical Modeling Phase, shallow Artificial Neural Networks (ANNs), typically with one or two hidden layers, were a breakthrough. They demonstrated the ability to model non-linear relationships between, for example, historical weather data and wind farm output, overcoming the linearity constraints of regression models [10]. However, their effectiveness was bottlenecked by the limited volume of historical data and computational power, often leading to overfitting on small datasets. This review follows a structured and transparent methodology to ensure a thorough and reliable synthesis of the literature on AI and data-driven methods in RES. The process adheres to PRISMA guidelines for systematic reviews. Relevant studies were identified through searches in major databases such as ScienceDirect, Scopus, and IEEE Xplore. The search strategy used targeted Boolean combinations of keywords related to AI, machine learning, renewable energy sources (e.g., solar and wind, etc.), and core applications like forecasting, optimization, and control. To focus on recent developments, the search was limited to literature published between 2020 and 2025.

Table 1
Comparative positioning of this review against recent related surveys.

Review Focus	This Work	Abisoye et al. (2024) [16]	Alam et al. (2025) [8]
Temporal Scope	2020–2025 (emphasizing recent advances)	Broad, including classical methods	Forward-looking frameworks
Methodological Breadth	Comprehensive: ML, DNN, CNN, RNN/LSTM, GNN, RL, RF, ANFIS, Hybrid & Metaheuristics	Forecasting-centric AI/ML methods	AI integration challenges (less algorithmic detail)
Application Spectrum	Holistic & Systemic: Solar, Wind, Fuel Cells, Microgrids, Storage, SOEC, Hydrogen, categorized by function.	Cross-energy type, but centered on prediction.	Smart grid integration
Key Distinguishing Feature	1. Four-dimensional taxonomy (Algorithm-Integration-System-Policy). 2. In-depth analysis of hybrid paradigms.	Useful taxonomy and insights for forecasting methods.	Highlights architectural frameworks for AI-integrated grids.

The selection of studies was conducted in two phases. Initially, the titles and abstracts of the articles were subjected to preliminary screening. Subsequently, studies deemed potentially relevant were subjected to a full-text assessment. Papers deemed eligible for consideration were required to concentrate on specific renewable energy applications, employ recognized AI or data-driven approaches, and present findings validated by real or simulated data. Exclusions were applied to papers outside the immediate field, those employing incompatible or unclear methods, work lacking adequate detail, and studies of lesser quality. From the original corpus of several thousand publications, approximately 150 core studies were identified for in-depth review. Excluded were: secondary reviews, opinion pieces, studies without clear methodological description, studies focusing solely on non-renewable systems, and publications in non-peer-reviewed venues. Purely focused on non-renewable systems (e.g., coal power optimization without renewable integration), or on broad policy/economic analysis without technical AI modeling. As illustrated in Fig. 1 (PRISMA flow diagram), this screening procedure is outlined to maintain transparency and reproducibility. All retrieved records were imported into Zotero reference management software for deduplication. Information was systematically collected from each included study, covering bibliographic data, renewable energy application, AI technique, dataset traits, performance indicators, crucial findings, and limitations. In view of the considerable disparities in study aims, data, and methodologies, a qualitative synthesis is undertaken to summarize prevailing technological trends, application patterns, and common obstacles. This method has certain limitations: lack of formal risk-of-bias assessment due to the review's scope. The clarity of methods, the rigor of experiments, and the objectivity in reporting results informed the assessment of study quality. This gives a structured basis for further analysis and discussion.

2.2. The proposed multidimensional framework and review structure

To systematically organize and analyze the diverse landscape of AI and data-driven applications in RES, this review is structured around a novel four-dimensional taxonomy. This framework is designed to move beyond conventional single-axis categorizations (e.g., by algorithm name or energy source alone) and to explicitly capture the interplay between methodological choice, system integration, practical application, and broader implementation context. The four dimensions are defined as follows: (1) Algorithm Type: Refers to the core computational paradigm or model architecture (e.g., Convolutional Neural Network, Random Forest, Reinforcement Learning). This dimension addresses the "how" of the AI solution. (2) Integration Approach: Describes how the AI method is combined with other techniques or models. This includes hybrid models (e.g., CNN-LSTM for spatiotemporal forecasting), AI-enhanced optimization (e.g., PSO-tuned neural networks), and physics-informed machine learning. This dimension highlights the trend towards methodological synthesis to overcome limitations of standalone approaches. (3) System Use Case: Categorizes the application domain and specific function within a RES. This spans prediction (solar/wind

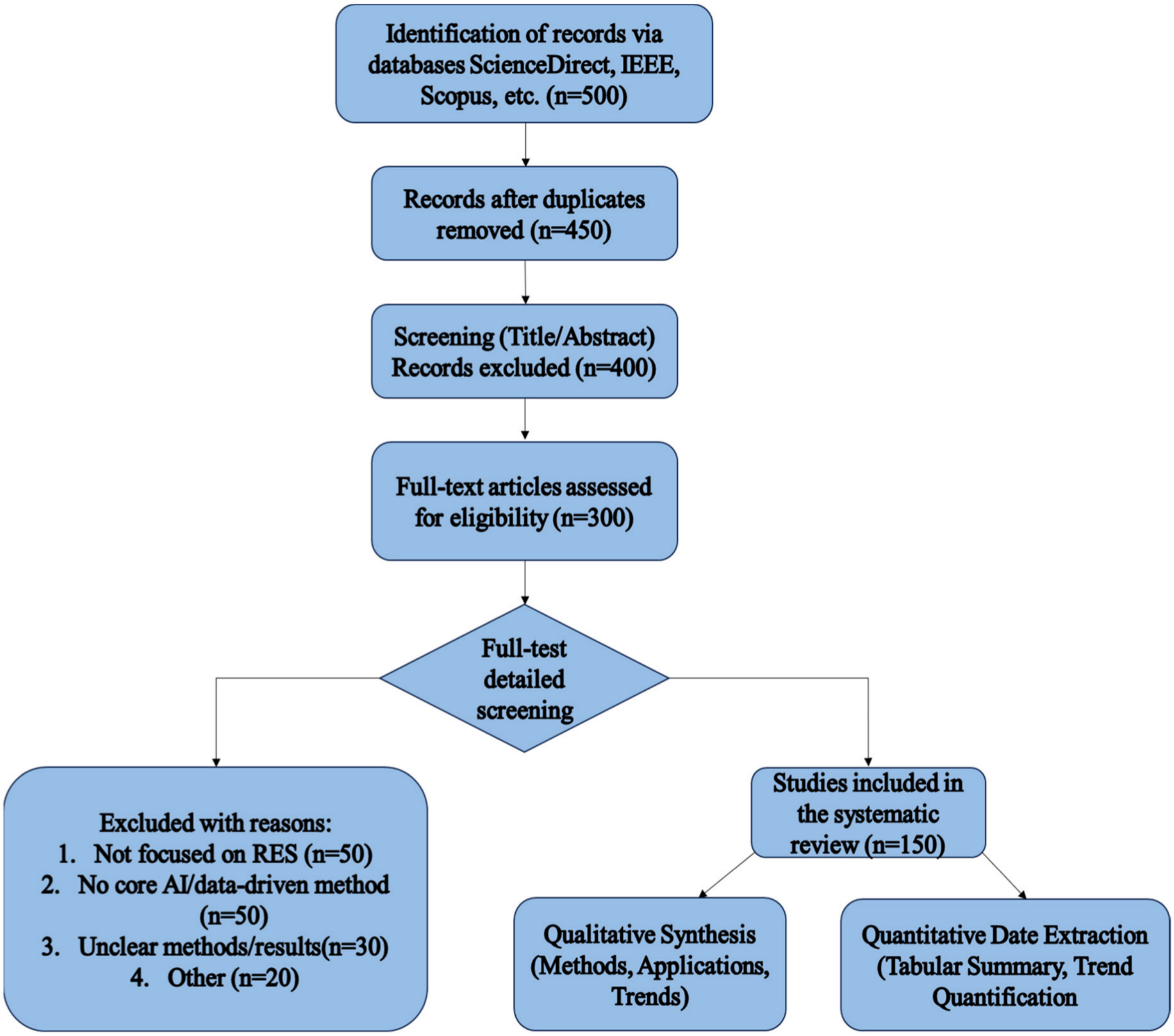

Fig. 1. Literature screening process.

power, load), optimization (sizing, dispatch, MPPT), control (LFC, voltage regulation), and fault detection & diagnosis. This dimension connects the method to a tangible engineering objective. (4) Policy & Reproducibility Considerations: Examines factors influencing real-world adoption and scientific rigor, such as data accessibility & quality, model interpretability/explainability, cybersecurity requirements, standardization needs, and validation protocols. This dimension bridges the technical analysis with practical deployment challenges and the research-to-practice pipeline.

This four-dimensional lens will guide the subsequent analysis. Section 3 details the core AI methodologies (Dimension 1), while Section 4 is explicitly organized to analyze Hybrid Methodologies (Dimension 2) and their applications across various System Use Cases (Dimension 3). Finally, Sections 5 and 6 synthesize findings and discuss overarching trends, challenges, and strategic implications directly stemming from the fourth dimension. This structured approach ensures our review delivers on its promise of a comprehensive, integrative analysis that addresses gaps in prior literature.

3. Artificial intelligence methodologies and their applications in RES

The increasing utilization of AI in the renewable energy sector highlights the profound integration of data-driven methodologies within this field. From fundamental machine learning techniques to advanced structures, including convolutional, recurrent, long short-term memory, and graph neural networks, as well as hybrid approaches such as reinforcement learning and random forests, AI has significantly enhanced the forecasting precision and operational performance of RES. Furthermore, it offers considerable potential in the mitigation of the inherent unpredictability and variability of renewable energy sources. These applications reflect the combined innovation and amplified advantages offered by AI and data-driven strategies in renewable energy.

3.1. *Machine learning (ML)*

Machine learning, a fundamental component of AI, focuses on giving computers the ability to learn from data without direct programming, relying on statistical and algorithmic models. Researchers typically categorize the field into three main types: supervised learning, unsupervised learning, and reinforcement learning [25]. Supervised methods train on labeled datasets to perform tasks such as classification and regression. Unsupervised approaches analyze unlabeled data, often for clustering or simplifying datasets. Reinforcement learning improves decisions through repeated environmental feedback, frequently applied in robotics and game theory. A standard machine learning process includes multiple phases: preparing data, choosing a model, training and testing it, and finally implementing the system [26]. Frequently employed algorithms include linear and logistic regression, support vector machines, decision trees, random forests, K-nearest neighbors, and Q-learning, among others [27].

Recent applications of ML in RES show that many researchers now favor hybrid ML algorithms, which tend to deliver stronger optimization results across different tasks. For example, Zahedi et al. [28] applied machine learning to model the energy supply–demand balance in a cold-climate community in St. Albert, Canada. Their model successfully matched peak thermal loads and met EV charging demand using PV generation, achieving high prediction accuracy. In another study, Zhou [29] developed a novel ML-based method for selecting algorithms to predict battery aging under variable renewable charging cycles and demand-dependent discharge conditions, with the proposed framework showing improved reliability and predictive performance. To address load forecasting needs, Naveena et al. [30] integrated multiple renewable systems through an ML-driven multi-objective optimization framework. They validated their approach using RMSE, MAE, and MAPE metrics across several prediction models, demonstrating its technical, economic, and environmental feasibility. Meanwhile, Shangguan et al. [31] employed machine learning on experimental data to holistically analyze alkaline water electrolysis systems, optimizing thermal balance models to accurately calculate electrolysis power, cooling requirements, and temperature maintenance for cost-effective operation. In the area of waste heat recovery, Deepak et al. [32] built a three-stage waste heat recovery system controlled by AI that incorporates both ML and reinforcement learning algorithms. By optimizing control strategies with real-time data, the system achieved a comprehensive energy efficiency of 62.3%, marking a 17.3% improvement over conventional waste heat recovery technologies. Zhou et al. [33] tackled multidimensional uncertainties in hybrid renewable systems under advanced parameters using a machine learning-based two-dimensional MCMC technique. They also employed supervised learning to forecast on-site renewable energy generation, significantly enhancing peak power capacity and total energy output compared to traditional methods. Jauhar et al. [34] integrated AI and ML techniques to address limitations in EV infrastructure, such as insufficient service capability and the need for optimized power demand at charging stations. In a different direction, Cao et al. [35] developed an ML framework to model green CO_2 emissions from bio-based feedstock co-processing. Their model allows real-time emission tracking with a mean error of just 2%, improving accuracy by 66% over standard lab measurements.

