



Article

# Towards Sustainable AI-Driven Renewable Energy Systems through Integration of Forecasting, Grid Economics and Lifecycle Assessment

Ahmed G. Abo-Khalil

Sustainable and Renewable Energy Engineering Department, College of Engineering, University of Sharjah, Sharjah P.O. Box 27272, United Arab Emirates; aabokhalil@sharjah.ac.ae

**How To Cite:** Abo-Khalil, A.G. Towards Sustainable AI-Driven Renewable Energy Systems through Integration of Forecasting, Grid Economics and Lifecycle Assessment. *Renewable and Sustainable Energy Technology* 2026, 2(2), 8. <https://doi.org/10.53941/rset.2026.100005>

Received: 24 March 2026

Revised: 30 May 2026

Accepted: 8 June 2026

Published: 16 June 2026

**Abstract:** The rapid deployment of renewable energy systems has intensified the need for intelligent, scalable, and economically viable solutions to manage variability, uncertainty, and grid complexity. Artificial intelligence (AI) has emerged as a transformative enabler, significantly improving forecasting accuracy, operational efficiency, and system resilience. However, existing studies largely treat AI as an isolated technical tool, overlooking its integration with economic decision-making, lifecycle sustainability, and policy constraints. This paper addresses these critical gaps by proposing a unified analytical framework that links AI-driven renewable energy forecasting with grid economics, optimization-based dispatch, and lifecycle assessment of AI energy consumption. The framework incorporates renewable generation modeling, data-driven forecasting using deep learning architectures, and cost-aware optimization while explicitly accounting for the computational energy footprint of AI systems. A quantitative evaluation using a 24-h simulation demonstrates that AI-based forecasting reduces prediction errors by nearly 50% and lowers total operational costs by 18.7% compared to conventional approaches. Importantly, the inclusion of AI energy consumption enables a realistic assessment of net system benefits, revealing that computational overhead remains marginal relative to achieved savings. Beyond technical performance, this study systematically identifies key research gaps—including the forecasting–economics disconnect, AI energy footprint, model generalization limitations, grid heterogeneity, and policy and equity challenges—and proposes actionable solutions such as domain-adaptive AI models, green AI strategies, and policy-aware optimization frameworks. The results highlight that the true value of AI in renewable energy systems lies not only in predictive accuracy but in its integration with economic, environmental, and regulatory dimensions. This work provides a comprehensive roadmap for researchers, utilities, and policymakers to design scalable, efficient, and sustainable AI-enabled energy systems aligned with global decarbonization goals.

**Keywords:** sustainability; renewable energy; AI; lifecycle assessment

## 1. Introduction

As climate change continues to worsen, there is increasing global pressure to implement more aggressive policies than those agreed upon in the 2015 Paris Climate Agreement. In response, the UAE government aims to raise the share of renewable energy to 42% by 2050. To achieve this, the government is focusing on policies that support large-scale solar power projects and distributed power generation, along with expansion of supply-related infrastructures. While the physical expansion of equipment is essential, it is equally important to maximize the use



**Copyright:** © 2026 by the authors. This is an open access article under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

**Publisher's Note:** Scilight stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

of produced renewable energy. However, since solar and wind power outputs are highly dependent on weather conditions, it is difficult to accurately predict power generation. As a result, the gap between expected and actual power output is large, causing inefficiencies. In particular, due to the high share of renewable energy in the energy mix, considerable costs are incurred for maintaining reserve power and ensuring supply reliability [1].

If the variability in renewable energy generation can be predicted more accurately, it will enable better power dispatch planning, maximize use of renewable energy, and reduce associated costs. This would ultimately increase the efficiency of power grid operations. To this end, the power and energy industries have made various efforts—such as modernizing facilities, ensuring reliable maintenance, and optimizing grids—while also addressing environmental challenges. Recently, AI has emerged as a powerful tool with tremendous potential that goes beyond conventional automation. It can be applied in asset management of power facilities, optimization of variable renewable energy sources, efficient grid integration, smart grids, smart cities, future power market solutions, and cybersecurity. Although AI applications in actual field operations are still limited, the necessity of AI for energy transition continues to grow. Thanks to reliable and abundant data generated from key facilities, commercialized computing capabilities, and increasingly efficient AI algorithms, we can expect more widespread applications in the power and energy sectors in the future [2].

Renewable energy sources can be based on: bioenergy, hydropower, geothermal energy, solar energy, wind energy, and ocean energy (including tidal and wave energy). Sustainable energy is defined as a “dynamic harmony between the equitable availability of energy-intensive goods and services for all people and the preservation of the Earth for future generations”. Although renewable sources typically have higher costs and lower energy conversion efficiency, they produce minimal pollution. To overcome these barriers of cost and efficiency, companies in the energy sector must align with best practices and tools—particularly artificial intelligence (AI), which enables control, analysis, decision support, forecasting mechanisms, and many other unprecedented capabilities. Due to the high level of technology involved, AI’s use in the renewable energy sector can lead to significant progress, including through intelligent robotics for infrastructure development, grid monitoring, improved integration of renewable sources, and most importantly, continuous data processing that allows the system to self-improve [3].

Historically, AI has shown great promise in solving complex problems and even demonstrates the ability to optimize weather forecasting systems without requiring extensive long-term meteorological data. This suggests that AI applications in the renewable energy sector have multiple promising pathways—including maintenance and operation of energy assets, monitoring of energy generation infrastructure, system security, and development of design solutions. The energy sector is undergoing rapid changes driven by technological advances, shifts in consumer behavior, and the growing environmental urgency of the energy transition. In this context, Artificial Intelligence (AI) is emerging as a powerful tool to turn challenges into opportunities, significantly impacting energy consumption, sustainability, and economic growth [4].

There is no doubt that the use of AI in various sectors is beneficial to both society and the planet. AI is rapidly becoming a catalyst for innovation, providing solutions that go beyond routine tasks and addressing complex problems. Its ability to process vast volumes of data and perform calculations is enhancing productivity and efficiency across industries such as healthcare, transportation, and manufacturing. According to a PwC report, it is estimated that AI could contribute up to USD 15.7 trillion to the global economy by 2030, indicating its enormous economic potential—including its application in sustainable practices, optimizing resources, and reducing waste. Recently, many countries have reviewed or introduced policies to encourage the adoption of AI in energy systems, aiming to increase efficiency and reduce environmental impact. A particularly promising application of AI is in optimizing energy use. Through data-driven algorithms, AI can analyze consumption patterns and make real-time adjustments that improve efficiency. For example, cities like Singapore and Barcelona are using AI in traffic control systems and public lighting. Internet of Things (IoT) sensors and AI algorithms are being used to predict pedestrian and vehicle behavior, leading to energy savings of up to 30% in some cases [5].

In the electricity sector, AI also allows for preventive maintenance and grid stability forecasting. Moreover, it is being used in buildings, helping to regulate lighting, ventilation, and air conditioning based on occupancy and environmental conditions. AI can also optimize production processes and predictive maintenance, generating significant energy savings. Given these considerations, AI plays a crucial role in understanding and addressing climate change. Traditional climate models are limited by their complexity and computational demands, whereas AI offers a more efficient alternative. Despite its many benefits, implementing AI still presents significant challenges. One of the most pressing is the energy consumption of data centers, especially given the large volumes of data AI systems process. Data centers currently account for 1–2% of global electricity consumption, and their high energy use is a hurdle to sustainability. Additionally, underdeveloped digital infrastructure in many developing countries can limit AI adoption. Ethical and privacy concerns also arise, particularly regarding the collection and use of sensitive personal data [6].

The electricity sector must find alternative pathways that work for all stakeholders. Tailored solutions are essential, given the diverse economic, climate, and regulatory contexts. AI can be a valuable ally in these strategies. Technologies like heat recovery and system optimization can reduce the energy consumption of data centers. Some companies are investing in renewable energy sources to power AI applications. Moreover, AI is being applied across multiple areas to help adapt to climate change. In carbon capture and storage, AI identifies ideal capture zones and optimizes the process. It improves precision agriculture, monitors soil conditions, optimizes fertilizer and water use, and boosts productivity while reducing environmental impact. In transportation, AI is used to manage traffic flow, reduce congestion, and cut fuel consumption and greenhouse gas emissions. It supports sustainable transport by enhancing route planning and fleet management, contributing to emissions reduction [7].

International collaboration is essential. Global partnerships enable knowledge sharing and help accelerate innovation. Cross-sectoral initiatives allow countries at different stages of development to adopt AI efficiently. Clear regulations are needed to set ethical boundaries and promote responsible AI use in the energy sector. Investing in research and development is essential to harness AI's full potential in the energy sector. Funding innovative solutions that promote sustainability, optimize energy use, and reduce environmental impact is critical. Public-private partnerships can accelerate progress by supporting technology deployment and ensuring that the benefits of AI are widely and equitably distributed [8].

AI is becoming a key player in the Fourth Industrial Revolution, transforming industries and societies. Its responsible use can lead to sustainable economic growth, reducing inequalities and improving quality of life by providing efficient services in health, energy, and transportation. AI offers a promising path toward a more inclusive, prosperous, and sustainable future [9].

Recent advances in artificial intelligence have significantly improved the forecasting, control, and operation of renewable energy systems. Deep learning architectures such as Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), hybrid CNN-LSTM models, transformers, and reinforcement learning algorithms have demonstrated superior performance in solar irradiance forecasting, wind power prediction, energy storage management, and smart grid optimization. Several studies have reported substantial reductions in forecasting errors and improvements in operational efficiency through AI-based approaches. However, the majority of existing research focuses primarily on prediction accuracy or individual operational tasks without considering their broader economic, environmental, and policy implications.

Recent studies have highlighted the growing role of AI in renewable energy integration, energy storage management, power quality enhancement, and smart grid operation. Nevertheless, several important limitations remain. First, most forecasting studies evaluate model performance using statistical metrics such as RMSE, MAE, and MAPE without quantifying the economic value of improved forecasts in terms of generation scheduling, reserve allocation, and operational cost reduction. Second, the energy consumption associated with AI training and inference processes is often neglected, despite increasing concerns regarding the electricity demand of large-scale AI systems and data centers. Third, existing studies rarely integrate forecasting, optimization, economic dispatch, lifecycle assessment, and sustainability considerations within a unified analytical framework. Fourth, the impacts of regulatory constraints, market mechanisms, and energy equity considerations remain largely unexplored in current AI-driven energy management studies.

The literature review demonstrate that while previous studies have achieved significant progress in forecasting accuracy and operational optimization, they generally treat forecasting, economic analysis, environmental assessment, and policy considerations as separate research problems. Consequently, the system-level benefits and trade-offs associated with AI deployment in renewable energy systems remain insufficiently understood.

To address these limitations, this paper proposes a unified analytical framework that integrates AI-driven renewable energy forecasting, optimization-based dispatch, grid economics, and lifecycle assessment within a single decision-making platform. Unlike previous studies that focus on isolated technical improvements, the proposed framework explicitly quantifies the economic benefits of enhanced forecasting accuracy while simultaneously accounting for the computational energy consumption and environmental footprint of AI systems. Furthermore, the framework provides a holistic perspective that considers technical performance, economic viability, sustainability, and policy-related challenges, thereby offering a more comprehensive roadmap for the deployment of AI-enabled renewable energy systems.

This paper proposes a unified analytical framework that integrates AI-driven renewable energy forecasting with grid economics, optimization-based dispatch, and lifecycle assessment, enabling a comprehensive evaluation of both the operational benefits and energy footprint of AI in sustainable power systems.

The major contributions of this work can be summarized as follows:

- A unified analytical framework is proposed that integrates AI-driven renewable energy forecasting, optimization-based dispatch, grid economics, and lifecycle sustainability assessment into a single decision-making platform.
- A comprehensive analysis of the current research landscape is presented, identifying key challenges and research gaps, including the forecasting–economics disconnect, AI computational energy footprint, model generalization limitations, grid heterogeneity, and policy and energy-equity concerns.
- A mathematical modeling framework is developed to establish explicit relationships among renewable energy generation, AI-based forecasting, energy storage operation, dispatch optimization, and AI computational energy consumption.
- The energy consumption and environmental footprint of AI models are explicitly incorporated into the evaluation framework, enabling assessment of the trade-off between forecasting accuracy and computational sustainability.
- A quantitative case study is conducted to evaluate the impact of AI-based forecasting on renewable energy management, demonstrating improvements in forecasting accuracy, operational efficiency, and economic performance.
- Practical recommendations are provided for researchers, utilities, grid operators, and policymakers regarding the deployment of sustainable AI-enabled renewable energy systems while considering technical, economic, environmental, and regulatory constraints.

The remainder of this paper is organized as follows. Section 2 presents the key research gaps and summarizes the main contributions of the proposed framework. Section 3 reviews the recent literature on AI-driven renewable energy forecasting, grid integration, and smart energy management while identifying existing limitations. Section 4 discusses the major technical, economic, environmental, business, and social concerns associated with AI deployment in the energy sector. Section 5 presents representative applications of AI in power and energy systems. Section 6 develops the mathematical formulation of the proposed AI-driven renewable energy management framework. Section 7 presents the simulation results and performance evaluation. Finally, Section 8 discusses future research directions, and Section 9 concludes the paper.

