DOI: 10.36297/vw.applsci.v7i4.101 ISSN: 2582-5615

VW Applied Sciences, Volume: 7, Issue: 4, 1-10

Artificial Intelligence and the Global Energy Transition: A Review of Computational Applications in Renewable Energy Systems

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Received: Aug. 25, 2025
Accepted: Sept. 29, 2025
Published online: Oct. 01, 2025

Abstract: Artificial Intelligence (AI) has emerged as a transformative technology offering essential solutions for optimizing sustainable energy systems and accelerating global decarbonization. This scientific literature review systematically examines advanced Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL) techniques deployed across renewable energy infrastructure. The analysis confirms the superiority of DL architectures, such as Hybrid Deep Neural Networks (HDNNs), in complex time-series forecasting, significantly improving the accuracy of solar and wind power predictions. Furthermore, RL algorithms have proven critical for dynamic energy management, achieving substantial operational improvements, including a 23.5% increase in cost savings and a 78.69% reduction in carbon emissions in Battery Energy Storage System (BESS) operation. AI applications also extend to critical operational control, enabling predictive maintenance for wind turbines and enhancing PV energy efficiency by 15–20% through automated fault detection. While the technical feasibility is robust, the review identifies critical systemic challenges, including data standardization, high computational costs, cybersecurity risks , and the necessity of developing standardized protocols and Safe RL frameworks to ensure the resilient and scalable implementation required for the full energy transition.

Keywords: Artificial Intelligence (AI); Renewable Energy Sources (RES); Deep Learning (DL); Energy Management; Smart Grid; Reinforcement Learning (RL)

1. Introduction

The global energy system occupies an essential and decisive role in all sectors of modern society, a factor exacerbated by sustained population increases and a vital, continuous demand for power [1]. In response to the escalating climate crisis and the urgent need for decarbonization, the backbone of a sustainable energy supply lies in the rapid scaling up and integration of intermittent Renewable Energy Sources (RES), primarily wind and solar power [2]. This transition, however, introduces a fundamental operational challenge: the inherent stochastic factors and variability of RES generation make balancing supply and demand significantly more complex compared to traditional, controllable fossil fuel sources [3]. To accelerate the integration process and improve the methods of responding to the increase in energy demand while maintaining grid stability, the utilization of models and algorithms based on artificial intelligence (AI) has become both common and mandatory in the energy sector. The transformative potential of AI is recognized as critical for shaping the future of sustainable infrastructure and construction practices globally [4-5].

Artificial intelligence encompasses a diverse set of computational techniques, including Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL), all applied to enhance the efficiency, reliability, and security of energy infrastructure [6]. The application of AI spans the entire energy value chain. Core applications include forecasting energy generation and load demand, optimizing energy systems, detecting faults, and managing dynamic energy storage [7].

The advanced development of DL algorithms, such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, is particularly significant. These models are generally more accurate and exhibit lower error rates than traditional methods, substantially increasing the capacity of the system to solve complex problems arising from the integration of high-penetration RES [1]. The necessity for AI is underscored by its capability to process vast quantities of data generated by sensors and smart grids, enabling real-time monitoring and advanced predictive analytics [6-9].

1.2. Scope and Contribution of this Review to Scientific Literature

This review provides a comprehensive and detailed examination of advanced ML and DL models applied within contemporary energy systems. A particular focus is placed on DL algorithms that have received less attention in previous studies, such as Recurrent Neural Networks (RNN), Adaptive Network-based Fuzzy Inference Systems (ANFIS), Deep Belief Networks (DBN), and Wavelet Neural Networks (WNN) [1]. A key contribution of this work is the synthesis of quantitative performance metrics, such as the Root Mean Square Error (RMSE) and the Coefficient of Determination (), across disparate studies. This synthesis facilitates a clearer, evidence-based comparative analysis of algorithmic efficacy, a crucial component often lacking in broad surveys [10]. Furthermore, this analysis aims to identify critical research gaps, focusing on challenges related to large-scale AI system integration, standardization protocols, economic viability in diverse markets, and ethical dimensions.