3.2. Artificial neural networks (ANNs)

Artificial neural networks (ANNs) are computational systems inspired by the biological brain's structure, first proposed by McCulloch and Pitts in 1943 [36] Serving as a foundation for deep learning [37], these networks employ a layered architecture of interconnected nodes, simulating neuronal connections. A basic ANN includes three parts: an input layer, at least one adjustable hidden layer, and an output layer. The hidden layers can be adapted for specific applications, allowing advanced feature detection and pattern analysis. Within each layer, artificial neurons calculate outputs by applying nonlinear activation functions to weighted inputs [38]. Common training methods for ANNs involve computational optimization algorithms, including Error Backpropagation and Particle Swarm Optimization. ANNs offer several advantages for tackling difficult problems, such as computational speed, effective input-output mapping, noise tolerance, error resilience, and ongoing learning capability. Consequently, they see extensive use in pattern recognition, classification tasks, approximating nonlinear systems, and computational simulation [39]. However, limited training data can reduce their effectiveness. Based on connection patterns, neural networks are commonly classified as feedforward or recurrent. Feedforward networks permit one-way signal flow from input to output, illustrated in Fig. 2 [40]. The next section examines ANN applications in renewable energy systems (RES) for prediction and optimization, where they frequently achieve positive results.

Khanmohammadi et al. [41] adopted an ANN as their main modeling framework to create a digital twin that links six performance metrics to nine design variables, allowing for comprehensive optimization of a geothermal energy system under various operational conditions. The ANN showed strong statistical alignment, and a follow-up sensitivity analysis helped quantify the cyclical influence of individual performance indicators. In another study focused on solar power prediction, Alassery et al. [42] compared ANN, SVM, and RF methods. Here, the ANN models delivered higher predictive accuracy during both training

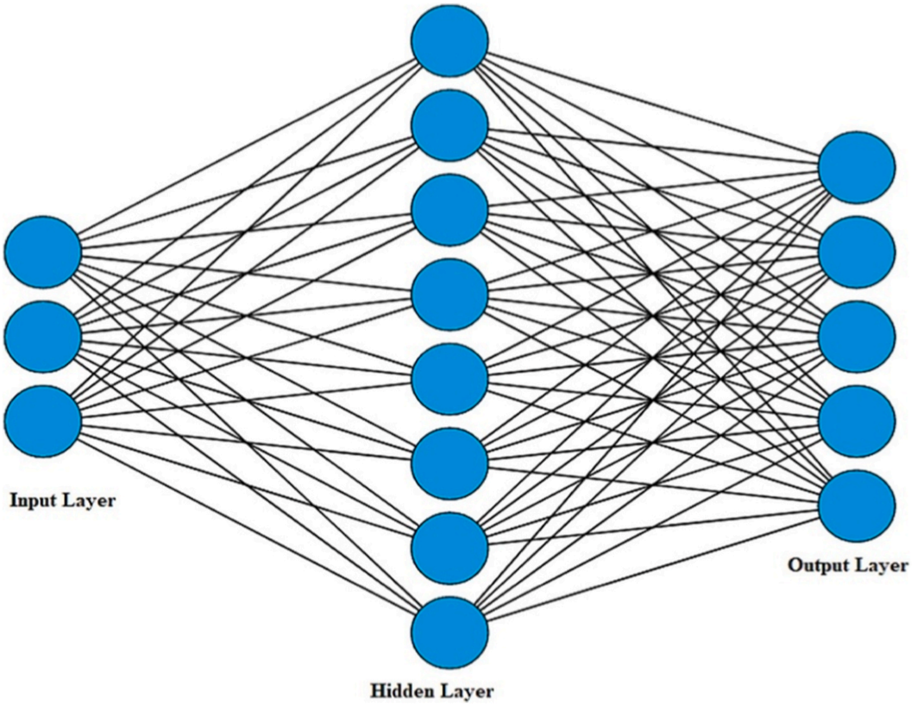

Fig. 2. Schematic diagram of feedforward ANN architecture [40].

and testing phases compared to SVM and RF alternatives.

While the studies above compare multiple AI algorithms and consistently highlight the strong performance of ANNs, other researchers have taken a complementary route—integrating ANNs with practical implementation strategies—with equally promising results. For example, Sadi et al. [43] developed a hybrid approach combining ANNs (using multilayer perceptron architectures) with genetic algorithms to analyze system configurations. They used simulation data fed through optimized ANN structures for performance prediction, followed by multi-objective optimization to identify Pareto-optimal solutions. Their work confirmed the effectiveness of dual-tank thermal storage in achieving peak system performance. Similarly, Saikia et al. [44] implemented a fusion of NARX networks and ANN architectures to process both experimental measurements and physical tank modeling data. This integration significantly improved predictions of ice storage thermal behavior, especially in estimating the State of Charge (SoC) and forecasting outlet temperatures.

3.3. Deep neural networks (DNNs)

Deep neural networks represent a powerful class of models in machine learning and AI, frequently applied to complex problems in pattern recognition and data modeling. Architecturally, they build upon traditional artificial neural networks by adding multiple layers. These layers enable the learning of hierarchical data representations through successive nonlinear transformations. This hierarchical feature extraction allows deep networks to identify intricate patterns within data. Compared to simpler structures like single-layer perceptrons, deep neural networks automatically learn multi-scale feature representations. This capability leads to enhanced performance in computationally intensive fields such as computer vision, acoustic processing, and language modeling. For instance, Samal et al. [45] introduced a hybrid control framework integrating a deep neural network with Particle Swarm Optimization to enhance load-frequency regulation in microgrids featuring vehicle-to-grid integration. Their experimental results demonstrated that this controller achieved higher efficiency and a faster response under dynamic grid conditions. In a similar study, Wu et al. [46] created a hybrid framework combining deep neural networks, Particle Swarm Optimization, and genetic algorithms. Here, the deep neural networks acted as surrogate models for optimizing microgrid load-frequency, while the genetic algorithm identified optimal parameter sets. This method produced better outcomes in system resilience, dynamic response, and frequency regulation accuracy when faced with random disturbances. In both microgrid studies, the PSO-DNN algorithm reliably enhanced system performance, providing a solid methodological foundation for future research and practical applications.

Within the family of DNNs, Time Delay Neural Networks (TDNN) represent a temporal variant designed with intentionally inserted time-shift operators in the connections between hidden layers. This modification introduces a form of short-term memory not present in standard feedforward ANNs, equipping TDNNs with essential capabilities for time-series analysis—a domain where conventional ANNs are limited due to their lack of temporal processing. Conte et al. [47] applied a TDNN-based methodology to predict performance in hybrid power systems with battery storage. The model yielded mean absolute errors of 1.6 kW for PV generation, 2.15 kW for total consumption, and 0.3 kW for ancillary services, confirming its measurement precision across several operational parameters.

3.4. Convolutional neural networks (CNNs)

Convolutional Neural Networks are a core deep learning architecture extensively applied in computer vision for image segmentation and facial recognition, as well as in processing sequential data like natural language. LeCun et al. conducted pioneering work using CNNs for handwritten digit recognition, paving the way for subsequent advancements in CNN technology [48]. Their effectiveness in recognizing multi-level patterns has been confirmed across numerous experimental studies [49]. Relative to other deep learning techniques, CNNs provide particular benefits in efficient feature extraction. Their architectural hallmarks—localized connectivity, weight sharing, pooling operations, and hierarchical organization—enable effective learning of high-dimensional features directly from raw data [50]. A standard CNN framework is built upon four core layers: (1) convolutional layers that identify local features, (2) pooling layers that lower dimensionality, (3) fully-connected layers that combine global patterns, and (4) a final classification layer that produces final outputs. As illustrated in Fig. 3, the convolutional layer uses filter kernels that sweep across the input to extract local features; these kernels are refined during training to capture essential patterns. The following pooling layer reduces spatial dimensions through max-pooling or average-pooling, decreasing computational demands and mitigates overfitting. After several cycles of convolution and pooling, the resulting feature maps are flattened and fed into fully-connected layers for higher-order integration, enabling classification or regression. The output layer commonly applies a SoftMax function to generate probability-based class distributions [50]. This feature-learning capacity enables CNNs to develop accurate deep representations even from noisy data, proving especially valuable for time-series prediction and similar temporal applications. Furthermore, CNNs perform exceptionally well with image and video data by autonomously learning hierarchical features. This automation minimizes reliance on manual feature design and often enhances the model's ability to generalize. In the subsequent discussion of CNN uses in renewable energy systems, studies report significant improvements through novel network designs and hybrid algorithms applied to smart grids, solar power, and wind energy systems. The following will outline research conducted by certain scholars concerning the application of CNNs within RES systems.

Christy et al. [51] proposed a novel adaptive Lyapunov function based on a Graph Dilated CNN for energy flow optimization. Simulations on an IEEE 68-node system verified the framework's superiority, showing a 12.7% improvement in voltage stability and an 18.3% reduction in line losses compared to traditional power flow control methods. Khan et al. [52]. created a hybrid CNN-ESN framework that merges convolutional processing with reservoir computing principles. Evaluated using four standard error metrics—RMSE: 0.023, MSE: 0.00053, NRMSE: 3.41%, MAE: 0.018—the model outperformed contemporary benchmarks in renewable energy forecasting. Abdoos et al. [53] used CNNs to analyze temporal patterns in solar energy production across Mediterranean countries from 2010 to 2022. Their model projected a 120–150% increase in regional solar capacity between 2030 and 2050, with prediction intervals established through ensemble techniques. For wind turbine optimization, Cheng et al. [54] implemented a hybrid CNN-BPNN-SVM framework processed with NSGA-II, achieving statistically significant reductions in structural mass ($p < 0.01$) and dynamic deflection ($p < 0.05$) for the IEA 15 MW reference turbine. In a different application, Signor et al. [55] applied transfer learning to a ResNet-50 CNN backbone, training it on 1261 high-resolution biofouling images (4000×3000 pixels). When validated on offshore structural images, the model achieved a mean detection accuracy of $69 \pm 3.2\%$ (F1-score: 0.71), surpassing conventional image processing methods by at least 22% in marine conditions. Lastly, Zhang et al. [56] proposed a CNN-SE hybrid control framework to enhance voltage stability in complex AC/DC grids. By embedding squeeze-and-excitation attention mechanisms within residual CNN blocks, their approach prioritized critical bus voltages. Simulations on a 500-kV East China grid test case showed a 28–35% reduction in voltage deviation duration during N-1 contingencies, with a 94.3% success rate in preventing instability.

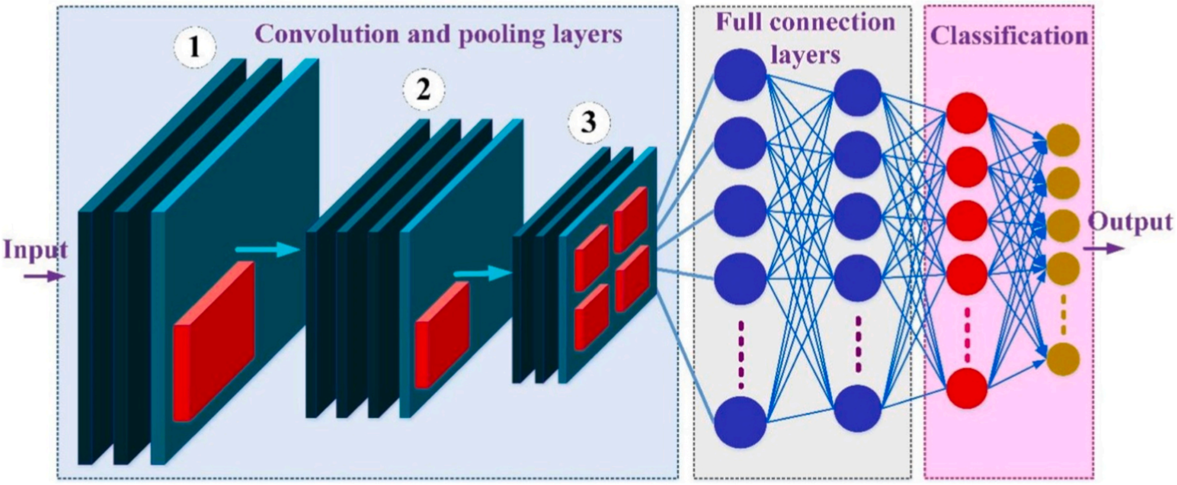

Fig. 3. Schematic representation of a conventional CNN architecture [50].

3.5. Recurrent neural networks (RNNs)

Recurrent Neural Networks (RNNs) are artificial neural networks tailored to handle sequential and time-series data. Unlike standard feedforward networks, which pass information directly from input to output layers, RNNs incorporate cyclic connections that act as an internal memory. This recurrent design allows hidden nodes to maintain and apply information from previous inputs, making RNNs inherently suited for identifying time-dependent patterns. [21]. Processing occurs stepwise across the sequence. At each time step, an internal state node retains processed information throughout the entire series. This setup enables RNNs to forward processed data via output nodes, as shown in Fig. 4. Given these attributes, RNNs show strong promise in applications like speech recognition, natural language processing, and handwritten text analysis. Researchers have also enhanced RNN performance by integrating them with other methods. In renewable energy forecasting, for example, such hybrid models have lowered prediction errors by 18.7% relative to conventional ARIMA benchmarks.

