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Advances in AI-powered energy management systems for renewable-integrated smart grids

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Abstract

The accelerating global shift toward renewable energy integration presents both a technical imperative and a systemic challenge to traditional power grid architectures. Variability, decentralization, and real-time balancing requirements have exposed the limitations of conventional control and forecasting strategies. This review critically examines how artificial intelligence (AI) is redefining energy management systems to meet the operational and strategic needs of renewable-integrated smart grids. It explores the state-of-the-art in AI-based load and generation forecasting, real-time grid state estimation, anomaly detection, and predictive maintenance, highlighting how machine learning and deep learning techniques enhance grid observability and fault resilience. Particular attention is given to AI-driven optimization of energy storage dispatch, multi-agent coordination in microgrids, and the deployment of edge intelligence for decentralized control. Furthermore, the review evaluates current barriers—ranging from data sparsity and model interpretability to lack of standardization—and proposes targeted research directions, including explainable AI, quantum-enhanced computing, and AI-powered coordination of distributed storage and vehicle-to-grid (V2G) networks. The convergence of AI, digital infrastructure, and policy innovation emerges as critical to unlocking the full potential of next-generation grids. This article provides researchers, engineers, and policymakers with a rigorous synthesis of current advancements and a forward-looking agenda for achieving intelligent, resilient, and decarbonized energy systems.

Keywords: Artificial Intelligence in Energy Systems; Smart Grid Optimization; Renewable Energy Integration; AI-Powered Grid Management; Energy Storage Dispatch; Microgrid Control and Coordination; Explainable AI in Power Systems; Vehicle-to-Grid (V2G) Intelligence

1. Introduction

The global energy landscape is undergoing a transformative shift characterized by the increasing integration of renewable energy sources (RES) into existing power grids. This transition is driven by the imperative to mitigate climate change, reduce greenhouse gas emissions, and achieve sustainable energy goals. However, the intermittent and variable nature of RES, such as solar and wind power, introduces significant challenges to grid stability, reliability, and efficiency. To address these complexities, the deployment of Artificial Intelligence (AI) in energy management systems has

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emerged as a promising solution. AI technologies offer advanced capabilities in data analysis, forecasting, optimization, and autonomous decision-making, which are essential for managing the dynamic behaviors of modern power systems. This review article explores the advancements in AI-powered energy management systems, focusing on their role in enhancing the integration of renewable energy into smart grids.

1.1. Background on the Rise of Smart Grids and Renewable Energy Integration

The traditional electrical grid, designed for unidirectional energy flow from centralized power plants to consumers, is increasingly inadequate in accommodating the decentralized and variable inputs from RES. Smart grids have emerged as an evolution of the conventional grid, incorporating digital communication technologies, sensors, and automated control systems to enable bidirectional energy flow and real-time monitoring. According to Biswas et al. [1], smart grids enhance the sustainability, reliability, and efficiency of electricity generation and distribution by integrating advanced technologies and facilitating better energy resource management.

The integration of RES into smart grids presents both opportunities and challenges. While RES contribute to reducing carbon emissions and diversifying energy sources, their variability necessitates sophisticated management strategies to maintain grid stability. The unpredictability of solar and wind energy generation requires real-time adjustments in energy distribution and consumption. As noted by Ruzbahani [2], the fluctuating nature of RES introduces new challenges in energy management, necessitating the development of intelligent systems capable of dynamic scheduling and enhanced energy routing.

1.2. Motivation for AI-Driven Energy Management Systems

The complexity of managing modern power systems with high penetration of RES has led to the exploration of AI as a tool for enhancing energy management. AI technologies, including machine learning (ML), deep learning, and reinforcement learning, offer the ability to process vast amounts of data, identify patterns, and make predictive decisions. These capabilities are crucial for forecasting energy demand and supply, optimizing energy distribution, and ensuring the efficient operation of the grid.

Integrating AI into energy management systems enables the automation of decision-making processes, reducing the reliance on manual interventions and improving response times to dynamic changes in the grid. According to Rashid et al. [3], the application of ML in smart grid systems enhances the efficiency, reliability, and sustainability of energy networks by enabling better management of renewable energy integration, demand response, and predictive maintenance. Furthermore, AI facilitates the development of decentralized energy markets and peer-to-peer energy trading platforms, allowing consumers to actively participate in energy generation and distribution. This democratization of energy systems aligns with the goals of sustainability and resilience in the face of growing energy demands and environmental concerns [3].

1.3. Research Gaps and Objectives of the Review

Despite the promising applications of AI in energy management, several research gaps persist. One significant challenge is the integration of AI algorithms into existing grid infrastructures, which often lack the necessary computational capabilities and data availability. Additionally, concerns regarding data privacy, cybersecurity, and the interpretability of AI models hinder widespread adoption.

Moreover, the scalability of AI solutions and their adaptability to different grid configurations and regulatory environments remain areas requiring further investigation. There is also a need for standardized frameworks and protocols to guide the implementation of AI technologies in energy systems. This review aims to address existing gaps by providing a comprehensive analysis of the current advancements in AI-powered energy management systems for renewable-integrated smart grids. The objectives include evaluating the state-of-the-art AI techniques applied in energy forecasting, grid optimization, and demand response; identifying the challenges and limitations associated with the deployment of AI in energy systems; and exploring future research directions and potential solutions to enhance the integration of AI in smart grids. By synthesizing existing research and highlighting emerging trends, this review seeks to contribute to the development of intelligent, resilient, and sustainable energy systems.

2. Smart Grids and Renewable Integration: The Evolving Landscape

The transformation of modern energy systems has been driven largely by the global imperative to decarbonize and diversify energy portfolios. As the share of renewables continues to grow, energy networks are no longer linear or centrally managed but are becoming highly interactive, distributed, and data-rich [4]. The traditional one-way power delivery model is being replaced by digitalized, multi-directional architectures capable of accommodating not just generation and consumption, but intelligent coordination. This evolving grid paradigm—referred to as the smart grid—is not simply an upgrade of physical infrastructure; it is a convergence of information technology, automation, and energy systems aimed at creating a more responsive, efficient, and resilient power sector. Within this dynamic context, the integration of intermittent renewable energy sources poses both technical and operational challenges that require a deeper understanding of the grid's architecture, operational principles, and the strategic role of enabling technologies like storage and demand response [4,5].

2.1. Architecture and Operation of Smart Grids

The transformation of traditional power systems into smart grids represents a significant evolution in the generation, transmission, distribution, and consumption of electricity [5]. This evolution is characterized by the integration of advanced information and communication technologies (ICT), automation, and real-time data analytics, enabling a more efficient, reliable, and sustainable energy infrastructure. The architecture of smart grids encompasses various components and operational mechanisms that collectively enhance the grid's performance and adaptability [5,6].

2.1.1. Core Components of Smart Grid Infrastructure

Smart grid architecture comprises several key components that work synergistically to modernize the power system. One of the foundational elements is the advanced metering infrastructure (AMI), which enables two-way communication between utilities and consumers. This infrastructure supports real-time monitoring of energy consumption, dynamic pricing, and demand response programs. Smart meters, central to AMI, deliver granular usage data, empowering consumers to make informed energy decisions [7].

In parallel, supervisory control and data acquisition (SCADA) systems play a vital role in real-time monitoring and control. These systems collect and analyze data from sensors and devices dispersed across the grid, providing operators with critical insights for outage management, anomaly detection, and system optimization [8]. Complementing SCADA are phasor measurement units (PMUs), which offer high-resolution, time-synchronized measurements essential for assessing grid stability and detecting power system disturbances [7,8]. Distributed energy resources (DERs), such as solar photovoltaics, wind turbines, and energy storage systems, are integral to smart grid frameworks. Their incorporation enhances energy diversification and bolsters system resilience. The effective management of DERs requires intelligent coordination to balance supply with demand while maintaining system stability [8]. Supporting this coordination is the smart grid's robust communication network, which ensures reliable data transmission and real-time interaction among grid components [9].

2.1.2. Communication and Control Mechanisms

The efficient operation of smart grids is deeply dependent on sophisticated communication and control systems. Unlike traditional grids, smart grids rely on bidirectional communication, facilitating the dynamic exchange of information between utilities and consumers. This interaction supports real-time monitoring, remote device control, and the implementation of adaptive demand response strategies [9]. Automation technologies, including intelligent electronic devices (IEDs) and distributed control systems, are central to maintaining operational stability. These technologies enable rapid and autonomous responses to evolving grid conditions. They adjust voltage, frequency, and load settings in real time, thereby optimizing grid performance without the need for manual intervention [9].

As smart grids become increasingly digitized, they also become more susceptible to cybersecurity risks. Protecting infrastructure and data from malicious threats requires robust cybersecurity frameworks. These include encryption protocols, secure authentication, and advanced intrusion detection systems designed to safeguard the integrity and confidentiality of grid communications [7]. The integration of renewable energy sources introduces additional complexity due to their variable nature. Managing these fluctuations demands predictive forecasting tools and adaptive control strategies that can respond swiftly to changes in generation and load. Smart grids leverage AI-enhanced models to accommodate these variables, maintaining supply-demand equilibrium and supporting stable grid operations under fluctuating renewable inputs [9].

Essentially, the architecture and operation of smart grids mark a critical advancement in the evolution of energy systems. Through the integration of digital technologies, real-time communication, automation, and decentralized energy management, smart grids provide the foundational framework necessary for supporting a resilient, flexible, and sustainable electricity network in the age of renewable energy transition.