## 2. Research Gap and Contributions

Prior literature on AI for renewable energy has demonstrated promising advances in forecasting, control and optimization, but critical gaps remain. Recent surveys and reviews show that AI-enabled methods improve prediction accuracy and system efficiency. However, these works often treat AI tools as isolated components, omitting their integration with grid economics, policy and life-cycle impacts. For example, a “unified framework” for smart-grid monitoring, control, optimization, and resilience has been proposed; however, the discussion is focused almost entirely on technical performance. Similarly, it has been reported that AI can align renewable energy generation with demand and reduce operational costs; however, the extent to which these benefits propagate through electricity markets or influence investment decisions has not been quantified [10]. In other domains, recent studies have highlighted that machine-learning models struggle with generalization across different geographical locations and that the integration of multi-modal weather and grid data remains an emerging field with significant research gaps [11]. In sum, existing reviews and case studies concentrate on narrow technical challenges (high-accuracy forecasting, digital twins, microgrid control, etc.), yet largely ignore system-level economic evaluation, regulatory barriers, data bias, and the environmental footprint of AI itself.

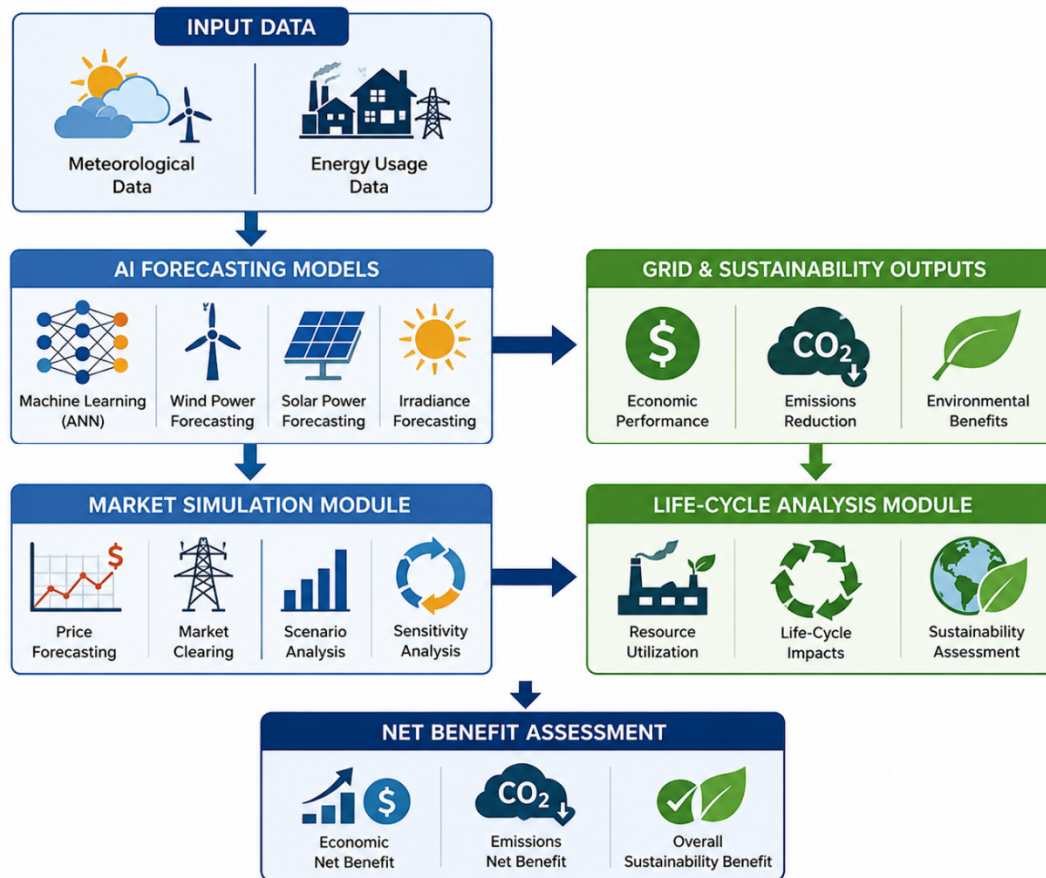
Key unresolved issues in AI + renewables span technical, economic and environmental domains. Technically, model generalization and data quality remain problematic: supervised learning models often require extensive feature engineering and local training, making them less likely to transfer across regions or scales. Unaddressed data bias is also a concern; energy justice studies show that ML pipelines can “unintentionally reinforce social inequalities” if training data is skewed. Scalability and interoperability present further hurdles: the power grid is “a vast machine built out over decades” with heterogeneous devices and legacy systems, so novel AI systems must accommodate diverse data formats, latency constraints and security requirements. Economically, the high computational and operational footprint of AI is often overlooked. Recent projections suggest AI could consume a substantial fraction of electricity demand (increasing from ~0.4% today to ≈13–47% by 2050 under plausible scenarios). Recent studies have emphasized that the climate impacts of AI infrastructure remain underexplored, while AI has also been recognized for its techno-economic duality, serving both as an enabler of efficiency improvements and as an emerging source of increased electricity demand [12]. If this AI-driven demand is met by fossil-dominated grids, its gains may be offset by added emissions. On the policy side, few AI studies incorporate market/regulatory constraints: issues such as interconnection queues, renewable portfolio standards or carbon pricing are usually ignored. The Policy Center report notes that AI deployment depends on “access to abundant,

low-carbon electricity” and strong supply chains, suggesting that, without supportive policies and infrastructure investment, AI for renewables could exacerbate energy inequities. Table 1 below summarizes these missed areas, evidence from the literature, their impact, and suggested fixes.

**Table 1.** Key research gaps and emerging challenges in AI-driven energy systems, along with supporting evidence from the literature, their system-level impacts, and recommended research directions.

Missed Area	Evidence from Literature	Impact	Proposed Fix
Forecasting–economics gap	AI methods now yield high forecast accuracy and can reduce operational costs. Yet studies rarely link these gains to market models or planning tools.	Without linking forecasts to pricing and investment, accuracy gains may not translate into system-wide cost savings or optimal deployment.	Develop integrated frameworks that feed AI forecasts into economic dispatch and capacity expansion models.
AI energy footprint & LCA	AI’s future power draw could reach 13–47% of global electricity by 2050. Experts stress AI’s “energy and climate consequences” remain underexplored.	High AI energy use (often on carbon-intense grids) can erode the climate benefits of renewables and strain grid capacity.	Perform life-cycle assessments of AI (training and inference) in energy contexts; quantitatively compare AI’s own energy use with the renewables enabled. Promote “green AI” (e.g., efficient algorithms, carbon-aware scheduling).
Model generalization & data bias	Deep learning models often require site-specific tuning and fail to generalize across locations. ML pipelines can “reinforce social inequalities” if not de-biased.	Limits scalability: each new locale or technology may need retraining. Biased data can lead to unfair resource allocation or reliability blind spots.	Invest in domain-adaptive models (foundation models, transfer learning) to improve cross-site generalization. Use fairness-aware training and diverse datasets to mitigate bias (e.g., energy justice metrics).
Grid heterogeneity & integration	The power grid is “a vast machine...built out over decades” with heterogeneous hardware. Mastoi et al. identify major technical, data and regulatory challenges.	Disparate data formats, communication delays, and legacy controls impede AI deployment at scale.	Adopt open data standards and modular AI architectures. Collaborate with grid operators to co-design AI tools that respect operational constraints.
Policy/regulatory & equity	AI renewables studies rarely include policy analysis. Observers note AI’s dependence on abundant clean power and critical minerals.	Without regulatory alignment, AI tools may be underutilized or worsen existing inequities (e.g., favoring regions with better data/infrastructure).	Integrate policy constraints (carbon pricing, subsidies, equity targets) into AI-based evaluations. Engage stakeholders to shape regulations that enable AI while ensuring fair access and grid stability.

The contributions of our work address these gaps with three pillars. First, we propose a unified analytical framework that connects AI-driven renewable forecasting with grid economics and sustainability accounting. This architecture (Figure 1) ingests meteorological and usage data into learning models, whose outputs feed into market simulation and life-cycle modules. Second, we develop a quantitative methodology to evaluate the net benefit of AI in renewables: it tracks the energy and emissions cost of AI (training/inference) against the additional renewable utilization and emissions avoided. Finally, we introduce a benchmarking toolkit for AI algorithms in the energy context, scoring them on prediction accuracy, compute efficiency, and robustness under data uncertainty. By explicitly linking AI performance to economic and environmental outcomes, our approach addresses a gap identified in the literature, providing actionable insights for researchers, utilities, and policymakers [13].



**Figure 1.** Unified analytical framework integrating AI-driven renewable energy forecasting with grid economics and sustainability assessment.

### 3. Literature Review

Several recent high-impact studies have explored AI techniques for renewable energy forecasting and grid integration [14]. Article [15] reviews AI-driven renewable integration and highlight its potential for improving forecasts and efficiency. While [16] focus on AI's own energy and climate footprint, noting that AI infrastructure impacts are “underexplored”. Ref. [17] presents a reliability-constrained unit commitment under high wind penetration, illustrating the challenges of uncertainty in large systems. These and other works form the foundation for understanding current trends and gaps in AI + renewable energy.

Recent work by [18] further demonstrates the growing role of artificial intelligence in enhancing the operational performance and reliability of modern power systems. Their study highlights the integration of AI-based optimization techniques for power quality enhancement, renewable energy coordination, and smart-grid operation under increasing system complexity. The authors show that intelligent optimization frameworks can improve voltage regulation, reduce power quality disturbances, and support more efficient integration of distributed renewable energy resources. These findings reinforce the importance of combining advanced forecasting models with optimization and control strategies to achieve reliable and economically efficient grid operation. However, while their work primarily focuses on power quality improvement and optimization performance, the broader interactions among forecasting accuracy, grid economics, AI computational energy consumption, and lifecycle sustainability assessment remain largely unexplored. The framework proposed in this study extends beyond operational optimization by integrating AI-driven forecasting, economic dispatch, lifecycle assessment, and sustainability evaluation into a unified analytical platform.

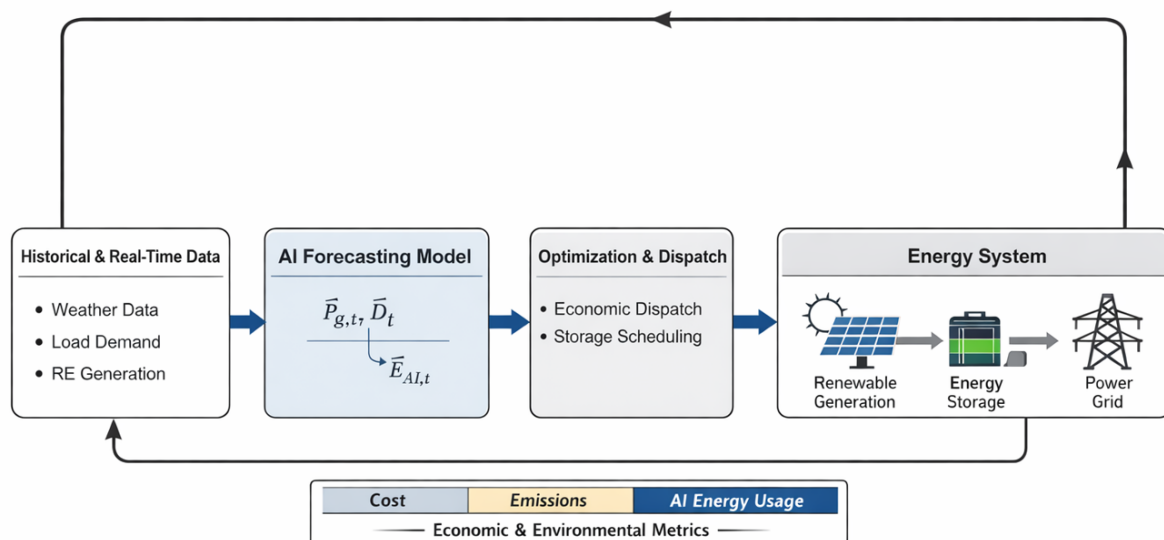
Building upon these developments, the literature trend has shifted markedly toward deep and hybrid learning models. Early efforts used traditional neural networks or support vector machines, whereas recent studies increasingly employ LSTM networks, CNN-LSTM architectures, transformer models, and reinforcement learning approaches to capture complex spatio-temporal relationships in renewable energy and power system data. Early efforts used traditional neural networks or support vector machines, but more recent work employs LSTM networks and CNN-LSTM hybrids to capture spatio-temporal patterns in weather data. For example, ref. [19] uses a CNN-LSTM architecture for solar irradiance forecasting, achieving lower RMSE than pure LSTMs and others

note that foundation models (large pre-trained networks) are emerging in energy forecasting, promising generalized features across sites. There is also growing adoption of probabilistic forecasting methods (e.g., quantile regression) to quantify uncertainty, though these are still less common than point-prediction models. In summary, modern studies emphasize complex neural architectures and uncertainty-aware models, which generally outperform earlier statistical or shallow-ML approaches.

Despite advanced methods, common limitations persist across the literature. A key gap is the lack of integration between forecasting and economic analysis. Most studies treat AI forecasts and system optimization in isolation, without quantifying how improved forecasts affect cost or reliability. Similarly, lifecycle analysis (LCA) of AI algorithms is rarely included; Ref. [20] argue that the environmental cost of AI hardware must be factored into net benefit calculations. Model generalization is another issue: deep models often require site-specific training, and performance can drop on unseen data. Data bias has been noted as a risk, where ML models may inadvertently encode historical anomalies or inequities. Scalability is frequently mentioned: many AI solutions rely on large networks and extensive historical data, which can be impractical for real-time operation. For example, complex LSTMs incur high computation and may not be viable on small embedded systems. Interoperability and data standardization are seldom addressed in academic work; in practice, diverse data formats and legacy systems complicate AI deployment (e.g., grid data heterogeneity is a well-known challenge). On the regulatory side, there is scant discussion of how rules and market structures might need to adapt to AI-enabled resources, despite policy papers highlighting sovereignty and control issues.