2. Review Methodology and Literature Selection

2.1. Search Strategy and Database Selection

The literature selection process was designed to ensure the inclusion of high-quality, peer-reviewed scientific sources. The research protocol targeted major academic databases and platforms [8].The search strategy employed complex logical operators combining keywords related to computational methods and energy systems. Key search strings included combinations of: ("artificial intelligence" OR "machine learning" OR "reinforcement learning") AND ("renewable energy" OR "smart grid" OR "energy storage" OR "demand response" OR "power system") [11-15] This approach was necessary to capture the multidisciplinary nature of AI applications in energy.

2.2. Inclusion and Exclusion Criteria for High-Quality Research

Inclusion criteria established a focus on recent research, primarily articles published between 2015 and 2025, to capture the latest advancements and practical applications. Only peer-reviewed articles detailing explicit methodologies, experimental designs, and quantitative performance results were considered [14]. The journals most frequently cited within the captured dataset, such as *IEEE Transactions on Transportation Electrification*, *Journal of Power Sources*, *Sensors*, and *Sustainability*, reflect a strong focus on high-impact research within electrical engineering, electrochemical technology, sensor integration, and sustainable practices [8]. This focused approach ensures the review addresses the most relevant and high-quality research within the domain.

2.3. Classification of AI Techniques and Application Domains

For clarity and structured analysis, the review classifies the applied computational methods into three major categories based on their functional architecture:

1. **Classical Machine Learning (ML):** This category includes algorithms such as Support Vector Machines (SVM), Random Forest (RF), and Gradient Boosting Regressors (GBR). These techniques are widely used for prediction and classification tasks, demonstrating robustness across various data types.
2. **Deep Learning (DL):** Encompassing complex multi-layered neural networks, this includes Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Hybrid Deep Neural Networks (HDNNs), and Deep Belief Networks (DBNs). DL is particularly valued for improved feature extraction and addressing issues like the gradient disappearance problem in time-series data.
3. **Reinforcement Learning (RL):** This paradigm, which includes Deep Reinforcement Learning (DRL) and Q-Learning, is specialized for solving sequential decision tasks. It is highly suitable for real-time optimization, control, and autonomous decision-making in dynamic energy environments [16-19]

3. Core Applications of AI in Renewable Energy Generation

3.1. Wind Energy Systems

3.1.1. Advanced Forecasting Models for Wind Power Output

Accurate prediction of wind power supply and subsequent demand is vital for integrating stochastic renewable energy sources into the grid and for optimizing energy management systems [19-21]. The development of reliable forecasting models requires rigorous data preparation to handle the complexity and inherent stochastic factors, such as equipment failures, which often lead to noise, outliers, and missing values in collected wind data [22].

Comparative studies illustrate the varied efficacy of different algorithmic approaches based on the chosen performance metrics. In one analysis, the Support Vector Machine (SVM) model demonstrated superior performance in prediction accuracy, achieving the lowest Mean Absolute Error (MAE) of 20.4 kW and Root Mean Square Error (RMSE) of 29.8 kW. Crucially, the model yielded a high Coefficient of Determination of 0.93, indicating that it could explain 93% of the variability in wind power output.[10] In contrast, a separate investigation focusing on regression performance found that Random Forest Regression achieved the lowest Mean Squared Error (MSE) score of 0.1102, narrowly surpassing the Long Short-Term Memory (LSTM) time series analysis score of 0.1171 [17].

This contradiction, where different studies identify distinct "best" models based on metrics such as versus MSE, highlights a critical challenge in methodological standardization. The selection of an evaluation metric fundamentally influences model assessment; for instance, RMSE penalizes larger errors more heavily than MAE.[9] Therefore, the choice of the optimal forecasting model often depends entirely on the operational priority of the stakeholder—whether the focus is on minimizing the financial or operational impacts associated with large power spike prediction errors (favoring RMSE) or minimizing overall average deviation (favoring MAE) [22-23].

3.1.2. Turbine Predictive Maintenance and Anomaly Detection

AI enables a fundamental shift in wind turbine operation from reactive maintenance to optimized predictive maintenance (PdM) through the rigorous analysis of Supervisory Control and Data Acquisition (SCADA) and sensor data.[24] Machine learning techniques are applied extensively to analyze turbine sensor data, signaling anomalous measurements that precede potential component failures [24].