2.2. Intermittency and Variability Challenges from Renewables

The integration of renewable energy sources (RES), particularly wind and solar, into modern power systems introduces significant challenges due to their inherent intermittency and variability. Unlike conventional energy sources, which can be dispatched based on demand, RES are dependent on environmental conditions, leading to fluctuations in power generation that can disrupt grid stability and reliability.

2.2.1. Nature of Intermittency and Variability

Renewable energy sources such as wind and solar are characterized by their dependence on weather conditions, resulting in unpredictable and non-dispatchable power outputs. Solar power generation is influenced by factors such as cloud cover and time of day, while wind energy is affected by wind speed and atmospheric conditions. These fluctuations can occur over various timescales, from seconds to days, posing challenges for grid operators in maintaining a balance between supply and demand [10].

The variability of RES leads to periods of overgeneration or undergeneration, necessitating rapid adjustments in other power sources to maintain grid stability. This unpredictability complicates the scheduling and dispatching of electricity, requiring more sophisticated forecasting and real-time management tools [11].

2.2.2. Impact on Grid Stability and Reliability

The intermittent nature of RES can lead to voltage fluctuations, frequency deviations, and challenges in maintaining the quality and reliability of power supply. High penetration levels of RES without adequate balancing mechanisms can result in grid congestion, increased need for ancillary services, and potential curtailment of renewable generation [7].

Moreover, the reduced inertia in power systems dominated by RES, due to the lack of rotating mass in inverter-based resources, diminishes the grid's ability to resist frequency changes, making it more susceptible to disturbances [12]. This necessitates the development of synthetic inertia solutions and advanced control strategies to emulate the stabilizing effects of traditional synchronous generators.

2.2.3. Forecasting and Predictive Challenges

Accurate forecasting of RES output is crucial for effective grid management. However, the stochastic nature of weather patterns limits the precision of predictive models. Short-term forecasting errors can lead to imbalances between generation and load, requiring the activation of reserve capacities or demand response measures to mitigate potential disruptions [11].

Advancements in machine learning and data analytics have improved forecasting accuracy, yet uncertainties remain, particularly in regions with highly variable weather conditions. Integrating high-resolution meteorological data and enhancing computational models are ongoing research areas aimed at reducing forecasting errors and improving grid resilience [1].

2.2.4. **Economic and Operational Implications**

The variability of RES imposes additional operational costs on power systems. Utilities must invest in flexible generation assets, energy storage systems, and grid infrastructure upgrades to accommodate fluctuating renewable outputs. These investments can be substantial, impacting the economic viability of renewable integration, especially in markets with limited financial resources [13].

Furthermore, the need for frequent ramping of conventional power plants to balance RES variability increases wear and tear on equipment, leading to higher maintenance costs and reduced operational lifespans. Developing cost-effective strategies to manage these operational challenges is essential for the sustainable integration of RES into the grid.

In essence, the intermittency and variability of renewable energy sources present multifaceted challenges to power system operation and planning. Addressing these issues requires a combination of technological innovations, advanced forecasting techniques, and strategic investments in grid infrastructure to ensure a reliable and resilient energy future.

2.3. Role of Storage, Demand Response, and Distributed Generation

The integration of renewable energy sources (RES) into modern power systems necessitates the adoption of complementary technologies and strategies to address the challenges posed by their intermittency and variability. Among these, energy storage systems (ESS), demand response (DR), and distributed generation (DG) play pivotal roles in enhancing grid flexibility, reliability, and efficiency. This section delves into the operational mechanisms, benefits, and research developments associated with these components [14,15].

2.3.1. Energy Storage Systems (ESS)

Energy storage systems are instrumental in mitigating the fluctuations associated with RES by storing excess energy during periods of low demand and releasing it during peak consumption or when renewable generation is insufficient. Various storage technologies, including lithium-ion batteries, pumped hydro storage, and flow batteries, offer different advantages in terms of response time, capacity, and duration. For instance, lithium-ion batteries are favored for their rapid response and scalability, making them suitable for frequency regulation and short-term energy balancing [16].

Recent advancements have seen significant deployments of utility-scale battery storage. In the United States, over 20 gigawatts (GW) of battery capacity have been added to the power grid in the past four years, equivalent to the output of 20 nuclear reactors. This expansion has been crucial in managing peaks and troughs in energy production, particularly in states like California and Texas, which lead in clean energy adoption [17].

Moreover, ESS contribute to grid stability by providing ancillary services such as voltage support and black-start capabilities. They also enable the deferral of infrastructure investments by reducing the need for additional generation and transmission capacity. However, challenges remain in terms of cost, lifecycle, and integration with existing grid infrastructure, prompting ongoing research into advanced materials, control algorithms, and hybrid storage solutions [18,19].

2.3.2. Demand Response (DR)

Demand response strategies involve the modulation of electricity consumption by end-users in response to grid conditions, price signals, or incentives. By adjusting demand patterns, DR contributes to peak load reduction, frequency regulation, and the accommodation of variable renewable generation. DR programs can be categorized into incentive-based and price-based schemes, each with distinct mechanisms and applications. Incentive-based DR programs offer financial rewards to consumers who reduce or shift their electricity usage during peak periods or in response to grid emergencies. Price-based DR, on the other hand, relies on dynamic pricing models, such as time-of-use or real-time pricing, to encourage consumers to modify their consumption behavior based on electricity costs [20,21].

The integration of advanced metering infrastructure and smart appliances has enhanced the effectiveness of DR programs by enabling real-time communication and automated load control. Furthermore, the application of artificial intelligence and machine learning algorithms facilitates the prediction of consumption patterns and the optimization of DR strategies. Research has demonstrated that DR can significantly improve grid reliability and reduce operational costs, particularly when coordinated with renewable generation and ESS [22].

2.3.3. Distributed Generation (DG)

Distributed generation refers to the decentralized production of electricity near the point of consumption, utilizing small-scale technologies such as solar photovoltaic panels, wind turbines, and combined heat and power systems. DG reduces transmission losses, enhances energy security, and supports the integration of RES by providing localized generation capacity. The proliferation of DG has been facilitated by advancements in renewable technologies, supportive policies, and declining costs. In smart grid environments, DG units can operate in coordination with central generation and other distributed resources, forming microgrids that can function autonomously or in conjunction with the main grid. This configuration enhances resilience against outages and enables more efficient energy management [23].

However, the integration of DG poses challenges related to grid stability, protection coordination, and voltage regulation. Addressing these issues requires the development of sophisticated control systems, grid codes, and interconnection standards. Ongoing research focuses on the optimization of DG placement, the design of adaptive protection schemes, and the implementation of advanced inverter functionalities to ensure seamless integration and operation within the smart grid framework [24,25]. Progress along these lines is illustrated in Figure 1, which depicts an AI-powered IoT-based Home Energy Management System (HEMS) designed for Distributed Generation (DG) integration. The system leverages real-time data and machine learning algorithms to optimize energy distribution and consumption at the household level.

In principle, the synergistic deployment of energy storage systems, demand response strategies, and distributed generation is essential for the effective integration of renewable energy sources into modern power systems. These components collectively enhance grid flexibility, reliability, and sustainability, forming the cornerstone of the evolving smart grid paradigm.

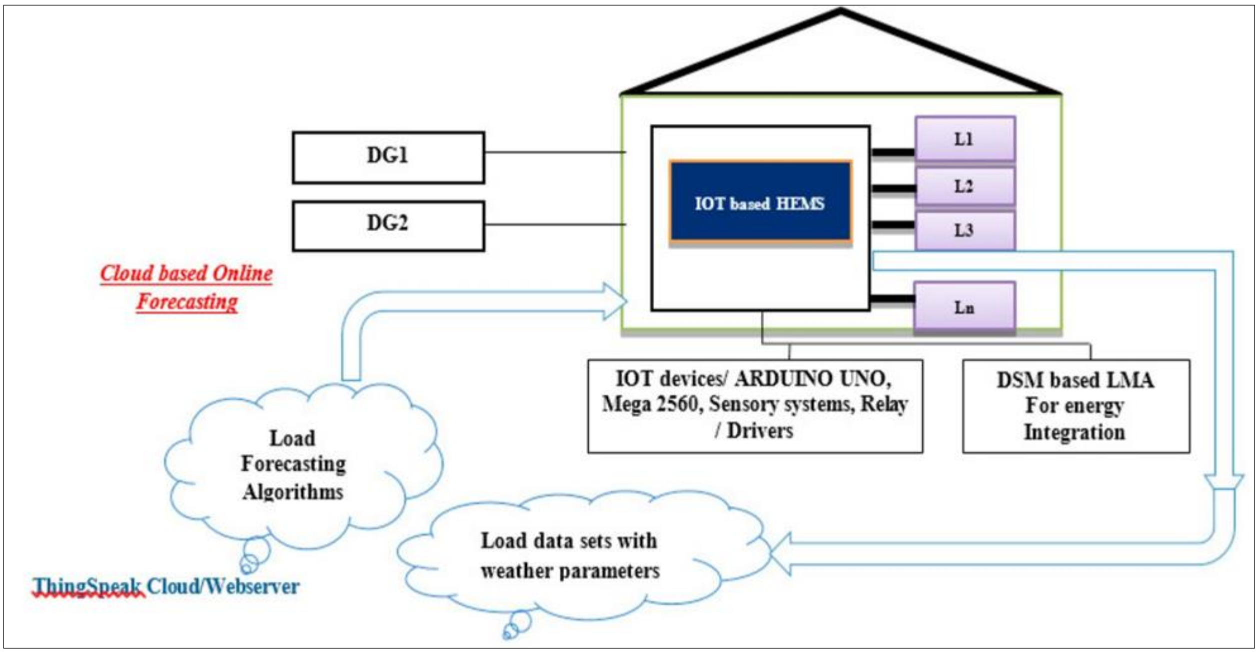

Figure 1 AI-Powered IoT-Based Home Energy Management System. Reproduced with permission from Ref. [19]

3. AI and Energy Systems: Conceptual Foundations

Artificial Intelligence (AI) is reshaping how energy systems are designed, operated, and optimized. In the context of increasingly complex, decentralized, and data-intensive power networks, AI brings new methods for understanding patterns, predicting system behavior, and making decisions in real time. From optimizing renewable energy integration to managing distributed assets, AI has begun playing a strategic role in transitioning the grid from reactive to proactive intelligence. To fully grasp its relevance in the smart grid context, it is crucial to explore what AI entails, how its branches differ, and the ways it supports dynamic system control, learning, and automation [26].