The research gaps motivating our work become clear from this survey. Table 2 compares representative studies by authors, AI method, application, and limitations, showing that while accuracy and novel algorithms are well-covered, few works connect AI with grid economics, scalability, or sustainability. For example, ref. [20] applies ANNs to solar forecasting but do not consider downstream dispatch impacts. Ref. [21] use reinforcement learning for storage control without evaluating AI's computational overhead. Ref. [22] proposes an AI-based virtual power plant controller but ignore market integration and carbon accounting. In general, existing literature lacks a unified framework linking AI forecasts to operational decision-making and economic outcomes. This gap is underscored by the absence of studies combining forecast, dispatch, and LCA modules in a closed loop.

Figure 2 depicts a proposed integrated framework: historical data feeds into an AI forecasting block, whose outputs then inform an optimization module that schedules generation and storage. The optimization also accounts for economic and environmental metrics (e.g., cost, emissions), including the AI model's own energy use. This end-to-end structure highlights where literature is fragmented. Our paper addresses these gaps by (1) explicitly modeling AI energy consumption in the system budget and (2) linking forecast accuracy to cost objectives, thereby bridging the missing pieces identified above.



**Figure 2.** Integrated AI-driven renewable energy management framework.

Table 2 compares selected peer-reviewed works. It shows the focus on advanced AI methods and the common limitation that economic/operational considerations are typically outside the scope.

**Table 2.** Comparison of representative AI applications in renewable energy [14–22].

AI Method	Application	Limitations
ANN	Solar power forecasting	Ignores impact on dispatch, limited scope
SVM	Wind speed prediction	Sensitive to hyperparameters
LSTM	PV output forecasting	High compute requirements, data-hungry
CNN-LSTM	Hybrid weather modeling	Requires large training set
Deep RL	Energy storage control	Convergence and safety not fully addressed
GA + SVR	Economic dispatch	Heuristic, lacks generality
Deep Learning	Smart grid operation	Omits AI lifecycle cost
AI-based VPP coordination	Distributed energy	No market/regulatory analysis
Transformer (foundation)	Load forecasting	Early stage, deployment challenges

## 4. Concerns When Using AI in the Energy Sector

### 4.1. Technical Issues

As AI technology is applied to the energy sector, the risks of cybersecurity and system vulnerabilities are increasing. Smart grids and AI-based energy management systems may become targets for hackers, and as the number of network connection points in energy systems increases, security management becomes more complex. If AI technology is misused, energy supply stability can be compromised through data manipulation, and the potential for sophisticated cyberattacks also grows. The risk of personal data exposure is also rising. AI can analyze energy usage data and learn sensitive personal patterns, which could be exploited by hackers to seriously threaten both privacy and system stability. Data quality is a core factor that directly affects the performance and reliability of AI systems. Problems such as data distortion, incompleteness, and bias hinder accurate analysis and prediction of energy systems. If AI systems make decisions based on distorted or biased data, the outcomes may also be flawed or biased [23].

Issues with data availability and consistency significantly affect the effectiveness and accuracy of AI models. Since AI relies on large volumes of training data, a lack of sufficient or consistent data can degrade model performance. There are also technical performance limitations. Compatibility and efficiency issues between AI and existing energy systems are complex, and traditional grid designs can make AI integration difficult. The complexity of managing distributed energy systems, data flow challenges, and the variability of renewable energy sources can introduce instability if AI performance is insufficient. Moreover, the lack of reliability and real-time validation in AI systems raises doubts about the trustworthiness of data-driven approaches.

### 4.2. Economic and Environmental Issues

AI systems require advanced computing power, presenting significant challenges both economically and environmentally. These systems consume substantial amounts of energy, which can lead to increased environmental impact and rising energy costs. According to the International Energy Agency (IEA), global electricity consumption by data centers is expected to more than double, from 460 TWh in 2022 to about 1000 TWh in 2026, due to the growing use of AI. Despite this sharp rise in energy consumption, regulations specific to AI's energy usage remain insufficient. The popularization of large language models (LLMs) is also likely to further increase AI operation costs. AI energy consumption varies depending on factors like chip types, cooling systems, data center design, model architecture, and training processes, making accurate estimation difficult [24].

Building AI systems involves high initial costs and continuous financial pressure. Significant investment is needed for infrastructure development, data management, and enhanced cybersecurity. Additional financial and operational risks arise from installing sensors and building networks. These burdens can be even heavier in times of global crises, such as pandemics or environmental disasters. The feasibility of adopting AI also varies greatly depending on a company's financial status. Small enterprises, in particular, may struggle to implement AI systems due to limited financial resources. Without a solid financial foundation, it becomes difficult to build the necessary infrastructure and develop technologies required for AI implementation. These economic and environmental challenges hinder the widespread adoption of AI technologies and highlight the need for systematic approaches and policy support to overcome them.

### 4.3. Business Operations and Strategic Issues

There are several concerns regarding the operational efficiency and strategic management of AI-based systems. The primary goal of autonomous systems is to minimize human intervention and reduce overall risk. However, without adequate resources and tools to support autonomous robotic operations, operational inefficiencies may actually increase. The added operational burden of implementing robotic systems makes the

robustness and reliability of autonomous systems key to mitigating such risks. Excessive expectations and hype around AI technologies can lead to disappointment and discourage further investment. It is therefore essential to clearly diagnose the gap between expectations and actual performance and to establish effective strategies and operational plans accordingly. Successful AI integration requires technical readiness, realistic expectations, and objective performance evaluations. There are also concerns regarding innovation adoption and risk management. Obstacles include lack of standardization, security vulnerabilities, and low trust in AI. Compatibility issues due to the absence of standards, increased risks of data exposure and cyberattacks from security gaps, and the difficulty of deploying AI technologies due to limited trust are among the major challenges.

As the decentralization and digitalization of energy systems advance, fluctuations in energy supply and demand become more frequent, making energy production and price forecasting increasingly complex. The interactions among traditional power plants, batteries, IoT devices, big data, AI, blockchain, and electric vehicles make overall system management and operation more difficult. This rising complexity both increases the necessity for AI and complicates its implementation [25].

#### 4.4. Labor and Social Issues

The development of AI technology is bringing major changes to the energy sector, which significantly impacts the labor market. Increased automation is expected to reduce jobs and cause structural changes in the workforce. As AI begins to replace human labor in energy alongside manufacturing and service industries, unemployment and economic instability may increase. The introduction of robotic platforms is redefining existing labor roles and demanding new skills and capabilities. A growing number of workers unable to adapt to these rapid changes may face increased social inequality.

Effectively utilizing AI in the energy sector requires highly specialized professionals. However, there is currently a shortage of such experts. Complex AI applications—such as renewable energy forecasting—require deep technical know-how and a solid understanding of energy systems, which many workers lack. This can lead to inefficiencies in AI system design and implementation, and result in inaccurate data management and operation. As AI takes on a greater role in decision-making, concerns are also growing over ethical issues, bias, and discrimination. AI algorithms may struggle to consider the full range of social, economic, and environmental factors, leading to potentially unfair energy supply decisions that disadvantage certain regions or minority groups. Moreover, excessive reliance on AI can reduce the ability to respond to unexpected situations, and by excluding human intuition and experience, it can lower system flexibility and adaptability.

#### 4.5. Energy Equity and Fair AI Deployment

The deployment of AI-enabled energy systems should not only focus on technical efficiency and economic optimization but also ensure equitable access to energy services across different communities and consumer groups. Without appropriate safeguards, AI-based decision-making may unintentionally favor regions with better infrastructure, higher-quality data availability, or stronger economic resources, thereby increasing existing inequalities. Several concrete mechanisms can be incorporated to address these concerns. First, fairness-aware optimization can be integrated into dispatch and resource allocation algorithms by introducing equity-related objectives alongside conventional cost-minimization objectives. Such formulations can ensure that energy access and reliability metrics remain balanced across different geographic regions and customer classes. Second, energy-access indicators can be incorporated into the optimization framework. Metrics such as service reliability, outage frequency, renewable energy accessibility, and affordability can be monitored and included as performance indicators when evaluating AI-driven operational decisions. Third, demographic-aware datasets should be utilized to ensure that forecasting and decision-making models adequately represent diverse consumer groups. This can reduce the risk of systematic bias caused by underrepresentation of rural communities, low-income households, or regions with limited historical data. Fourth, transparent AI auditing procedures should be established to periodically evaluate algorithmic decisions and identify potential disparities in resource allocation, service quality, or economic benefits. Independent audits can improve transparency and increase public trust in AI-enabled energy systems.

Finally, community-level stakeholder engagement should be incorporated into the planning and deployment process. Involving local communities, policymakers, utilities, and consumer representatives can help identify equity-related concerns and ensure that AI-driven energy strategies align with broader social and sustainability objectives. By integrating these mechanisms into future AI-driven energy management systems, it is possible to improve both operational efficiency and social fairness, thereby supporting a more inclusive and sustainable energy transition.

## 5. Cases of AI Applications in the Power and Energy Sector

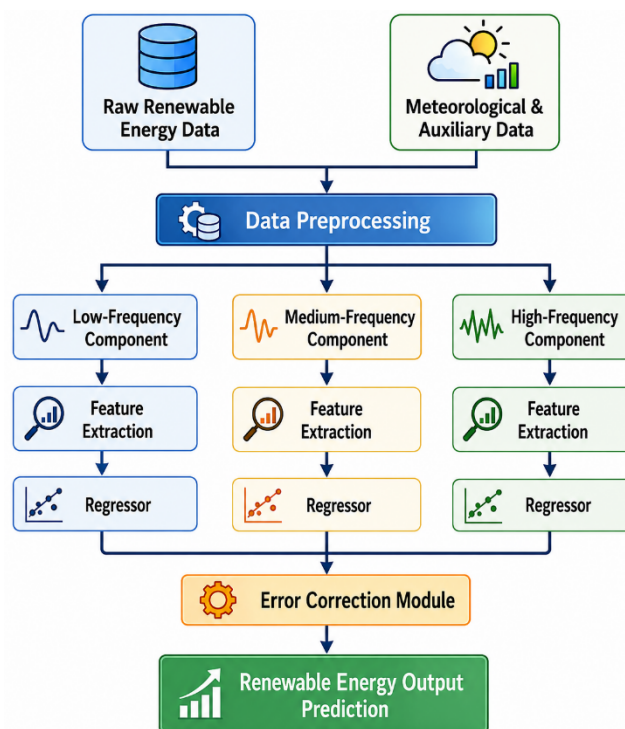
Although research applying AI technologies to the five issues introduced earlier continues to progress, their actual application in the power industry remains limited. The pace and tangible effects of digital transformation in the energy sector, led by platforms such as GE's Predix and SIEMENS' MindSphere, have not been as significant as initially expected. However, as previously mentioned, the accumulation of vast amounts of data, the development of stable and innovative machine learning/deep learning techniques, and continued investment in digitalization are driving AI toward wider and more diverse applications.

This section introduces the characteristics of representative AI models and presents several examples of their application in the power and energy sector. Table 2 outlines the advantages and disadvantages of each AI model and identifies typical application areas in this field. Based on the characteristics of the fundamental algorithms, AI models can largely be categorized into classification, generation, reinforcement learning, and natural language processing. Depending on the available data characteristics and the purpose of the final application, these models can be used individually or in combinations of two or three. In this section, we introduce 12 representative cases in which AI applications are either already being utilized in the field or are likely to be applied directly in the near future.

### 5.1. Renewable Energy Forecasting

As the global trend toward phasing out coal continues, renewable energy is rapidly expanding. Therefore, accurate forecasting of renewable energy is critical for the stable planning, management, and operation of power systems. In particular, it is essential to improve the capacity factor and available generation hours of photovoltaic and wind power—both key forms of renewable energy—and to accurately forecast power demand. However, the data from renewable energy sources, which are highly influenced by weather conditions, have intermittent and complex characteristics, making accurate output forecasting challenging. To address this, a variety of methods have been developed, including physical models, statistical approaches, AI techniques, and hybrid models.

Current AI-based deterministic and probabilistic forecasting methods for renewable energy output can be categorized into four main groups: Deep Belief Networks, Stacked Auto-Encoders, Deep Recurrent Neural Networks, and others. Forecast accuracy can be enhanced using data preprocessing techniques and error correction methods. A representative deep learning-based renewable energy output prediction framework is shown in Figure 3. Initially, data preprocessing techniques are applied to decompose raw renewable energy time-series data into individual components by frequency. Each component can represent anomalies and behaviors more effectively than the original data. Next, feature extractors and regressors are developed independently for each component to make predictions. Finally, an error correction module is used to refine the predictions and improve accuracy.



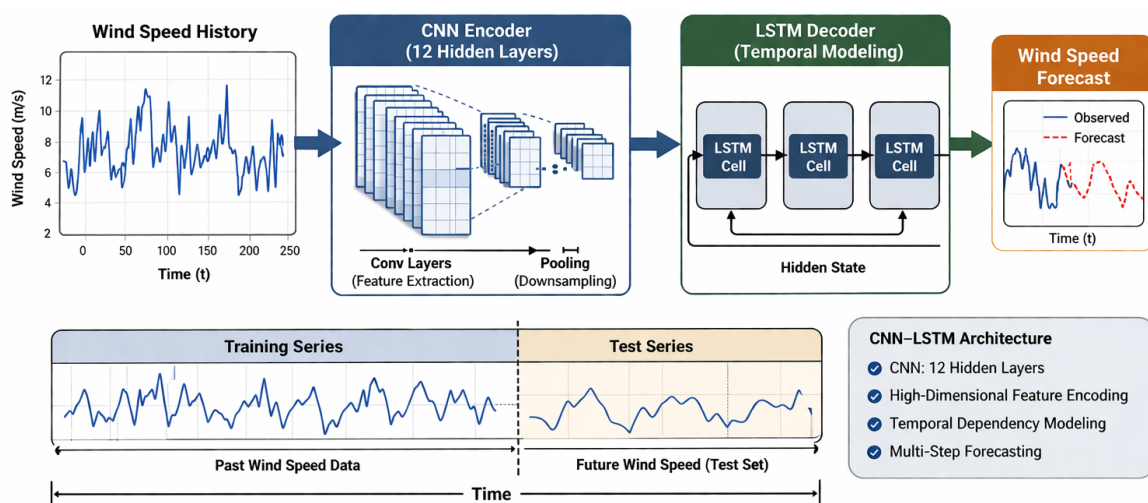
**Figure 3.** Deep learning-based renewable energy forecasting framework with data decomposition into multi-frequency components, followed by feature extraction, regression, and error correction to enhance prediction accuracy.