Deep Learning models, particularly LSTMs and SVMs, are proven tools for predicting maintenance needs, including failures in unsupervised components of offshore wind turbines [25]. The implementation process involves critical initial steps, including the careful partitioning of the dataset into training, validation, and test sets, along with comprehensive feature scaling and extraction processes designed to normalize input variables and mitigate the detrimental effects of redundant information.[22] The capability to predict wind turbine failure days in advance has profound economic implications. By enabling early detection, these advanced computational methods transform maintenance economics by allowing operators to transition from costly, unscheduled downtime and repairs to optimized, planned servicing. This directly translates to significant reductions in operational expenditure (OPEX) and improved annual capacity factors.

3.1.3. Optimization of Wind Farm Layout and Wake Effect Mitigation

Optimizing the layout and placement of wind turbines within a designated area, known as Wind Farm Layout Optimization (WFLO), is complex due to the "wake effect"—the aerodynamic interaction wherein the turbulence created by upstream turbines reduces the efficiency and power output of downstream units [26]. AI techniques provide a powerful solution to this optimization challenge. Algorithms based on Artificial Neural Networks (ANNs) are used to model and optimize turbine spacing and layout [27]. Quantifiable results demonstrate the efficacy of this approach: ANN-based wake models enhance design simulations, yielding a 40% speed increase compared to traditional Computational Fluid Dynamics (CFD) methods. Moreover, optimizing the plant layout has been shown to reduce the overall area required for the farm by an average of 18% per plant. The acceleration of design simulations afforded by the 40% speed increase provides a critical competitive advantage during the capital expenditure (CAPEX) phase of development, significantly reducing engineering time and speeding up project approval and deployment timelines.

3.2. Solar Photovoltaic (PV) Systems

3.2.1. Solar Irradiance and PV Power Forecasting

Forecasting the output of Solar Photovoltaic (PV) systems relies on analyzing historical time-stamped data of solar radiation using time-series analysis models. The objective is to increase the accuracy and performance of predictions to support grid management [9]. Deep Neural Networks (DNNs) are widely favored in this domain. Architectures such as CNNs, DBNs, and LSTMs are robust tools for forecasting, primarily due to their superior capability in feature extraction and their ability to capture complex non-linear patterns and long-term dependencies in the data [19]. Recent research highlights the development of Hybrid Deep Neural Networks (HDNNs), which leverage the combined strengths of CNN (for extracting spatial data characteristics, such as cloud movement) and LSTM (for handling long-term temporal sequence dependencies). This hybrid approach has demonstrated superior performance in short-term solar PV power prediction. Comparative performance studies are critical for model selection. Random Forest and XGBoost algorithms consistently appear as reliable ML models for forecasting. For instance, Random Forest recorded robust metrics, including an average R-squared value of 0.89 and an RMSE of 0.28, across prediction intervals ranging from 30 minutes to 24 hours [11]. However, predictive accuracy is highly sensitive to the forecasting horizon: the highest accuracy was recorded at the 30-minute prediction window (up to 0.9890), demonstrating the decreasing reliability of models as the time horizon extends.

3.2.2. Input Data Integration and Complexity

Modern solar forecasting necessitates the integration of diverse, complex data inputs beyond simple meteorological readings. Advanced techniques combine All-Sky Imagery (ASI), satellite observations, and Numerical Weather Prediction (NWP) data [4]. Deep Convolutional Neural Networks (CNNs) are employed to process satellite images, and their outputs are subsequently combined with meteorological "cloud factors" via a multilayer perceptron to significantly improve solar irradiance forecasts. Furthermore, identifying and analyzing key influencing factors, such as specific weather patterns, geographical location, and shading, enables a more precise forecast of energy generation and optimization of system management strategies.

3.2.3. Fault Detection and Diagnosis in PV Arrays

AI applications extend beyond forecasting to include critical operational control, notably fault detection and diagnosis within PV arrays. Machine learning algorithms are used to classify system health, frequently employing thermal images collected from PV panels [29]. A hybrid feature dataset combined with an SVM algorithm achieved a testing accuracy of **92%** in classifying PV panels into three states: healthy, non-faulty hotspot, and faulty.[29] The measurable impact of these AI-driven systems is substantial, achieving an 85% defect detection rate and correlating with a quantifiable 15-20% enhancement in energy efficiency [30]. This deployment of AI in fault detection demonstrates a crucial shift from purely predictive analysis to actively enhancing operational efficiency and defect handling, which directly results in higher overall system yield and extended component longevity.