3.1. Definitions and Classifications: AI, ML, Deep Learning, Reinforcement Learning

Understanding the different facets of AI is foundational to appreciating its application in energy systems. Artificial Intelligence broadly refers to computational systems that mimic cognitive functions such as learning, reasoning, and problem-solving. It encompasses a range of methods, from rule-based systems to statistical learning and neural networks. To clarify the distinctions and operational strengths of the various AI approaches applied within energy systems, a comparative summary of their characteristics, data requirements, and application outcomes is presented in Table 1. This comparison helps contextualize their selection for different smart grid tasks.

Table 1 Comparative Analysis of AI Techniques Used in Smart Grid Applications

AI Technique	Grid Application Domain	Input Data Types	Strengths	Limitations	Notable Case Studies	Reported Performance
Machine Learning (ML)	Load forecasting, anomaly detection	Historical demand, weather, SCADA logs	Easy to implement, interpretable models	Poor handling of non-linearities in high-dimensional data	Rashid et al. [3], Li et al. [61]	MAE improvement by 15–20% vs. traditional models
Deep Learning (DL)	Renewable energy forecasting,	Sensor data, images, weather	Captures non-linearity, handles high	Requires large datasets, high computational cost	Sun et al. [35], Tortora et al. [37]	RMSE reduction of 25–30% in PV forecasting

	predictive maintenance	maps, PMU time series	dimensional data			
Reinforcement Learning (RL)	Battery dispatch, frequency control	Real-time grid states, pricing signals, SOC metrics	Learns optimal policies over time, adapts to uncertainty	Requires extensive training episodes, risk of unsafe actions	Al-Saadi et al. [28], Kang et al. [62]	Reduced system loss by up to 20%; extended battery life
Graph Neural Networks (GNN)	Grid state estimation	Grid topology, PMU node data	Captures spatial dependencies in network data	Still emerging in energy contexts	Cheng et al. [47]	Improved state estimation accuracy under missing data
Hybrid Neuro-Symbolic Models	Fault detection, explainable diagnostics	Sensor time-series + logic constraints	Combines reasoning with learning; improved transparency	Computationally intensive	Chen et al. [81]	Achieved 89% fault classification with 78% interpretability rating

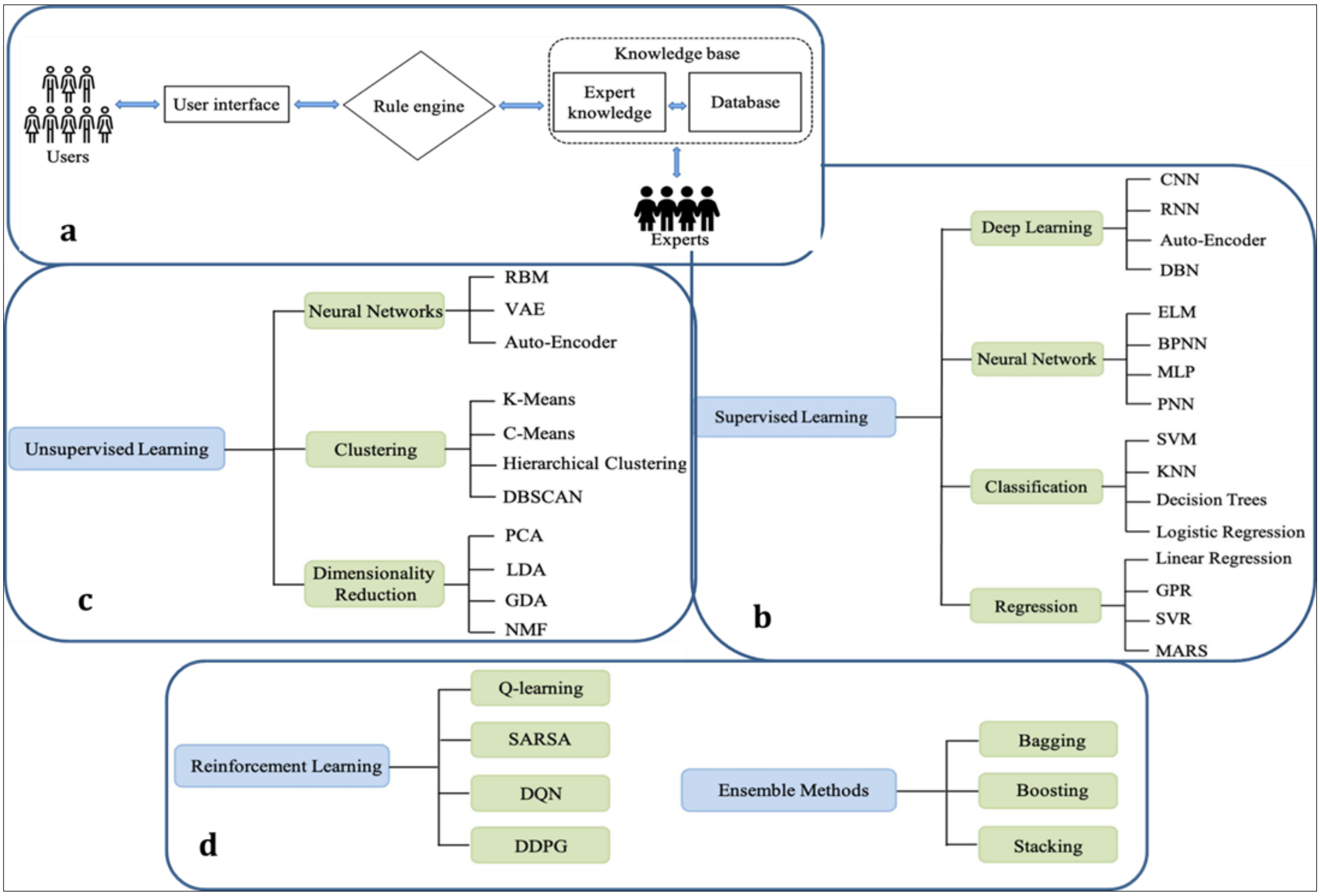

Figure 2 AI Techniques in Smart Grid Applications, which include, (a.) the Expert Systems, (b.) Supervised learning techniques, (c.) Unsupervised learning techniques, (d.) Reinforcement Learning and ensemble methods. Adapted from Ref. [24] with permission

AI techniques applied in smart grid systems can generally be classified into several key areas. One of these is expert systems (ES), which involve human experts in the loop to guide decision-making processes in specific problem domains. Another prominent category is supervised learning, an AI paradigm where a model is trained on labeled datasets to learn the mapping between inputs and outputs, enabling it to accurately predict outcomes for new, unseen inputs. In contrast, unsupervised learning deals with unlabeled data and is employed to uncover hidden patterns, similarities, and differences within datasets without predefined categories. Reinforcement learning (RL) stands apart from both supervised and unsupervised learning due to its use of intelligent agents that interact with an environment and learn to make optimal decisions by maximizing cumulative rewards over time. Lastly, ensemble methods combine the outputs of multiple AI algorithms to mitigate the limitations of individual models, thereby improving overall prediction accuracy and robustness in smart grid applications [24]. To provide a comprehensive overview of AI methodologies applicable to smart grids, Figure 2 categorizes various AI techniques and their respective applications within the energy sector, facilitating a clearer understanding of their roles and benefits.

3.1.1. Artificial Intelligence and Machine Learning

Machine Learning (ML) is a core subset of AI that focuses on algorithms capable of learning patterns from data without being explicitly programmed. According to Chen et al. [27], ML techniques such as supervised and unsupervised learning allow systems to adapt over time, improving prediction accuracy in tasks such as load forecasting and fault detection. While AI includes rule-based automation, ML enables data-driven insights through iterative learning processes.

3.1.2. Deep Learning and Reinforcement Learning

Deep Learning (DL) builds on ML by using multi-layered neural networks that can process large, unstructured datasets such as weather images or electricity usage logs. Its ability to model nonlinear and high-dimensional relationships makes it particularly useful in grid applications involving sensor data and time series. Reinforcement Learning (RL), on the other hand, enables agents to learn through trial and error by interacting with an environment and optimizing cumulative rewards. Researchers like Al-Saadi et al. [28] and Akbulut et al. [29] report successful RL implementations in adaptive grid dispatch and storage control, where learning-based strategies outperform rule-based methods in uncertain environments.

3.2. Role of AI in Dynamic Systems Modeling and Decision-Making

In energy systems, real-time control and operational decision-making rely on accurate models of system behavior. Traditional methods based on first-principles physics can be limited by modeling complexity and data inaccuracy. AI-based approaches offer data-driven alternatives for dynamic system modeling and fast decision-making.