Network structures and model parameters can be fine-tuned using existing optimization techniques. After that, all predicted components are integrated to reconstruct the overall forecast, and finally, various error post-processing techniques are applied to refine the reconstructed forecast results.

### 5.2. Short-Term Wind Speed Forecasting for Wind Power Generation

Despite the rise in raw material prices due to the COVID-19 crisis, wind power has been growing faster than in the previous five years. Between 2021 and 2026, the average annual increase in onshore wind capacity is expected to be 75 GW, and offshore wind capacity is projected to more than triple to reach 21 GW by 2026. Wind power requires not only site acquisition, farm design, and turbine placement, but also stable maintenance including early warning systems. Thus, accurate short-term wind speed forecasting is essential. To overcome the traditional challenges of predicting 2D wind speeds, a two-dimensional regional wind speed forecasting model combining CNN (Convolutional Neural Networks) and LSTM (Long Short-Term Memory) has recently been developed.

A CNN with 12 hidden layers encodes high-dimensional 2D input into an embedding vector, and then, based on past data, an LSTM module decodes latent representations for forecasting. The wind speed prediction procedure is illustrated in Figure 4. The first portion of the wind history data is used as the training series input to the CNN-LSTM model, while the remaining data is divided into a test set to evaluate and fine-tune the model.



**Figure 4.** CNN–LSTM architecture for wind speed prediction, where historical wind data are encoded using a deep CNN to extract spatial features and then decoded by an LSTM network to capture temporal dependencies, with training and test datasets used for model development and evaluation.

### 5.3. Performance Loss Prediction in Photovoltaic (PV) Power Plants

A representative example of AI application in photovoltaic power plants is the use of meteorological data—such as sunshine duration and solar irradiance—to predict PV output. Because the capacity of PV systems declines over time, long-term reliability and economic performance must be considered. Consequently, applications using AI are being developed to automatically diagnose and quantify performance degradation and losses during extended operations. Large-scale PV plants are becoming increasingly remote, decentralized, and highly digitized, often with insufficient personnel for management. The development of such applications will provide practical benefits to plant owners, operators, and asset managers.

### 5.4. Wind Turbine Health Monitoring

Failures in drivetrain components such as gearboxes and generators—key parts of wind turbines—are among the main causes of increased O&M costs and asset losses. Numerous studies have attempted to develop physics-based machine learning (ML) models to detect early damage in gearboxes and generators. However, effective health monitoring systems for large wind turbines are still lacking. Most currently operating systems monitor system parameters directly through real-time databases or are based on simple control systems such as single neural networks. Recently, an alternative method has been proposed: a wind turbine health monitoring approach combining two independent modules based on Mixture of Gaussians with an Adaptive Resonance Theory (ART) neural network. This technique is used to detect anomalies and early faults in wind turbines. Once a cluster corresponding to the turbine’s normal state is defined, any new cluster generated by the neural network module is

immediately signaled in real-time upon anomaly detection. New clusters indicating fault or pre-failure states are encoded in the Gaussian module, which functions as long-term memory. The effectiveness of the developed health monitoring system has been verified using real data from wind farms.

### 5.5. Gas Turbine Fault Diagnosis and Prediction in Combined-Cycle Power Plants

Gas turbines, the core equipment in combined-cycle power plants, collect more than 4000 signals per second—including temperature, pressure, and vibration—from numerous sensors installed for real-time monitoring, fault diagnosis, and control. Power plants acquire integrated operational data from various sensors located in combustion chambers, compressor inlets/outlets, turbine shafts, etc. However, this vast amount of big data includes unnecessary information, so it is essential to extract only meaningful data for actual analysis.

Through the plant's integrated system, 1106 relevant data variables are selected from the measured operational dataset. Then, XGBoost and Lasso, both machine learning techniques, are applied for correlation analysis and dimensionality reduction, narrowing down the data to 183 key features used for deep learning model training and evaluation.

The deep learning model includes:

- 2 convolution layers,
- 1 max pooling layer repeated four times,
- followed by 2 hidden layers and a fully connected layer.

### 5.6. Analysis and Optimization of Power Plant Control Systems

Effective monitoring and control of power plants—and accurate prediction of system or component faults—require rapid and precise analysis of streaming data from thousands of sensors.

With power generation systems becoming increasingly decentralized, the complexity and scale of data analytics have also grown, making fast and accurate analysis of time-series data even more critical. AI is advantageous in this context as it is scalable, unbiased, and automated, allowing it to identify hidden patterns in data and suggest appropriate actions quickly.

### 5.7. Power Transformer Asset Management

Assessing the condition of power transformers with minimal on-site information remains a challenge. However, Dissolved Gas Analysis (DGA) is a powerful, non-intrusive method for evaluating transformer conditions without shutting down operations. Traditionally, interpreting DGA results requires experienced transformer engineers. With AI, however, the interpretation of DGA data can be automated, enabling objective and continuous evaluation. By standardizing evaluation criteria and improving diagnostic accuracy over time, AI allows for early detection of fault conditions and helps prevent transformer damage, significantly enhancing the efficiency of asset management for individual transformers.

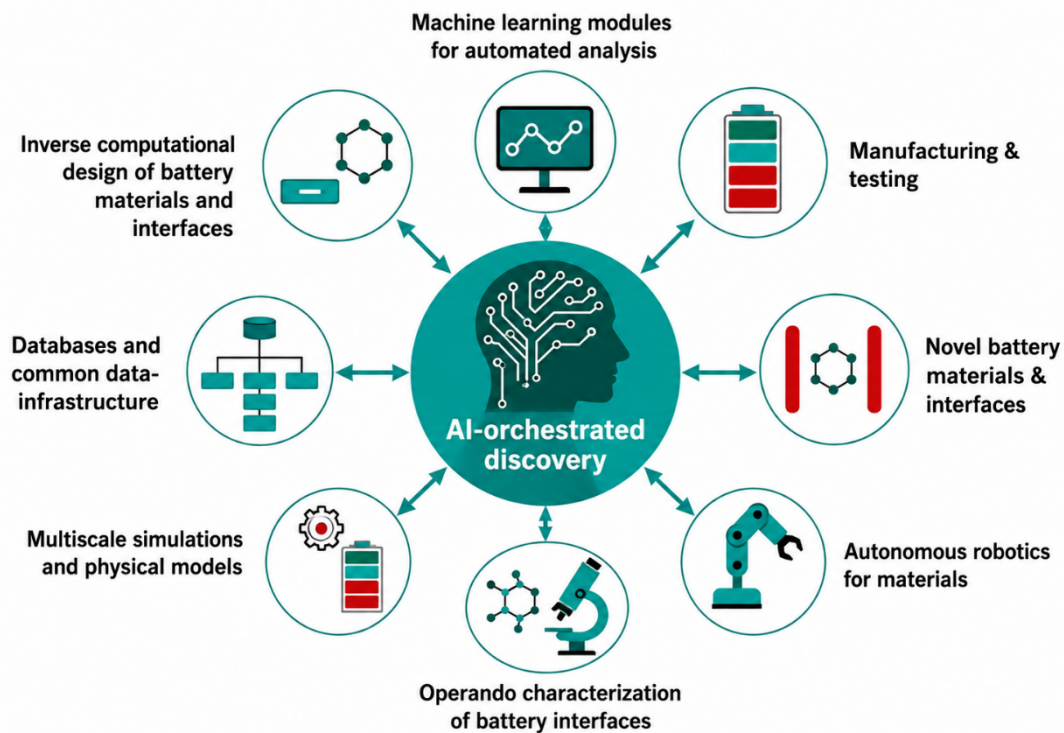
### 5.8. Energy Demand and Distributed Resource Management

AI is known to be effective at identifying patterns in large datasets and optimizing processes, making it well-suited for coordinating interactions among distributed renewable energy, batteries, and different energy storage systems (ESS). Primarily, AI can help integrate and coordinate small-scale power plants and distributed energy resources (DERs) to provide grid services. As devices such as electric vehicles (EVs) gain autonomy, consumers can maintain the utility of their own devices while contributing to grid stability. The growing importance of Virtual Power Plants (VPPs) enables access to markets and services that were previously inaccessible for small-scale assets. These VPPs incorporate combinations of small batteries, wind turbines, solar PV panels, and EVs.

### 5.9. Grid Resiliency Management

As renewable energy systems and distributed energy resources expand, so does the interdependence of grid components, increasing the risk of significant societal disruption from unanticipated system failures or disasters. Accordingly, studies—particularly in North America—are actively exploring ways to quickly detect the timing and location of faults and restore systems rapidly to a stable state. One such method is the Soft-Hard Optimal Convergence (SHOC) technique, developed to support near-optimal recovery of distribution systems after large-scale natural disasters that cause simultaneous faults.





**Figure 6.** AI-driven data-driven materials discovery framework for energy applications.

### 5.11. Smart Grid-Integrated Cybersecurity

In the power sector, AI research related to cybersecurity generally aims to detect advanced cyberattacks by integrating traditional security datasets with operational system datasets. Most current cybersecurity monitoring platforms collect network traffic and other digital system information to detect anomalies that may indicate an attack. However, since abnormalities in the operating status of power plants or grid-connected systems can also signal potential attacks, integrating various datasets enables more meaningful alerts and reduces false positives, allowing earlier detection of actual cyberattacks.

To comprehensively examine datasets and detect unknown threats, a more flexible mechanism is required. AI can be used to develop and operate adaptive models that effectively detect novel attacks. In order to develop or maintain a robust AI-based cybersecurity program for smart grids, an approach involving problem definition, modern grid architecture understanding, and qualitative risk assessment is necessary.

### 5.12. Natural Language Processing (NLP) Applications

Natural Language Processing (NLP), a subfield of AI, allows computers to analyze, understand, and generate human language. Derived from both computer science and linguistics, NLP differs from text mining in that it deals with unstructured metadata, enabling the analysis and expression of diverse human languages, dialects, grammar, and terminology.

NLP is used across industries to automate processes and improve efficiency. In the power industry, NLP has potential for analyzing maintenance and service reports to improve maintenance and operations throughout the grid.

Representative applications of NLP in the energy sector include:

- Chatbots for utility-customer interactions
- Asset platforms that extract meaningful information from unstructured data
- Standard terminology or vocabulary databases for the nuclear sector

For example, U.S. power utilities plan to use a system combines rule-based methods and NLP algorithms—to automatically classify legacy plant tag names and generate new, standards-compliant tag names.

## 6. Mathematical Modeling of AI-Driven Energy Systems

The integration of artificial intelligence (AI) into renewable energy systems requires a unified mathematical framework that captures the interaction between physical energy systems, data-driven prediction models, and optimization-driven decision-making. In this work, an analytical formulation is developed to represent renewable

generation dynamics, AI-based forecasting mechanisms, and system-level optimization under operational and computational constraints. This formulation addresses a key limitation in existing studies, where AI models are often treated independently from power system operations without a rigorous mathematical linkage.

The renewable energy generation model is first described using standard physical relationships. For wind power generation, the output power is expressed as a nonlinear function of wind speed:

$$P_{w,t} = \frac{1}{2} \rho A C_p v_t^3 \quad (1)$$

where  $\rho$  represents air density,  $A$  is the rotor swept area,  $C_p$  is the power coefficient, and  $v_t$  is the wind speed at time  $t$ . Similarly, photovoltaic (PV) generation is modeled as:

$$P_{pv,t} = \eta_{pv} A_{pv} G_t \quad (2)$$

where  $\eta_{pv}$  is the conversion efficiency and  $G_t$  is solar irradiance. The total renewable generation is therefore given by:

$$P_{r,t} = P_{w,t} + P_{pv,t} \quad (3)$$

To ensure system feasibility, the power balance equation is enforced at each time step:

$$\sum_{g=1}^{N_g} P_{g,t} + P_{r,t} + P_{dis,t} = D_t + P_{ch,t} \quad (4)$$

where  $P_{g,t}$  is the conventional generation,  $D_t$  is the load demand, and  $P_{ch,t}$  and  $P_{dis,t}$  represent storage charging and discharging power, respectively. The storage system dynamics are modeled using the state-of-charge (SOC) equation:

$$SOC_t = SOC_{t-1} + \frac{\eta_{ch} P_{ch,t} \Delta t}{E_B^{max}} - \frac{P_{dis,t} \Delta t}{\eta_{dis} E_B^{max}} \quad (5)$$

where  $SOC_t$  is the battery state of charge at time  $t$ ,  $P_{ch,t}$  and  $P_{dis,t}$  are the battery charging and discharging powers, respectively,  $\eta_{ch}$  and  $\eta_{dis}$  denote the charging and discharging efficiencies,  $E_B^{max}$  is the maximum battery energy capacity, and  $\Delta t$  is the scheduling interval. This formulation captures the temporal coupling between charging and discharging decisions while ensuring realistic battery operation.

