Artificial Intelligence-Driven Renewable Energy Systems: A Targeted Review of Key Applications and the Emerging Role of OASIS Colab as a Collaborative Research Environment

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Abstract

The accelerating global transition toward renewable energy systems has intensified the need for intelligent, data-driven methodologies capable of addressing challenges related to variability, uncertainty, and large-scale system integration. In this context, artificial intelligence (AI) has emerged as a key enabler for enhancing the performance, reliability, and operational efficiency of renewable energy technologies. This paper presents a targeted and structured review of 50 high-impact peer-reviewed studies that collectively define the current state-of-the-art of AI-driven renewable energy systems.

The review systematically examines core AI paradigms including machine learning, deep learning, and reinforcement learning and their practical applications in renewable energy generation forecasting, demand prediction, predictive maintenance, energy storage optimization, and intelligent management of smart and decentralized energy networks. Particular attention is given to solar and wind energy systems, where AI-based models have demonstrated significant improvements in forecasting accuracy, system resilience, and adaptive control under dynamic operating conditions.

Beyond algorithmic developments, this study adopts a data-centric perspective to highlight the growing importance of scalable, reproducible, and collaborative research environments in advancing AI-enabled energy research. Within this framework, OASIS Colab is discussed as a representative collaborative AI research environment that supports large-scale experimentation, facilitates the integration of heterogeneous energy datasets, and enhances the reproducibility and transparency of AI workflows. Rather than functioning as a standalone solution, OASIS Colab is positioned as a computational research enabler that assists researchers in bridging the gap between theoretical AI models and practical renewable energy applications.

Emerging research directions including hybrid physics-informed learning models, digital twin–assisted energy systems, and advanced reinforcement learning strategies for grid and storage management are also analyzed for their potential to reshape future renewable energy infrastructures. Finally, the review identifies key technical, data-related, computational, and regulatory challenges that currently limit the widespread adoption of AI in renewable energy systems and outlines research-oriented recommendations aimed at maximizing the impact of AI-enabled methodologies and collaborative research environments on sustainable energy transitions and long-term climate change mitigation.

Keywords : Renewable Energy Systems; Artificial Intelligence; Machine Learning; Deep Learning; Smart Grids; Energy Forecasting; Collaborative AI Research Environments; OASIS Colab

Introduction

The rapid expansion of global energy consumption has become one of the defining challenges of the twenty-first century. Driven by population growth, accelerated urban development, and increasing industrialization, worldwide energy demand has risen at an unprecedented rate [1]. This trend has historically been satisfied through extensive use of fossil fuel–based resources, including coal, oil, and natural gas, which continue to dominate the global energy supply. However, this dependence has imposed severe environmental costs, most notably through the accumulation of greenhouse gas (GHG) emissions that contribute directly to climate change, global warming, and the intensification of extreme weather phenomena [2].

Recent assessments indicate that energy-related carbon dioxide emissions reached approximately 37.2 $GtCO_2$ in 2023, marking the highest level recorded to date and reflecting an increase of more than 50% compared to the early 2000s [3]. Climate projections published by international energy and environmental agencies suggest that, without decisive mitigation measures, global mean temperatures could increase by several degrees Celsius within this century, amplifying risks to ecosystems, infrastructure, and socioeconomic stability [4]. These developments underscore the urgent necessity of transforming existing energy systems toward more sustainable and low-carbon alternatives.

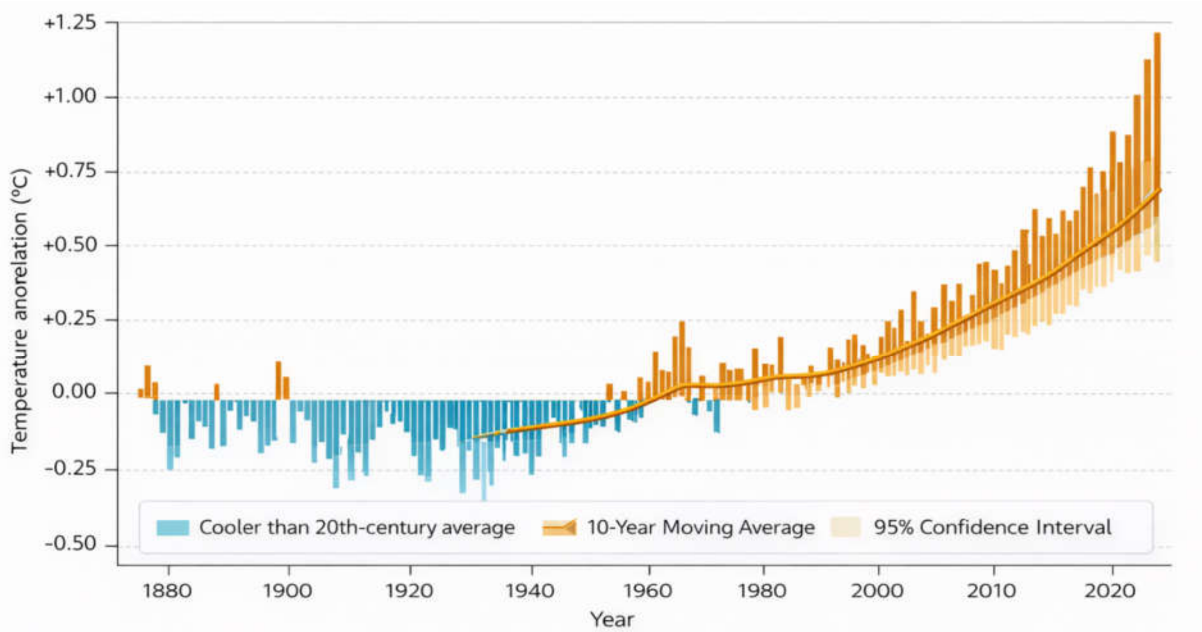

Figure 1. Global land and ocean surface temperature anomalies relative to the 20th-century average, illustrating a significant warming trend consistent with increasing greenhouse gas emissions.

As illustrated in Fig. 1, global land and ocean surface temperature anomalies exhibit a persistent upward trend, providing clear empirical evidence of ongoing climate change driven largely by energy-related greenhouse gas emissions. This visual representation reinforces the urgency of mitigating carbon-intensive energy practices and accelerating the deployment of sustainable energy solutions.

Despite mounting climate concerns, non-renewable energy sources continued to account for the majority of global primary energy consumption between 2000 and 2023 [5]. In response to this imbalance, renewable energy (RE) technologies—particularly solar, wind, and hydropower—have gained increasing attention as viable pathways toward decarbonization. Renewable energy systems offer several inherent advantages, including negligible operational emissions, long-term resource availability, and reduced vulnerability to fuel price fluctuations and geopolitical disruptions [6]–[9]. Beyond environmental benefits, large-scale deployment of renewable energy contributes to improved public health outcomes by reducing air pollution–related diseases [10], enhances energy access in remote and underserved regions, and supports economic growth and employment creation across energy value chains [11], [12].

Technological progress has further strengthened the role of renewable energy in modern power systems. Advances in energy storage technologies, grid interconnection, and system-level efficiency have improved the reliability and flexibility of renewable generation, enabling higher penetration levels in national and regional electricity markets [13]. By the end of 2023, global installed renewable energy capacity exceeded 3.8 TW, reflecting sustained annual growth driven by policy support, declining technology costs, and increased private-sector investment [14]. In parallel, renewable energy has emerged as a central component of global climate mitigation strategies, particularly in light of rising surface temperatures, shifting precipitation patterns, and the increasing frequency of climate-induced disasters [15], [16].