3.2.1. System Identification and Predictive Modeling

System identification involves constructing mathematical models from observed data, particularly when physical models are difficult to derive or implement. AI methods such as recurrent neural networks (RNNs) and long short-term memory (LSTM) networks have demonstrated strong performance in modeling grid dynamics, as highlighted by Alazab et al. [30]. These models capture temporal dependencies and enable real-time prediction of system variables, which are essential for forecasting load and generation fluctuations.

3.2.2. Decision-Making Under Uncertainty

In grid operations, decisions often need to be made in uncertain or rapidly changing conditions. AI facilitates decision-making by evaluating possible outcomes and optimizing actions in real time. Reinforcement learning frameworks are being used in energy management systems to control distributed energy resources and respond to market prices or demand surges. From the findings of Akbulut et al. [29], hybrid approaches combining deep learning with rule-based constraints enhance operational safety while preserving learning adaptability.

3.3. Overview of AI Application Domains in Grid Infrastructure

AI's value in energy systems lies not only in theoretical models but also in its deployment across different layers of the power infrastructure. These applications include forecasting, optimization, anomaly detection, and control. To illustrate the integration of AI within building energy systems, Figure 3 presents an architecture of an intelligent energy management system. This diagram highlights the interplay between AI algorithms, sensor networks, and control mechanisms in optimizing energy consumption within smart buildings.

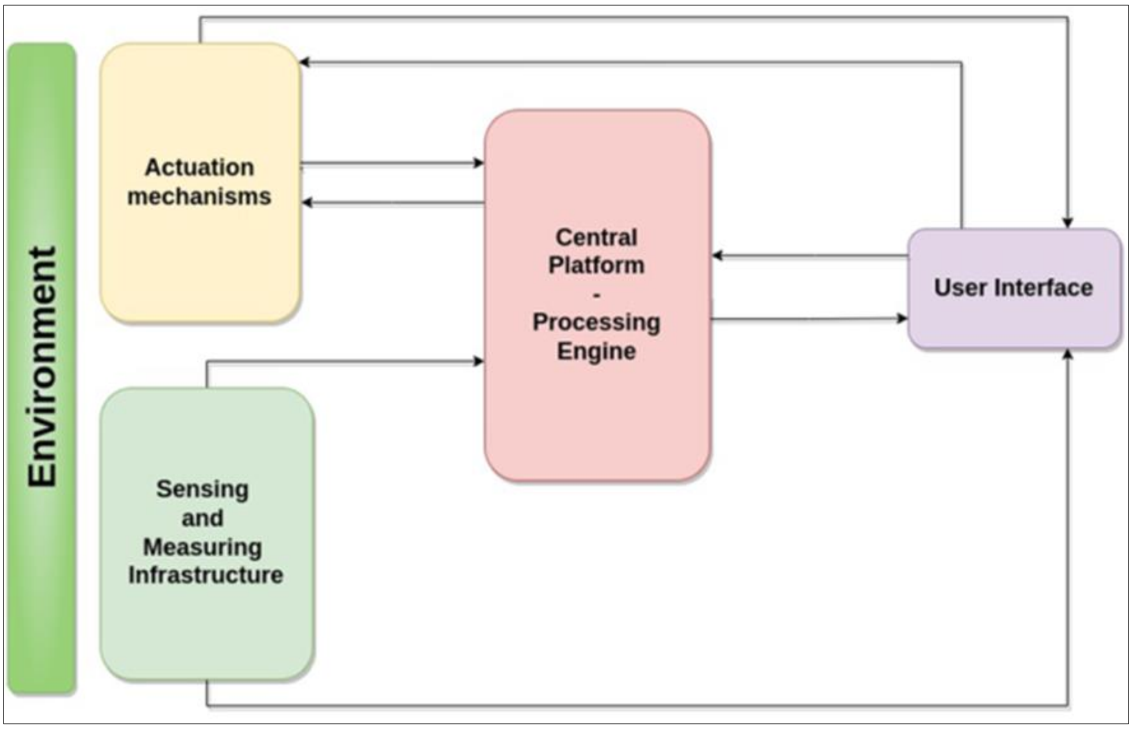

Figure 3 Intelligent Energy Management System Architecture. Reproduced with permission from Ref. [25]

3.3.1. Forecasting and Optimization

Load forecasting is one of the most established AI applications in grid operations. AI models, particularly those based on ensemble learning and deep learning, have shown high accuracy in short- and long-term load predictions. According to Soofastaei et al. [31], integrating AI forecasting tools into control centers reduces overgeneration risks and improves scheduling efficiency. Optimization algorithms, particularly those based on evolutionary computing or convex approximations, are used to optimize grid dispatch, power flow, and resource allocation.

3.3.2. Anomaly Detection and Condition Monitoring

AI techniques are increasingly used for early detection of faults, voltage instability, and equipment degradation. By analyzing high-frequency data streams from sensors and PMUs, AI models identify abnormal behaviors and trigger preventive maintenance actions. A study by Fahim et al. [32] demonstrates how unsupervised learning methods, such as autoencoders, can detect anomalies in distribution networks, minimizing downtime and improving grid resilience.

Beyond theoretical models, AI deployment in energy systems spans numerous operational domains, from forecasting to control. Table 2 categorizes these functional areas and presents specific examples of AI applications, their corresponding tools, and documented performance improvements.

Table 2 Functional Areas of AI Deployment in Smart Grids with Use Cases and Technology Platforms

Smart Grid Function	AI Application	Specific Use Case	AI Tools/Models	Performance Gains	Tech Stack/Platform
Grid Monitoring	Anomaly detection	Voltage swell/frequency sag detection	Autoencoder, LSTM	92% accuracy (Arif et al., 2021)	SCADA + PMUs
Energy Scheduling	Forecast-driven storage dispatch	Charge/discharge control	DRL, Random Forest	Up to 25% reduction in energy costs	Python + TensorFlow
Demand Response	Load modulation via	Consumer-side peak shaving	SVM, RL agents	18–22% load shifting observed	Smart meters + Home IoT

	real-time signals				
Predictive Maintenance	Insulator fault prediction	Transformer thermal failure	Random Forest + RL	89% reliability rate in advance alerts	IoT + Digital Twins
Voltage/Frequency Control	Fast-response regulation	BESS response to frequency drop	RL-based inverter control	35% reduction in excursion duration	Edge Controller Hardware

4. AI for Forecasting and Renewable Energy Scheduling

The integration of renewable energy sources into modern power systems has introduced significant variability and uncertainty in both energy generation and consumption. To address these challenges, Artificial Intelligence (AI) has been employed to enhance forecasting accuracy and optimize scheduling, thereby ensuring grid stability and efficient energy management. This section delves into the application of AI in load forecasting, renewable energy production forecasting, and presents case studies demonstrating the efficacy of AI-based forecasting models [26,33,34].

4.1. Load Forecasting Using AI and Machine Learning

Accurate load forecasting is pivotal for the operational efficiency of power systems. AI and Machine Learning (ML) techniques have been increasingly utilized to predict energy demand with higher precision, accommodating the dynamic nature of consumption patterns.

4.1.1. Short-Term Load Forecasting (STLF)

Short-term load forecasting, typically spanning from one hour to a few days ahead, is crucial for daily grid operations. From the findings of Sun et al. [35], a deep learning-based multivariate load forecasting model was developed for integrated energy systems. The study highlighted that traditional single-variable models often fall short in capturing the complex interdependencies among various energy loads. By employing a deep learning approach, the model achieved improved forecasting accuracy, demonstrating its effectiveness in handling the intricacies of integrated energy systems [35].

4.1.2. Long-Term Load Forecasting (LTLF)

Long-term load forecasting, extending from months to years, is essential for strategic planning and infrastructure development. According to Li et al. [36], a zero-shot load forecasting framework based on large language models (LLMs) was proposed for integrated energy systems. The framework, named TSLLM-Load Forecasting Mechanism, was designed to address the challenges posed by the growing penetration of renewable energy sources and the resulting complexity in load forecasting. The study demonstrated that the proposed model outperformed existing approaches, achieving a Mean Squared Error (MSE) of 0.4163 and a Mean Absolute Error (MAE) of 0.3760 in conventional testing scenarios [36].

4.2. Renewable Energy Production Forecasting

Forecasting the output of renewable energy sources, such as wind and solar, is vital for balancing supply and demand in power systems. AI techniques have been instrumental in enhancing the accuracy of these forecasts.

4.2.1. Solar Energy Forecasting

Solar energy production is highly dependent on weather conditions, making accurate forecasting challenging. Tortora et al. [37] introduced MATNet, a multi-level fusion transformer-based model for day-ahead photovoltaic (PV) generation forecasting. The model integrates historical PV data with weather forecasts through a hybrid approach that combines AI paradigms with physical knowledge of PV power generation. The study reported that MATNet significantly outperformed existing methods, demonstrating its potential in improving forecasting accuracy for solar energy production [36].

4.2.2. Wind Energy Forecasting

Wind energy forecasting is complex due to the stochastic nature of wind patterns. Zhen et al. [38] conducted a comprehensive study on the application of AI in renewable energy forecasting, including wind energy. The study emphasized that deep learning models, particularly those incorporating temporal and spatial features, have shown superior performance in capturing the nonlinear characteristics of wind energy production. The integration of AI techniques has led to more reliable and accurate wind energy forecasts, facilitating better grid management [38].