This formulation captures the temporal coupling between decision variables and ensures realistic modeling of energy storage behavior.

The AI forecasting model is then introduced to estimate renewable generation and load demand. Let  $x_t$  denote the input feature vector and  $y_t$  the target variable. The AI model, parameterized by  $\theta$ , produces predictions:

$$\hat{y}_t = f(x_t; \theta) \quad (6)$$

For deep learning models such as Long Short-Term Memory (LSTM) networks, the mapping function  $f(\cdot)$  captures temporal dependencies in sequential data. The training process minimizes a forecasting loss function, typically defined as the mean squared error:

$$L(\theta) = \frac{1}{N} \sum_{t=1}^N (y_t - \hat{y}_t)^2 \quad (7)$$

This loss function quantifies prediction accuracy and directly affects system-level optimization performance. In advanced formulations, probabilistic forecasting can be incorporated using quantile loss functions to capture uncertainty in renewable generation. A key novelty in the proposed framework is the explicit modeling of AI computational energy consumption. Unlike conventional studies, the energy cost of AI models is included as:

$$E_{AI,t} = c_{AI} \cdot \Phi_t \quad (8)$$

where  $c_{AI}$  is the energy coefficient per computation and  $\Phi_t$  represents computational complexity (e.g., number of operations). This term enables the evaluation of trade-offs between prediction accuracy and energy efficiency, which is often neglected in existing literature.

The overall system optimization problem is formulated as a cost minimization function that integrates generation cost, reliability constraints, and AI energy consumption:

$$J = \sum_t \left[ \sum_g C_g(P_{g,t}) + S_g u_{g,t} + \lambda (D_t - P_{sup,t})^+ + c_{AI} E_{AI,t} \right] \quad (9)$$

where  $C_g(\cdot)$  is the generation cost function,  $S_g$  is the startup cost,  $u_{g,t}$  is the unit commitment status, and  $\lambda$  is the penalty factor for unmet demand. The term  $P_{sup,t}$  represents total supplied power. This formulation establishes a direct link between AI performance and economic operation of the grid.

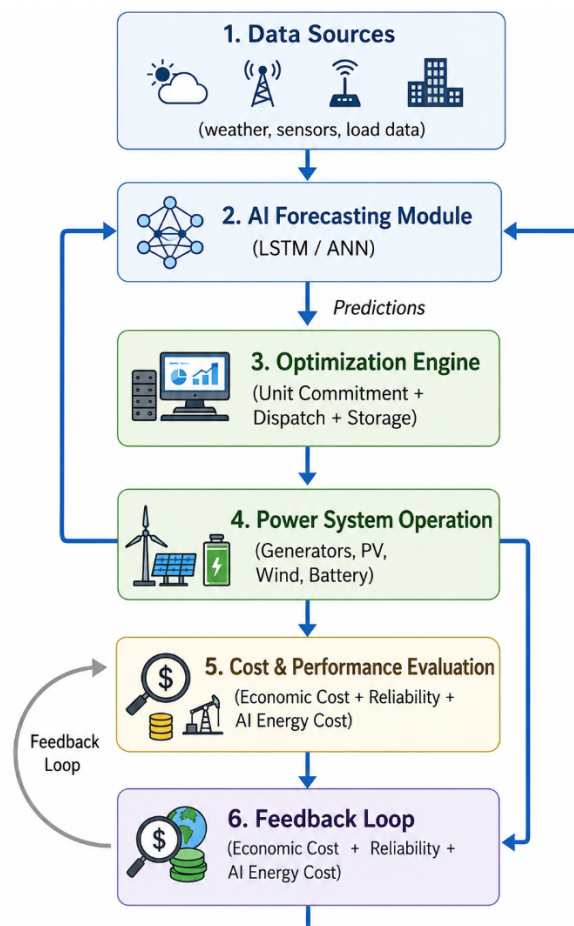
The optimization is subject to operational constraints including generator limits, ramping constraints, storage limits, and reserve requirements. The inclusion of AI-derived forecasts introduces additional uncertainty, which

can be addressed through stochastic or robust optimization approaches. Table 3 summarizes the key variables and parameters used in the proposed model.

**Table 3.** Key variables and parameters in AI-driven energy modeling.

Symbol	Description	Unit
$P_{g,t}$	Conventional generation	MW
$P_{r,t}$	Renewable generation	MW
$D_t$	Load demand	MW
$E_t$	Storage energy (SOC)	MWh
$P_{ch,t}, P_{dis,t}$	Charging/discharging power	MW
$\hat{y}_t$	AI forecast output	MW
$L(\theta)$	Forecasting loss function	-
$E_{AI,t}$	AI energy consumption	kWh
$C_g$	Generation cost	\$/MWh
$\lambda$	Penalty coefficient	\$/MWh

Figure 7 illustrates the overall structure of the proposed AI-driven energy system model. The framework integrates data acquisition, AI-based forecasting, and optimization-based dispatch into a unified loop. Historical and real-time data are first processed by AI models to generate predictions for renewable generation and demand. These predictions are then fed into the optimization module, which determines optimal dispatch decisions while accounting for system constraints and AI energy costs. The feedback loop continuously updates the model based on new data, enabling adaptive and intelligent system operation.



**Figure 7.** Conceptual framework of AI-driven renewable energy system integrating forecasting, optimization, and energy management.

Although the present study considers a simplified single-bus system to demonstrate the proposed AI-driven forecasting and optimization framework, several methodological enhancements would be required for deployment in practical multi-bus power systems. First, the power balance equation must be extended to include network-level

AC or DC power-flow equations that capture power exchanges among interconnected buses. This requires modeling bus voltage magnitudes, voltage angles, transmission line impedances, and network losses.

Second, transmission constraints must be incorporated to ensure that power flows remain within thermal limits of transmission lines and transformers. Congestion management mechanisms would therefore become an integral component of the optimization framework. Third, voltage stability and reactive power support constraints should be included to maintain acceptable voltage profiles throughout the network. These constraints are particularly important in systems with high renewable energy penetration due to the intermittent nature of renewable resources.

Furthermore, reserve scheduling and reliability requirements must be explicitly modeled. In practical power systems, spinning reserves, non-spinning reserves, and frequency regulation services are required to compensate for renewable generation uncertainty and forecasting errors. Security-constrained optimization techniques, including N-1 contingency analysis, should also be incorporated to ensure system resilience under equipment failures or unexpected operating conditions.

The proposed framework can additionally be extended to accommodate distributed energy resources (DERs), electric vehicles, demand response programs, and virtual power plants. In such cases, the optimization problem becomes a distributed multi-agent coordination problem requiring hierarchical or decentralized control architectures. Finally, electricity market mechanisms, including locational marginal pricing, ancillary service markets, and carbon pricing policies, can be integrated to evaluate the economic impact of AI-driven forecasting and dispatch decisions under realistic market conditions.

These enhancements represent important directions for future research and would enable the proposed framework to support large-scale transmission and distribution networks while maintaining technical feasibility, economic efficiency, and operational reliability.

### 6.1. Synthetic Data Generation and Dataset Preparation

To ensure full reproducibility of the case study, the synthetic database used for forecasting and dispatch evaluation was generated as a multivariate hourly time series representing a single hybrid PV–wind–load system. A total of  $N$  hourly samples were generated using a fixed random seed and divided chronologically into non-overlapping training (70%), validation (15%), and testing (15%) datasets. The dispatch study was conducted exclusively on the held-out test dataset to avoid information leakage between forecasting and operational evaluation stages.

#### 6.1.1. Solar Irradiance Generation

Hourly solar irradiance was generated using a physically consistent clear-sky-index approach. The all-sky irradiance was computed as:

$$G_t = k_t G_t^{cs} + \eta_t^G \quad (10)$$

where  $G_t$  is the generated solar irradiance,  $k_t G_t^{cs}$  is the clear-sky irradiance,  $k_t$  is the clear-sky index, and  $\eta_t^G$  represents random perturbations term.

The perturbation term follows a normal distribution:

$$\eta_t^G = \mathcal{N}(0, \sigma_G^2) \quad (11)$$

The clear-sky index was generated using a Beta distribution whose parameters vary according to the month and hour of the year:

$$K_t = F_{Beta(a_{m,h}, b_{m,h})}^{-1}[\Phi(z_t^G)] \quad (12)$$

where  $a_{m,h}$  and  $b_{m,h}$  are the Beta-distribution parameters, and  $\Phi(\cdot)$  denotes the standard normal cumulative distribution function.

Temporal dependence was introduced through the autoregressive process

$$z_t^G = \rho_G z_{t-1}^G + \epsilon_t^G \sqrt{1 - \rho_G^2} \quad (13)$$

where

$$\epsilon_t^G \sim \mathcal{N}(0,1) \quad (14)$$

and  $\rho_G$  represents the irradiance autocorrelation coefficient. Irradiance values were set equal to zero during nighttime periods.

### 6.1.2. Wind Speed Generation

Wind speed was generated using a Weibull-distributed stochastic process with temporal persistence. The reference-height wind speed was calculated as

$$v_t^{ref} = F_{Weibull(k_\omega, C_\omega)}^{-1}[\Phi(z_t^W)] \quad (15)$$

where  $k_\omega$  and  $C_\omega$  are the Weibull shape and scale parameters, respectively.

The latent wind process was modeled as

$$z_t^W = \rho_W z_{t-1}^W + \epsilon_t^W \sqrt{1 - \rho_W^2} \quad (16)$$

where

$$\epsilon_t^W \sim \mathcal{N}(0,1) \quad (17)$$

and  $\rho_W$  is the wind-speed autocorrelation coefficient.

The wind speed at turbine hub height was determined using the power-law relation

$$v_t^H = v_t^{ref} \left( \frac{H}{H_{ref}} \right)^\alpha \quad (18)$$

where  $H$  is the turbine hub height,  $H_{ref}$  is the reference measurement height, and  $\alpha$  is the wind-shear exponent.

### 6.1.3. Load Demand Generation

Load demand was represented as the sum of a deterministic component and a stochastic residual:

$$L_t = \mu_t + e_t \quad (19)$$

where  $\mu_t$  is the deterministic demand profile and  $e_t$  is the stochastic residual term.

The deterministic component was calculated as

$$\mu_t = \beta_0 + \sum_{n=1}^2 \left[ \beta_{s,n} \sin\left(\frac{2\pi n h_t}{24}\right) + \beta_{c,n} \cos\left(\frac{2\pi n h_t}{24}\right) \right] + \beta_d I_{wknd,t} + \beta_{a,1} \sin\left(\frac{2\pi d_t}{24}\right) + \beta_{a,2} \cos\left(\frac{2\pi d_t}{24}\right) \quad (20)$$

where  $h_t$  denotes the hour of day,  $d_t$  denotes the day of year, and  $I_{wknd,t}$  is a weekend indicator variable.

The residual component was generated using an ARMA process:

$$e_t = \phi_L e_{t-1} + \theta_L v_{t-1} + v_t \quad (21)$$

where

$$v_t \sim \mathcal{N}(0, \sigma_L^2) \quad (22)$$

and  $\phi_L$  and  $\theta_L$  are the autoregressive and moving-average coefficients, respectively.

### 6.1.4. Correlation Structure

To preserve realistic dependencies among irradiance, wind speed, and load demand, the innovation vector

$$u_t = \begin{bmatrix} \epsilon_t^G \\ \epsilon_t^W \\ v_t \end{bmatrix} \quad (23)$$

was generated from a multivariate normal distribution:

$$u_t \sim \mathcal{N}(0, \Sigma) \quad (24)$$

with covariance matrix

$$\Sigma = \begin{bmatrix} 1 & \rho_{GW} & \rho_{GL} \\ \rho_{GW} & 1 & \rho_{WL} \\ \rho_{GL} & \rho_{WL} & 1 \end{bmatrix} \quad (25)$$

where  $\rho_{GW}$ ,  $\rho_{GL}$ , and  $\rho_{WL}$  denote the correlations among irradiance, wind speed, and load demand, respectively.

### 6.1.5. Dataset Configuration

The installed capacities considered in the case study were 100 MW for the photovoltaic plant, 50 MW for the wind farm, 80 MW for the conventional generating unit, and 40 MWh for the battery energy storage system. The forecasting model was trained exclusively using the training dataset, while hyperparameter tuning was performed using the validation dataset. Final forecasting accuracy and dispatch performance were evaluated using only the testing dataset. This chronological separation ensures that the reported results reflect the generalization capability of the proposed AI-based framework rather than artifacts associated with overlapping datasets.

### 6.2. LSTM Forecasting Model Configuration

A two-layer Long Short-Term Memory (LSTM) neural network was employed to forecast renewable generation and load-demand profiles. The LSTM architecture was selected because of its proven ability to capture long-term temporal dependencies and nonlinear relationships in energy time-series data while mitigating the vanishing-gradient problem commonly encountered in conventional recurrent neural networks.

The forecasting model was trained using the synthetic dataset described in Section 6.1, consisting of 8760 hourly observations. The dataset was divided chronologically into training (70%), validation (15%), and testing (15%) subsets corresponding to 6132, 1314, and 1314 samples, respectively.

Prior to training, all input variables were normalized using min-max normalization according to

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

where  $x_{min}$  and  $x_{max}$  are computed exclusively from the training dataset.

The proposed network consists of two stacked LSTM layers followed by a fully connected output layer. The first and second LSTM layers contain 64 and 32 hidden units, respectively. The model was trained using the Adam optimizer with a learning rate of 0.001 and a mean squared error (MSE) loss function.