Renewable energy sources accounted for more than 30% of global electricity generation in 2023, with solar and wind energy exhibiting the most rapid growth among all technologies [27]. Forecasts indicate that renewable electricity generation could surpass 40% of total global output within the next decade, supported by continued innovation in storage solutions, digital grid management, and market integration mechanisms.

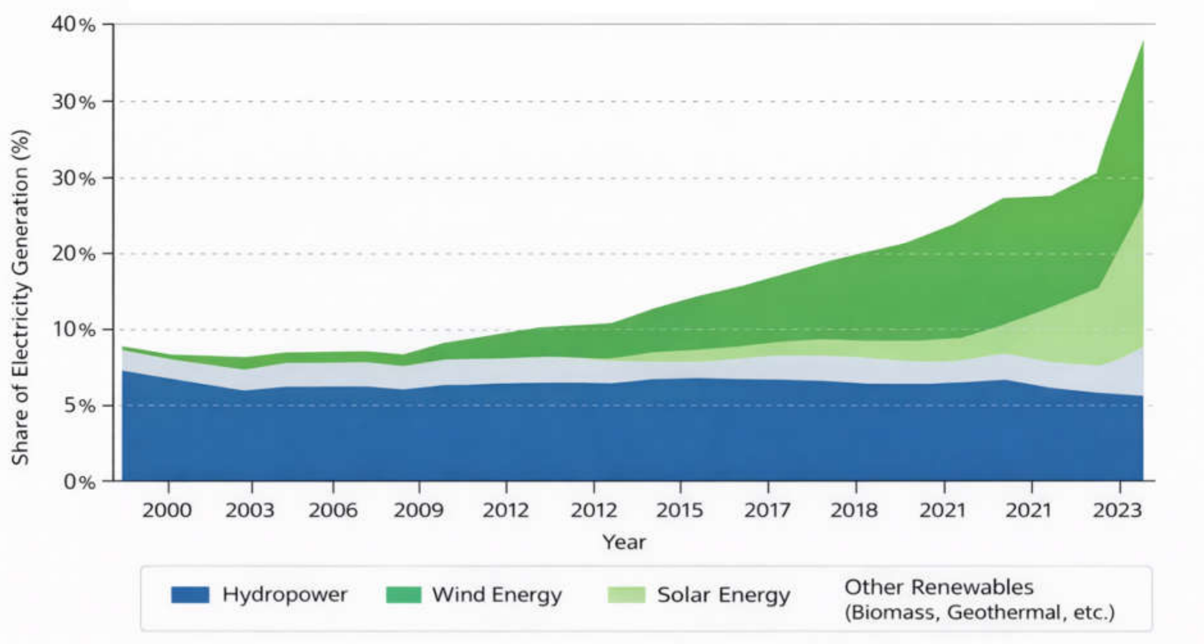

Figure 2. Evolution of global electricity generation from renewable energy sources (2000–2023), highlighting the increasing contribution of wind and solar power.

As shown in Fig. 2, the contribution of renewable energy to global electricity generation has increased steadily over the past two decades, with wind and solar energy demonstrating particularly strong growth trajectories. This trend highlights the accelerating role of renewables in reshaping the global electricity mix and supporting long-term decarbonization objectives.

Nevertheless, the large-scale integration of renewable energy into existing power systems remains technically complex. Key challenges include resource intermittency, forecasting uncertainty, grid stability constraints, and heterogeneous regulatory environments that vary across regions and markets.

Addressing these challenges increasingly requires advanced data-driven approaches capable of operating under dynamic and uncertain conditions. In this context, artificial intelligence (AI) has emerged as a powerful enabling technology for renewable energy systems. AI techniques—encompassing machine learning, deep learning, and reinforcement learning—have demonstrated strong potential in improving energy forecasting accuracy, optimizing system operation, enhancing predictive maintenance strategies, and supporting real-time decision-making in decentralized and smart energy networks [33]. The effectiveness of AI has already been validated across multiple domains, including healthcare, transportation, agriculture, and industrial systems [28]–[32], motivating its growing adoption within the energy sector.

Within renewable energy applications, AI-based models have been successfully employed to forecast solar irradiance and wind power generation, optimize energy storage utilization, enhance system reliability, and reduce operational costs [38]–[47]. These approaches enable renewable energy systems to respond adaptively to fluctuating environmental conditions and demand patterns, thereby improving overall efficiency and resilience. However, the practical deployment of AI solutions in renewable energy research and applications is often constrained by data availability, computational resources, and reproducibility challenges.

In addition to algorithmic innovation, recent attention has shifted toward the role of collaborative and scalable research environments in supporting AI-driven energy research. Cloud-based and collaborative platforms—such as OASIS Colab—are increasingly recognized as enabling infrastructures that facilitate data integration, large-scale experimentation, and reproducible model development. Rather than serving as standalone solutions, such environments function as computational research assistants that support interdisciplinary collaboration, accelerate prototyping of AI models, and enhance transparency in renewable energy studies.

Against this backdrop, this paper presents a targeted and systematic review of 50 high-impact peer-reviewed studies on artificial intelligence applications in renewable energy systems. The review synthesizes recent advances in AI-driven energy forecasting, predictive maintenance, energy storage optimization, and smart grid management, while also discussing emerging research directions and unresolved challenges. By integrating technical insights with methodological considerations—including the role of collaborative AI research environments—this work aims to provide researchers, engineers, and policymakers with a comprehensive understanding of how artificial intelligence can effectively support the global transition toward sustainable and resilient renewable energy systems.

II. Methodology

This review adopts a **systematic and transparent methodological framework** to analyze the present state and future directions of artificial intelligence (AI) applications in renewable energy systems (RES). The methodology was explicitly designed to meet international standards for high-impact review articles, ensuring clarity, reproducibility, and analytical rigor. The overall workflow of the study is illustrated in **Fig. 3**.