Bai et al. [57] proposed a novel framework that combines temporal processing using an RNN with topological reasoning via a Graph Attention Network for power systems with high renewable penetration. Their case studies confirmed a 23.7 percent improvement in temporal generalization and an 18.2 percent enhancement in topological adaptability compared to conventional deep reinforcement learning methods, establishing the viability of this approach for distributed grid control. In another application, Li et al. [58] developed a multivariate RNN forecasting system to process six stochastic inputs, including water demand and temperature. This system yielded an 18.2 percent reduction in the power loss probability of the supply for a hybrid renewable installation. The optimized siting strategy also decreased capital costs by 12.7 percent while improving system availability to 99.92 percent under IEC 61400 26 3 standards.

To enhance both predictive and diagnostic capabilities in renewable energy, researchers have also implemented hybrid models that merge convolutional and recurrent networks. Obatola et al. [59] developed a CNN RNN model integrated with attention mechanisms for predicting faults in grid connected photovoltaic systems. By employing Reptile Population Based Optimization and the Zebra Optimization Algorithm for feature selection, their model achieved significant improvements in sensitivity, specificity, and accuracy, demonstrating performance superior to that of standalone architectures.

3.6. Long short-term memory (LSTM) networks

Despite promising results in renewable energy forecasting with RNNs, a persistent issue has been the gradient vanishing problem, which occurs during backpropagation through time when processing long sequences. In critical situations, unstable gradient amplification can also occur, often reducing training stability. To overcome these limitations of standard RNNs, LSTM networks were developed as an advanced RNN architecture. LSTMs employ specialized gating units to control information movement, which alleviates gradient-related issues when handling long sequences [60]. LSTM networks were introduced by Hochreiter and Schmidhuber as a solution to the vanishing gradient problem in standard Recurrent Neural Networks (RNNs), enabling the learning of long-term dependencies in sequential data [61]. As shown in

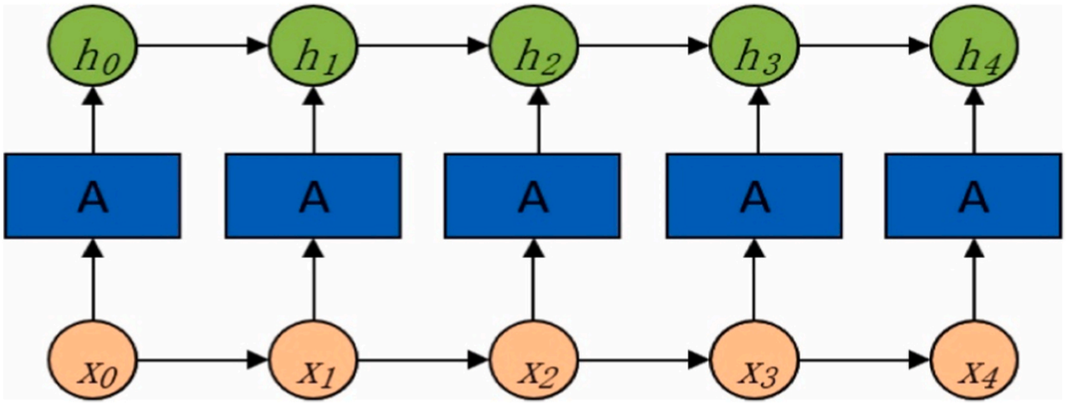

Fig. 4. Schematic diagram of a standard RNN architecture [21].

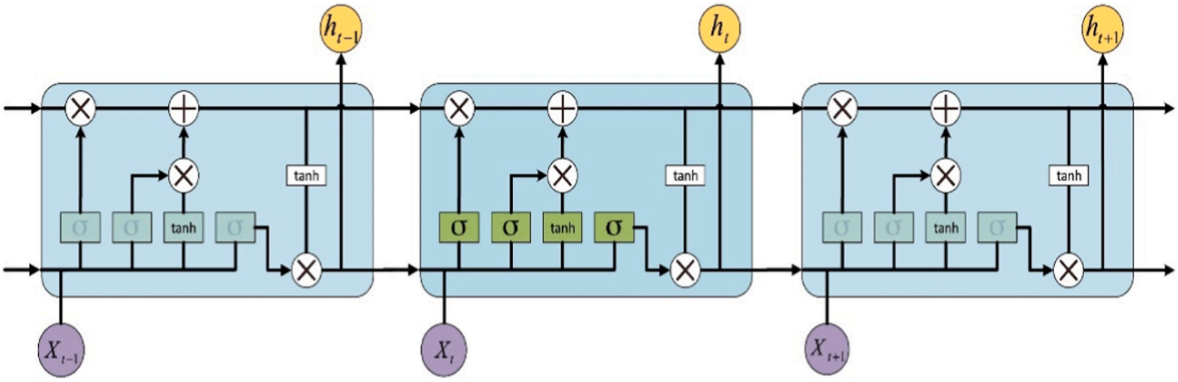

Fig. 5. Schematic illustration of the four interacting layers within an LSTM recurrent module [60].

Fig. 5, the gating mechanism in an LSTM governs information through three distinct gates: the forget gate, the input gate, and the output gate. Together, these gates enable sophisticated management of both LSTM. The update procedure of an LSTM cell, illustrated in Fig. 6, shows that at each timestep t, every gating unit processes a state variable. The output of the forget gate, $f_t \in [0,1]$, quantifies how much of the previous cell state Ct_{-1} is retained. A value near 0 indicates almost complete removal, while a value near 1 represents full retention. Thus, the forget gate removes nonessential information from the cell state for the current prediction, while preserving important features in the updated cell state C_t. This operation is expressed mathematically in Eq. (1) [60]:

$$f_t = \sigma\left(W_f{}^*[h_{t-1}, X_t] + b_f\right) \qquad \text{Eq. (1)}$$

where denotes the sigmoid activation function, as defined in Eq. (2):

$$\sigma(X) = 1/1 - e^{-x} \qquad \text{Eq. (2)}$$

Subsequently, this process utilizes the forget gate's output to activate a novel input candidate gate (C'_t), which generates an updated cell state C'_t for propagation to the next timestep t+1. Within this architecture:

$$i_t = \sigma(W_i{}^*[h_{t-1}, X_t] + b_t) \qquad \text{Eq. (3)}$$

$$C'_t = \tanh(W_c[h_{t-1}, X_t] + b_c) \qquad \text{Eq. (4)}$$

The hyperbolic tangent activation function (tanh) is formally defined by Eq. (5):

$$\tanh(X) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \qquad \text{Eq. (5)}$$

When compared to standard RNNs, Long Short-Term Memory networks demonstrate superior performance in tasks that require modeling long-range dependencies. This is particularly evident in areas such as natural language processing, where contextual relationships can span hundreds of words, and in temporal sequence prediction for renewable energy forecasting or equipment fault diagnosis. The advantage of LSTMs originates from their gated architecture, which maintains a stable gradient flow across extended sequences. This stands in contrast to vanilla RNNs, which are prone to exponential gradient decay ($\partial h_t/\partial h_{t-1} \approx \lambda$ˆt, $|\lambda|<1$).

Sankarananth et al. [62] proposed a hybrid LSTM-RL model for forecasting and managing renewable energy in smart grids, achieving significant improvements in predicting energy demand patterns. In another study, Ghaemi et al. [63] employed a novel methodology combining Time-Varying Parameter Vector Autoregression frequency

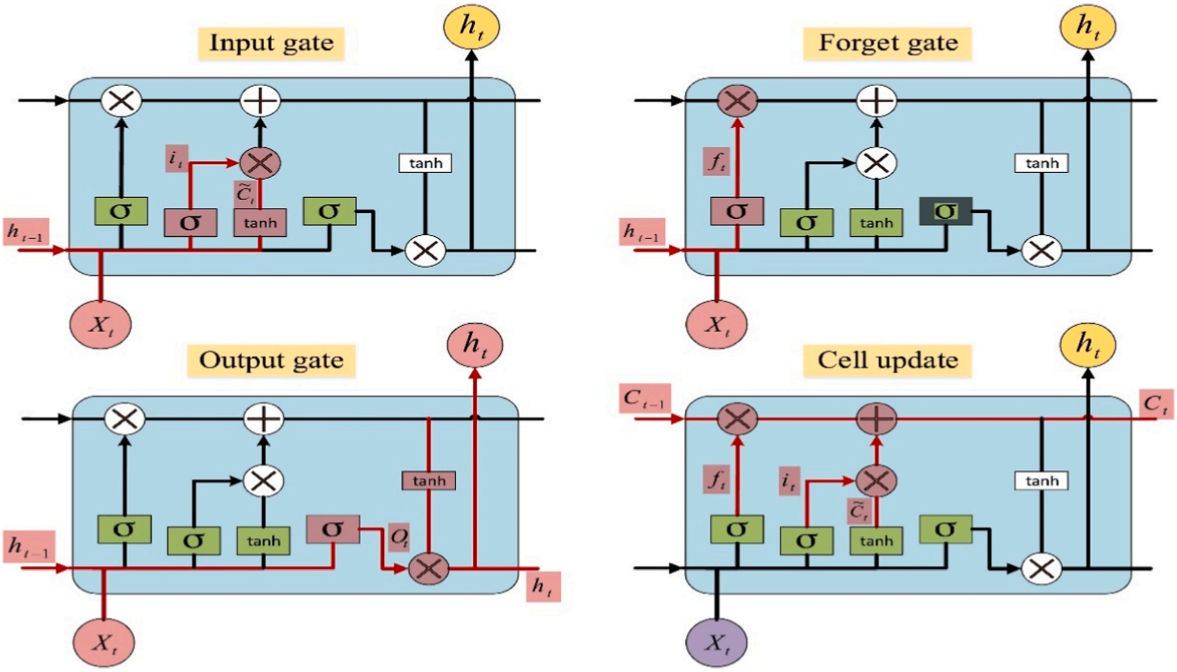

Fig. 6. Schematic diagram of the LSTM cell state update process [60].

connectivity analysis with LSTM networks to investigate long-term interdependencies between the renewable energy sector and emerging technologies like quantum computing, AI, and big data. Their results indicated that quantum computing exhibited relatively low connectivity, while particularly strong linkages were identified for specific entities like Microsoft within the renewable energy domain. The analysis further revealed persistent long-memory relationships between AI and renewables, whereas weaker long-term associations were observed between business intelligence and AI technologies.

Building on this foundation, various novel hybrid algorithms based on LSTM architectures have been developed. Avar et al. [64] employed a Bidirectional Long Short-Term Memory network to address uncertainties in photovoltaic and wind turbine power generation alongside load demand fluctuations. Their numerical results demonstrated the superior performance of this B-LSTM approach over conventional benchmark methods, validating its effectiveness in resolving integration challenges for RES. Similarly, Faritha et al. [65] developed an attention-optimized bidirectional LSTM technique for optimizing energy storage systems. Their simulations showed this approach achieved minimal computation times for forecasting electricity prices, wind power, and solar generation, outperforming existing benchmarks. Other architectural innovations include the Encoder LSTM and Convolutional LSTM models introduced by Arbaoui et al. [66] for battery state-of-health prediction, where the E-LSTM model achieved a mean absolute error below one percent. Zhao et al. [67] proposed a CNN-BiLSTM-based method for fault detection in offshore wind-hydrogen systems, attaining high detection accuracy and improvements in system reliability and operational efficiency. Niu et al. [68] developed a hybrid forecasting framework integrating Bidirectional LSTM with Attention mechanisms, which significantly enhanced both point forecasting accuracy and probabilistic prediction reliability for wind power.

3.7. *Graph neural networks (GNNs)*

Graph Neural Networks are deep learning methods specifically developed for data structured as graphs. Unlike conventional neural networks, GNNs can simultaneously process node features and the connections between them, capturing both local attributes and overall relational patterns [69]. Scarselli et al. first proposed an early GNN framework for processing graph domain data, demonstrating its generalization capabilities [70]. This is accomplished through a message-passing framework that operates in two stages: first, aggregating information from neighboring nodes, and second, updating the target node's representation [71].

(1) Message Aggregation Phase: Information from neighboring nodes is aggregated into a unified message for the target node, typically through permutation-invariant operations (e.g., mean/sum/max pooling).
(2) Node Update Phase: The collected messages are fused with the target node's current features via learnable transformations (often implemented as neural networks), thereby generating updated node embeddings.

In application, Taghizadeh et al. [69] introduced a multi-fidelity GNN-based model for power flow calculation that reduced training costs while enhancing performance. Owerko et al. [72] designed a GNN model for solving optimal power flow problems, though its applicability was noted to be constrained to specific grid topologies. To improve interpretability, Li et al. [73] applied a framework using Graph Attention Networks to identify critical grid nodes and their correlations with weather patterns, significantly enhancing the computational performance and clarity of optimal power flow solutions. By integrating typed GNNs, such models can effectively process heterogeneous nodes and edges in power system graphs, enabling more sophisticated, context-aware analysis. The addition of attention mechanisms further allows the model to focus selectively on mission-critical data components, boosting overall performance [74].

In forecasting, Kim et al. [75] developed a spatiotemporal model based on Adaptive Graph Convolutional Recurrent Networks, which significantly improved renewable energy prediction accuracy. They concurrently introduced the FxRE-Plan planning methodology, which achieved an 11.5 percent reduction in greenhouse gas emissions through optimized renewable integration. Another innovative model, the Graph Patch Informer proposed by Liu et al. [76]. combines Transformer architecture with GNNs. By implementing adaptive adjacency matrices, this framework enhanced forecasting accuracy, reducing the mean squared error between 23.67 and 40.75 percent across multiple benchmark datasets compared to existing models.