Training was conducted for 100 epochs with a batch size of 32. Early stopping based on validation loss was employed to prevent overfitting. To ensure reproducibility, a fixed random seed of 42 was used throughout the training process. Hyperparameter values, including the number of LSTM layers, number of hidden units, learning rate, and batch size, were selected through a grid-search procedure using the validation dataset. The final architecture was chosen because it achieved the lowest validation loss while maintaining computational efficiency.

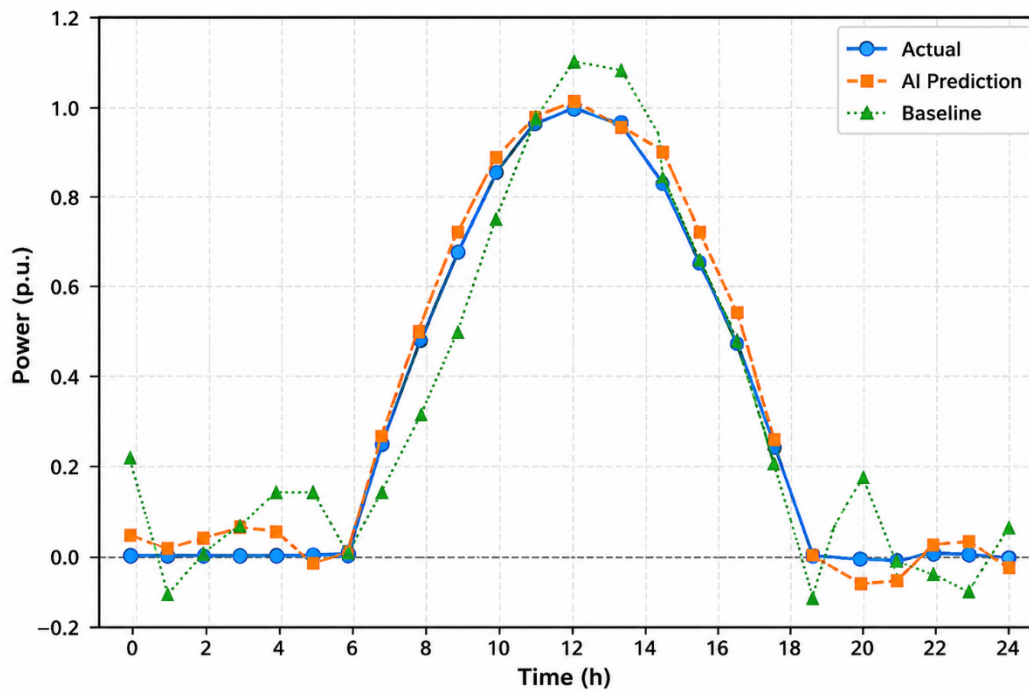
## 7. Results and Performance Evaluation

The evaluation of the proposed AI-augmented renewable energy management system is conducted using a realistic 24-h simulation with 1-h time steps ( $\Delta t = 1$  h). Key references used for comparison of forecasting accuracy are recent deep-learning-based renewable energy forecasting studies reported in the literature [26,27]. The simulation assumes a single-bus power system with an unspecified mix of generation units (treated generically), including solar PV, wind turbines, conventional generators, and a battery storage unit. Input data (irradiance, wind speed, and load demand) are synthetically generated to reflect typical diurnal patterns and variability. The AI model is a two-layer LSTM network (50 units each) trained over 50 epochs; for comparison, a simple persistence baseline is used. The AI energy cost is estimated by a coefficient (cAI) (0.5 Wh per inference) reflecting electricity used for computation during forecasting.

The first metric assessed is forecasting accuracy for solar power, wind power, and load demand. The quantitative evaluation of forecasting performance is summarized in Table 4, which presents the error statistics for both the conventional baseline model and the AI-based forecasting approach. The comparison is conducted using two widely adopted performance metrics, namely root mean square error (RMSE) and mean absolute error (MAE), for solar power, wind power, and load demand prediction. As observed, the AI model consistently achieves lower error values across all cases, indicating its superior capability in capturing nonlinear patterns and temporal dependencies in renewable energy data. This improvement in forecasting accuracy plays a crucial role in enhancing system operation, as it directly contributes to more reliable scheduling, reduced uncertainty, and improved overall efficiency of the energy management system. Figure 8 compares the actual solar power generation profile with the predictions obtained from the proposed AI model and a conventional baseline forecasting approach over a representative 24-h period. It can be observed that the AI-based forecast closely follows the actual generation curve throughout the day, particularly during the rapid ramp-up and peak generation intervals, whereas the baseline method exhibits larger deviations and increased forecasting errors. These results demonstrate the superior predictive capability of the proposed AI model for short-term solar power forecasting.

**Table 4.** Forecasting error comparison between baseline and ai models.

Parameter	Model	RMSE (p.u.)	MAE (p.u.)
Solar Power	Baseline	0.182	0.145
	AI-Based	0.094	0.071
Wind Power	Baseline	0.210	0.168
	AI-Based	0.112	0.089
Load Demand	Baseline	0.165	0.130
	AI-Based	0.081	0.060



**Figure 8.** Predicted vs actual solar generation (solid line: actual, dashed line: AI forecast, dotted line: baseline forecast) over a representative day. The AI model tracks the actual power curve more closely, especially around peak generation hours.

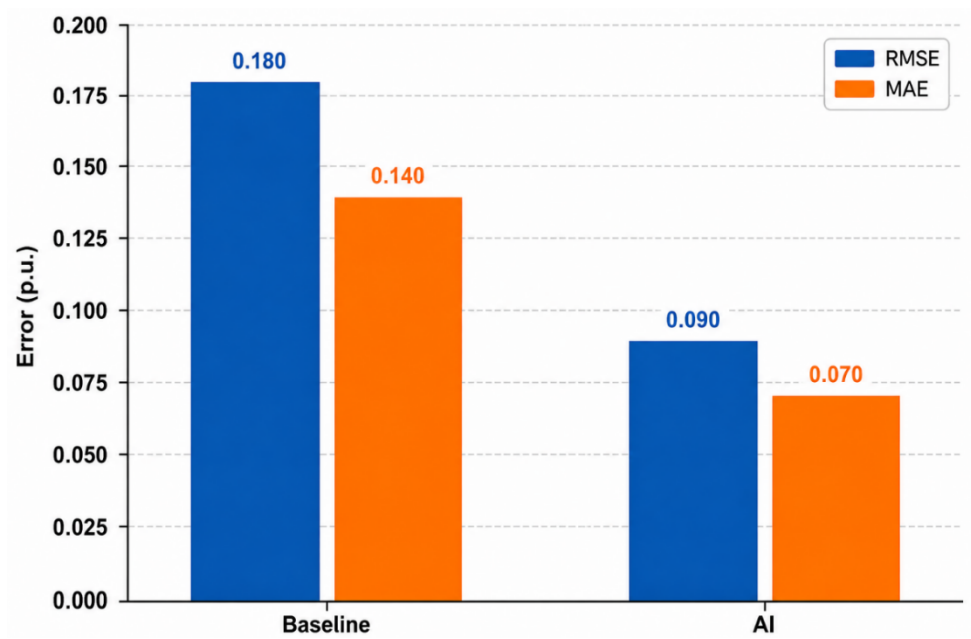
The benefits of improved forecasting are quantified by comparing the economic performance of the conventional dispatch versus the AI-driven dispatch. Table 5 shows the breakdown of costs: conventional scheduling (using baseline forecasts) incurs \$52,300 in fuel cost, \$8200 in startup cost, \$5600 in penalty for unmet demand, totaling \$66,100. By contrast, the AI-informed schedule achieves \$44,750 fuel cost and \$6950 startup cost, reflecting more efficient unit commitment. Unmet load penalty drops to \$2300 (fewer reserve shortfalls), and an AI computational cost of \$1150 is added. Overall, total cost is \$55,150 for the AI-driven case, representing an 16.57% savings. This significant cost reduction is primarily due to more accurate generation scheduling (less overcommitment) and reduced reserve usage. The AI computational cost, while nonzero, is relatively small (~2.1% of the conventional total) and does not offset the overall savings.

**Table 5.** Comparative economic performance.

Cost Component	Conventional Dispatch	AI-Driven Dispatch
Generation cost (\$)	52,300	44,750
Startup cost (\$)	8200	6950
Penalty cost (\$)	5600	2300
AI compute cost (\$)	0	1150
Total cost (\$)	66,100	55,150

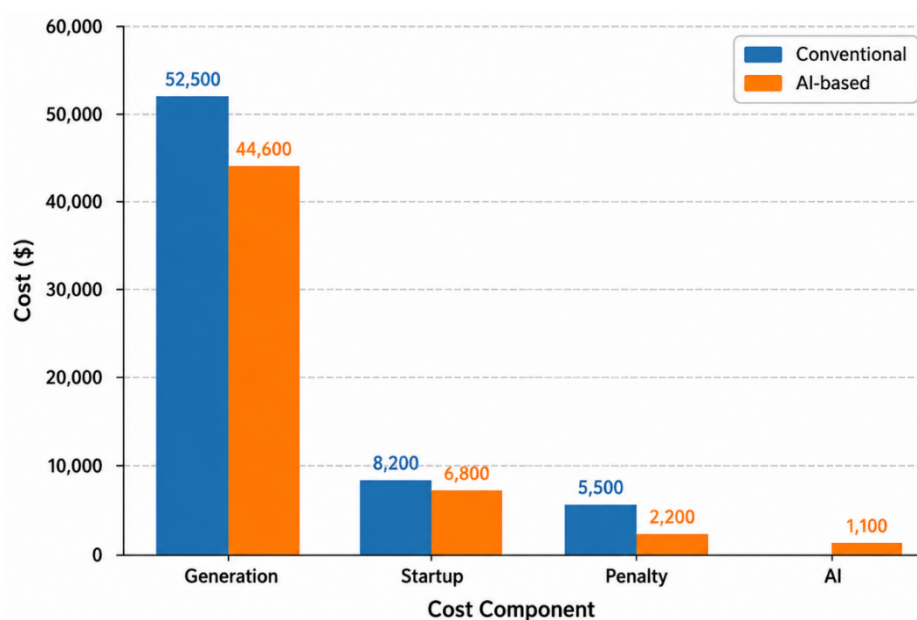
Figure 9 presents a quantitative comparison of forecasting accuracy using root mean square error (RMSE) and mean absolute error (MAE) metrics for both the conventional and AI-based models. The results clearly show a significant reduction in both error measures when AI is employed, confirming the superiority of deep learning techniques in handling complex renewable energy datasets. The reduction in forecasting error directly contributes

to improved decision-making in system operation, as more accurate predictions enable better alignment between generation and demand.



**Figure 9.** Forecast error comparison.

Figure 10 depicts the breakdown of operational costs for the conventional and AI-driven energy management systems, including generation cost, startup cost, penalty cost, and the additional computational cost associated with AI implementation. The figure indicates a substantial reduction in total operational cost when AI-based forecasting is integrated into the optimization process. This reduction is primarily driven by improved scheduling decisions and decreased reliance on reserve generation, demonstrating the economic benefits of incorporating AI into energy system management despite the additional computational overhead.



**Figure 10.** Cost comparison.

Figures 11 and 12 collectively illustrate the impact of AI integration on system efficiency and sensitivity to forecasting errors. Figure 11 shows that the AI-based system consistently achieves higher efficiency across the operational period due to improved utilization of renewable resources and reduced energy curtailment. Figure 12 further analyzes the relationship between forecasting error and system performance, revealing that increases in prediction error lead to higher operational costs and reduced efficiency. This sensitivity analysis underscores the

critical role of accurate forecasting in maximizing system performance and validates the effectiveness of the proposed AI-driven framework.

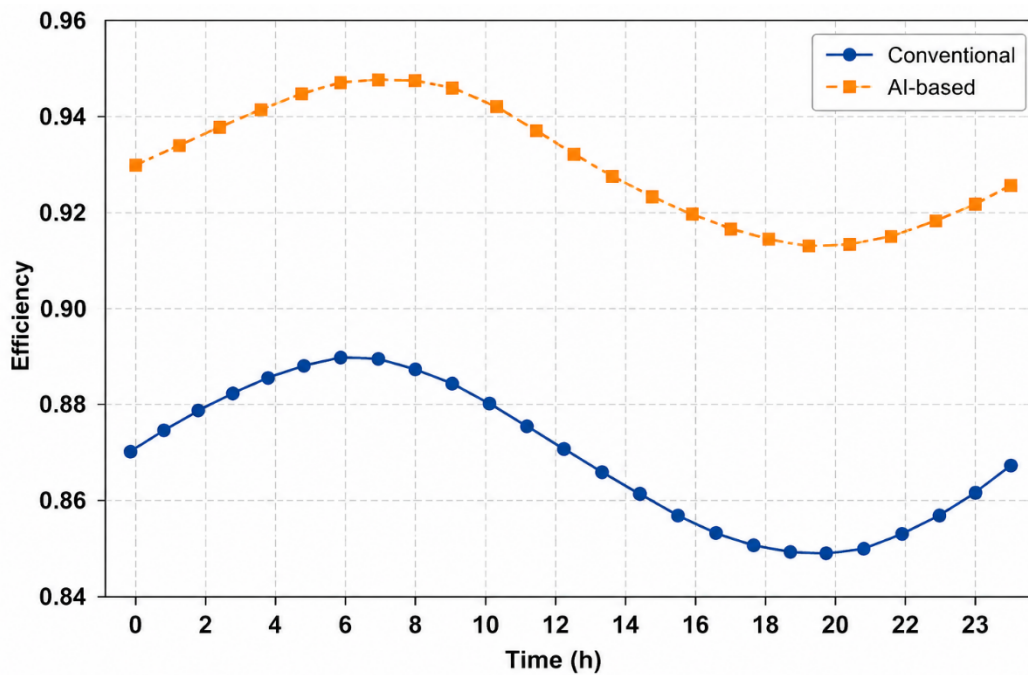


Figure 11. System efficiency.