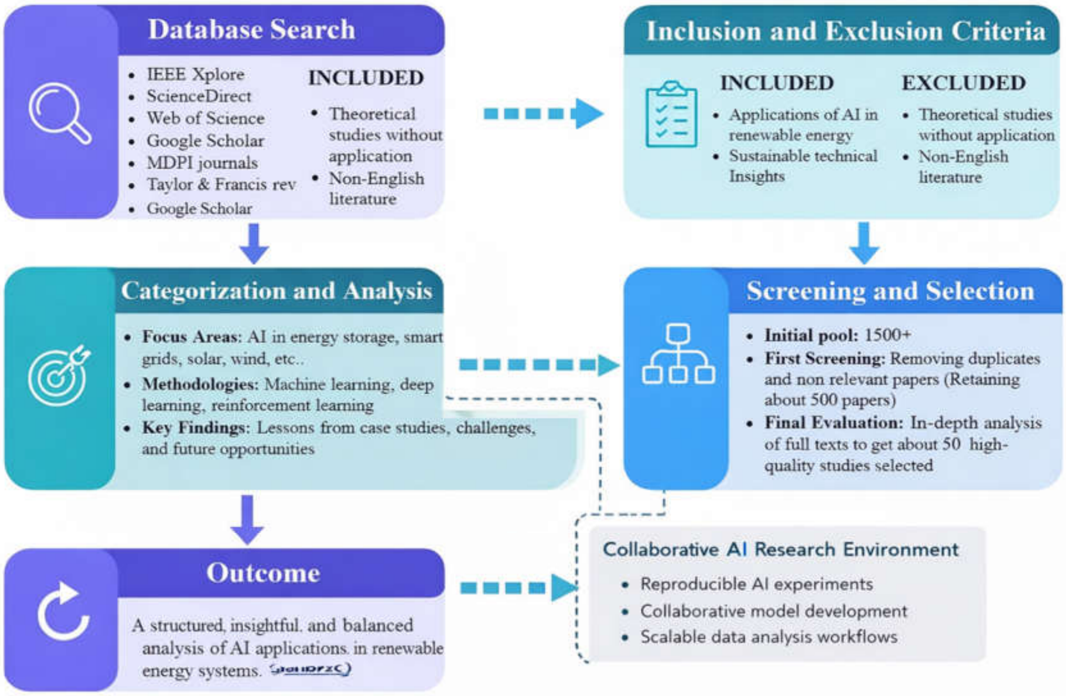

Figure 3. Systematic literature review workflow for artificial intelligence applications in renewable energy systems, highlighting the role of collaborative AI research environments (OASIS Colab)

A. Study Scope and Timeframe

The review focuses on scientific literature published between **January 2020 and December 2024**, a period characterized by accelerated growth in both renewable energy deployment and advanced AI-driven methodologies. This timeframe was selected to capture the most recent technical developments while ensuring sufficient maturity of the reviewed approaches for critical assessment.

The scope of the study encompasses AI applications across major renewable energy domains, including **solar energy, wind energy, energy storage systems, hybrid renewable configurations, and smart grid infrastructures**. In addition to established AI techniques, emerging paradigms—such as advanced neural architectures, data-centric learning, and AI-supported immersive and collaborative environments—are also considered within the defined period.

B. Data Sources and Literature Search Strategy

A comprehensive literature search was conducted across **explicitly identified scientific databases** to ensure coverage of high-quality and peer-reviewed research. The databases included:

- IEEE Xplore
- ScienceDirect
- Web of Science
- SpringerLink
- MDPI Journals
- Taylor & Francis Online
- Google Scholar

Search queries were constructed using combinations of keywords related to artificial intelligence and renewable energy systems, including terms associated with learning paradigms, energy domains, and system-level applications. Boolean operators were applied to refine search results and reduce redundancy.

The search strategy targeted **peer-reviewed journal articles, selected conference proceedings, and authoritative technical reports**, published in English within the defined timeframe.

C. Article Identification and Selection Process

The article selection process followed a **multi-stage filtering procedure**, designed to progressively refine the literature set while preserving relevance and technical depth.

- **Initial identification stage:**
  The database search yielded **more than 1,500 records**, including journal articles, conference papers, and technical reports.
- **Preliminary screening stage:**
  Duplicate entries and clearly non-relevant publications were removed through title and abstract screening, resulting in a reduced pool of approximately **500 candidate studies**.
- **Full-text evaluation stage:**
  The remaining articles underwent in-depth full-text assessment to evaluate methodological quality, application relevance, and contribution significance. This process led to the final selection of **50 high-quality and representative studies**, which constitute the analytical foundation of this review.

This progressive refinement ensures that the final corpus balances breadth, depth, and methodological robustness.

D. Inclusion and Exclusion Criteria

To maintain analytical consistency and relevance, explicit inclusion and exclusion criteria were applied.

Inclusion criteria:

- Studies that directly address AI applications in renewable energy systems
- Publications presenting technical, experimental, or simulation-based results
- Works focusing on operational optimization, forecasting, system management, or decision support
- Peer-reviewed articles written in English

Exclusion criteria:

- Purely theoretical studies without application or validation
- Publications unrelated to renewable energy systems
- Non-English literature
- Duplicate or incomplete studies

These criteria ensured that only studies with tangible technical contributions and practical relevance were retained.

E. Data Extraction and Analytical Categorization

The selected studies were systematically analyzed and categorized based on:

- Renewable energy domain (solar, wind, storage, hybrid systems, smart grids)
- AI methodology employed (machine learning, deep learning, reinforcement learning, fuzzy systems, generative models)
- Application objective (forecasting, optimization, predictive maintenance, control, decision support)

This structured categorization directly informed the organization of subsequent sections of the review, enabling a coherent comparison of methodologies, performance trends, and research gaps.

F. Role of Collaborative AI Research Environments

Beyond algorithmic techniques, the methodology explicitly acknowledges the role of **collaborative and scalable AI research environments** in supporting modern renewable energy research. In particular, platforms such as **OASIS Colab** are considered as **supportive research infrastructures** that facilitate:

- Reproducible AI experimentation
- Collaborative model development across research teams
- Scalable data analysis and benchmarking workflows

Within this study, OASIS Colab is not treated as an analytical tool or experimental variable, but rather as an **enabling environment** that supports the organization, evaluation, and synthesis of AI-based renewable energy studies—particularly during the categorization and analysis stages illustrated in Fig. 3.

G. Methodological Rigor and Reliability

By combining a clearly defined timeframe, explicit data sources, quantitative selection criteria, and structured analytical procedures, the adopted methodology ensures a **robust, balanced, and reproducible review process**. This approach provides a reliable foundation for synthesizing current knowledge, identifying methodological trends, and outlining future research directions in AI-enabled renewable energy systems.

III. Overview of AI Technologies

A. Foundational AI Approaches in Energy Management (with the Emerging Role of OASIS Colab)

Prior to the widespread integration of artificial intelligence (AI) into the energy sector, renewable energy (RE) technologies had already matured into diverse, well-established families—including solar, wind, hydropower, geothermal, and biomass—each characterized by distinct technical constraints and deployment challenges [1]. During this earlier phase, engineering progress was largely driven by efforts to improve conversion efficiency, reduce levelized costs, and manage operational risks, particularly those arising from the variability and uncertainty of renewable resources when deployed at scale [2].

However, as renewable penetration increased, conventional analytic and rule-based approaches became insufficient to address the speed, complexity, and data intensity of modern power systems. Bibliographic evidence indicates a rapid growth of the “AI–energy” research landscape, reflecting the transition from deterministic planning toward data-driven forecasting, control, and decision support [3]. This shift is tightly coupled to the availability of large-scale measurements and the need for models that can learn non-linear relationships, adapt under uncertainty, and support near-real-time operation in complex networked environments [4]. These requirements are especially pronounced in microgrids, where load–generation coordination must be optimized continuously under fluctuating renewable supply and consumption patterns [5].

Despite their promise, AI-driven renewable energy systems introduce additional structural and infrastructural requirements. Successful deployment depends on computational resources, sensing and communication layers, and long-term data pipelines for model development and updating. Edge AI has therefore emerged as a practical direction for reducing latency and enabling local intelligence near data sources (e.g., smart meters, inverter controllers, IoT gateways), improving responsiveness while limiting bandwidth dependence [7]. In parallel, federated learning offers a pathway for learning predictive models—such as load forecasting in smart grids—without centralizing sensitive consumption data, helping mitigate privacy and data-governance concerns [8]. These technical evolutions also intersect with broader societal and ethical considerations: energy systems are critical infrastructure, and AI interventions must be aligned with sustainability goals, accountability, and fairness in access and outcomes [9].