3.8. *Reinforcement learning (RL)*

Reinforcement Learning, a pivotal machine learning branch, operates on a trial-and-error principle where an agent learns optimal policies by maximizing cumulative rewards through iterative interactions with an environment. This process is typically formalized using Markov decision processes. As shown in Fig. 7, the agent perceives a state s_t, selects an action a_t based on its policy π, and then receives a reward r_t while the environment transitions to a new state s_{t+1}. The essence of RL is to learn the policy that prescribes the highest-value action for any given state, with algorithms broadly categorized into value-based methods like Q-Learning and policy-based methods like Policy Gradient Methods [77].

As previously mentioned, Sankarananth et al. [62] had enhanced the accuracy of renewable energy generation forecasting by integrating RL with LSTM networks. Similarly, other researchers have achieved notable breakthroughs in RES through hybrid RL-based approaches, as demonstrated in the following case studies.

Similarly, other researchers have achieved notable breakthroughs using hybrid RL-based approaches. Kharat et al. [78]. proposed a thermal management strategy integrating Generative Adversarial Networks with RL. By using GANs to generate synthetic training scenarios, improving fuel cell system thermal efficiency 15.2 percent compared to baseline thermal management strategies, extending operational lifespan 23.7 percent, and maintaining 89.4 percent stability under load fluctuations. Yang et al. [79] implemented a Multi-Agent Markov Reinforcement Learning framework for smart grid-integrated systems, achieving benchmark results including 95 percent prediction accuracy and 96 percent energy efficiency improvement. For wind farm optimization, Pinciroli et al. [80] developed a deep reinforcement learning framework that autonomously discovered optimal control policies, outperforming other DRL algorithms in operational efficiency and cost reduction. In integrated energy system optimization, Ruan et al. [81] developed a DRL-based framework for hybrid energy systems that optimized real-time energy management, achieving cost reductions up to 14.17 percent. A DRL-based framework was developed by Zhang et al. [82] for hybrid energy systems, which optimized real-time dynamic energy management strategies and achieved a cost reduction of up to 14.17% through adaptive policy iteration. A Deep Q-Network (DQN)-based DRL methodology was proposed by Shrestha et al. [83] for modern power system applications. This approach had effectively optimized energy portfolio allocations while simultaneously evaluating system stability through real-time Short-Circuit Level (SCL) analysis, demonstrating enhanced operational reliability under dynamic grid conditions.

3.9. *Random forest (RF)*

Random Forest is an ensemble method that combines predictions from numerous decision trees to improve overall accuracy. Each tree is built using bootstrap samples and a random subset of features at every split, which lowers model variance and enhances generalization. This approach introduces randomness to reduce overfitting in individual

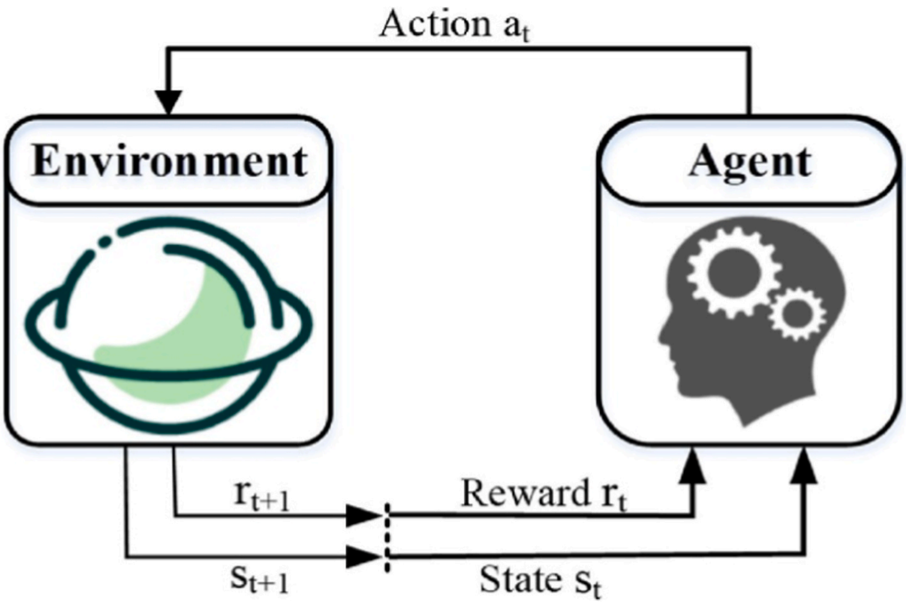

Fig. 7. Schematic representation of the RL framework [77].

trees, while final outputs are determined by majority voting in classification tasks or averaging in regression. By selecting a random feature set at each node, RF decreases the correlation among trees, further strengthening its ability to generalize [84]. In regression, the final prediction is computed as the mean of all individual decision tree outputs, whereas for classification tasks, the majority voting mechanism determines the predicted class label. The operational workflow of RF is illustrated in Fig. 8. RF exhibits the following characteristics.

(1) Parameter Simplicity: Intuitive hyperparameter tuning, with primary parameters being the number of trees and features per node.
(2) Overfitting Resistance: Inherent robustness to overfitting due to ensemble-based variance reduction.
(3) Feature Importance Quantification: Capability to rank input features by their predictive contribution (e.g., Gini importance).
(4) Generalization Error Estimation: Utilization of out-of-bag (OOB) error as an unbiased proxy for model performance [68].

In RES, RF has demonstrated superior performance in prediction and optimization tasks compared to alternative algorithms, particularly in scenarios requiring high-dimensional feature processing and interpretability.

In their investigation into predicting wind and solar power curtailment, Shams et al. [86] developed an AI model. They established their predictive framework using several machine learning approaches, such as Regression Trees, Gradient Boosting Trees, Random Forest, Artificial Neural Networks, Long Short-Term Memory networks, and Support Vector Regression. Their findings demonstrated that the Random Forest model produced the smallest prediction error, outperforming the other algorithms in the comparison. In a separate effort to improve wind turbine power output prediction, Talaat et al. [87] created a data-driven model that incorporated site-specific climatic data to aid generation

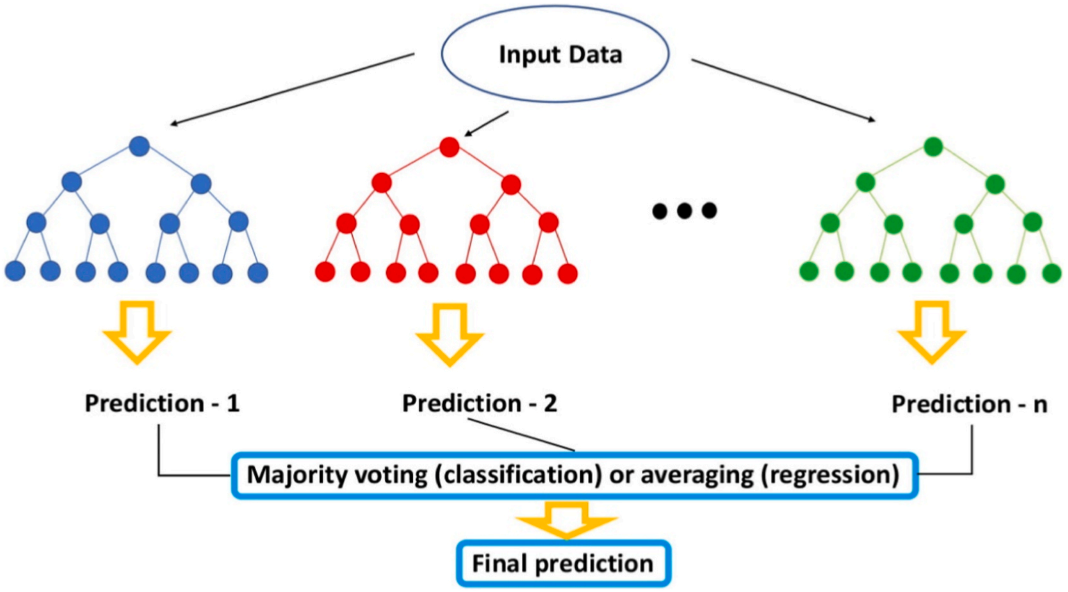

Fig. 8. Schematic architecture of RF for classification and regression tasks [85].

scheduling. This framework utilized XGBoost and Random Forest regressors for 15-day-ahead power generation forecasts. Experimental results validated its high computational efficiency, with a training duration under 2.5 min, a prediction accuracy of 94% reflected in the R^2 score, and a mean absolute percentage error of 6%. For research on parabolic trough solar collectors, Tao et al. [88] employed Random Forest Regression and other ensemble methods to generate high-precision predictions of energy output and efficiency. A particularly accurate result was observed with their Classification and Regression Tree model, which predicted the thermal efficiency of Syltherm 800-SiO_2 nanofluids with a coefficient of determination (R^2) of 0.9999. Regarding hybrid microgrid systems that combine renewable energy with hydrogen storage, Elabbassi et al. [89] implemented a Random Forest-based approach. This RF model showed better predictive performance for critical components than the k-Nearest Neighbors method, attaining a macro-average accuracy of 90% compared to 82% for k-NN, and a macro-average F1-score of 90% versus 85%. Furthermore, Sun et al. [90] applied Random Forest combined with SHAP analysis to tackle the spatial siting challenge for offshore wind energy. Their work successfully predicted the optimal scale and location for facilities and produced detailed suitability and size maps to guide installation planning.

Some researchers have also combined Random Forest with deep neural networks for predictive optimization in RES. Amer et al. [91], for instance, used a DNN based on a Random Forest Bayesian surrogate model to predict the maximum power output and efficiency of photovoltaic modules with high precision. Their model achieved an R^2 value of 0.998, which corresponded to a significant reduction in prediction errors. Similarly, other studies have applied RF models for optimization in power systems. Toubeau et al. [92] employed an RF-based method for contingency analysis on the Belgian regional transmission system, achieving notable results with prediction accuracy above 90%. Their analysis also provided key insights into how increasing renewable energy generation might affect system maintainability. Finally, Liang et al. [93] implemented a KMeans-RF model within an intelligent energy management system for photovoltaic buildings. This model integrated a data-driven prediction module with a mixed-integer programming module, leading to significant improvements: it effectively resolved data imbalance issues, enhanced the management of battery residual energy, and optimized the balance between thermal comfort and energy consumption. These RF-based computational models, EMS models [94], and training frameworks all demonstrate strong predictive capabilities in RES.

3.10. Adaptive neuro-fuzzy inference system (ANFIS)

The Adaptive Neuro-Fuzzy Inference System is a hybrid model that integrates the reasoning of fuzzy logic with the adaptive learning of neural networks. It is designed to model and predict complex nonlinear relationships by structuring the three stages of fuzzy inference—fuzzification, rule evaluation, and defuzzification—within a neural network. Based on the Takagi-Sugeno framework, ANFIS can adaptively derive fuzzy rules from input-output data while fine-tuning the parameters of its membership functions. This allows the system to efficiently model sophisticated processes [95].

An intermediate layer within the network utilizes a weighted mechanism to effectively map inputs to their target outputs. What distinguishes ANFIS is its integration of two distinct machine learning techniques: backpropagation and least squares error estimation. The model can be formally described by the conditional rules of a first-order Takagi-Sugeno model [96], expressed as follows:

Rule 1: IF a is X_1 AND b is Y_1, THEN $f_1 = m_1a + n_1b + o_1$

Rule 2: IF a is X_2 AND b is Y_2, THEN $f_2 = m_2a + n_2b + o_2$

where: a and b denote input variables, X and Y represent fuzzy linguistic variables, f corresponds to the output of the fuzzy set. The design parameters (m, n, o) are dynamically optimized during ANFIS training through its hybrid learning mechanism.

The workflow of the five-layer ANFIS architecture is illustrated in Fig. 9. Mehta et al. [96] implemented ANFIS to develop a maximum power point tracking algorithm, dynamically adjusting the duty cycle to enhance power output. Their comprehensive simulations and experimental validation demonstrated the controller's superior stability and performance under varying operational conditions, with it significantly outperforming conventional approaches. For grid-connected solar photovoltaic systems, Bakare et al. [97] employed an integrated modeling approach that combined ANFIS with Gene Expression Programming. This hybrid methodology led to notable advancements, realizing enhanced energy management while simultaneously improving system reliability, economic performance, and environmental sustainability. In the domain of microgrid optimization, Durairasan et al. [98] successfully applied an EHO-ANFIS methodology, which demonstrated superior performance in energy allocation by achieving a remarkable 97% optimal solution attainment rate. This hybrid strategy significantly enhanced both energy management efficiency and overall system performance.