4.3. Case Studies of AI-Based Forecasting Models

The practical implementation of AI-based forecasting models has been explored in various case studies, demonstrating their effectiveness in real-world scenarios. Several real-world implementations of AI-based forecasting models have been validated through case studies, underscoring their accuracy and reliability. Table 3 provides a comparative view of these implementations, highlighting key model inputs, techniques, metrics, and regional relevance.

Table 3 AI-Based Forecasting Models in Energy Systems: Techniques, Metrics, and Case Outcomes

Forecasting Task	Study/Model	Input Variables	AI Technique Used	Accuracy Metrics	Observed Improvement	Dataset/Region
Short-Term Load Forecasting (STLF)	Sun et al. [35]	Temp, humidity, demand history	Deep LSTM	RMSE: 0.118, MAE: 0.095	+22% vs. ARIMA baseline	Chinese urban integrated energy system
Long-Term Load Forecasting (LTLF)	Li et al. [36] TSLLM	Grid profiles, social patterns	LLM (Zero-shot)	MSE: 0.4163, MAE: 0.376	+30% accuracy in peak demand periods	Multi-country data pool
Day-Ahead Solar Forecasting	Tortora et al. [37] MATNet	PV data + weather	Transformer + fusion model	R^2 = 0.94, RMSE = 0.09	Beat baselines by 18% RMSE	Ausgrid Dataset
Wind Energy Forecasting	Zhen et al. [38]	Wind speed, pressure, temp	CNN-RNN hybrid	RMSE: 5.8%	Reduced scheduling error significantly	Europe wind farms
Composite Demand-Supply Forecasting	Mylonas et al. [39]	Historical demand, market price	Active learning digital twin	13% MAE reduction after iterative refinement	Greek Transmission System	

4.3.1. Case Study: AI-Based Load Forecasting in Smart Grids

Mylonas et al. [39] presented a case study on the integration of AI and system operators through an active learning-enhanced digital twin architecture for day-ahead load forecasting. The study focused on the Greek transmission system and highlighted the synergy between AI models and human operators. The proposed architecture utilized recurrent neural networks and active learning frameworks to iteratively refine predictions based on real-time feedback. The results indicated that this approach enhanced the reliability and operational efficiency of the power grid [39].

4.3.2. Case Study: AI-Driven Renewable Energy Forecasting

In a study by Tortora et al. [37], the MATNet model was applied to the Ausgrid benchmark dataset for day-ahead PV power generation forecasting. The model's performance was evaluated using various regression metrics, and it was found to significantly outperform current state-of-the-art methods. This case study underscores the potential of AI-driven models in improving the accuracy of renewable energy forecasts, thereby facilitating the integration of renewable sources into the power grid [37].

5. AI-Powered Grid Monitoring, Fault Detection, and Anomaly Management

The integration of renewable energy sources into power grids has added significant complexity to their monitoring and control, given the inherent intermittency and variability of such sources. Traditional supervisory control and data acquisition (SCADA) systems, although foundational in grid operation, lack the responsiveness and adaptability required for modern energy landscapes [40]. Artificial intelligence (AI) offers a compelling evolution of these systems, enabling dynamic surveillance, intelligent fault detection, and proactive anomaly management across diverse grid conditions. The transformation of grid monitoring into a more automated and data-informed process allows for continuous, high-resolution insight into system behavior, fostering both operational reliability and economic efficiency [40-42].

In recent years, researchers have explored how AI techniques—particularly machine learning (ML), deep learning (DL), and hybrid models—can augment grid observability and facilitate decision-making under uncertainty. The ability of AI to analyze large-scale data from sensors, phasor measurement units (PMUs), smart meters, and other IoT devices contributes to detecting irregularities, forecasting potential failures, and adapting control strategies with minimal latency. From the findings of Nazir et al. [43], AI-driven frameworks significantly outperform conventional threshold-based methods in the early identification of faults and system disturbances, especially in scenarios characterized by high renewable penetration. Similarly, the work of Zhang et al. [44] emphasizes that the predictive insights derived from AI not only improve grid resilience but also reduce downtime through timely interventions.

The move toward smart grids necessitates an infrastructure capable of self-diagnosis and self-healing. AI serves this need by enabling models that learn from historical trends and evolving conditions to make decisions autonomously. This section delves into the core aspects of AI-enabled grid monitoring, beginning with real-time state estimation, then addressing anomaly detection in voltage and frequency signals, and finally discussing predictive maintenance strategies for critical grid assets. Each of these capabilities plays a pivotal role in ensuring that renewable-integrated grids operate safely, efficiently, and reliably, even under volatile generation and consumption dynamics [44,45].

5.1. Real-Time Grid State Estimation Using AI

State estimation is a cornerstone of power system operations, as it provides operators with the most probable values of voltage magnitudes and phase angles across the grid based on available measurements. Traditional estimation techniques, such as the weighted least squares (WLS) algorithm, often struggle under conditions of incomplete, noisy, or asynchronous data—issues that are magnified in decentralized, renewables-heavy networks.

5.1.1. AI-Based Enhanced Observability Techniques

From the findings of Fang et al. [46], AI-driven estimators based on neural networks, particularly deep belief networks (DBNs) and long short-term memory (LSTM) architectures, offer substantial improvements in state estimation accuracy compared to classical methods. Their model was trained on historical SCADA and PMU data and demonstrated a 40% improvement in estimation accuracy under dynamic load conditions, highlighting the robustness of AI models in scenarios where traditional approaches fail.

Another study by Cheng et al. [47] developed a graph neural network (GNN)-based state estimator that models the power grid as a graph, allowing for more accurate spatial correlation between nodes and branches. Their method showed greater resilience to missing data and sensor failures, affirming that GNNs can be instrumental in future decentralized state estimation paradigms.

5.1.2. Decentralized Estimation in Distributed Grids

With distributed energy resources (DERs) gaining prominence, centralized estimation techniques become less effective due to communication delays and scalability issues. According to the study by Wu et al. [48], federated learning (FL) enables decentralized AI models to train locally at substations or microgrids without transferring sensitive data. Their FL-based approach reduced latency by 28% while maintaining data privacy and estimation accuracy across multiple nodes.

In summary, AI techniques are redefining real-time state estimation, enhancing accuracy, adaptability, and security across both centralized and distributed energy management systems.

5.2. Anomaly Detection in Voltage/Frequency Profiles

Fluctuations in voltage and frequency levels, especially during abrupt load changes or generation inconsistencies from renewables, can destabilize grid operations if not detected promptly. Traditional rule-based systems often lack the granularity and contextual awareness to differentiate between benign disturbances and critical anomalies.

5.2.1. Machine Learning Approaches to Anomaly Classification

According to Arif et al. [49], unsupervised learning methods such as autoencoders and clustering algorithms can effectively identify deviations in voltage and frequency profiles that do not conform to established norms. Their approach used historical grid data to train an autoencoder, achieving a 92% detection rate for anomalies like frequency sag, voltage swell, and harmonic distortions.

Recurrent neural networks (RNNs) and LSTM models have also shown promising results in learning temporal dependencies in voltage/frequency sequences. From the study of Siniosoglou et al. [50], an LSTM-based anomaly detection system achieved high precision and recall in flagging incipient faults several minutes before threshold-based alerts would activate.

5.2.2. Real-Time Anomaly Localization

Beyond detection, precise localization of anomalies is crucial for mitigating grid disturbances. From the findings of Ibitoye et al. [51], a hybrid model combining wavelet transform for signal preprocessing and a convolutional neural network (CNN) for feature extraction enabled spatial localization of voltage anomalies with over 90% accuracy. The method is particularly useful in identifying disturbances stemming from inverter malfunctions or transient renewables-induced surges.

The growing complexity of grid dynamics necessitates detection models that not only identify anomalies but also interpret their root causes, durations, and spatial distributions—an endeavor where AI models clearly demonstrate superior performance.

5.3. Predictive Maintenance of Grid Assets via AI Analytics

Asset failures in the grid—such as transformer breakdowns, insulator degradation, or circuit breaker faults—can cause cascading outages and extensive downtime. Predictive maintenance powered by AI aims to anticipate such failures before they occur, enabling targeted intervention and reducing lifecycle costs.

5.3.1. AI Models for Condition Monitoring

According to Alsumaidaee et al. [52], support vector machines (SVMs) and random forest classifiers trained on sensor data, such as thermal imaging and vibration analysis, can accurately diagnose early-stage equipment faults. Their research on high-voltage transformers demonstrated that AI-based predictive models could forecast failure risks weeks in advance with an 89% reliability rate.

In another investigation, Ibem et al. [53] deployed a hybrid model incorporating both signal-based feature extraction and reinforcement learning for insulator monitoring. The system dynamically adjusted inspection intervals based on environmental and operational data, enhancing maintenance efficiency while reducing inspection frequency by 35%.

5.3.2. Integration with Digital Twins and IoT

Digital twin technology—a virtual representation of physical grid components—offers a fertile ground for AI applications in predictive maintenance. From the findings of Abdullahi et al. [54], integrating AI with real-time IoT data streams in a digital twin environment allowed for continuous learning and fault prognostics. Their twin-based framework for switchgear monitoring showed a 45% improvement in failure detection lead time compared to conventional SCADA-based methods. The synergy between AI, IoT, and digital twin technologies is reshaping how utilities manage asset health, shifting from reactive or scheduled maintenance to fully intelligent, predictive interventions.