From a planning and governance perspective, modern energy systems increasingly rely on modeling tools to evaluate transition pathways and environmental impacts, especially when balancing sustainability objectives with reliability and affordability [10]. Since energy demand is shaped by demographic, economic, and urbanization drivers [11], effective energy management must integrate technology, behavior, and adoption readiness. For example, evidence from residential contexts shows that awareness, behavior, and perceived value strongly influence the success of smart energy interventions [12]. Moreover, IoT-based energy infrastructures—while enabling real-time monitoring and control—introduce multi-actor coordination challenges and practical barriers spanning reliability, interoperability, and stakeholder incentives [13], [14].

Policy and transition roadmaps further shape the feasibility of AI-enabled renewables. International transition assessments and sectoral reporting provide policy-relevant benchmarks and highlight strategic technology directions (e.g., hydrogen and system transformation pathways) [15], while national energy statistics offer insight into sectoral pressures and consumption structure [16]. To handle integration complexity across electricity, heat, fuels, and storage, Multi-Energy Systems Integration (MESI) has gained traction as a systems-level approach that increases flexibility and helps absorb renewable variability through coordinated operation and planning [17]. Yet, smart local energy systems still face adoption barriers beyond technology alone—requiring institutional design, market alignment, and implementation capacity [18]. Recent evidence also points to AI’s potential contribution to accelerating the energy transition by improving techno-economic decision making and operational efficiency [19], while integrated renewable energy systems (IRES) frameworks emphasize the coupled role of generation, storage, optimization, and system-level constraints [20]. Importantly, research highlights persistent gaps between modeling insights and policy implementation, underscoring the need for transparent, decision-relevant modeling and governance alignment [21]. Operationally, scheduling and coordination in hybrid energy networks remains a key technical domain where AI-enabled optimization can support more resilient and cost-effective system behavior [22].

Within this ecosystem, **OASIS Colab** can be positioned as a **collaborative AI research and experimentation environment** that supports reproducible workflows for renewable energy intelligence. Conceptually, OASIS Colab aligns with the needs of modern AI-for-energy pipelines by enabling: (i) shared development of forecasting and optimization models across teams, (ii) structured experimentation using distributed or privacy-preserving learning paradigms (e.g., federated learning) [8], and (iii) practical integration of edge-oriented AI prototypes for latency-sensitive applications [7]. In this sense, OASIS Colab acts as an enabling layer that strengthens collaboration and reproducibility in AI-enabled renewable energy research, complementing the technical foundations and governance requirements emphasized across the transition literature [9], [19].

B. Key AI Techniques in Renewable Energy Systems (RES)

AI has become a critical technical pillar for renewable energy systems, enabling forecasting, optimization, anomaly detection, and adaptive control in environments dominated by uncertainty and intermittency. Contemporary transition-oriented surveys emphasize that AI is increasingly treated as a system enabler rather than a standalone prediction tool, supporting operational intelligence across the full value chain of renewable integration [24]. Accordingly, the dominant methodological families applied in RES include **machine learning (ML), deep learning (DL), reinforcement learning (RL), fuzzy logic**, and, increasingly, **data-generative models such as GANs**—each contributing differently depending on the task, data structure, and deployment constraints.

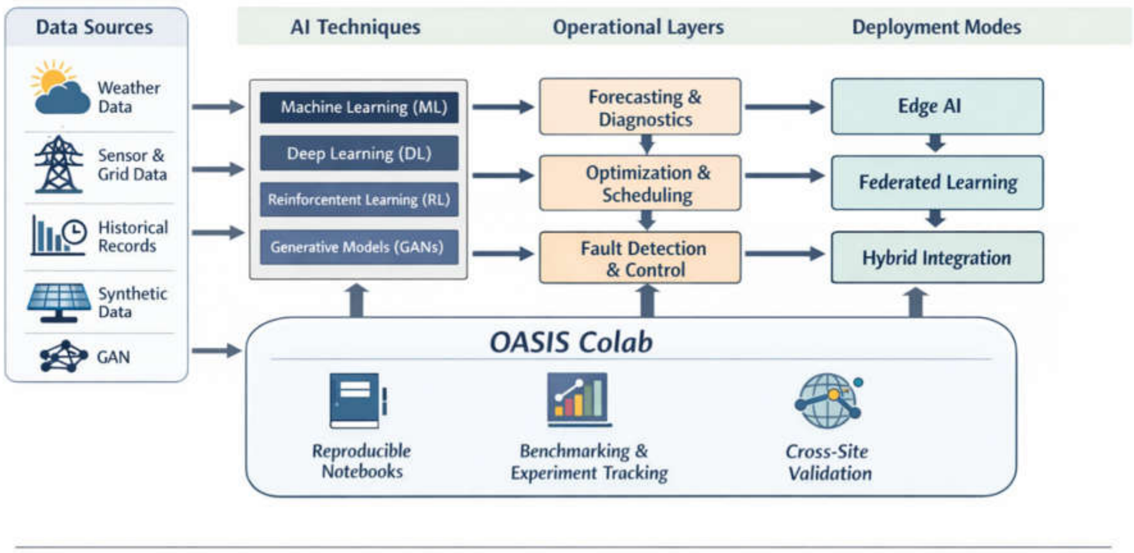

Figure 4. *Key AI Techniques in Renewable Energy Systems and OASIS Colab Framework*

C. Machine Learning (ML)

Machine learning refers to computational methods that learn predictive or decision functions from data rather than relying on explicitly hard-coded rules [25]. In renewable energy contexts, ML is widely used for forecasting and operational support in data-rich environments, particularly where system operators must anticipate fluctuating production and demand. ML-based approaches are especially relevant for microgrids, where predictive and managerial intelligence directly improves coordination under renewable intermittency and local constraints [5]. Likewise, big-data-driven ML analytics in networked energy systems can enhance decision support and situational awareness in smart grid contexts [4].

Classic algorithmic families—such as decision trees—remain important as interpretable baselines and as components within ensemble methods [39]. Beyond forecasting, ML has also been explored for market-facing applications, including distributed learning approaches that support energy trading and bidding strategies in decentralized settings [40].

D. Deep Learning (DL)

Deep learning extends ML by leveraging multi-layer neural architectures to learn complex, non-linear mappings from high-dimensional data. In renewable energy systems, DL is particularly impactful when the data structure includes spatial or signal-rich observations (e.g., imagery, thermographic patterns, and sensor streams). For example, DL-supported PV fault diagnosis has been demonstrated using remote sensing and thermography-driven pipelines [41]. More recent directions incorporate **digital-twin concepts** to support PV fault analysis through dynamic representation of system behavior, strengthening interpretability and operational alignment [42]. Privacy-preserving DL workflows are also emerging, including federated learning approaches for PV fault detection—allowing model training across distributed sites while limiting centralized exposure of sensitive operational data [43].

These developments reinforce the role of DL as a practical tool for reliability enhancement in renewables—particularly when fault diagnosis and condition monitoring must be performed at scale.