4. Synthesis of applications and hybrid methodologies in renewable energy systems

As RES have become more complex, single-algorithm solutions frequently prove inadequate for handling multi-objective optimization and uncertainty. This limitation has spurred the advancement of hybrid methods that merge AI with data-driven techniques, fostering deeper interdisciplinary synergy. This section provides a systematic review of hybrid methods, including AI hybrid approaches such as convolutional neural networks-long short-term memory networks (CNN-LSTM) and graph neural networks-transformers (GNN-Transformer), data-driven hybrid methods combining AI with other algorithms, and optimization frameworks enhanced by meta-heuristic algorithms like particle swarm optimization, genetic algorithms, and harmonic search. By integrating these approaches, significant gains have been achieved in system robustness and adaptability, with notable applications in battery aging assessment, load frequency regulation, and the optimization of solid oxide electrolyzer cells [99]. The emergence of these hybrid strategies marks a critical transition from isolated algorithmic applications toward system-level integration of AI and data-driven methods within renewable energy. They further present novel directions for coordinating multiple energy sources and enabling intelligent scheduling.

4.1. AI and data-driven hybrid models

Beyond the specialized AI algorithms previously discussed, many researchers are adopting hybrid data-driven approaches that combine AI modeling techniques with data optimization strategies. The data-driven paradigm itself is a methodological framework centered on the systematic acquisition, processing, analysis, and interpretation of data to inform decision-making, optimization, and innovation. It emphasizes extracting valuable insights from data to guide practice, optimize processes, and drive innovation toward efficient goal attainment. Algorithms based on this paradigm have garnered significant attention due to their advantages in handling systems with nonlinear, dynamic, and complex updatable characteristics. They typically demonstrate strong generalization capabilities, high accuracy, rapid convergence, and robust learning abilities. Crucially, data-driven methods do not rely on complex first-principles mathematical models or predefined filters; instead, they can enhance functionality through machine learning, making them particularly suitable for renewable energy forecasting [100]. Recently, hybrid data-driven methods have attracted widespread interest due to their improved performance in terms of efficiency, accuracy, and robustness. As renewable sources like hydropower, wind,

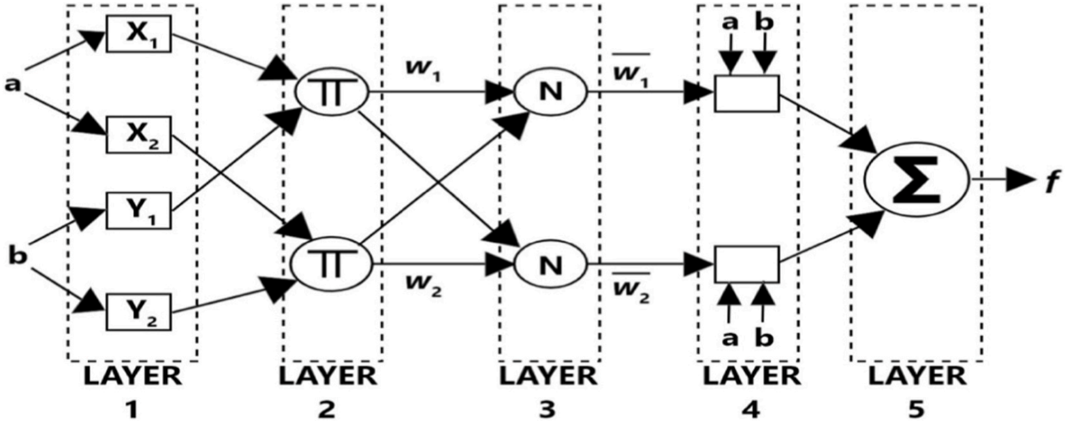

Fig. 9. Five-layer architecture of ANFIS structure [96].

and solar power constitute a larger share of the energy mix, issues such as wind and solar curtailment have become prominent, acting as critical bottlenecks to efficient utilization. To mitigate curtailment and enhance accommodation capacity, developing accurate forecasting strategies to optimize energy system dispatch and operation is imperative [101]. In this context, data-driven hybrid algorithms have emerged as a promising solution for renewable energy forecasting, offering notable advantages in accuracy, efficiency, and robustness [102]. For instance, deep learning-based hybrid models like CNN-LSTM have been shown to effectively capture the spatiotemporal characteristics of renewable generation, significantly improving prediction accuracy. Furthermore, forecasting models that integrate improved optimization algorithms (e.g., CSFSSA) with neural networks also exhibit superior performance in wind power prediction. These findings indicate that data-driven hybrid algorithms can not only adapt to the complex, fluctuating nature of renewables but also provide robust support for the economic dispatch and stable operation of power systems [103]. By combining the flexibility of data-driven methods with the interpretability of model-driven approaches, these hybrid techniques offer novel solutions for the optimization, forecasting, and dispatch of RES, playing a pivotal role in decarbonization and mitigating renewable generation uncertainties.

4.2. Analysis by System Use Case

Currently, numerous scholars have employed data-driven hybrid methods in renewable energy applications—such as power generation analysis, microgrid testing, and battery pack training—to investigate their impact on system development [104]. For example, Zhou [105] developed an exponential Gaussian Process Regression model by integrating data fitting with machine learning to address battery cycle aging in intermittent renewable systems, demonstrating notable feasibility and accuracy. In another study, Hoseinzadeh et al. [106] applied a series of data-driven techniques to analyze data from greenhouse agricultural energy systems, finding that AI significantly reduces heating energy consumption and improves efficiency, but has limited impact on mitigating greenhouse gas emissions and optimizing broader resource use.

The application of this methodology has also been extended to Load Frequency Control systems by several researchers. Cai et al. [107] proposed a robust data-driven predictive LFC scheme to handle uncertainties induced by renewable integration, demonstrating superior performance over conventional Proportional-Integral controllers and model-based predictive control. For interconnected grid management, Li et al. [108] employed a Sea Computing-based Multiagent Deep Meta Reinforcement Learning approach to develop a Sector-Connected Grid Area Coordination LFC strategy aimed at renewable energy optimization. Simulation validation showed this methodology significantly reduces frequency deviations and regulation mileage costs. Focusing on system security, Syrmakesis et al. [109] implemented a data-driven attack recovery methodology for LFC in power systems, conducting comprehensive single-area and two-area simulations in MATLAB/Simulink to verify the approach's effectiveness and scalability.

Current research indicates that most hybrid data-driven algorithms are predominantly applied within various renewable energy generation systems for assessment, prediction, and optimization. Typical application domains include fuel cells, solar and wind power generation, rare-earth resource-based systems, and microgrids. Castro et al. [110] used an econometric model to evaluate whether renewable energy generation could meet global electricity demand driven by digital data growth, concluding that data-driven electricity demand may exceed global production capacity by 2033. For fuel cell performance, Siddiqa et al. [111] developed a hybrid framework for proton exchange membrane fuel cells by integrating computational fluid dynamics with data-driven modeling, achieving high-precision current density prediction and enhanced operational capability. Liu et al. [112] employed a data-driven strategy incorporating CoAtNet and SHAP values for online Frequency Stability Prediction in power systems, demonstrating significant improvements in both prediction accuracy and computational efficiency. In solar power prediction, Khan et al. [100] proposed a hybrid model integrating MLP, SVR, and CatBoost through data mining techniques, showing significant enhancement in accuracy. For materials research, Lee et al. [113] constructed a robust dataset and developed an interpretable machine learning model based on knowledge-driven feature selection to study perovskite solar cells, successfully establishing an accurate predictive model and revealing the critical influence of bandgap and band energy levels on performance. For renewable technology assessment, Seikh et al. [114] implemented the SWARA-ARAS method within a confidence-based interval-valued Fermatean fuzzy environment to evaluate solar, wind, and geothermal systems, finding significant expansion potential for solar and wind but identifying geothermal as currently unsuitable for large-scale deployment. From a strategic perspective, Zhang et al. [115] developed a SWOT analysis framework using Latent Dirichlet Allocation-based text analytics to examine rare-earth resource recycling in renewable energy from an ESG viewpoint, revealing a paradigm shift toward prioritizing environmental impacts and sustainable development. In microgrid research, Dwivedi et al. [116] applied a cooperative game theory approach to evaluate energy resilience, introducing a quantifiable percolation threshold metric in an IEEE-123 node test system with distributed energy resources and peer-to-peer trading; their results showed a 25.07% enhancement in resilience coupled with a 67.91% reduction in total costs. Qi et al. [117] proposed a hybrid optimization strategy integrating the Grey Wolf Optimizer with advanced algorithms, confirming its effectiveness on IEEE 57-node and 118-node systems with achieved reductions of 12% in voltage deviation and 18% in total costs. For battery modeling, Ryzhov et al. [118] implemented a Tensor Train decomposition-based estimation method coupled with relaxation time distribution algorithms for data-driven state estimation and dynamic model reconstruction, demonstrating strong performance on commercial solid-state battery data with relative errors below 5%. In forecasting, Teng et al. [119] developed a Domain Adaptation for Zero-shot Sequence Learning strategy incorporating similar tensor methods for solar and wind prediction in substation systems, achieving lower root mean square error than conventional transfer learning models. For planning under uncertainty, Wu et al. [120] formulated a robust collaborative planning model via second-order cone programming and solved it with the Column-and-Constraint Generation algorithm, verifying its effectiveness on modified test systems. Duan et al. [121] developed a novel information-enhanced grey Lotka-Volterra model integrating system mechanisms and data-driven approaches for energy forecasting in China's West-East Electricity Transfer project, showing significant accuracy improvements. In microgrid applications, Habib et al. [122] advanced a two-stage Hybrid Data-Linkage Model architecture integrating complex decomposition with machine learning clustering for short-term PV fluctuation forecasting in isolated grids, achieving a 15% reduction in processing time while enhancing accuracy. Yin et al. [123] proposed a novel two-stage Data-Driven Adaptive Robust Distributed Generation Planning framework using Bayesian nonparametric methods in a modified IEEE 33-bus system, demonstrating reductions in both uncertainty estimation errors and operational costs. Zhang et al. [124] developed a data-driven Distributionally Robust Optimization approach integrated with the Alternating Direction Method of Multipliers to establish a decentralized energy negotiation mechanism, improving robustness and economic efficiency in handling PV uncertainty.

Regarding condition monitoring for offshore wind turbines, Zhang et al. [125] proposed an integrated data-driven model, combining LightGBM-based Normal Behavior Modeling with a GRU-Bayesian Neural Network for degradation analysis to enable high-accuracy probabilistic prediction of gearbox pump remaining useful life. For solar power generation forecasting, Li et al. [126] introduced a novel data-driven seasonal multivariate grey model for capturing seasonal fluctuations and underlying nonlinear trends, demonstrating superior generalization capability, stability, and reliability on quarterly or monthly time-series data compared to conventional methods. In the domain of electric vehicle integration, Wu et al. [127] created a data-driven optimization approach. This method incorporated probabilistic forecasting models to characterize uncertainties inherent in EV charging behaviors and regulatory signals, with a day-ahead scheduling model formulated to maximize profit. Experimental results confirmed that this model effectively enhances the capability of EV aggregators to provide ancillary services. Further advancing system reliability, Sudhakar et al. [128] proposed a defect prediction model by integrating physical failure prototypes with data analytics theory. By implementing an IoT-enabled deep learning architecture, they successfully achieved simultaneous fault diagnosis and type prediction within wind power generation systems.

Research on hybrid data-driven algorithms for solid oxide electrolyzer cell (SOEC) optimization remains relatively limited. Among the existing studies, Sun et al. [129] advanced a hybrid model that integrates multiphysics simulation (MPS) with deep learning algorithms. This framework achieved both precise and rapid optimization for RES producing syngas via SOEC technology. In a closely related study, Liu et al. [130] also developed a hybrid model combining multiphysics simulation with deep learning for SOEC-based, renewable-powered syngas production systems. Their results highlighted that incorporating thermal energy storage (TES) led to a 53% reduction in the SOEC inlet temperature fluctuation rate, while concurrently enhancing overall operational stability and system efficiency. Accordingly, Table 2 summarizes the research focus and variations among key studies. It is notable that some hybrid algorithms are designed to target specific

Table 2
Summary of hybrid data-driven methodologies.