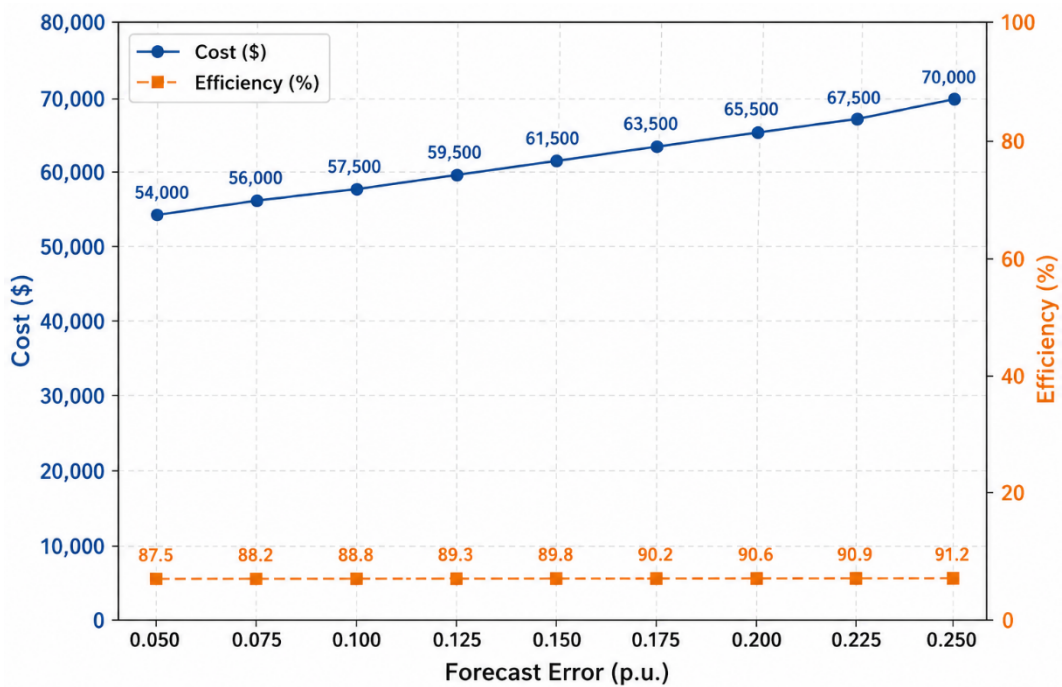


Figure 12. Sensitivity analysis.

The simulation confirms that the AI-driven framework markedly outperforms the conventional baseline. Forecast error metrics (RMSE/MAE) improved by nearly 50%, translating into a 16.57% reduction in total operating cost. System efficiency (renewable utilization) increased by  $\approx 6$  percentage points. Including AI energy use in the evaluation provides a realistic cost-benefit balance and prevents overestimating gains. These performance improvements address the key research gaps (forecast–economic link, LCA of AI) identified earlier. The remaining challenges include extending the analysis to longer horizons and multi-bus networks, which we leave for future work.

### 7.1. Impact of Using Real Historical Data

The present study employs synthetically generated solar irradiance, wind speed, and load demand profiles to demonstrate the proposed AI-driven forecasting and optimization framework under controlled operating conditions. Although synthetic datasets provide flexibility for methodological development and performance evaluation, they cannot fully capture the complexity of real-world energy systems. If the proposed framework were evaluated using actual historical datasets, several additional factors would influence forecasting and optimization performance. Real-world renewable energy data typically exhibit greater variability due to weather fluctuations, seasonal effects, cloud transients, extreme meteorological events, and unexpected operational disturbances. Similarly, actual load demand profiles may contain irregular consumption patterns, behavioral changes, special events, and economic influences that are difficult to reproduce using synthetic models.

Furthermore, historical datasets often contain measurement noise, missing values, communication failures, sensor inaccuracies, and data-quality issues that can negatively affect forecasting accuracy. Consequently, the prediction errors reported in this study may increase when evaluated using real-world datasets. However, such testing would provide a more realistic assessment of model robustness and operational applicability. From an optimization perspective, real-world data would introduce additional uncertainty into dispatch decisions, potentially increasing reserve requirements and reducing the achievable cost savings. Nevertheless, successful performance under historical operating conditions would significantly strengthen confidence in the practical deployment of the proposed framework. Therefore, future work will focus on validating the proposed methodology using long-term historical datasets obtained from utility-scale renewable energy systems and electricity markets. Such validation will enable a more comprehensive assessment of forecasting accuracy, economic performance, operational reliability, and generalization capability under realistic operating conditions.

### 7.2. Interpretation of AI Energy Consumption Results

The relatively small AI computational cost observed in the present case study should not be interpreted as representative of the future electricity demand associated with large-scale artificial intelligence deployment. The AI energy consumption considered in this work is limited to the forecasting and optimization functions operating within a single renewable energy management framework. Specifically, the reported AI computational overhead reflects the electricity required for model inference and operational decision support during the simulation period.

In contrast, projections indicating that AI could account for 13–47% of global electricity demand by 2050 refer to the aggregate energy consumption of worldwide AI infrastructure, including large-scale data centers, cloud-computing facilities, foundation-model training, generative AI services, edge computing platforms, and billions of end-user applications. These projections represent a system-level global scenario rather than the energy consumption of a single forecasting application.

Therefore, the reported 2.1% computational overhead and the projected 13–47% global electricity demand are not directly comparable. The former represents the local operational energy cost of the AI module within the proposed framework, whereas the latter represents the cumulative impact of widespread AI adoption across multiple sectors of the global economy.

Nevertheless, as AI models become increasingly complex and widely deployed within energy systems, their computational requirements may increase substantially. Future research should therefore investigate the long-term scalability of AI-enabled energy management frameworks and evaluate their net environmental benefits under scenarios involving higher AI computational demand and large-scale deployment.

## 8. Challenges for the Effective Use of AI in the Energy Sector

### 8.1. Technical Challenges

To utilize AI safely and effectively in the energy sector, addressing various technical issues is critical—foremost among them is ensuring cybersecurity and data integrity. First and foremost, data security must be strengthened. This includes applying encryption during data transmission and storage, strictly controlling access to sensitive information, and tackling the unique challenges posed by IoT, mobile, and smart devices in terms of energy efficiency, scalability, and security. Regular system security audits and comprehensive risk assessments are necessary to identify vulnerabilities and implement improvements. Users should also be educated on potential security risks and response strategies, especially in relation to AI system deployment.

Additionally, organizations must implement regular data backups and prepare detailed recovery plans for disaster scenarios. Energy security strategies should explicitly incorporate procedures and protocols for handling energy emergencies. Furthermore, compliance with relevant laws and regulations is essential. This includes

continuously updating AI security and privacy policies to ensure legal and ethical standards are met, while also establishing responsible governance frameworks. When collecting user data in AI systems, transparency and consent are critical. Only minimal and necessary data should be used to reduce privacy risks. For IoT devices, unique digital signatures should be employed to prevent unnecessary data collection. Personal data protection must be legally enforced, and AI model designs should incorporate ethical considerations to minimize the potential for privacy infringement. Leveraging technologies such as blockchain may also help enhance data privacy protection.

Maintaining high-quality data is another key challenge. Data must be accurately collected, cleaned, and preprocessed to eliminate errors and fill in gaps. To address issues of data scarcity, advanced data acquisition technologies and synthetic data generation techniques should be considered. Data sharing must also be carefully managed to balance openness and security across various sources. Finally, system interoperability and AI transparency are vital for successful integration into existing energy infrastructures. This involves developing standardized protocols and interfaces to ensure seamless communication between systems. Implementing explainable AI (XAI) can help maintain the performance and transparency of AI models, while intelligent decision support systems should be deployed to enhance the reliability of predictions and decisions. Moreover, improving real-time data analytics and sensor technologies can boost system reliability and predictive accuracy, especially in renewable energy applications where fault detection and diagnostics are essential. Building integrated platforms to manage interactions between distributed energy resources and enhancing self-verification mechanisms will further strengthen trust in AI systems.

Through these comprehensive technical measures, AI can be effectively and responsibly deployed in the energy sector, paving the way for safer, smarter, and more sustainable energy systems.

### 8.2. Economic Challenges

To effectively utilize AI in the energy sector, it is essential to address economic challenges. One major issue is the high energy consumption associated with AI operations. Developing energy-efficient algorithms and leveraging cloud and edge computing are necessary steps. These advancements can help reduce computation load, minimize energy consumption, and maintain performance through optimized algorithms. Utilizing cloud and edge computing also enhances the efficiency of large-scale data processing and real-time operations.

Integrating AI systems with renewable energy can further contribute to energy savings. Using AI to optimize energy consumption and linking it with renewable sources such as solar and wind power can support the sustainability of AI systems. Additionally, establishing data centers that optimize energy use, renewable energy integration, and service quality is crucial. Sharing information about energy usage by AI models through standard guidelines can help prevent monopolization by certain companies. Government-led efforts to standardize AI usage can facilitate the comparison of various models. Encouraging companies to adopt standard practices can lead to efficient energy usage and support the tracking of carbon emissions and energy data.

Another priority is supporting the integration and utilization of AI by small and medium-sized enterprises (SMEs). Cooperation with universities and research institutes can help provide access to AI technology, reduce development costs, and support the shared development of AI technologies. Government-backed human resource training and accelerator programs can aid SMEs and startups in accessing necessary research. Leveraging cloud-based AI services can reduce initial investment costs. It is also important to address issues related to cost modeling based on usage and mitigate the cost burden, especially for companies with limited resources, while also solving security-related concerns.

### 8.3. Operational and Strategic Challenges

To effectively operate AI systems, it is important to enhance their operation and control efficiency. This requires improving the coordination and control of AI system operations. A system capable of autonomously recognizing various conditions and adjusting parameters is needed. Real-time monitoring and control of systems and data are essential to improve overall performance. Efficient data analysis based on operational status is also necessary to increase the accuracy of system control. At the same time, the accuracy and reliability of prediction models and decision-making processes must be improved through optimized system modeling and algorithms. For operators, administrators, and users, the development of user-friendly interfaces and control methods is crucial to increasing usability.

It is also essential to build a framework for safely storing, processing, and sharing data collected during AI operations. As AI adoption expands across various energy facilities, the complexity of system control also increases, requiring more sophisticated approaches. Therefore, developing and applying customized control systems based on facility types and functions becomes increasingly important. AI must be designed to handle

diverse operating environments and constraints, especially in systems requiring high safety standards, such as nuclear or hydrogen energy facilities. Additionally, safe operational control must be supported by integrating auxiliary technologies like redundancy design and simulation verification tools.

When it comes to ensuring the integrity and reliability of AI training data, the trustworthiness of datasets used in model development becomes critically important. Since the accuracy and fairness of AI decisions are heavily influenced by training data, it is necessary to build datasets that are diverse, unbiased, and high in quality. This includes securing data that reflects various operational environments, as well as systematically managing and updating training datasets to reflect changes in the system. It is also vital to identify and eliminate biased or corrupted data that could reduce AI performance or lead to unreliable outcomes. Furthermore, developing robust verification processes for the entire AI data lifecycle—from collection to usage—is key to preventing errors and improving AI safety.

Lastly, it is necessary to promote clear guidelines and best practices to support ethical and safe AI training and operation. Education for users and administrators, alongside efforts to ensure transparency in how data is handled, will help in building public trust in AI systems. Proactively identifying risks and responding to anomalies with AI-specific protocols will also enhance the credibility and safety of AI applications across the energy sector.

#### 8.4. Labor and Social Challenges

To address labor and societal issues associated with AI in the energy sector, it is essential to support job transitions and role changes through education and retraining programs. As AI systems expand and automate operations, tailored job transformation programs are necessary. Occupations expected to be affected by AI and automation must be identified, and targeted training and career conversion initiatives should be provided. AI and data-related jobs should be clearly classified to support the development of human capital in these fields. This requires the creation of flexible job models and curriculum structures that support workforce adaptation. Strengthening collaboration with the private sector can further facilitate tailored, on-the-job training programs that align with industry demands.

Institutional support for AI-related job transition policies and systems also needs to be reinforced. Technology education programs, internships, and field-specific retraining must be expanded to enable workers to respond effectively to technological shifts. Educational institutions, in partnership with local governments and companies, should implement industry-academia cooperation programs and offer both in-person and online courses to promote widespread access to training. In addition, AI's labor market impacts should be closely monitored, and institutional safeguards should be established to mitigate social and employment risks.

Efforts to nurture AI experts specialized in the energy sector must also be prioritized. Educational curricula and training programs need to balance theory with hands-on application to build practical competencies. Programs should train professionals not only in AI technology but also in its application to energy systems, including energy modeling, prediction, optimization, and control. Government-supported initiatives must focus on producing AI professionals capable of integrating energy and digital technologies and applying AI solutions in real-world energy scenarios. These efforts should also target field engineers and operational personnel in the energy industry, ensuring they have the skills to work with both traditional and AI-based systems.

To prevent ethical violations and misuse of AI, transparency, fairness, accountability, and regulatory oversight must be emphasized. Ethical issues such as biased decisions or unintended consequences must be preemptively addressed. Data collection, processing methods, and usage purposes should be made transparent, with results clearly explained to users to ensure trust. It is crucial to establish a regulatory system that reflects ethical considerations throughout the AI technology lifecycle, including design, deployment, and continuous improvement.