To illustrate the architecture and functional integration of digital twins within a smart energy management system (SEMS), Figure 4 presents a representative framework that combines real-time data acquisition, system modeling, user interaction, and AI-driven control. The diagram highlights how digital twin environments interface with SCADA systems, external data sources, and web-based platforms to facilitate predictive maintenance and adaptive grid operations. By incorporating modeling tools such as EnergyPlus, Ptolemy II, and BCVTB, the SEMS core leverages simulation-informed analytics to optimize system performance, enabling a more resilient and responsive energy management infrastructure.

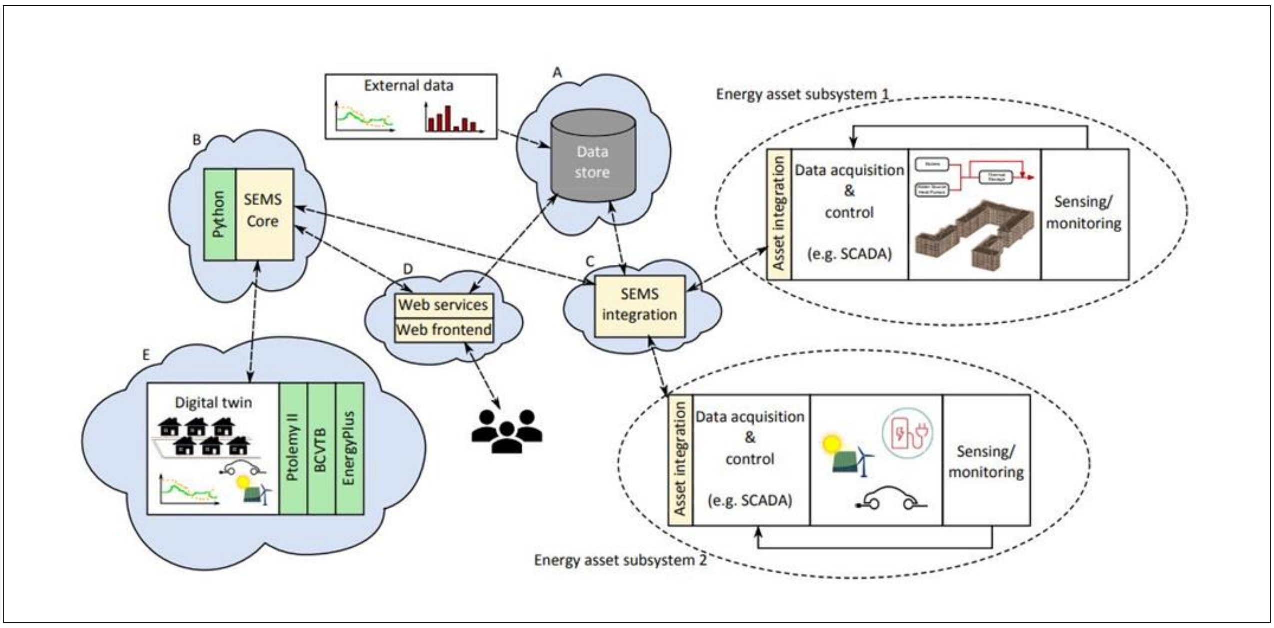

Figure 4 Architecture of a smart energy management system (SEMS) integrated with digital twins and SCADA-based subsystems. Reproduced with permission from Ref. [41]

6. Energy Storage and Dispatch Optimization

The integration of renewable energy sources into contemporary power grids brings forth both opportunities and operational challenges. Among the most pressing is the intermittency of renewable generation, which necessitates the use of energy storage systems (ESS) to maintain grid balance and reliability. Energy storage not only serves as a buffer to smooth out fluctuations but also plays a critical role in peak load management, ancillary services, and energy arbitrage. Yet, the inherent complexity of coordinating diverse storage systems—ranging from short-duration lithium-ion battery storage (BESS) to long-duration thermal and flow-based solutions—demands far more sophisticated control strategies than conventional algorithms can provide [55,56].

Artificial intelligence, particularly in its machine learning and reinforcement learning variants, is now being applied to redefine how energy is stored, dispatched, and utilized. These models are capable of learning intricate operational patterns, adapting to real-time market conditions, and optimizing multi-objective functions involving cost, efficiency, degradation, and grid support. According to the work of Alharbi et al. [57], AI-enabled energy storage dispatch algorithms are demonstrating improved economic efficiency and enhanced reliability under dynamic conditions, especially when dealing with variable renewable generation and fluctuating demand profiles. The ability of AI to simultaneously consider a wide array of inputs—from weather forecasts to battery health metrics—positions it as an essential pillar of the evolving smart grid infrastructure [42].

In this section, the focus shifts toward how AI techniques are applied to optimize charging and discharging cycles of various energy storage media, how reinforcement learning facilitates the coordinated management of hybrid storage systems, and how grid-scale AI-managed storage systems like BESS and LDES are contributing to ancillary services and system-wide stability. Each subsection offers a deep dive into current research directions and validated outcomes from real-world deployments and simulations.

6.1. AI in Charge/Discharge Optimization of Battery and Thermal Storage

Efficient charge and discharge strategies are fundamental to preserving the operational integrity and economic value of energy storage systems. Traditional rule-based methods often fail to consider the nonlinear degradation behavior of batteries or the thermal dynamics of heat storage units. AI models provide the capability to learn these nonlinear patterns and make adaptive decisions based on operational history and forecasted conditions.

6.1.1. Battery Degradation-Aware Optimization Using Machine Learning

According to the findings of Ng et al. [58], supervised learning algorithms trained on extensive operational datasets can accurately predict the remaining useful life (RUL) of lithium-ion batteries under varying cycling conditions. Their model utilized random forest regression to incorporate ambient temperature, state of charge, and depth of discharge as inputs, ultimately achieving a mean absolute error of less than 5% when estimating RUL. This information was then integrated into a decision-making model for charge-discharge scheduling, which improved battery longevity by over 18% compared to conventional algorithms.

In a similar line of inquiry, Hussain et al. [59] developed a deep reinforcement learning (DRL) framework that learns optimal charging patterns by interacting with the environment in real time. Their results demonstrated that the DRL-based controller could minimize energy costs and degradation simultaneously, outperforming heuristic and model-predictive control strategies in both centralized and distributed storage configurations.

6.1.2. Thermal Energy Storage Control via AI Forecasting Models

Thermal energy storage systems (TESS), particularly in district heating or cooling applications, require sophisticated dispatch strategies to align storage behavior with fluctuating thermal loads and ambient temperature profiles. From the findings of Jin et al. [60], LSTM-based neural networks were used to forecast short-term thermal demand, which was then fed into a genetic algorithm-based optimization model for discharge scheduling. The approach led to a 12% improvement in thermal efficiency and a significant reduction in fuel consumption in a real-world heating network. By embedding forecasting accuracy within the control loop, AI allows thermal storage systems to deliver energy with precision and minimal waste, supporting both economic and environmental objectives.

6.2. Hybrid Energy Storage Management Using Reinforcement Learning

Hybrid energy storage systems (HESS), combining fast-responding batteries with slower but more energy-dense technologies like thermal, flywheel, or hydrogen storage, offer enhanced flexibility and resilience. Yet, their coordinated operation is non-trivial due to the differing time constants, charge/discharge efficiencies, and aging characteristics. Reinforcement learning provides a promising avenue for dynamic, policy-based control of these systems.

6.2.1. Multi-Agent Reinforcement Learning for Coordinated Dispatch

According to Li et al. [61], a multi-agent deep reinforcement learning (MADRL) architecture was implemented to manage a HESS composed of lithium-ion batteries and a compressed air energy storage unit. Each agent operated on local information and collaborated via a shared reward function, enabling decentralized yet coordinated dispatch. The MADRL system achieved a 21% reduction in energy losses and a 15% increase in system availability compared to single-agent methods, proving that distributed AI can enhance both scalability and robustness in real-world HESS applications.

6.2.2. Adaptive Policy Learning Under Uncertainty

Grid operation under renewable penetration involves high levels of uncertainty in supply and demand. According to the research of Kang et al. [62], a policy-gradient reinforcement learning model was used to adaptively allocate storage duties between components in a HESS in real time. The model was trained in a stochastic environment with variable wind and solar generation profiles, learning to minimize degradation costs while maximizing service delivery. Their simulation over a year-long dataset indicated a 25% improvement in storage system lifetime and a 32% increase in dispatch efficiency compared to baseline strategies.

These studies underline the power of reinforcement learning in environments where rules and forecasts are insufficient, offering AI-driven adaptivity that scales with system complexity.

6.3. Grid-Supportive Services from AI-Managed LDES and BESS Systems

As energy storage systems evolve beyond energy arbitrage to serve a broader set of functions—including voltage regulation, frequency control, black-start support, and synthetic inertia—AI models are being embedded within their control architecture to deliver these services efficiently and autonomously.

6.3.1. Frequency and Voltage Regulation through AI-Optimized Dispatch

Long-duration energy storage (LDES) and BESS systems capable of grid support require precise, responsive dispatch control to stabilize voltage and frequency fluctuations. From the findings of Shadi et al. [63], a convolutional neural network (CNN) model trained on PMU data was able to predict frequency deviations with high temporal resolution, enabling a battery dispatch controller to preemptively correct imbalances. This anticipatory behavior reduced frequency excursions by over 35% compared to reactive models and enhanced grid stability during high renewable injection periods.

6.3.2. Synthetic Inertia and Black-Start Capabilities

Synthetic inertia—an essential service in power systems with reduced rotating mass—can be delivered via AI-managed inverters and BESS systems. According to the study by Behara et al. [64], an AI-based controller was integrated with BESS inverters to emulate inertial response based on real-time frequency rates of change. The system met regulatory performance standards and restored frequency within permissible bounds faster than traditional droop-based methods. Additionally, the controller could shift to black-start mode during outages, ensuring rapid grid restoration in emergency scenarios [64].