4. AI for System Integration and Energy Management

4.1. Intelligent Smart Grid Management and Stability

4.1.1. Real-time Monitoring and Load Forecasting

The smart grid (SMG) represents an intelligent, automated energy network that uses digital technology, IoT sensors, and AI-driven analytics to monitor, analyze, and optimize electricity distribution in real time. Unlike traditional grids, smart grids facilitate two-way communication and possess self-healing capabilities, which are essential for the integration of highly variable renewable energy sources [31]. Trustworthy short-term load and renewable energy forecasting are paramount for maximizing energy storage utilization and ensuring the effective use of generated renewable resources. Machine Learning models analyze historical load data, satellite imagery, and real-time meteorological inputs to refine these predictions. Deep Learning techniques such as CNNs and LSTMs, alongside conventional regression models, are mostly utilized for these forecasting tasks [3]. The effectiveness of these AI-powered systems is quantitatively established: for example, one implementation using AI demonstrated a **20% improvement** in wind energy forecasts [31].

4.1.2. Dynamic Energy Optimization via Reinforcement Learning (RL)

Reinforcement Learning (RL) is particularly well-suited to address the complex optimization and control challenges in sustainable energy systems because it is designed to solve sequential decision tasks. RL models optimize the dynamic dispatch of diverse energy sources and storage assets. These techniques enable autonomous control systems, such as intelligent HVAC regulation, to learn optimal operational policies through iterative interaction with their environment. The objective is to dynamically minimize energy usage without compromising service quality [2,10,12].

In a real-time optimization scenario, RL models demonstrated competitive predictive performance, recording an RMSE of 165.2 kWh and an score of 0.91. This performance profile validates the utility of RL models in real-time control environments, such as smart grid response systems and dynamic energy management, where adaptive learning is crucial for maintaining performance thresholds while achieving optimization objectives. RL's unique characteristics, including learning via trial and error and optimizing for delayed rewards, enable it to achieve high accuracy (up to 99.98% in some optimized systems) compared to typical supervised methods [32].

4.2. Battery Energy Storage System (BESS) Optimization

4.2.1. RL Frameworks for Charge/Discharge Strategy

As the penetration of renewable generation increases, the integration of grid-scale energy storage, such as expensive Lithium-ion (Li-ion) Battery Energy Storage Systems (BESSs), becomes necessary for services like load shifting, frequency regulation, and grid stabilization [33]. Maximizing the financial and operational value of these expensive assets requires advanced management strategies. Reinforcement Learning algorithms provide a robust methodological solution for this task. Model-free RL techniques, such as Q-learning, are used to derive optimal control policies. The RL agent interacts dynamically with the microgrid or energy market, making automated decisions (charge, discharge, or remain idle) by learning the optimal state-action value function. Key environmental inputs driving these decisions include real-time energy demand, available renewable generation, and the current Battery State of Charge (SoC) [34,35].

4.2.2. Quantitative Impacts of Optimized BESS Operation

Simulation results comparing RL-optimized hybrid energy storage systems against baseline models demonstrate substantial, multi-dimensional benefits [36]. The optimized operation strategies achieved significant improvements in sustainability, cost efficiency, and utilization:

- Reduction in carbon emissions: 78.69%.
- Improvement in cost savings: 23.5%.
- Enhanced renewable energy utilization: over 13.2%.

These strong quantitative metrics provide the robust economic justification required for the significant capital investment associated with large-scale energy storage. Advanced AI management is therefore the critical enabling technology that transitions BESS technology from a technical possibility to a financially viable operational necessity in the modern power system.

4.3. Comparative Performance Analysis of AI Algorithms

A wide array of AI algorithms is deployed across the renewable energy sector. Tree-based algorithms like Random Forest (RF) and Gradient Boosting Regressors (GBR) are frequently chosen for their operational efficiency and robustness, offering strong baselines often compared against Deep Learning techniques. To consolidate the comparative findings across different domains and computational models, the following tables summarize key performance metrics and taxonomic classifications derived from the literature.