E. Reinforcement Learning (RL)

Reinforcement learning is a decision-making paradigm in which an agent learns control policies through interaction with an environment, optimizing long-term outcomes. RL is well-suited to energy problems characterized by sequential decisions under uncertainty (e.g., storage scheduling, demand response coordination, and multi-agent control). Foundational evidence supports RL's growing role in energy systems research and deployment discussions [44]. Multi-agent RL formulations have also been proposed for building-level energy coordination, exemplified by frameworks that facilitate scalable experimentation for such settings [45].

In storage and hybrid systems, deep RL has been applied to planning and operational control problems to improve long-term performance objectives [46]. Related approaches address cloud energy storage coordination via DRL formulations, emphasizing adaptive dispatch strategies under dynamic conditions [47]. Overall, RL contributes to autonomy and resilience by enabling systems to learn and adapt as operating contexts evolve.

F. Fuzzy Logic

Fuzzy logic provides a formal mechanism for reasoning under uncertainty using degrees of membership rather than binary truth values. This paradigm is relevant to RES because renewable resources and operational environments often exhibit measurement uncertainty, variability, and incomplete information. The foundational formulation of fuzzy logic remains a reference point for uncertainty-aware control and decision models [48]. In energy settings, fuzzy logic is typically used to build robust control rules in uncertain environments, offering practical flexibility when precise system modeling is difficult or costly.

G. Generative Adversarial Networks (GANs)

GANs are a prominent class of generative deep learning models based on adversarial training principles [49]. In renewable energy applications, their primary value arises in **data augmentation and synthetic data generation**, especially when historical meteorological or operational datasets are sparse, inconsistent, or geographically limited. Recent work highlights the use of GANs to generate synthetic meteorological datasets, strengthening training data availability and potentially improving forecasting robustness in data-constrained contexts [50]. This capability is particularly relevant for low-resource regions and emerging markets, where limited sensing coverage can otherwise restrict AI model reliability.

H. Synergistic and Deployment-Oriented Integration (OASIS Colab as an Enabler)

Modern RES applications increasingly benefit from combining methodological families into integrated pipelines (e.g., ML/DL for forecasting + RL for control + privacy-preserving learning for distributed settings). Transition-focused analyses emphasize that AI's strategic value lies in end-to-end integration across planning, operation, and governance rather than isolated algorithm selection [24].

Here, **OASIS Colab** can be framed as an enabling environment that supports such integrated pipelines by facilitating:

1. **Reproducible experimentation** across forecasting, fault detection, and control workflows;
2. **Collaborative development** of models and benchmarking across distributed research teams;
3. **Deployment-oriented research**, including edge-compatible prototypes aligned with low-latency needs [7]; and
4. **Privacy-preserving learning experiments**, particularly relevant to federated learning settings in smart grids and distributed renewable assets [8].

In other words, OASIS Colab functions as a structured collaboration layer that strengthens rigor and repeatability for AI-in-RES research, while remaining consistent with sustainability and governance priorities discussed in the broader AI-for-SDGs context [9].

Table 1. **Comparative Summary of AI Algorithms Applied in Renewable Energy Systems**

AI Algorithm	**Key Advantages**	**Main Weaknesses**	**Areas for Improvement**	**Most Common Applications in Renewable Energy**
Linear Regression	• Simple and interpretable • Very low computational cost	• Limited to linear relationships • Sensitive to outliers	• Feature engineering • Non-linear extensions	Solar energy forecasting Wind power prediction
Support Vector Machines (SVM)	• Strong generalization capability • Effective in high-dimensional spaces	• Computationally expensive • Performance degrades with noisy data	• Scalability improvement • Robust kernel design	Energy demand forecasting Solar PV fault detection
Decision Trees	• Transparent and interpretable • Handles mixed	• Prone to overfitting • Sensitive to noise	• Pruning strategies • Ensemble	Energy consumption prediction

	data types		integration	Fault diagnosis
Random Forests	• Reduced overfitting via ensemble learning • Handles large feature sets	• Limited interpretability • Slower inference	• Explainability techniques • Training efficiency	Wind energy prediction Solar power optimization
Gradient Boosting	• High predictive accuracy • Effective bias–variance trade-off	• Computationally intensive • Risk of overfitting	•Regularization • Faster convergence	Energy consumption forecasting Solar irradiance prediction
k-Nearest Neighbors (k-NN)	• Simple and non-parametric • Flexible decision boundaries	• High inference cost • Noise sensitivity	• Efficient indexing • Noise handling	Predictive energy management Smart grid load balancing
Artificial Neural Networks (ANNs)	• Models complex non-linear systems • High adaptability	• Black-box nature • Overfitting risk	• Explainable AI integration • Regularization methods	Solar power prediction Energy load forecasting
Convolutional Neural Networks (CNNs)	• Automatic spatial feature extraction• Excellent for image-based data	• Requires large datasets• High computational demand	• Lightweight architectures• Transfer learning	Solar panel fault detection Satellite-based analysis
Recurrent Neural Networks (RNNs)	• Captures temporal dependencies • Suitable for sequential data	• Vanishing gradient problem • Training instability	• Gated architectures • Training optimization	Wind energy forecastingSolar time-series modeling
Long Short-Term Memory (LSTM)	• Handles long-term dependencies • High time-series accuracy	• Data-intensive• Computationally demanding	• Training acceleration • Small-sample learning	Energy demand forecasting Wind power generation
Reinforcement Learning (RL)	• Adaptive decision-making • Suitable for dynamic systems	• Sample-inefficient training • Convergence instability	• Stable learning frameworks • Data efficiency	Energy storage optimization Smart grid management
Fuzzy Logic	• Robust under uncertainty • Effective for non-linear systems	• Rule-based dependency • Limited scalability	• Automated rule generation • Hybrid AI integration	Renewable resource management Energy efficiency

				control

I. Data Foundations: Big Data, IoT, and Privacy-Preserving Learning

The performance and trustworthiness of AI models in renewable energy depend strongly on data quality, scale, and governance. Big data analytics has been identified as a key driver of ML effectiveness in networked energy systems, especially for smart grid decision support and scalable forecasting [4]. Meanwhile, IoT infrastructures provide the sensing and communication substrate that enables real-time observation and control, although practical implementation challenges remain due to interoperability and multi-actor coordination constraints [13], [14].

To address privacy risks and governance limitations, federated learning has emerged as a promising strategy for smart grid load forecasting and distributed intelligence—allowing models to learn from multiple sites without direct data pooling [8]. Complementarily, edge AI supports low-latency inference and improved operational responsiveness, particularly where centralized processing is infeasible or costly [7]. These directions collectively support more scalable and ethically responsible AI adoption in RES, consistent with sustainability-aligned AI frameworks [9].