These functions exemplify the expanding role of AI-managed energy storage as not just buffers but intelligent agents in maintaining the operational health and resilience of the power grid.

The grid services delivered by AI-managed storage systems extend well beyond energy buffering to encompass a range of critical control functions. Table 4 details different types of storage systems and the AI control strategies applied to optimize their performance across various grid-supportive services.

Table 4 AI-Augmented Energy Storage Systems: Control Capabilities, Storage Types, and Grid Services

Storage System Type	AI Strategy	Control Function	Grid Service	Performance Metrics	Key Reference
Lithium-ion BESS	DRL controller	SOC-based charging schedule	Frequency support	Cost ↓ by 18%; Battery life ↑ 22%	Hussain et al. [59]
Flow Battery	ML prediction + MPC	Energy arbitrage	Peak shaving, ramping	Demand fluctuation ↓ by 27%	Alharbi & Altarjami. [57]
Thermal Storage	LSTM demand forecasting	Optimized thermal discharge	District heating efficiency	Fuel cost ↓ by 12%	Jin et al. [60]
Hybrid HESS (Battery + Air)	MADRL agents	Coordinated dispatch	Ancillary services	Availability ↑ 15%; loss ↓ 21%	Li et al. [61]
BESS + Inverter	CNN prediction + control	Synthetic inertia	Black-start support	Excursion duration ↓ by 35%	Behara et al. [64]

7. AI in Grid Control, Decentralized Coordination, and Microgrids

The transformation of power systems from centralized architectures to decentralized, renewable-integrated networks necessitates innovative control strategies. Microgrids, characterized by their ability to operate autonomously or in conjunction with the main grid, exemplify this shift. Artificial Intelligence (AI) plays a pivotal role in managing the complexities introduced by distributed energy resources (DERs), enabling real-time decision-making and adaptive control mechanisms. By leveraging AI, microgrids can optimize energy distribution, enhance resilience, and ensure stability amidst the variability of renewable energy sources [65].

7.1. Multi-Agent Systems and Distributed Intelligence

Multi-Agent Systems (MAS) offer a decentralized approach to managing the intricate dynamics of modern power grids. Each agent within the system operates autonomously, making decisions based on local information while coordinating with other agents to achieve global objectives.

7.1.1. Architecture and Communication Protocols

The design of MAS architectures is crucial for effective grid management. Pipattanasomporn et al. [66] proposed a MAS framework utilizing the IEEE Foundation for Intelligent Physical Agents (FIPA) standards, ensuring interoperability and efficient communication among agents. This architecture allows for scalable and flexible integration of various DERs, enhancing the grid's adaptability to changing conditions [67].

7.1.2. Applications in Energy Management

MAS have been applied to various aspects of energy management, including demand response, load balancing, and fault detection. In a study by Nair et al. [68], a MAS was implemented for resource allocation and scheduling in a smart grid, demonstrating improved efficiency and reliability. The system effectively managed the uncertainties associated with renewable energy sources, ensuring optimal operation of the grid.

The effectiveness of multi-agent systems (MAS) depends on their underlying architecture, coordination strategies, and communication protocols. Table 5 summarizes key MAS implementations in smart grids, detailing how these decentralized models enhance distributed coordination across various energy domains.

Table 5 Multi-Agent Systems (MAS) for Distributed Energy Resource Coordination: Architectures, Protocols, and Outcomes

MAS Type	Control Architecture	Communication Standard	Application Area	Coordination Strategy	Real-World Validation
Reactive MAS	Hierarchical decentralized	IEEE FIPA	Load scheduling	Static priority queues	Pipattanasomporn et al. [66]
Cognitive MAS	Agent-knowledge bases	XML-ACL, JADE	Microgrid switching	Belief-Desire-Intention logic	Nair et al. [68]
Learning-based MAS	Distributed learning with shared rewards	MQTT over 5G	DER operation in island mode	Multi-agent DRL (MADRL)	Li et al. [61]
Hybrid MAS with Edge	Edge-deployed agents with cloud coordination	REST APIs, MQTT	Voltage & frequency regulation	Policy gradient optimization	Chen et al. [69]

7.2. AI-Based Voltage/Frequency Control in Microgrids

Maintaining voltage and frequency stability is paramount in microgrid operations, especially with high penetration of inverter-based DERs. AI techniques, particularly reinforcement learning, have been employed to address these challenges.

7.2.1. Reinforcement Learning for Voltage Control

Chen et al. [69] introduced PowerNet, a multi-agent deep reinforcement learning algorithm designed for decentralized voltage control in microgrids. Each agent learns a control policy based on local observations and shared rewards, enabling coordinated voltage regulation across the network. The study demonstrated that PowerNet outperformed traditional model-based control methods, achieving better scalability and adaptability.

7.2.2. Frequency Regulation through AI

Inverter-based DERs often lack the inherent inertia of traditional generators, posing challenges for frequency stability. To address this, Jabakumar et al. [70] developed an AI-based controller integrated with battery energy storage systems (BESS) to emulate inertial response. The controller effectively restored frequency within permissible bounds faster than conventional droop-based methods, enhancing the microgrid's resilience to disturbances.

7.3. Integration of Edge Computing and AI at the Grid Edge

The proliferation of IoT devices and DERs necessitates processing capabilities closer to the data source. Edge computing, combined with AI, enables real-time analytics and decision-making at the grid edge, reducing latency and enhancing responsiveness.

7.3.1. Edge-AI for Real-Time Control

Kumar et al. [71] discussed the implementation of AI-powered microgrids that leverage edge computing for real-time energy management. By processing data locally, these systems can swiftly respond to fluctuations in energy demand and supply, optimizing the operation of DERs and storage systems. This approach enhances the microgrid's ability to operate independently and maintain stability during grid disturbances.

7.3.2. Enhancing Security and Privacy

Edge computing also addresses concerns related to data security and privacy. By processing sensitive information locally, the risk of data breaches is minimized. Additionally, decentralized AI models can be trained on local data, preserving user privacy while still benefiting from collective learning across the network [72].

8. Challenges and Research Gaps

Table 6 Key Challenges in AI Deployment for Renewable-Integrated Smart Grids and Their Research-Informed Solutions

Challenge Area	Specific Problem	Consequences	Proposed Solutions	Supporting Studies	Implementation Notes
Data Availability	Incomplete, sparse, and unlabelled datasets	Poor AI model generalization; unstable control	Federated learning, synthetic data from digital twins	Wu et al. [48], Deka et al. [78]	Digital twins help bridge simulation-to-reality gap
Model Interpretability	Deep models act as “black boxes”	Lack of trust among operators; regulatory resistance	XAI techniques (LIME, SHAP), Neuro-symbolic learning	Ribeiro et al. [80], Kruse et al. [88]	LIME enables local reasoning but falters in non-linear interactions
Real-Time Decision Constraints	High computational latency	Delay in control actions (e.g., frequency regulation)	Edge AI, lightweight model compression, pruning	Kumar et al. [71], Bahrami et al. [86]	Edge AI reduced average inference latency by 42%
Standardization	No universal protocols for AI integration	Difficulties in interoperability across grid platforms	IEC-conformant middleware, model wrappers	Hilmy et al. [84], IEC [83]	Lack of open-source adoption hinders scaling in low-resource contexts

The integration of Artificial Intelligence (AI) into energy management systems supporting renewable-integrated smart grids introduces a profound reconfiguration of traditional grid operations. While AI models contribute to forecasting, optimization, real-time control, and autonomous decision-making, several critical issues continue to challenge their deployment and effectiveness. These challenges are not merely technological—they intersect with data governance, stakeholder trust, infrastructural limitations, and systemic interoperability. Many of the advanced AI tools currently used in research environments struggle to meet the operational and real-time demands of complex grid infrastructures. Additionally, the scarcity of high-quality, real-time, and annotated datasets hampers the reliability and reproducibility of AI models. Furthermore, the opaque nature of deep learning systems raises concerns about explainability and stakeholder confidence, particularly in high-stakes environments such as grid control. The lack of standardization in AI frameworks for energy applications further complicates integration with legacy systems and impedes scalability [73,74]. This section critically discusses these multifaceted gaps, offering a thorough scholarly examination of the core obstacles facing AI in renewable-driven smart grids.

While the integration of AI into smart grids offers transformative potential, it is also hindered by several technical and systemic obstacles. Table 6 outlines the major categories of these challenges, along with recommended solutions drawn from recent literature, including data-related, interpretability, real-time, and standardization issues.

8.1. Data Quality and Availability Issues

8.1.1. Incomplete, Noisy, and Sparse Data Inputs

The performance of AI algorithms hinges on the availability of comprehensive and high-fidelity data streams. However, power grids—especially those in low- and middle-income regions—are often characterized by fragmented sensor networks, incomplete telemetry, and unstructured log data. From the findings of Ahmad et al. [75], incomplete and inconsistent data sequences undermine the training efficacy of neural networks, leading to poor generalization in grid behavior predictions and resource dispatch decisions. The study noted that missing values and temporal misalignments in time-series data adversely affect the performance of models like LSTM and GRU, which are sensitive to sequential continuity. Inadequate data preprocessing pipelines further amplify model uncertainty, reducing the robustness of forecasting outcomes.