Table 1: Comparative Performance Metrics in Energy Forecasting and Optimization

Algorithm	Application Domain	Key Metric	Value	Insight	References
LSTM	Energy Consumption Forecasting	Score	0.93	Best at capturing long-term temporal dependencies	12
Support Vector Machine (SVM)	Wind Power Forecasting	Score	0.93	Achieved highest prediction accuracy in tested wind models	10

Random Forest (RF)	Solar PV Forecasting (GHI)	R-squared	0.89	Reliable ML baseline model across various forecasting intervals	11
Random Forest (RF)	Wind Power Regression	MSE	0.1102	Recorded the best Mean Squared Error score among tested regression models	17
XGBoost	Energy Consumption Forecasting	RMSE (kWh)	174.1	Strong predictive performance, high interpretability via SHAP	12
Reinforcement Learning (RL)	Energy Optimization/Control	Score	0.91	Effective in generating optimal policies for real-time control scenarios	12

Table 2: Taxonomy of AI Applications and Techniques Across Renewable Energy Sectors

Energy Sector	**Primary Application**	**Dominant AI Techniques**	**Key Function/Goal**	**References**
Wind Energy	Predictive Maintenance	DL, SVM, Anomaly Detection	SCADA data analysis, early warning failure prediction	24
Solar PV	Power Forecasting	HDNN (CNN+LSTM), ANNs, RF	Improved irradiance and output prediction using spatial-temporal modeling	4
Wind Energy	Layout Optimization	ANN-based Wake Models	Maximizing energy yield, 40% simulation speed increase	27
Smart Grids/BESS	Energy Management	DRL, Q-Learning, Multi-Agent Systems	Dynamic charging/discharging, grid stability, 23.5% cost reduction	2
Solar PV	Fault Detection	SVM, Image Classification	Defect detection (85% rate), 15–20% energy efficiency enhancement	29

5. Critical Analysis: Challenges, Limitations, and Economic Feasibility

5.1. Data Interoperability, Quality, and Consistency

Despite the rapid advancements in AI algorithms, the widespread adoption of AI in the energy sector faces fundamental barriers related to data. Data availability and quality remain critical obstacles, largely because energy sectors often lack standardized and interoperable datasets necessary for training generalized models.[7]

Furthermore, methodological rigor in research is frequently compromised by inconsistencies in training protocols. The necessity of using consistent training data is paramount to ensure fair and reliable comparisons between different machine learning methods [28]. Studies that violate this principle—for example, by training one model (such as a CNN) on a substantially larger dataset (e.g., 24 months) than others (e.g., 12 months)—yield unrealistic and unreliable results, fundamentally undermining the integrity of comparative scientific findings [28]. This prevalence of non-standardized datasets and inconsistent training protocols inhibits reliable meta-analysis and hinders the transition of validated models from research environments to industrial deployment. Consequently, prioritizing improvements in the *scientific reporting* and *data provenance* is as essential for advancing the field as developing novel algorithmic architectures.

5.2. Computational Resource Demand and Environmental Footprint of AI

The growth of Artificial Intelligence generates a substantial energy demand, leading to the dictum that there is "no AI without energy," specifically electricity for data centers [16]. The high computational costs associated with training and running large-scale AI models pose a significant operational obstacle to widespread sustainable adoption.[7] Policy makers and stakeholders often lack the comprehensive tools needed to analyze both the optimization potential and the energy demand side of AI concurrently [16]. Addressing this requires a systematic approach to evaluating the energy consumption of ML at both the training and inference stages [37]. Researchers are actively developing methods to mitigate these costs, including techniques such as structured pruning, which involves removing whole filters or channels from deep neural networks to optimize memory consumption while maintaining performance [38]. Furthermore, experimentation with different quantization settings (e.g., 32 bits vs. 16 bits) during the fine-tuning phase is essential for reducing the computational footprint of deployed models [38].

5.3. Cybersecurity, Regulatory, and Ethical Concerns

The integration of complex, real-time AI systems into critical infrastructure introduces significant operational risks. Cybersecurity vulnerabilities in smart grids, which rely on extensive digital communication, present a major challenge that must be addressed before widespread adoption [7]. Beyond technical risks, the proliferation of AI raises broader societal and ethical concerns. These include the potential for AI to exacerbate resource and energy use, contribute to job displacement, and be used to generate misinformation—for instance, downplaying the threat of climate change [39]. Despite these clear risks, a regulatory lag exists where governments, while racing to develop national AI strategies, often fail to incorporate environmental and sustainability guardrails. To address this, organizations recommend establishing standardized procedures for measuring AI's environmental impact and developing regulations that require companies to disclose the direct environmental consequences of AI-based products and services [40].