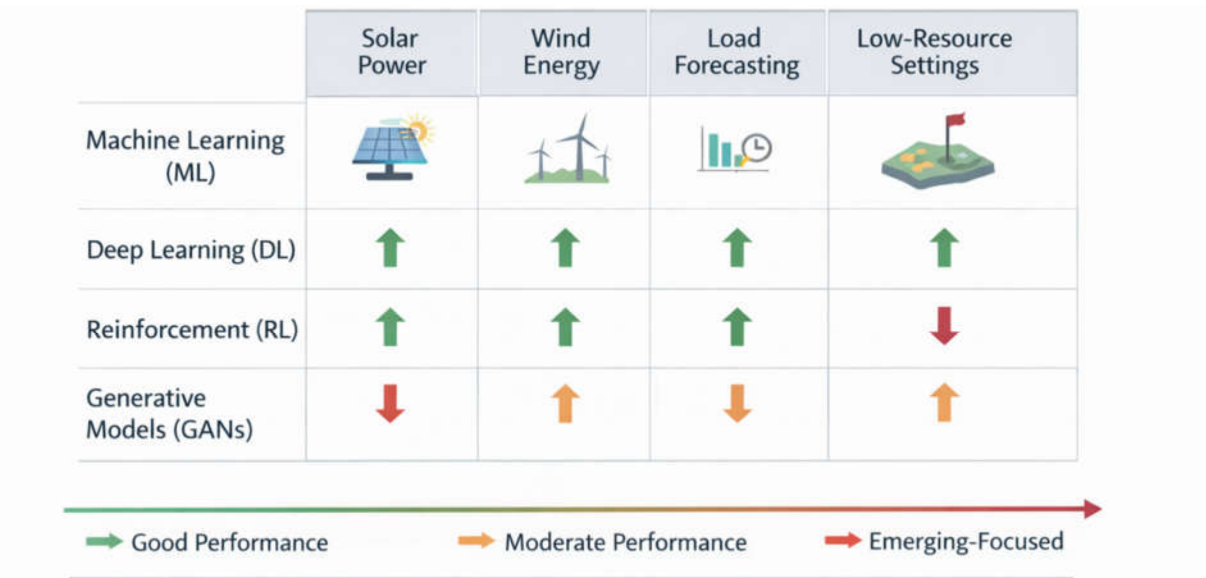

Figure 5. Comparative Mapping of AI Techniques vs. Renewable Domains and Data Constraints (Conceptual Performance Trends Recommended)

AI's Role in Future Renewable Energy Systems

Emerging AI Techniques for Next-Generation RES

Recent studies confirm that artificial intelligence has evolved beyond isolated forecasting and fault diagnosis toward **system-level decision support** for renewable energy systems (RES), particularly under high renewable penetration and tightening grid constraints [24]. As variability and uncertainty increase in solar- and wind-dominated systems, AI is increasingly embedded in planning, scheduling, and coordination layers to support operational feasibility and resilience [6], [20].

A notable shift concerns the **transition from centralized, cloud-dependent intelligence to distributed and low-latency AI architectures**, where inference and control are executed closer to physical assets such as PV plants, wind farms, microgrids, and distribution feeders [7]. This paradigm directly addresses operational requirements in RES, where decisions must respond to fast-changing meteorological and load conditions that cannot tolerate excessive communication delays.

To support scientific rigor under this paradigm, **reproducible and collaborative experimentation frameworks** become increasingly important. In this context, *OASIS Colab* is positioned as a research-enabling environment that supports standardized benchmarking, shared datasets, and transparent evaluation of AI pipelines across forecasting, diagnostics, and control tasks—particularly in multi-institution and cross-climate studies

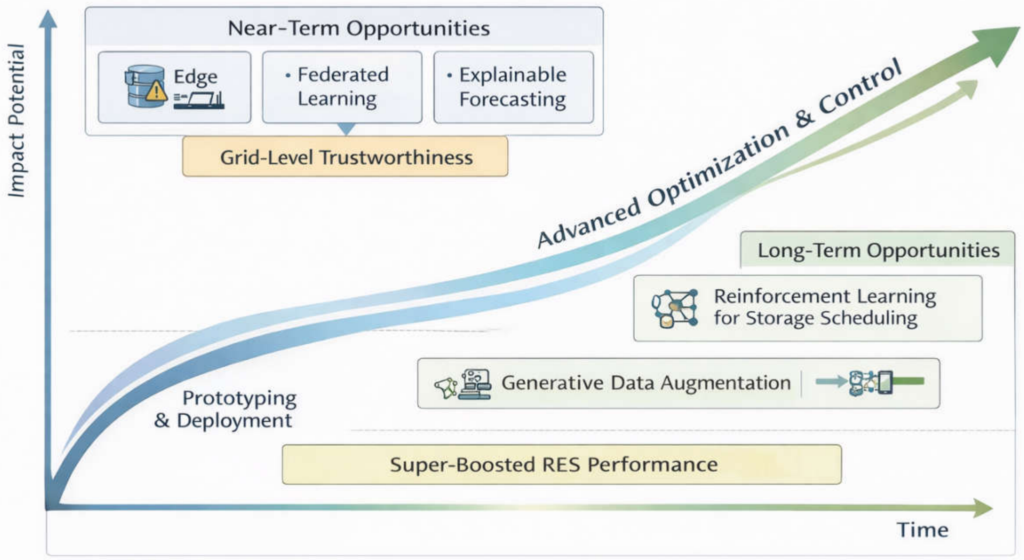

Figure 6. Roadmap of Near-and Long-Term AI Opportunities in Renewable Energy Systems [7], [8], [24], [38], [44], [50]

Edge AI and Federated Intelligence for Low-Latency Control

A major bottleneck in operational AI deployment arises from the fact that many RES installations cannot rely on persistent high-bandwidth connectivity or centralized computation. **Edge AI mitigates this limitation by shifting inference and local analytics closer to data sources**, improving response times and reducing communication overhead [7]. In distribution networks with high PV penetration, edge-enabled intelligence supports faster fault localization, localized forecasting, and near-real-time control actions, which are critical under rapid irradiance or load fluctuations [6], [20].

Complementarily, **federated learning enables distributed model training across geographically separated assets**—such as substations, buildings, or microgrids—while limiting the exchange of raw data [8]. This approach is particularly relevant in smart grids where data ownership, privacy, and interoperability constraints restrict centralized data aggregation. Federated load forecasting has already demonstrated feasibility in distributed grid settings [8].

When federated and edge-based workflows are combined within a reproducible research environment such as *OASIS Colab*, experimental configurations, hyperparameters, and evaluation protocols can be consistently documented and validated, improving transparency and accelerating community-level adoption without compromising data governance.

Explainability as a Design Requirement for Grid-Critical AI

As AI systems increasingly influence operational decisions in energy infrastructure, **interpretability becomes a non-negotiable requirement**. Black-box models are difficult to justify in grid-critical contexts where safety, reliability, and regulatory compliance must be demonstrated. Explainable AI approaches have therefore gained traction in wind power curve modeling and fault diagnosis, where transparency supports engineering validation and risk mitigation [38].

Similarly, explainable demand forecasting helps operators and policymakers understand the drivers of consumption variability under demand response schemes or evolving usage patterns [33]. Standardizing explainability outputs—such as feature attributions or sensitivity analyses—strengthens the evidence chain from data to decision. Collaborative frameworks like *OASIS Colab* can support this process by enforcing consistent reporting of explainability metrics alongside predictive performance, aligning with expectations of high-impact IEEE/Q1 publications.

Data Scarcity Mitigation and Robustness via Generative Models

Data scarcity remains a structural challenge in many RES deployments, particularly in remote or emerging regions where sensor density and historical records are limited. **Generative modeling provides a viable pathway to mitigate these constraints by synthesizing realistic meteorological and operational time series** [50]. Such augmentation is especially valuable when training deep or hybrid models that require high-resolution wind or solar data unavailable at all sites.