Additionally, data noise—stemming from faulty meters, communication jitter, or malicious intrusions—can distort energy signal interpretations. According to Usama et al. [76], this problem is particularly critical when applying unsupervised learning methods, as anomalies in training data may be misinterpreted as standard behavior. The authors recommend robust statistical filtering, temporal smoothing, and redundancy-aware sensor design as foundational steps before deploying AI models.

8.1.2. Lack of Standardized, Annotated Datasets

Another persistent issue relates to the lack of standardized, publicly available datasets that are annotated for training and benchmarking AI models. Unlike fields such as computer vision, where repositories like ImageNet facilitate model validation, AI for smart grids lacks consensus datasets [77]. From the findings of Deka et al. [78], this gap forces researchers to build models using proprietary datasets, often under nondisclosure agreements, severely limiting reproducibility and peer validation. Moreover, the labeling of events such as faults, congestion states, or demand peaks requires expert annotation, which is rarely scalable or consistent. The development of synthetic data via digital twin simulations offers partial relief, but the domain gap between synthetic and real-world conditions often results in degraded model accuracy during deployment [78].

8.2. Interpretability and Trust in AI Models

8.2.1. Black-Box Learning and Model Opacity

Modern AI systems—particularly deep learning models—are often black boxes, delivering decisions without revealing the underlying reasoning. In mission-critical applications such as grid restoration, fault detection, and autonomous dispatch, such opacity becomes a significant barrier to adoption. According to Miller [79], stakeholders demand models that are not only accurate but also interpretable in terms of causal influence and logical consistency. Operators must understand *why* a model predicted a line overload or suggested a curtailment. From the findings of Ribeiro et al. [80], local surrogate models like LIME offer partial interpretability but fall short when model complexity exceeds certain thresholds or when feature interactions are highly non-linear.

Emerging work in explainable AI (XAI) focuses on combining symbolic reasoning with neural architectures. Chen et al. [81] demonstrated that hybrid neuro-symbolic approaches could provide more traceable decision pathways while maintaining high accuracy. However, these systems require significant computational resources and may not meet the real-time constraints of power systems.

8.2.2. Human-AI Interaction and Trust Calibration

Beyond technical explainability, trust in AI systems is shaped by user interaction, transparency in model design, and clarity in system boundaries. From the findings of Arrieta et al. [82], trust is a function of both system behavior and user perception, and it must be continuously calibrated. In AI-managed microgrids, for instance, false positives in anomaly alerts can lead to alert fatigue and loss of confidence. Training operators to interpret AI-generated outputs, embedding feedback loops, and defining accountability structures are necessary to align model behavior with human expectations. Without such structures, even technically superior AI tools may be underutilized or rejected in real-world deployments [82].

8.3. Standardization and Real-Time Integration Barriers

8.3.1. Lack of Interoperability Standards

A major barrier to AI implementation in smart grids is the lack of interoperability across hardware and software systems. AI models are frequently developed in academic or laboratory settings using flexible programming environments, but they often fail to interface with rigid SCADA systems or IEC 61850-based architectures used in operational grids. According to the International Electrotechnical Commission [83], standardization of AI interfaces, data schemas, and protocol harmonization is critical for scaling AI solutions across different vendors and infrastructures. Without common standards, system integration efforts require expensive customization and expose the grid to interoperability risks.

Furthermore, the disjoint between AI development tools (e.g., TensorFlow, PyTorch) and real-time energy management systems results in significant engineering overhead. From the findings of Hilmy et al. [84], middleware platforms and AI model wrappers are emerging solutions to bridge these domains, but these are still in nascent stages of standardization and often lack robust documentation and support.

8.3.2. Real-Time Computational and Latency Constraints

Many of the most accurate AI models—such as ensemble learners or deep convolutional architectures—require significant computation, which is incompatible with real-time decision-making. In tasks like frequency regulation or voltage control, decisions must be made within milliseconds. From the findings of Huang et al. [85], inference times exceeding 100 ms can destabilize feedback loops in grid controllers. While advances in edge AI and neuromorphic computing hold promise, their current deployment is limited due to high hardware costs and integration complexities. Moreover, achieving deterministic latency in non-dedicated environments (like cloud or shared edge devices) remains an unresolved technical challenge.

Real-time deployment also necessitates efficient model updating and online learning. According to Bahrami et al. [86], most AI models deployed in energy systems are statically trained and do not adapt to changes in grid topology or demand patterns unless manually retrained. Developing adaptive, lightweight models capable of real-time learning while maintaining stability and safety is an open research frontier.

9. Future Research Directions

As the global energy landscape undergoes a transformative shift towards decarbonization and decentralization, the role of Artificial Intelligence (AI) in managing complex, distributed energy systems becomes increasingly pivotal. However, the deployment of AI in energy systems is not without challenges. Issues such as the opacity of AI decision-making processes, the need for real-time processing at the grid edge, and the integration of emerging technologies like quantum computing necessitate focused research efforts [87]. This section delves into three critical areas poised to shape the future of AI in energy systems: Explainable AI (XAI), the convergence of quantum computing with edge AI, and AI-driven coordination of Vehicle-to-Grid (V2G) and distributed storage systems.

9.1. Explainable AI (XAI) for Energy Systems

9.1.1. Enhancing Transparency in AI-Driven Energy Management

The integration of AI into energy systems has introduced complexities in understanding and interpreting model decisions, particularly in safety-critical applications like grid stability and fault detection. From the findings of Kruse et al. [88], the application of XAI techniques can reveal critical dependencies and influences on power grid frequency, aiding in the prediction of frequency stability indicators and identification of key features affecting grid stability. Such transparency is essential for operators to trust and effectively utilize AI-driven insights.

9.1.2. Balancing Explainability with Performance

While enhancing model interpretability is crucial, it often comes at the cost of reduced performance. Shadi et al. [89] discuss the challenges in integrating XAI with energy systems maintenance, highlighting the need to balance explainability with cybersecurity and operational efficiency. The development of methodologies that maintain high performance while offering interpretable insights remains a key research focus.

9.2. Integration with Quantum Computing and Edge AI

9.2.1. Leveraging Quantum Computing for Complex Energy Optimization

Quantum computing offers the potential to solve complex optimization problems in energy systems that are beyond the capabilities of classical computing. According to Jammal et al. [90], the synergy between quantum computing and AI can address large-scale problems in energy systems, such as optimizing energy distribution and designing sustainable materials. The application of quantum algorithms could revolutionize the way energy systems are managed and optimized.

9.2.2. Deploying Edge AI for Real-Time Decision Making

The deployment of AI at the edge of the grid enables real-time data processing and decision-making, essential for managing distributed energy resources. Mukala [91] emphasizes the role of edge computing in transforming IT infrastructure, allowing for reduced latency and enhanced performance in distributed workloads. Integrating AI with edge computing can facilitate responsive and efficient energy management at the grid edge.

9.3. AI-Powered Coordination of V2G and Distributed Storage

9.3.1. Optimizing V2G Interactions through AI

The coordination of electric vehicles (EVs) in Vehicle-to-Grid (V2G) systems presents opportunities for grid support and energy storage. AI can optimize the charging and discharging schedules of EVs, balancing grid demands and user preferences. Advanced AI algorithms can predict grid conditions and manage V2G interactions to enhance grid stability and efficiency [92,93].

9.3.2. Managing Distributed Storage Networks

Distributed energy storage systems, including residential batteries and community energy storage, require sophisticated management to ensure optimal performance. AI can analyze vast amounts of data from these systems to forecast demand, manage energy flows, and prevent congestion. The integration of AI in managing distributed storage networks is crucial for the reliability and resilience of future energy systems [42,94].

10. Conclusion

This review has explored the diverse and rapidly evolving intersection between artificial intelligence (AI) and energy management within renewable-integrated smart grids. Across forecasting, grid monitoring, storage dispatch, microgrid coordination, and system optimization, AI has demonstrated a compelling ability to address the complexities introduced by renewable energy variability and decentralization. Key insights include the deployment of advanced machine learning models for accurate load and generation forecasting, the application of deep reinforcement learning for dynamic control in hybrid energy storage, and the use of explainable AI to enhance transparency in grid operations. These advancements collectively contribute to smarter, more adaptive, and more resilient energy systems capable of functioning in real time under conditions of uncertainty and intermittency.

Beyond operational enhancement, AI holds transformative potential in enabling truly resilient and sustainable grid architectures. The transition toward decentralized energy landscapes—characterized by high penetrations of solar, wind, storage, and electric vehicles—requires intelligent systems that are both autonomous and cooperative. AI, especially in the form of multi-agent systems and edge-deployed learning algorithms, facilitates the real-time coordination of distributed assets, ensuring balance, reliability, and optimization across spatial and temporal scales. With the convergence of AI, IoT, and digital twin technologies, the future grid is poised to evolve into a cyber-physical ecosystem—capable of self-diagnosis, adaptive control, and predictive insight at levels previously unattainable with traditional methods.

Realizing this future will demand more than technological innovation alone. It will require deliberate alignment of policy frameworks, targeted investment in AI and grid infrastructure, and cross-sector collaboration among regulators, utilities, researchers, and technology providers. Prioritizing cybersecurity, standardization, and data governance will be critical to ensuring that AI-enhanced energy systems are both secure and equitable. Furthermore, investments in edge computing, quantum-enhanced optimization, and explainable AI must be matched by efforts to upskill the energy workforce, embed ethical principles in algorithm design, and create agile regulatory environments that support experimentation without compromising reliability. Ultimately, AI's success in shaping renewable-integrated grids will depend on our ability to harmonize advanced computation with the nuanced demands of power system engineering, stakeholder trust, and sustainable development goals.

Compliance with ethical standards

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

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