5.4. Economic Sustainability Development and Financial Impact of AI Adoption

The economic case for AI adoption in energy systems is robust. The application of AI can boost productivity, accelerate decision-making through the analysis of vast amounts of data, and potentially create new goods and services, resulting in job growth (ESD-AI) [41]. The optimization provided by AI, such as the predicted reduction in capital investment through the rapid development of renewable energy and energy-efficient technologies [42], contributes significantly to overall sustainable growth [43].

AI-integrated Economic Sustainability Development (ESD) helps minimize costs and enhance profitability by facilitating the optimum use and recovery of resources [41]. The combination of AI and RES has been shown to contribute significantly to the environmental, social, and economic goals outlined in the 2030 Agenda for Sustainable Development [43]. It is, however, crucial to adopt a balanced approach that ensures AI systems effectively tackle sustainability challenges and minimize costs without inadvertently compromising other crucial economic or social aims, such as equitable access or mitigating job displacement [39].

6. Conclusions

Artificial intelligence has rapidly matured from a tool for static prediction to a complex system for dynamic control and operational optimization within the renewable energy landscape. Deep Learning techniques, notably Hybrid Deep Neural Networks (HDNNs) that combine CNN and LSTM architectures, successfully address the complex, non-linear challenges of solar and wind time-series forecasting. Simultaneously, Reinforcement Learning (RL) has defined the next generation of dynamic energy management, exemplified by the quantifiable substantial cost savings (23.5%) and environmental benefits (78.69% reduction in carbon emissions) achieved in Battery Energy Storage System (BESS) operations. Furthermore, AI-driven operational improvements, such as the 15-20% enhancement in energy efficiency through PV fault detection, underscore the vital role of computational intelligence in maximizing asset yield and longevity.

The necessity of managing the high uncertainty inherent in RES generation drives the development of next-generation hybrid AI models. Future advancements will integrate probabilistic modeling, fuzzy logic, and Bayesian inference with existing neural networks to enhance predictive accuracy and decision-making robustness under conditions of high variability. Furthermore, the conceptual shift toward "Agentic AI" suggests a future where energy infrastructure is managed by highly autonomous, self-learning systems.[45]

Two specific methodological trajectories are emerging to address current limitations:

- **Transfer Learning:** To overcome the critical dependence on massive, consistent datasets, transfer learning (reusing pre-trained RL models from similar domains, such as Electric Vehicle batteries) is being investigated. This approach has demonstrated a pathway to mitigate data scarcity and can improve real-world policy performance by up to 18%.
- **Safe Reinforcement Learning (Safe RL):** The exploratory nature of standard RL poses risks (e.g., battery overcharging, grid instability) during real-world implementation. The maturation of Safe RL techniques, including constrained policy optimization and the implementation of dynamic safety layers to respect physical limits (e.g., battery thermal constraints), is crucial for enabling the secure transition of RL systems from simulation to full-scale deployment.

7. Future Research

The literature indicates that the principal research frontier is transitioning from the refinement of individual algorithms to addressing the systemic and non-technical challenges of large-scale AI deployment. Future research must urgently focus on the following domains:

- **Standardization and Economic Viability:** There is a critical need to establish standardization protocols for data collection, preprocessing, and model evaluation to close the methodological integrity gap.[13] Research must also investigate the economic viability and scalable implementation of these advanced AI systems specifically within emerging economies.
- **Systemic Resilience and Policy Integration:** Future efforts must concentrate on achieving large-scale integration of AI systems, focusing on ensuring system resilience against faults and cyber threats.[47] This must be accompanied by interdisciplinary studies that align AI-driven energy optimization with complex energy economics, policy regulations, and social equity considerations.
- **Decarbonization Roadmaps:** A key applied direction is the creation of comprehensive, AI-based decarbonization roadmaps tailored for specific countries, regions, and island grids, leveraging the forecasting and optimization capabilities developed to date.

This sustained systemic focus—addressing scalability, safety (via Safe RL), regulatory alignment, and social impact—is essential to realize the full promise of artificial intelligence in achieving a reliable and sustainable global energy transition.

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