Reference	Method of Use	Focused areas	Research gaps
Zhou [105].	Exponential Gaussian Process Regression (GPR)	Intermittent RES, battery cycle aging models, machine learning, algorithm selection strategies	Limited validation across diverse battery types and energy systems, need for more comprehensive uncertainty quantification
Hoseinzadeh et al. [106].	Series of Data-Driven Techniques	Greenhouse applications, AI technology, energy efficiency, crop quality, greenhouse gas emissions	Limited long-term impact assessment, need for more holistic sustainability evaluations
Cai et al. [107].	Robust Data-Driven Predictive LFC Scheme	High renewable energy penetration power systems, frequency control, data-driven predictive load frequency control	Limited consideration of extreme operating conditions, need for more extensive real-world testing
Li et al. [108].	Sea Computing-based Multiagent Deep Meta Reinforcement Learning	Interconnected power grid energy management, renewable energy optimization, multi-agent deep meta-reinforcement learning	Limited scalability assessment, need for more detailed economic analyses
Syrmakesis et al. [109].	Data-Driven Attack Recovery Methodology	Power system resilience, data-driven attack recovery, deep neural networks	Limited generalizability to different grid configurations, need for more extensive security testing
Castro et al. [110].	Econometric Model	Renewable energy capacity expansion, digital data growth, electricity demand	Limited regional-specific analysis, need for more detailed technology cost projections
Siddiqa et al. [111].	Hybrid Framework (CFD + Data-Driven Modeling)	Proton exchange membrane fuel cells, hybrid modeling, computational fluid dynamics	Limited experimental validation, need for more comprehensive durability assessments
Liu et al. [112].	Data-Driven Strategy (CoAtNet + SHAP values)	Power system frequency stability prediction, data-driven strategies	Limited real-time performance evaluation, need for more extensive uncertainty quantification
Khan et al. [100].	Hybrid Model (MLP, SVR, CatBoost via Data Mining)	Power prediction models, data mining, hybrid machine learning approaches	Limited interpretability analysis, need for more detailed computational efficiency assessments
Lee et al. [113].	Interpretable ML Model based on Knowledge-Driven Feature Selection	Perovskite solar cells, data-driven analysis, interpretable machine learning	Limited long-term stability assessment, need for more comprehensive material property evaluations
Seikh et al. [114].	SWARA-ARAS Method within Confidence-based Interval-Valued	Renewable energy expansion potential, multi-attribute group	Limited dynamic uncertainty modeling, need for more detailed

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Table 2 (*continued*)

Reference	Method of Use	Focused areas	Research gaps
	Fermatean Fuzzy Environment	decision-making, Fermatean fuzzy numbers	economic feasibility analyses
Zhang et al. [115].	SWOT Analysis Framework using LDA-based Text Analytics	Renewable energy generation, rare earth resource recycling, text data analysis	Limited circular economy perspective, need for more detailed life cycle assessments
Dwivedi et al. [116].	Cooperative Game Theory Approach	Microgrid energy resilience, distributed energy resources, peer-to-peer energy trading	Limited consideration of cyber-security aspects, need for more detailed regulatory impact analysis
Qi et al. [117].	Hybrid Optimization Strategy (Grey Wolf Optimizer + Advanced Algorithms)	Power system optimization, hybrid grey wolf optimization, cost reduction	Limited real-world application testing, need for more comprehensive sensitivity analyses
Ryzhov et al. [118].	Tensor Train Decomposition-based Estimation + Relaxation Time Distribution Algorithms	Battery dynamics modeling, data-driven state estimation, tensor train methods	Limited multi-battery system applications, need for more detailed model interpretability assessments
Teng et al. [119].	Domain Adaptation for Zero-shot Sequence Learning Strategy + Similar Tensor Methods	Renewable energy prediction, data-driven transfer learning, zero-shot learning	Limited cross-regional applicability testing, need for more detailed error source analysis
Wu et al. [120].	Robust Collaborative Planning Model (Second-Order Cone Programming + C&CG Algorithm)	Renewable energy planning, robust collaborative planning, uncertainty modeling	Limited real-world implementation examples, need for more detailed computational complexity analysis
Duan et al. [121].	Information-Enhanced Grey Lotka-Volterra Model (System Mechanisms + Data-Driven Approaches)	Energy forecasting, grey Lotka-Volterra models, system mechanism modeling	Limited application to emerging energy markets, need for more detailed model adaptability assessments
Habib et al. [122].	Two-Stage Hybrid Data-Linkage Model (Complex Decomposition + ML Clustering)	Photovoltaic power prediction, hybrid data linking models, microgrids	Limited generalization to different climate zones, need for more detailed computational resource assessment
Yin et al. [123].	Two-Stage Data-Driven Adaptive Robust Distributed Generation Planning Framework (Bayesian Nonparametric Methods)	Distributed generation planning, adaptive robust optimization, microgrid operation	Limited real-world implementation testing, need for more comprehensive uncertainty source integration
Zhang et al. [124].	Data-Driven Distributionally Robust Optimization + ADMM	Decentralized energy trading, robust optimization, data-driven mechanisms	Limited scalability testing, need for more detailed market dynamics analysis
Zhang et al. [125].	Integrated Data-Driven Model (LightGBM-based NBM + GRU-Bayesian Neural Network)	Offshore wind energy, fault prediction, data-driven modeling	Limited application to other energy systems, need for more comprehensive uncertainty source integration
Li et al. [126].	Data-Driven Seasonal Multivariate Grey Model	Solar power prediction, seasonal multivariate grey models	Limited application to other renewable sources, need for more detailed long-term trend analysis
Wu et al. [127].	Data-Driven Optimization Approach (Probabilistic Forecasting Models)	Electric vehicle grid integration, data-driven optimization	Limited consideration of vehicle-to-grid interactions, need for more detailed market impact assessment
Sudhakar et al. [128].	Defect Prediction Model (Physical Failure Prototypes + Data Analytics Theory via IoT-enabled DL Architecture)	Wind energy fault diagnosis, deep learning, IoT integration	Limited application to other energy systems, need for more comprehensive real-time performance evaluation
Sun et al. [129].	Hybrid Model (Multiphysics Simulation + Deep Learning Algorithms)	Solid Oxide Electrolysis Cell, multi-physics simulation, deep learning	Limited real-world operational validation, need for more detailed economic feasibility analysis
Liu et al. [130].	Hybrid Model (Multiphysics Simulation + DL)	Solid Oxide Electrolysis Cell, thermal energy storage, system efficiency	Limited long-term stability assessment, need for more comprehensive economic viability analysis

challenges within these systems.

4.3. Other optimization/metaheuristic frameworks

Beyond the methods already covered, a variety of hybrid algorithms and frameworks are also applicable to Renewable Energy Systems (RES). These include multiple metaheuristic algorithms and other specialized computational techniques [131]. Metaheuristics represent a class of high-level strategies for solving complex optimization problems, employing guided search processes to find optimal or near-optimal solutions. Commonly recognized categories of metaheuristics encompass: evolutionary algorithms, which mimic principles of natural selection, such as Differential Evolution (DE) [132] and Genetic Algorithms (GA) [133]; swarm intelligence algorithms that model collective biological behavior, including Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO); human-inspired algorithms grounded in social systems, for instance Teaching-Learning-Based Optimization (TLBO) and Harmony Search (HS) [131]; and physics or chemistry-inspired algorithms that reflect natural phenomena, like Simulated Annealing (SA) and the Gravitational Search Algorithm (GSA). As a sophisticated form of heuristic optimization, metaheuristics are generally characterized by their generality—applicable across diverse problem domains—adaptability to different problem structures, and strong global search capability. By imitating processes like evolution, social learning, or physical laws, these methods can efficiently navigate complex solution spaces to identify high-quality solutions.

Furthermore, there exist specialized computational approaches, largely mathematical methods that build upon AI algorithms. These alternative optimization solutions, rooted in AI and data-driven methodologies, also make substantial contributions to RES advancement. Recent applications by researchers illustrate their use: Wang et al. [132] combined a modified DE algorithm with random forest regression to model and predict power generation optimization in smart building microgrids. This synergistic integration was shown to fully leverage the strengths of each method, resulting in a robust predictive framework. In another study, Alshamrani et al. [133] optimized an integrated residential energy system using TRNSYS simulation software and GA techniques, incorporating passive geothermal boreholes and waste heat recovery heat pumps. Their approach achieved notable reductions in energy expenses, total operational costs, and CO_2 emissions. Yilmaz et al. [134] implemented an AI and GA optimization framework within a geothermal-solar polygeneration system that integrated an organic Rankine cycle (ORC) with a geothermal-solar absorption cooling cycle. Under Afyonkarahisar geothermal conditions, the optimized system exhibited a significant increase in net power output and cooling capacity, alongside a 12.1% reduction in electricity generation costs and a 41.9% decrease in cooling production costs.

While the studies above employed nature-inspired metaheuristics like GA and DE, the following cases represent canonical examples of human- or bio-mimetic metaheuristic optimization. Zhang et al. [135] developed an enhanced metaheuristic approach based on a modified Global Dynamic HS algorithm, applying it to an off-grid hybrid renewable energy system consisting of wind power, fuel cells, and hydrogen storage. Their optimized system simultaneously minimized the total net annual cost and the probability of power supply loss, with the second modified version showing superior accuracy, computational speed, and operational stability. Araoye et al. [136] employed the Grasshopper Optimization Algorithm (GOA), a metaheuristic method, for techno-economic modeling and sizing optimization of hybrid renewable energy systems (HRES). A comparative analysis with HOMER Pro software indicated that the GOA-optimized HRES offered better cost-effectiveness and higher renewable energy penetration rates. Guo et al. [137] implemented a hybrid Hunger Games Search and Nelder-Mead Chimp Optimization Algorithm (HGS-NChOA) to optimize grid-connected desalination plants powered by renewable sources. The optimized system significantly reduced freshwater production costs and greenhouse gas emissions while improving economic viability and operational efficiency. Gao et al. [138] developed an economic-emission dispatch model (HDEED) for hybrid wind-PV-storage systems, featuring dual objective functions of operational cost and pollutant emissions. They proposed and implemented a Pelican Optimization Algorithm with a clustering strategy (POA-CS) under optimal grid-connection strategies based on load fluctuations, achieving a substantial reduction in net load variance. The POA-CS algorithm was also verified to effectively generate the Pareto optimal frontier. Saleem et al. [139] integrated multiple renewable sources—solar, wind, and geothermal energy—for polygeneration via TRNSYS®-based simulation. They conducted system optimization using the Hooke-Jeeves algorithm in the GenOpt environment, conclusively establishing the feasibility and superior operational performance of the designed system. Astaneh et al. [140] developed an integrated modeling approach that combined macroscopic system analysis with microscopic battery aging mechanisms for lithium-ion battery-based off-grid renewable systems. Through systematic enumeration, they determined the optimal balance between capital expenditure and battery lifetime extension, with comparative testing quantitatively verifying a 14.6% cost reduction and a 78.4% improvement in lifespan.

The following examples highlight paradigmatic implementations of machine learning-enhanced optimization paradigms in energy systems. Tai et al. [141] accomplished a comprehensive artificial intelligence system for optimizing renewable-powered electrochemical CO_2 conversion processes. By employing adaptive reaction control strategies, they effectively mitigated the inherent intermittency of renewable sources, significantly improving system stability and conversion efficiency. Tian et al. [142] rigorously examined the asymmetric relationship dynamics among AI development, climate policy volatility, and renewable energy expansion using NARDL modeling. They identified statistically significant positive asymmetries for both factors, with greater marginal effects observed during contractionary phases compared to expansionary periods. Liu et al. [143] designed and optimized a multi-source renewable energy system integrating wind, PV, concentrated solar power, PEM electrolyzers, and fuel cells through life cycle assessment and integrated energy management strategies. Their results demonstrated that scaling PV capacity from 25 MW to 150 MW considerably reduced grid dependence and energy costs while increasing net present value, with the 150 MW configuration achieving the highest sustainability index. Cao et al. [144] achieved significant improvements in both environmental and economic performance via their proposed IEGS framework, which effectively mitigated CO_2 emissions and substantially enhanced wind power integration, culminating in a greater-than-20% reduction in overall operational expenditures compared to conventional approaches. Through a Spanish case study, Lisbona et al. [145] confirmed the essential role of Power-to-Gas technology for renewable energy integration and its considerable decarbonization potential, thoroughly examining the technical feasibility of long-term surplus power utilization. Stunjek et al. [146] formulated a novel water-energy nexus optimization approach using MILP techniques, synergistically coordinating reverse osmosis desalination processes and Power-to-Water (PtW) conversion systems. They verified superior system flexibility and cost-efficient operation across multiple renewable integration and battery energy storage (BES) pricing regimes. Uddin et al. [147] proposed a demand-responsive decentralized P2P energy trading system that leveraged fuzzy optimization (FO) techniques to achieve efficient grid interoperability under uncertainty. The framework incorporated a fuzzy logic controller to dynamically adjust trading strategies and pricing mechanisms based on prosumer power deviations. Simulation results substantiated the system's efficacy and its environmental benefits through reduced energy consumption via optimized generation-load balancing. Hassan et al. [148] conducted an in-depth examination of renewable integration challenges in modern power grids, deploying advanced storage technologies and adaptive control methodologies to mitigate generation volatility. Their work systematically verified consequent improvements in power delivery reliability. El-Nagar et al. [149] achieved an advanced flywheel control architecture that leveraged six-phase machine dynamics for superior renewable integration. They conducted comprehensive performance verification through numerical modeling and laboratory prototypes, confirming system robustness under variable renewable generation profiles. Xiong et al. [150] developed an integrated dispatch strategy to optimize renewable energy integration—solar, wind, and tidal—in port microgrids (PMGs) through distributed algorithmic control. The proposed methodology enhanced power supply reliability and flexible load scheduling during port operations. Simulation results demonstrated cost reductions of 12.4% and 21.7% under two distinct tidal patterns, verifying the strategy's adaptive efficiency. Bhayo et al. [151] accomplished an advanced microgrid power management framework that optimized predictive control of power electronic interfaces for multi-objective operation. They experimentally confirmed superior performance in voltage regulation, power smoothing, EV integration, and operational mode flexibility across five distinct test cases representing extreme renewable penetration scenarios. Asante et al. [152] conducted a systematic assessment of renewable energy deployment obstacles using combined CRITIC-F-TOPSIS analysis. They determined that formulating integration policies, establishing mandatory renewable quotas, and implementing workforce development initiatives represented the highest-priority solutions for the Ghanaian energy transition.