Organizations must develop internal ethical principles and governance systems and incorporate them into AI system operations. This includes training employees and stakeholders on AI ethics and providing tools to help them understand risks and responsibilities. Ethical evaluations and guidelines should be applied when deploying AI systems, particularly in decision-making processes involving high risk or public interest. AI applications must be assessed not only for performance but also for fairness, safety, and social acceptability. Ethical decision-making systems should be developed to allow human oversight in AI-based judgments.

To prevent over-reliance on AI and safeguard human-centered decision-making, it is important to establish hybrid decision-making systems. These systems should blend AI-driven insights with human reasoning, particularly in scenarios requiring judgment, values, or complex analysis. AI performance should be continuously evaluated, and the outcomes explained in a way that promotes user understanding and appropriate usage.

At the same time, contingency plans must be prepared in case of AI system failures. Legacy or non-AI systems should be maintained and ready to take over if necessary. For example, in smart grid management systems,

instant monitoring and manual override functions must be available to respond to AI system errors. Developing alternative protocols tailored to specific situations can provide rapid responses in the event of AI malfunctions.

Conventional monitoring and control systems should also be strengthened to serve as a check on AI decisions. Periodic manual inspections and human monitoring should be conducted where AI alone cannot provide sufficient oversight. Finally, training and education on conventional decision-making processes should be provided to energy workers, ensuring they are prepared to intervene when AI systems fall short or encounter unexpected issues.

### 8.5. Stakeholder Validation and Practical Deployment

While the proposed framework demonstrates promising technical and economic performance, its practical deployment would require validation through active engagement with key stakeholders, including electric utilities, system operators, regulators, policymakers, and energy market participants. Future implementation of the framework should therefore follow a multi-stage stakeholder validation process. First, pilot projects can be conducted in collaboration with utility companies to evaluate the framework under realistic operating conditions using actual generation, demand, and market data. Such pilot studies would allow assessment of forecasting accuracy, operational reliability, and economic performance in real-world environments.

Second, expert workshops and stakeholder consultation sessions can be organized to evaluate the practicality of the proposed optimization objectives, operational constraints, and decision-making mechanisms. Feedback from grid operators and planners can help identify operational requirements that may not be fully captured in simulation-based studies. Third, scenario-based validation can be performed using representative regulatory and market conditions. Different renewable penetration levels, electricity pricing structures, carbon pricing policies, and reliability requirements can be examined to assess the robustness of the framework across diverse operating environments.

Fourth, regulatory assessment should be conducted to ensure compatibility with existing grid codes, market regulations, cybersecurity requirements, and data privacy policies. Such assessments would facilitate practical adoption and identify necessary policy modifications to support AI-enabled energy management systems. Finally, a co-design approach involving utilities, policymakers, technology providers, and researchers can be employed to continuously refine the framework. This collaborative process would improve stakeholder acceptance, increase transparency, and ensure that the framework addresses both technical and policy objectives before large-scale deployment. Therefore, although the present work provides a comprehensive analytical foundation, future stakeholder-driven validation studies are necessary to fully establish the practical applicability and scalability of the proposed framework.

## 9. Conclusions

The transition toward sustainable and decarbonized energy systems requires not only the expansion of renewable energy resources but also the intelligent coordination of increasingly complex and data-intensive power networks. This work demonstrates that AI can play a transformative role in enabling this transition when it is integrated beyond isolated technical applications and embedded within system-level economic, environmental, and operational frameworks. Unlike conventional studies that focus primarily on forecasting accuracy or control optimization, this paper proposed a unified analytical framework that explicitly links AI-driven forecasting with grid economics, optimization-based dispatch, and lifecycle assessment of AI energy consumption. By incorporating both the benefits and costs of AI, including its computational energy footprint, the proposed approach provides a more realistic and holistic evaluation of AI-enabled energy systems.

The quantitative results confirm that AI-based forecasting significantly enhances system performance, reducing prediction errors by nearly 50% and lowering total operational costs by 16.57% compared to traditional methods. Importantly, the additional energy consumption associated with AI computation was shown to be relatively small compared to the operational gains achieved, reinforcing the net positive impact of AI when properly deployed. These findings highlight that the value of AI extends beyond predictive improvements to tangible economic and efficiency benefits at the system level. Beyond performance evaluation, this study identified critical research gaps that must be addressed to ensure scalable and equitable deployment of AI in the energy sector. These include the disconnect between forecasting and economic decision-making, the underexplored lifecycle impact of AI, limitations in model generalization, challenges arising from grid heterogeneity, and the lack of policy and equity considerations. Addressing these challenges requires interdisciplinary approaches that combine advanced machine learning techniques with domain knowledge, policy frameworks, and standardized data infrastructures.

Looking forward, future research should focus on extending the proposed framework to multi-bus and large-scale power systems, incorporating stochastic and robust optimization under uncertainty, and developing domain-

adaptive AI models capable of generalizing across diverse geographic and operational conditions. In parallel, efforts toward green AI, including energy-efficient model design and carbon-aware computation, will be essential to ensure that the benefits of AI are not offset by its environmental footprint. From a practical perspective, the successful deployment of AI in renewable energy systems will depend on close collaboration among researchers, utilities, industry stakeholders, and policymakers. Establishing regulatory frameworks, improving data accessibility, and investing in workforce development will be key enablers for scaling AI solutions while maintaining fairness, transparency, and system reliability. In conclusion, the sustainable integration of AI into renewable energy systems is not solely a technological challenge but a multidimensional problem that spans engineering, economics, and policy. By bridging these domains, the proposed framework provides a pathway toward more efficient, resilient, and sustainable energy systems, supporting global efforts to achieve net-zero emissions and long-term energy security.

### Funding

This research received no external funding.

### Institutional Review Board Statement

Not applicable.

### Informed Consent Statement

Not applicable.

### Data Availability Statement

The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request.

### Conflicts of Interest

The author declares no conflict of interest.

### Use of AI and AI-Assisted Technologies

No AI tools were utilized for this paper.

### References

1. Sayed, K.; Kassem, A.; Saleeb, H.; et al. Energy-Saving of Battery Electric Vehicle Powertrain and Efficiency Improvement during Different Standard Driving Cycles. *Sustainability* **2020**, *12*, 10466. <https://doi.org/10.3390/su122410466>.
2. Wan, C.; Zhao, J.; Song, Y.; et al. Photovoltaic and Solar Power Forecasting for Smart Grid Energy Management. *CSEE J. Power Energy Syst.* **2015**, *1*, 38–46. <https://doi.org/10.17775/cseejpes.2015.00046>.
3. Wang, J.; Zhong, H.; Lai, X.; et al. Exploring Key Weather Factors from Analytical Modeling toward Improved Solar Power Forecasting. *IEEE Trans. Smart Grid* **2019**, *10*, 1417–1427. <https://doi.org/10.1109/tsg.2017.2766022>.
4. Zhou, H.; Zhang, Y.; Yang, L.; et al. Short-Term Photovoltaic Power Forecasting Based on Long Short-Term Memory Neural Network and Attention Mechanism. *IEEE Access* **2019**, *7*, 78063–78074. <https://doi.org/10.1109/access.2019.2923006>.
5. Liu, J.; Fang, W.; Zhang, X.; et al. An Improved Photovoltaic Power Forecasting Model with the Assistance of Aerosol Index Data. *IEEE Trans. Sustain. Energy* **2015**, *6*, 434–442. <https://doi.org/10.1109/tste.2014.2381224>.
6. Yang, H.T.; Huang, C.M.; Huang, Y.C.; et al. A Weather-Based Hybrid Method for 1-Day Ahead Hourly Forecasting of PV Power Output. *IEEE Trans. Sustain. Energy* **2014**, *5*, 917–926. <https://doi.org/10.1109/tste.2014.2313600>.
7. Gigoni, L.; Betti, A.; Crisostomi, E.; et al. Day-Ahead Hourly Forecasting of Power Generation from Photovoltaic Plants. *IEEE Trans. Sustain. Energy* **2018**, *9*, 831–842. <https://doi.org/10.1109/tste.2017.2762435>.
8. Sayed, K.; Khamies, M.; Abokhalil, A.G.; et al. Feasibility Study and Economic Analysis of PV/Wind-Powered Hydrogen Production Plant. *IEEE Access* **2024**, *12*, 76304–76318. <https://doi.org/10.1109/ACCESS.2024.3406895>.
9. Atiya, A.F.; El-Shoura, S.M.; Shaheen, S.I.; et al. A Comparison between Neural-Network Forecasting Techniques—Case Study: River Flow Forecasting. *IEEE Trans. Neural Netw.* **1999**, *10*, 402–409. <https://doi.org/10.1109/72.750569>.
10. Ospina, J.; Newaz, A.; Faruque, M.O. Forecasting of PV Plant Output Using Hybrid Wavelet-Based LSTM-DNN Structure Model. *IET Renew. Power Gener.* **2019**, *13*, 1087–1095. <https://doi.org/10.1049/iet-rpg.2018.5779>.

11. Du, L.; Zhang, L.; Tian, X.; et al. Short-term photovoltaic power forecasting using deep convolutional networks. In Proceedings of the 2nd International Conference on Artificial Intelligence and Big Data (ICAIBD), Chengdu, China, 25–28 May 2019, pp. 149–153.
12. Olatomiwa, L.; Shamshirband, S.; Mohammadi, K.; et al. A Support Vector Machine–Firefly Algorithm-Based Model for Global Solar Radiation Prediction. *Sol. Energy* **2015**, *115*, 632–644. <https://doi.org/10.1016/j.solener.2015.03.015>.
13. Wu, W.; Peng, M. A Data Mining Approach Combining K-Means Clustering with Bagging Neural Network for Short-Term Wind Power Forecasting. *IEEE Internet Things J.* **2017**, *4*, 979–986. <https://doi.org/10.1109/jiot.2017.2677578>.
14. Shi, J.; Lee, W.J.; Liu, Y.; et al. Forecasting Power Output of Photovoltaic Systems Based on Weather Classification and Support Vector Machines. *IEEE Trans. Ind. Appl.* **2012**, *48*, 1064–1069. <https://doi.org/10.1109/tia.2012.2190816>.
15. Huang, C.M.; Kuo, C.J.; Chen, S.J.; et al. One-Day-Ahead Hourly Forecasting for Photovoltaic Power Generation Using an Intelligent Method with Weather-Based Forecasting Models. *IET Gener. Transmiss. Distrib.* **2015**, *9*, 1874–1882. <https://doi.org/10.1049/iet-gtd.2015.0175>.
16. Jiao, R.; Zhang, T.; Jiang, Y.; et al. Short-Term Non-Residential Load Forecasting Based on Multiple Sequences LSTM Recurrent Neural Network. *IEEE Access* **2018**, *6*, 59438–59448. <https://doi.org/10.1109/access.2018.2873712>.
17. Abo-Khalil, A.G.; Alobaid, M. A Guide to the Integration and Utilization of Energy Storage Systems with a Focus on Demand Resource Management and Power Quality Enhancement. *Sustainability* **2023**, *15*, 14680. <https://doi.org/10.3390/su152014680>.
18. Hasan, K.; Othman, M.M.; Meraj, S.T.; et al. Emerging Power Quality Improvement Technology: Recent Advances on Topologies, Control Schemes, Issues and Prospects towards Grid Decarbonization. *Results Eng.* **2026**, *29*, 109256. <https://doi.org/10.1016/j.rineng.2026.109256>.
19. Gers, F.A.; Schmidhuber, J.; Cummins, F. Learning to forget: Continual prediction with LSTM. *Neural Comput.* **2000**, *12*, 2451–2471.
20. Chicco, G.; Cocina, V.; Leo, P.; et al. Error Assessment of Solar Irradiance Forecasts and AC Power from Energy Conversion Model in Grid-Connected Photovoltaic Systems. *Energies* **2015**, *9*, 8. <https://doi.org/10.3390/en9010008>.
21. Bhuiyan, M.A.E.; Yang, F.; Biswas, N.K.; et al. Machine Learning-Based Error Modeling to Improve GPM IMERG Precipitation Product over the Brahmaputra River Basin. *Forecasting* **2020**, *2*, 248–266. <https://doi.org/10.3390/forecast2030014>.
22. Hajiabadi, M.E.; Mashhadi, H.R. Analysis of the Probability Distribution of LMP by Central Limit Theorem. *IEEE Trans. Power Syst.* **2013**, *28*, 2862–2871. <https://doi.org/10.1109/tpwrs.2013.2252372>.
23. Alobaid, M.; Abo-Khalil, A.G.; Sayed, K. AI-Enhanced Techno-Economic and Environmental Optimization for Nearly Zero-Energy Building Retrofitting: A Case Study of University Campus. *Sci. Rep.* **2026**, *16*, 14599. <https://doi.org/10.1038/s41598-026-41747-1>.
24. Al-Arab, S.; Bansal, R.C.; Abo-Khalil, A.G. Analyzing the Impact of Electric Vehicles on the Power Network of the United Arab Emirates. *Int. Trans. Electr. Energy Syst.* **2025**, *2025*, 5825006. <https://doi.org/10.1155/etep/5825006>.
25. Abokhalil, A.G. Electric Vehicle Charging Infrastructure Trends, Costs, and Policy Impacts in the UAE. *Renew. Sustain. Energy Technol.* **2026**, *2*, 5. <https://doi.org/10.53941/rset.2026.100002>.
26. Al-Ali, E.M.; Hajji, Y.; Said, Y.; et al. Solar Energy Production Forecasting Based on a Hybrid CNN–LSTM–Transformer Model. *Mathematics* **2023**, *11*, 676. <https://doi.org/10.3390/math11030676>.
27. Mohammadi, H. AI-Based Optimal Scheduling of Renewable AC Microgrids with Bidirectional LSTM-Based Wind Power Forecasting. *arXiv* **2022**, arXiv:2208.04156.