While generative adversarial networks (GANs) were originally introduced for general-purpose generative learning [49], recent work demonstrates their effectiveness in producing synthetic wind speed and solar irradiance sequences suitable for RES forecasting pipelines [50]. Packaging these augmentation workflows within reproducible pipelines allows fair comparisons between models trained with and without synthetic data, improving robustness assessment across studies.

Table 2. Recent AI Applications in Renewable Energy Systems

Reference	AI Model Used	Application Domain	Main Result Reported	Advantages	Limitations
[26]	ML/DL-based regression models	Solar irradiance & PV output modeling	Improved irradiance estimation accuracy	Robust handling of nonlinear meteorological effects	Sensitive to data quality and sensor coverage
[27]	Transformer-based DL	Solar power forecasting	Superior temporal dependency modeling	Captures long-range dependencies	High computational cost
[28]	CNN–BiLSTM	Wind speed forecasting	Reduced MAE and RMSE	Effective spatial–temporal feature extraction	Requires large training datasets
[29]	CNN–LSTM + Bayesian Optimization	Wind power prediction	Improved forecasting robustness	Optimized hyperparameters	Increased model complexity
[30]	Hybrid Neural Networks	Day-ahead solar and wind forecasting	Enhanced prediction stability	Handles multi-source variability	Limited interpretability
[31]	ML-based comparative	Load	Identification of best-	Comprehensive	Results dataset-

	review	forecasting	performing models	benchmarking	dependent
[32]	ML (SVM, RF, ANN)	Demand-side load forecasting	Improved short-term demand accuracy	Scalable to smart grid data	Requires careful feature engineering
[33]	Explainable ML (XAI)	Load forecasting	Interpretable demand drivers	Enhances trust and transparency	Slight accuracy trade-offs
[38]	Explainable DL	Wind power curve modeling	Transparent performance diagnosis	Supports engineering validation	Model-specific explainability
[40]	Distributed ML	Energy trading	Improved decentralized trading efficiency	Supports scalable markets	Communication overhead
[41]	CNN + Thermography	PV fault diagnosis	High fault detection accuracy	Non-intrusive monitoring	Weather sensitivity
[42]	Digital Twin + AI	PV fault diagnosis	Accurate fault localization	Physics-informed modeling	High implementation cost
[43]	Federated Learning	PV fault detection	Privacy-preserving diagnostics	Enables multi-site learning	Slower convergence
[44]	Reinforcement Learning	Energy system control	Adaptive policy learning	Handles dynamic environments	Training instability
[45]	Multi-agent RL	Building/grid energy coordination	Improved coordination efficiency	Distributed decision-making	Scalability challenges
[46]	Deep RL	Hybrid ESS planning	Optimized storage planning	Long-term performance gains	High computational demand
[47]	DRL	Cloud energy storage control	Adaptive scheduling strategies	Handles uncertainty	Requires extensive training
[49]	GAN	Synthetic data generation	Realistic data augmentation	Addresses data scarcity	Mode collapse risk
[50]	GAN-based	Synthetic	Improved	Enhances	Limited

	modeling	meteorological data	forecasting robustness	generalization	extreme-event fidelity

Challenges and Limitations of AI in Renewable Energy Systems

Despite rapid progress, AI-enabled RES face **multi-layered constraints** spanning data, computation, integration, and trust. These challenges are amplified in hybrid and multi-energy systems, where operational coupling and uncertainty increase system complexity.

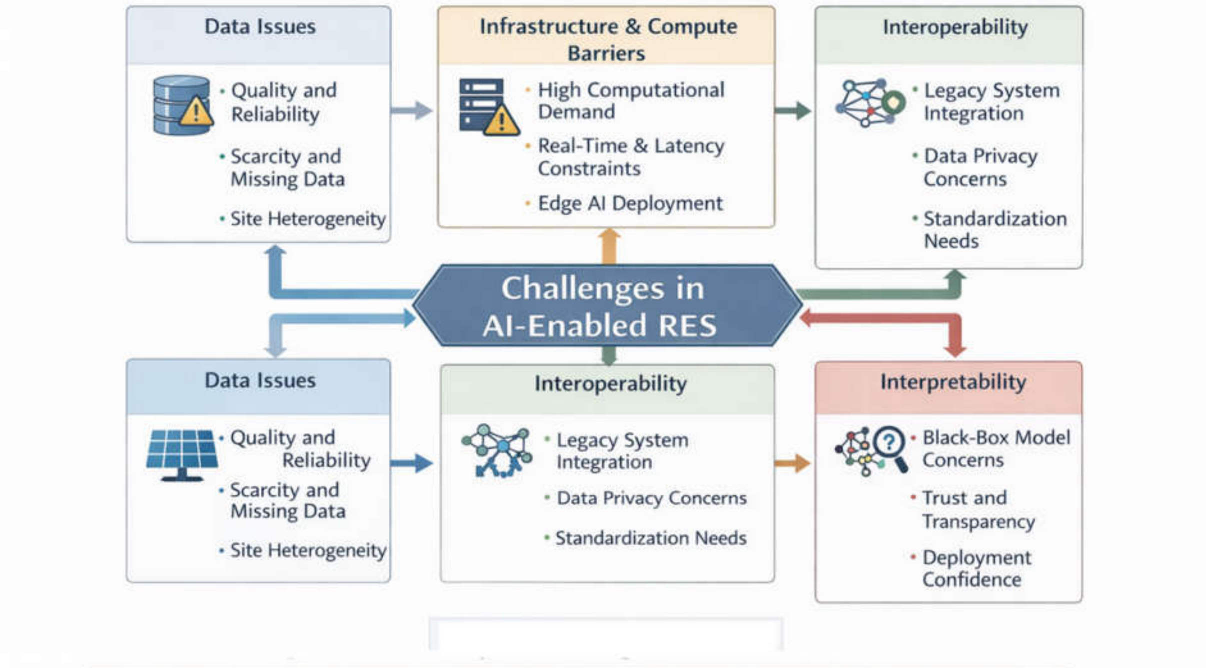

Figure 7. *Taxonomy of Challenges in AI-enabled RES* [6–8], [20], [24], [38], [34], [38]

Data Quality, Coverage, and Heterogeneity

AI performance is fundamentally bounded by data quality. Renewable generation and demand datasets often suffer from missing values, inconsistent sampling, site heterogeneity, and measurement noise, which degrade forecast accuracy and generalization [4], [25]. In solar applications, satellite-derived surface solar irradiance combined with ML improves spatial coverage but introduces multi-source fusion challenges that require careful handling [35], [36]. Similar issues arise in wind systems under non-stationary operating conditions, where explainability can help expose failure modes [38].

Computational and Real-Time Constraints

Advanced models—including DL, RL, and ensemble methods—are computationally demanding. In grid-connected RES, latency constraints can render heavy models impractical without optimized inference or edge deployment [7]. Moreover, coordinating distributed assets in smart grids introduces additional engineering complexity that must be addressed to ensure scalable operation [6].

Integration in Hybrid and Multi-Energy Systems

Integrated renewable energy systems require coordinated scheduling across generation, storage, and dispatchable units. Studies on hybrid energy networks emphasize that AI must support **decision-making under uncertainty while respecting physical and operational constraints** [20], [22]. This elevates the role of AI from prediction to feasibility-aware optimization.