Apart from metaheuristic algorithms and optimization frameworks, many domain-specific optimization techniques have been developed and applied across various engineering fields. Qi et al. [153]developed an advanced coordination strategy for hybrid energy storage systems that synergistically combined empirical hydrogen modeling with virtual queue optimization. This approach achieved superior economic and reliability outcomes, with 60% and 90% improvements in respective operational metrics, while facilitating long-term performance optimization through dynamic reference adaptation. Wang et al. [154]

proposed an advanced distributed optimization framework that enabled accurate assessment of voltage stability margins in renewable-penetrated power networks through systematic implementation of hybrid OPF formulations. Validation across both standardized and large-scale real-world test cases confirmed the methodology's exceptional precision and computational efficiency relative to conventional approaches.

Based on the above, the integration of hybrid artificial intelligence with optimization techniques has seen extensive application. For example, researchers have used fully decentralized collaborative planning mechanisms to achieve low-carbon operations within integrated offshore energy system clusters [155]. Separate studies have focused on hydrogen communities, integrating sustainable transport and social welfare into collaborative computational frameworks. Similarly, several stochastic optimization models have emerged for the coordinated expansion of specific microgrids in the renewable energy sector [156]. As a result, technologies such as digital twins, explainable artificial intelligence, and multi-energy integration are increasingly becoming pivotal elements in improving the controllability and transparency of systems. These approaches not only enable more accurate simulation and state prediction, but also make decision-making processes within complex systems clearer and more credible.

In the application of hybrid data-driven models related to artificial intelligence within the renewable energy systems domain, understanding current cutting-edge advancements hinges on several fundamental foundational works. Hybrid models offer a crucial approach to addressing the challenges posed by multi-source heterogeneous data in energy systems. They are not a single method but advocate integrating data-driven models with traditional physical models or rule-based expert systems. Second, the concept of transfer learning profoundly influences how models are applied to new scenarios with sparse data or vastly different conditions. Simply put, a model trained in an environment with abundant data (such as a specific wind farm) can rapidly adapt to new environments with insufficient data (like a newly constructed power plant) through knowledge transfer. Finally, physics-informed neural networks represent a paradigm shift in embedding domain knowledge deeply within AI models. Unlike traditional neural networks that merely learn statistical correlations in data, they incorporate mathematical equations describing physical laws—such as energy conservation or fluid dynamics equations—directly as constraints within the model training process.

5. Critical analysis and comparison

5.1. Comprehensive comparison and applicability analysis

Different AI and data-driven techniques exhibit distinct attributes, each applicable to varied renewable energy system (RES) scenarios. This section systematically compares these methods across four essential dimensions: main application areas, technical advantages and constraints, and typical performance metrics. Table 3 summarizes the fundamental characteristics of major approaches, covering conventional machine learning, neural networks, convolutional and recurrent neural networks, graph neural networks, reinforcement learning, random forests, neuro-fuzzy systems, and hybrid models. It is important to note that the ‘Representative Performance Metrics and Indicative Ranges' presented in Table 3 are synthesized from the results reported in individual studies reviewed. They serve as illustrative examples of achieved performance in specific contexts and are not derived from a formal meta-analysis with associated confidence intervals. The evaluation highlights that method selection should consider multiple crucial factors, including data characteristics, computational capacity, interpretability requirements, and implementation conditions. Hybrid approaches, which combine the strengths of multiple algorithms, show particular promise for optimizing complex systems. To provide researchers undertaking forthcoming studies on AI and data-driven optimization solutions within the RES systems with a reference summary of methodologies and selection criteria.

5.2. Gaps in emerging and under-researched systems

AI offers potential for emerging and under-researched renewable energy systems, addressing unique challenges through specialized approaches. In geothermal energy, AI shifts from static resource assessment to dynamic lifecycle management, using machine learning for prospecting and exploring reinforcement learning for reservoir optimization. For marine energy, Physics-Informed Neural Networks (PINNs) and surrogate models help model complex fluid dynamics and extreme conditions to accelerate device design and predict output. In biomass and waste-to-energy, AI optimizes processes, predicts yields, and sorts waste, with further potential in hybrid supply chain logistics. Advanced nuclear also employs AI for safety-critical monitoring, anomaly detection, and predictive maintenance. Across these domains, a common need is for hybrid methodologies that integrate limited data with domain-specific physical models, unlike the often purely data-driven solar and wind applications. Key research frontiers include transfer learning from data-rich fields and generative AI for synthetic data creation in these data-scarce contexts.

6. Concluding remarks and future directions

In recent years, the escalating severity of environmental issues and excessive exploitation of non-renewable energy resources have propelled RES into global prominence. Research on RES continues to attract growing global interest. This is reflected in the expanding body of work, including this review, which examines the use of AI and data-driven models within these systems. A wide range of studies now apply these methodologies to tasks like modeling, forecasting, simulation, and optimization in RES. This trend, however, introduces a significant practical difficulty: choosing the most appropriate algorithm or framework for a specific operational objective and technical constraint set has become increasingly challenging. This complexity arises primarily from two factors. First, there is a rapid and ongoing expansion in the variety of available AI and data-driven algorithms. Second, different algorithms yield divergent outcomes for the same renewable energy problem, often involving trade-offs in computational efficiency, predictive accuracy, response time, and other essential performance indicators. Consequently, identifying a single solution that optimally satisfies all requirements remains a substantial obstacle.

To address this issue, based on the data from all retrieved RES-related literature and within the indicative ranges across the surveyed case studies, this review has yielded the following graphical results and conclusions. It systematically categorizes the methods, research themes, and core characteristics identified across studies, offering an organized reference to facilitate methodological selection and encourage further research. Toward this aim, Table 4 provides an integrated classification of RES that apply AI and data-driven approaches. The systems are divided into five main categories: solar energy, wind energy, thermoelectric energy, other renewable sources, and other renewable-related systems. Each category is further subdivided into more specific domains. This classification is based on literature published up to 2025, with the detailed outcomes structured as follows.

In light of the aforementioned literature review, the following conclusions can be drawn.

1. Neural network architectures—especially Convolutional Neural Networks (CNNs), Graph Neural Networks (GNNs), and Long Short-Term Memory networks (LSTMs)—have become the leading modeling approaches in AI-driven RES, demonstrating superior performance over other algorithmic paradigms.
2. Fig. 10 highlights notable differences in the focus of research across various renewable energy types. The landscape is largely shaped by

Table 3
Comprehensive comparison of AI and data-driven methodologies in RES.

Method Category	Typical Application Domains	Strengths	Limitations	Representative Performance Metrics and Indicative Ranges
ML/ANN/DNN	Load forecasting, power generation prediction, battery aging prognosis, system efficiency modeling.	High flexibility for nonlinear mapping; strong feature learning capability (ANN/DNN).	Requires extensive training data; low model interpretability ("black-box"); prone to overfitting.	MAE: 1–5% (forecasting); RMSE: 2–8%; Cost Reduction: 10–25% (system optimization); Efficiency Gain: 5–15% (e.g., electrolyzers).
CNN	Spatio-temporal forecasting (solar/wind), image-based fault detection (PV panels, biofouling), grid state classification.	Powerful spatial feature extraction; highly efficient for image/grid data; suitable for large-scale spatio-temporal data.	Requires structured data (e.g., images, grids); needs specialized architectures (e.g., ConvLSTM) for temporal modeling.	RMSE Reduction: 15–40% (vs. statistical benchmarks); Fault Detection Accuracy: >90%; Classification Accuracy: 85–98%; Voltage Stability Improvement: 12–28% (control applications).
RNN/LSTM	Time-series forecasting (power, load), state estimation (battery SoC/SoH), electricity price prediction.	Designed for sequential data; LSTM captures long-term dependencies; effective for multivariate time-series.	High computational cost for training; sensitive to hyperparameters; risk of vanishing/exploding gradients.	MAE: 1–3% (short-term forecast); NRMSE: 3–8%; Prediction Interval Coverage (PICP): >90%; SoH Estimation Error: <1% MAE.
GNN	Power flow calculation, topology optimization, grid stability analysis, coordinated dispatch of DERs.	Explicitly models system topology and nodal relationships; suitable for graph-structured data (e.g., grids); good generalization and transferability.	Highly dependent on graph-structured data; high model complexity; significant computational resource requirements.	Power Flow Error: <1%; Optimization Solving Speedup: 10–100x (vs. conventional OPF); Superior Adaptability to topological changes; Carbon Emission Reduction: 10–20% (coordinated dispatch).
RL	Real-time energy management (EMS), microgrid control, optimal storage dispatch, MPPT.	Learns optimal policies via trial-and-error in uncertain environments; suitable for sequential decision-making; adapts to dynamic conditions.	Unstable and difficult-to-converge training; requires accurate simulation or extensive interaction data; potential safety risks during exploration.	Cumulative Reward/Cost Reduction: 10–20% (operational cost); Frequency Deviation Reduction: 30–60% (LFC); Renewable Curtailment Reduction: 5–15%; Training Steps: 10^4–10^6 (problem-dependent).
RF	Feature importance analysis, generation forecasting, equipment fault classification, site suitability assessment.	Robust to outliers and noise; provides feature importance rankings; fast training and resistant to overfitting.	Poor extrapolation capability; large model size (storage overhead); requires manual feature engineering for time-series data.	Forecast Accuracy (R^2): 0.90–0.99; Feature Importance Ranking (for interpretation); Macro-average F1-score: >85%; MAPE: 3–8% (forecasting).
ANFIS	Nonlinear control systems, MPPT, parameter adaptation, hybrid system modeling.	Combines interpretability of fuzzy logic with learning capability of NNs; suitable for knowledge-data fusion scenarios.	Rule base design can become complex; suffers from rule explosion in high-dimensional problems; training may converge to local optima.	Control Precision: 20–40% better dynamic response vs. PID; Steady-state Error Reduction: >50%; MPPT Efficiency: >99%; Interpretable Outputs via fuzzy rules.
Hybrid Methodologies	Integrated forecasting (CNN-LSTM), optimal design (ML + GA/PSO), fault diagnosis (multi-model fusion), digital twins.	Synergizes strengths of individual methods; performance typically surpasses single-model approaches; addresses multi-objective, constrained problems.	High design complexity; difficult parameter tuning; potentially high computational/deployment costs; further reduced interpretability.	Composite Error Reduction: 10–30% beyond best single model; Superior Pareto Front in multi-objective optimization; System Reliability/Resilience Improvement: 15–25%.

Table 4
Classification of implemented RES and associated research fields.

Categories	Research field				
Solar	Solar Power	PV Energy	Thermal Solar Energy	Solar Energy	Perovskite Solar Cell
Wind	Wind Power	Wind Turbine	Wind Speed	Wind Energy	
Heat and Electricity	Geothermal Energy	Microgrid	Electric Power System	Fuel Cell	Energy Storage
Other renewable-related applications	Hydropower	Biomass energy	SOFC voltage	Renewable energy generation	
Other	Electric Load	Greenhouse Agriculture	Seawater Desalination	Carbon Emissions	Fault detection
	Electric vehicles	P2P	Control system	Energy management	

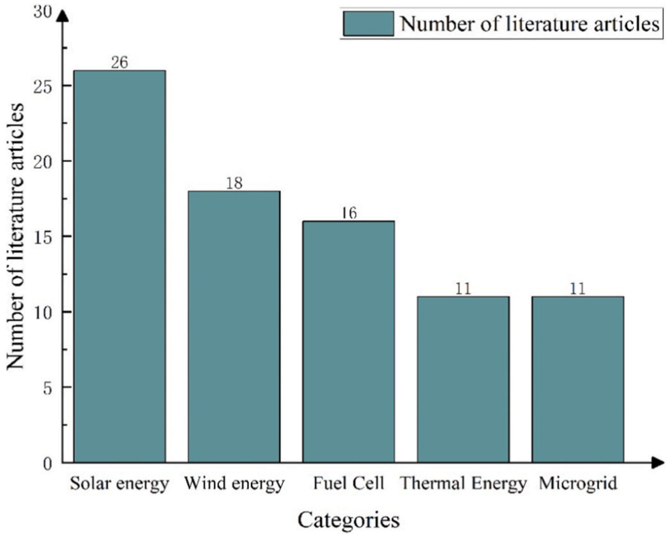

Fig. 10. Statistics of publication quantity on major renewable energy categories (2020–2025).

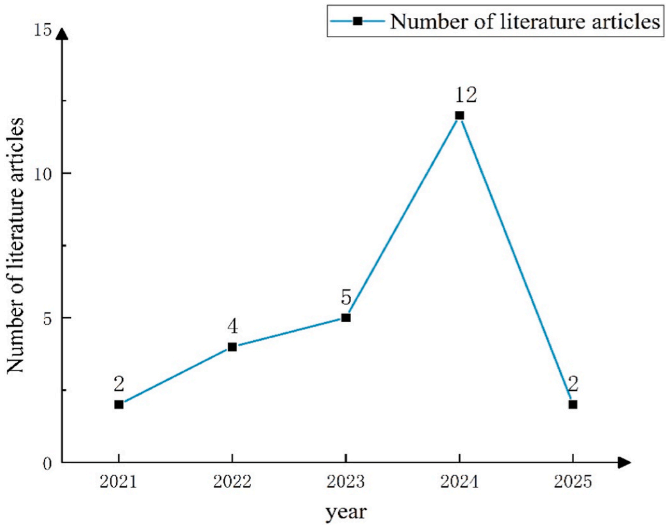

Fig. 11. Annual publication trends in solar energy research (2021–2025).

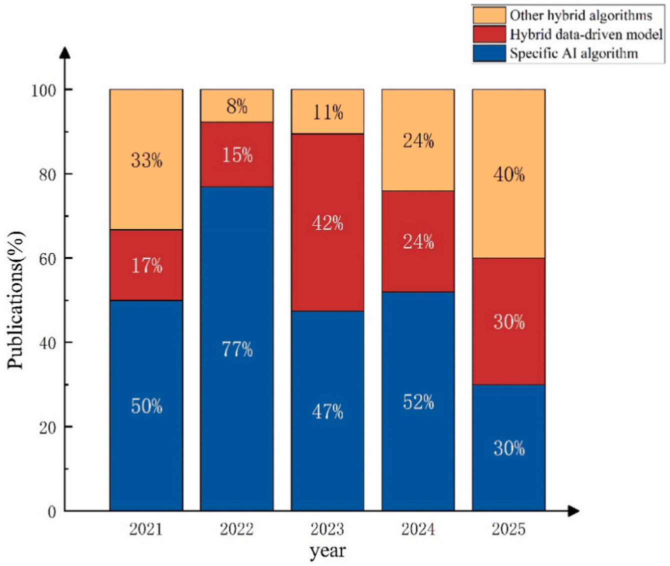

Fig. 12. Methodological distribution trends in renewable energy research (2021–2025).

studies on solar and wind energy, supplemented by work on other sources. Solar energy—covering photovoltaics, solar-thermal systems, and related technologies—is the most extensively researched area, driven by its established technology and wide range of applications. Wind energy follows as the second most studied domain, with research primarily aimed at addressing its intermittent nature through improved forecasting and grid integration. Fuel cell systems have become a significant and growing area of research, ranking third in prevalence as they support the broader shift to renewable energy. Thermoelectric hybrid systems, including geothermal applications and energy storage, form another key research tier, with studies concentrating on integration and operational challenges. Research on other renewable sources, such as hydropower and biomass, appears more specialized and less consolidated but often features notable technological innovation.

3. As shown in Fig. 11, solar energy—the most widely studied area—shows a steady annual rise in the use of AI and data-driven methods, with research output reaching its highest point in 2024. Since this review covers literature only up to 2025, the volume of solar energy research is expected to continue growing in the following year.
4. As shown in Fig. 12, analysis of methodological trends shows that certain core AI algorithms have consistently held a dominant share of annual research output, underscoring their foundational role in renewable energy prediction and optimization. At the same time, hybrid data-driven methods and other integrated solutions have seen steady growth since 2022, reflecting their renewed importance as emerging priorities in recent research.
5. In RES, hybrid AI algorithms combined with data-driven methods have become the approach of choice for a growing number of researchers, surpassing the use of single-method techniques. These integrated models are widely applied across diverse systems—such as fuel cells, solar and wind installations, and microgrids—where they improve system evaluation, predictive accuracy, and operational optimization. This leads to stronger system reliability and more precise forecasting.
6. Data-driven hybrid methods have proven to be both feasible and highly accurate in applications such as analyzing battery cycle aging, managing load frequency control, and optimizing energy

management systems. They also show strong potential for advancing emerging technologies, including SOEC and other sophisticated RES.

7. Metaheuristic algorithms have become a leading methodological approach in RES research, proving highly effective for system prediction and optimization. Prominent techniques such as Genetic Algorithms (GA), Differential Evolution (DE), Harmony Search (HS), and Grasshopper Optimization Algorithms (GOA) have demonstrated significant benefits across multiple studies. Based on a synthesis of the performance outcomes reported in over 20 reviewed studies applying these metaheuristics to RES optimization, the indicative ranges of improvements include reducing operational costs by an average of 18–22% compared to non-optimized or rule-based dispatch strategies, lowering carbon intensity by 12–15% against fossil-fuel dominated scenarios, and enhancing system stability—for example, by cutting voltage deviations by approximately 23% relative to systems without AI-enhanced control.
8. AI-enhanced optimization frameworks have introduced innovative solutions for managing the intermittency and uncertainty of renewable energy. Strategies such as dynamic optimization of electrochemical CO_2 reduction processes, nonlinear autoregressive distributed lag models, and multi-stage day-ahead and intraday coordination schemes leverage adaptive computational power and precise multi-timescale decision-making to improve system reliability and performance.
9. Based on the research trends observed in Figs. 12 and 13, neural networks—such as CNNs and LSTMs—along with hybrid algorithms like those enhanced by metaheuristics, have emerged as the dominant methodologies in the field. Across all energy-specific AI applications, common challenges persist, including a high reliance on data quality and a lack of sufficient validation in real-world operating environments.

AI and data mining are interconnected fields that both depend on reliable data to generate insights and address real-world challenges [157]. Data mining is primarily concerned with uncovering hidden patterns and relationships within datasets, while AI focuses on creating systems that can perceive, reason, and make decisions in ways that emulate human intelligence. Data mining frequently serves as an underlying element in artificial intelligence systems, delivering the organized insights necessary for intelligent modeling [158]. In real-world engineering contexts, these technologies enable data-informed design, simulation, and analysis of user behavior through methods such as text mining, sentiment analysis, and optimization. Growing trends show that emerging approaches increasingly merge data-driven models with physics-based methods and AI-guided controllers—encompassing neural networks and hybrid algorithms—to enhance flexibility and effectiveness in fields like energy systems and smart manufacturing. Collectively, these tools underpin intelligent, evidence-based decision-making in dynamic and intricate operational settings [159].

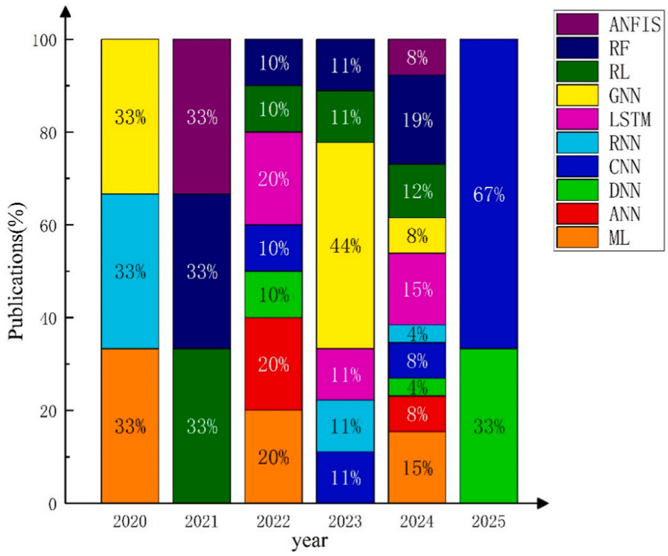

Fig. 13. Temporal evolution of AI methodologies in renewable energy research (2020–2025).

System-level optimization—such as coordinating wind, solar, and energy storage operations—is emerging as a pivotal area in renewable energy research. This review examines the role of AI and data-driven methods within renewable energy systems (RES), emphasizing the variety of sophisticated frameworks available for modeling, forecasting, and optimizing system performance. The results reveal a clear movement toward methodological integration and affirm the practical utility of two principal technological directions: AI and data-driven analysis. The evaluation indicates that neural networks—particularly CNNs, LSTMs, and GNNs, along with their hybrid variants—are now the most commonly applied techniques. These have demonstrated reliable performance in key domains such as solar and wind energy applications. Furthermore, integrating AI algorithms with data-driven strategies or metaheuristic optimization has repeatedly outperformed single-method solutions across diverse prediction and optimization tasks. These combined approaches also show considerable potential for system-wide coordination. Despite progress, existing studies still encounter common limitations, notably a heavy reliance on data quality and availability, as well as insufficient validation in real operational environments. Addressing the fundamental barriers to inconsistent data quality and availability across research findings [122] requires coordinated efforts on two fronts. On one hand, developing standardized data formats and open benchmark datasets for critical RES applications—such as battery cycling and irradiation sequences—is essential for fair model comparisons and accelerating reproducibility. On the other hand, advancing robust transfer learning and domain adaptation techniques [116] will be key to enabling models trained in data-rich environments (e.g., a well-equipped wind farm) to perform reliably in novel, data-scarce settings (e.g., a newly commissioned plant or a region with different climatic conditions). This directly overcomes the limitations of real-world validation and enhances model adaptability. Future work should prioritize the development of uniform evaluation frameworks, encourage cross-disciplinary methodological integration, and extend applications to nascent energy technologies. These measures will be essential to fully realize the innovative capacity of AI and data-driven approaches in advancing the worldwide shift toward renewable energy.

Based on the aforementioned literature and supporting data. The review points out three ongoing problems that are holding the field back. These are a lack of prepared measurements, the lack of ways to compare results, and a lack of real-world testing. These problems are pushing the field in two different directions. First, we train models to create data about the weather and demand that keeps the same spatial and temporal patterns as real data. These synthetic records, which can be as long as a decade, let micro-grids or developing economies check their forecasting tools without waiting years for site-specific data. Secondly, there are international projects under Horizon Europe and the Chinese carbon-peaking program. These are using digital technology to connect physical inverters, battery racks and market-clearing engines. This allows any algorithm to be compared under the same climatic and regulatory conditions. The results can then be traced back to their source. History shows us that when the Paris Agreement set a temperature target of 1.5 °C, the same time as cutting the uncertainty of wind predictions from about 20% to 10% using a special type of computer model, countries like Ireland and Denmark felt confident enough to aim for at least 40% wind power. Similarly, the improvement in the accuracy of solar energy forecasts, with forecasts now being within 5% of the actual energy produced, led to California and Spain deciding to move their zero-carbon power goals to 2035. For the tripling of global renewable capacity envisioned by 2030, the coupling of synthetic-data engines with open, hardware-in-the-loop testbeds offers a direct route from laboratory model to policy instrument: algorithms validated in shared environments can be written directly into grid codes, accelerating the translation of international climate pledges into verifiable decarbonization schedules. In order to facilitate progress in this field, it is recommended that standardized test cases are utilized in order to perform systematic performance benchmarks for AI and data-driven methods. This enables a quantitative assessment of their accuracy, practical limitations and computational efficiency. Moreover, these important areas of research will significantly improve capabilities in this field through the systematic integration and development of novel hybrid algorithms and the expansion of artificial intelligence applications to new technologies in the field of renewable energy, such as hydrogen systems and marine energy. Hybrid modeling, transfer learning, and physically informed neural networks have become central tools in the current field of synergy between AI and renewable energy. By integrating data-driven methods with physical principles, these techniques improve the adaptability and reliability of models in dynamic environments, laying an important foundation for future technological progress.

7. Strategic implications and policy relevance

The following energy strategies and policy support measures have been summarized from the content of all the literature that was found in this study. The technological advancements synthesized in this review—particularly the demonstrated efficacy of hybrid AI-data-driven methods in forecasting [45], optimization, and real-time control [81]—carry direct and significant implications for long-term energy strategy and policy formulation. The following strategic insights and recommended support measures are derived systematically from the evidence reviewed in Sections 3 and 4, moving beyond generic assertions to provide concrete, evidence-based guidance. The technological advancements explored in this study are of significant strategic importance for long-term energy strategy and resource coordination. For example, recent studies have demonstrated that enhancing forecast accuracy and system optimization through AI and data-driven approaches can strengthen grid operators' capacity to manage networks with high proportions of renewable energy. This enhanced capability offers broad prospects for making informed infrastructure investment decisions and mitigating risks during the transition to decarbonized power systems. However, the implementation of these measures is encumbered by substantial institutional and regulatory challenges. Major challenges to be addressed are as follows: the establishment of data governance frameworks that balance data quality, accessibility, and security while safeguarding data integrity and ownership; the strengthening of cybersecurity for AI-dependent infrastructure; the improvement of model transparency for RES systems often regarded as “black boxes” in regulatory assessments; and the bridging of skill gaps through focused training initiatives. Current guidelines and regulations frequently fail to keep pace with technological advancements. The adoption of new technologies can be impeded by a number of factors, including outdated network standards, restrictive data exchange rules, and ambiguous guidance on accountability for automated decisions. Conversely, forward-looking regulatory measures, such as the establishment of standardized performance benchmarks, the creation of controlled testing environments, and the incentivization of the use of explainable AI in network operations, have the potential to significantly accelerate the integration of these approaches. This will propel them from the realm of experimental tools into that of reliable components of resilient energy systems.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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