Societal and Sustainability Dimensions

AI deployment pathways influence who benefits from the energy transition. Without equitable access to data, infrastructure, and expertise, AI may reinforce existing inequalities [9]. Transparent benchmarking and open experimentation are therefore essential to align AI-driven RES with broader sustainability goals.

Future Opportunities and Research Directions

Forecast-to-Decision Pipelines

Forecasting remains foundational, supporting scheduling, trading, and storage dispatch. Progress spans solar forecasting with modern architectures [26], [27], [35]–[37], wind forecasting with hybrid deep pipelines [28]–[30], [38], and demand forecasting with explainability-aware models [31]–[33]. A high-impact research direction is integrating these forecasts directly into operational decision pipelines under uncertainty [5], [20], [22].

Reinforcement Learning for Storage and Grid Interaction

Reinforcement learning is well-suited to sequential decision problems in energy systems [44]. Applications include multi-agent coordination in buildings [45] and adaptive storage operation [46], [47]. Systematic, reproducible comparison of RL strategies under standardized scenarios remains an open research need.

Microgrids and Local Resilience

Microgrids are central to decentralized energy futures. ML-based prediction and management in microgrids are increasingly supported by edge intelligence and federated learning [5], [7], [8]. These approaches are particularly relevant for low-resource settings and align with sustainability-driven deployment priorities.

Methodological Standardization

High-impact research increasingly depends on standardized baselines, shared datasets, and transparent evaluation. Here, *OASIS Colab* can be positioned as an enabling layer that supports reproducible pipelines, consistent metrics, and cross-site validation—without being framed as a dependency or commercial platform.

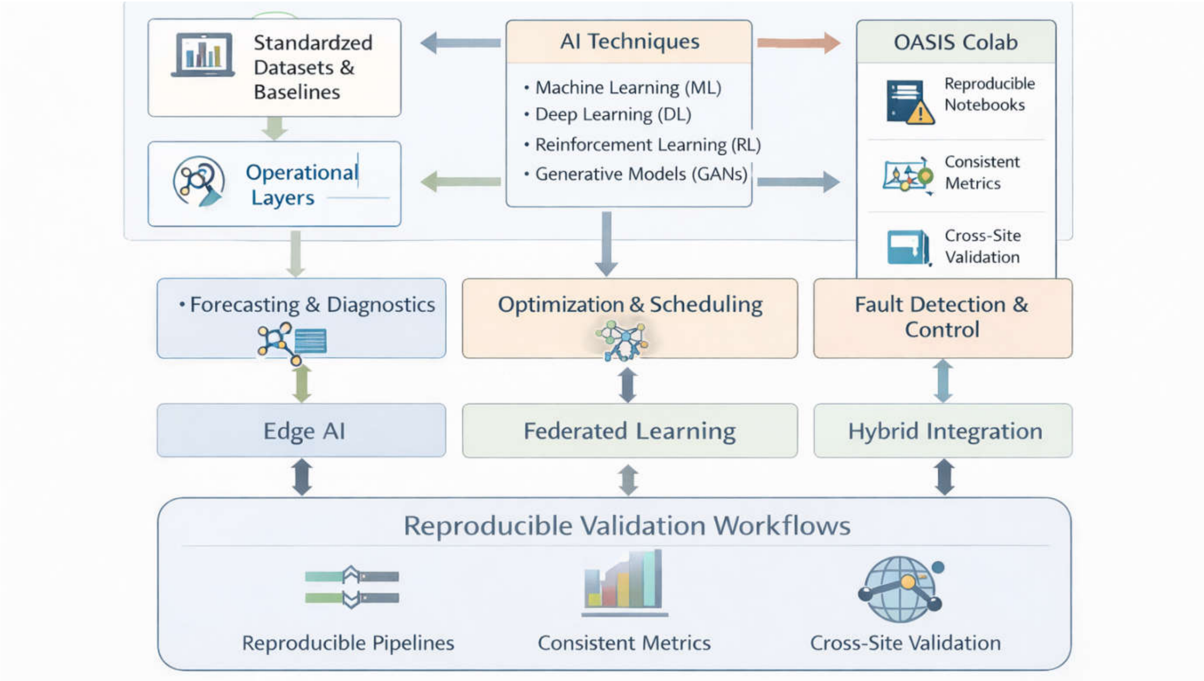

Figure 8. Conceptual framework linking AI techniques, operational layers, deployment modes and reproducible validation workflows [7], [8], [24], [38].

Conclusion

This survey has critically examined the state of the art in artificial intelligence enabled renewable energy systems, emphasizing the transition from isolated, model-centric applications toward system-level intelligence that supports forecasting, diagnostics, operational planning, and control across heterogeneous renewable domains. The reviewed evidence demonstrates that contemporary AI techniques particularly machine learning, deep learning, reinforcement learning, and generative modeling have substantially improved predictive accuracy and operational awareness for solar, wind, demand, and storage systems . These advances have strengthened the technical feasibility of high renewable penetration while mitigating uncertainty, intermittency, and operational risk.

Nevertheless, the analysis also reveals that large-scale deployment of AI in renewable energy systems remains fundamentally constrained by structural challenges. Data heterogeneity, limited sensor coverage, non-stationarity across sites, and stringent real-time requirements continue to restrict model generalization and operational reliability. In grid-critical contexts, these limitations are further compounded by the need for interpretability, traceability, and engineering validation, without which AI-driven decisions cannot be safely or credibly integrated into energy infrastructures.

Emerging paradigms most notably edge intelligence, federated learning, and generative data augmentation represent pragmatic responses to these constraints rather than purely algorithmic innovations. By enabling low-latency inference, privacy-preserving collaboration, and robustness under data scarcity, these approaches align AI development more closely with the physical, regulatory, and operational realities of renewable energy systems. Reinforcement learning further expands the control frontier by supporting sequential decision-making in storage scheduling and grid interaction, particularly under time-varying and uncertain conditions.

Beyond algorithmic performance, this survey highlights that the next phase of progress in AI-enabled renewable energy will be methodological. Reproducibility, transparent evaluation, standardized baselines, and cross-site validation are no longer optional but essential to ensure scientific credibility and real-world transferability. In this context, collaborative research environments such as OASIS

Colab can support structured experimentation and comparative evaluation without constraining methodological independence, thereby strengthening the evidence chain from data to deployment.

In conclusion, artificial intelligence has matured from a supportive analytical tool into a foundational enabler of next-generation renewable energy systems. Realizing its full potential, however, requires aligning technical innovation with rigorous evaluation practices, system-level thinking, and responsible deployment strategies.

Abbreviations

AI:
Artificial Intelligence

RES:
Renewable Energy Systems

RE:
Renewable Energy

ML:
Machine Learning

DL:
Deep Learning

RL:
Reinforcement Learning

IoT:
Internet of Things

GHGs:
Greenhouse Gases

IEA:
International Energy Agency

ESS:
Energy Storage Systems

LSTM:
Long Short-Term Memory

CNN:
Convolutional Neural Network

RNN:
Recurrent Neural Networks

SVM:
Support Vector Machines

ANN:
Artificial Neural Network

RMSE:
Root-Mean-Square Error

MAPE:
Mean Absolute Percentage Error

DT:
Digital Twin

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