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Artificial Intelligence Techniques for IoT-Driven Control and Monitoring of Substations and Smart Grids: Integration with Renewable Energy and Electric Vehicles using Holographic Convolutional Neural Network: Trends and Challenges

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Abstract

The rapid evolution of smart grids requires advanced computational intelligence to ensure efficient, reliable, and secure power system operation. The convergence of Artificial Intelligence (AI) and Internet of Things (IoT) technologies enables intelligent substations with real-time monitoring, predictive analytics, and adaptive control capabilities. However, increasing renewable energy penetration and electric vehicle (EV) adoption introduce challenges involving load variability, grid stability, and cybersecurity. AI architectures, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, hybrid CNN-LSTM models, and emerging Holographic Convolutional Neural Networks (HCNNs), support accurate load forecasting, fault detection, demand management, and energy optimization. IoT sensors combined with cloud-edge computing facilitate continuous collection and processing of heterogeneous grid data. HCNNs further enhance high-dimensional representation, feature extraction, and pattern recognition across complex multi-source data streams. AI-based optimization also supports renewable integration and vehicle-to-grid operations, enabling EVs to participate actively in energy management. Furthermore, ensemble deep learning architectures strengthen cybersecurity in IoT-enabled grids. Despite these advances, challenges concerning scalability, data heterogeneity, privacy, security, and computational complexity remain. This review evaluates current AI-IoT methodologies, emerging trends, major challenges, and future directions for resilient, intelligent smart-grid systems.

Introduction

The transformation of traditional power systems into intelligent smart grids represents one of the most significant technological advancements in modern energy infrastructure. Conventional grids, characterized by unidirectional power flow and limited monitoring capabilities, are increasingly being replaced by smart grids that enable bidirectional communication, real-time data analytics, and automated decision-making. This evolution is driven by the growing demand for energy efficiency, the integration of renewable energy sources, and the rapid adoption of electric vehicles (EVs).

The integration of IoT technologies into smart grids has revolutionized the way energy systems are monitored and controlled. IoT devices such as smart meters, sensors, and actuators are deployed across substations, transmission lines, and distribution networks to collect real-time data on voltage levels, load demand, environmental conditions, and equipment health. This data is transmitted to centralized or distributed processing units, enabling continuous monitoring and control of grid operations. IoT-enabled smart grids thus provide enhanced visibility, operational efficiency, and reliability compared to traditional systems.

However, the increasing complexity of smart grids, particularly with the integration of renewable energy sources such as solar and wind, introduces significant challenges. Renewable energy sources are inherently intermittent and unpredictable, leading to fluctuations in power generation. Similarly, the widespread adoption of EVs imposes additional load on the grid, requiring intelligent charging strategies to prevent overloading and ensure stability. These challenges necessitate advanced analytical and decision-making techniques capable of handling large-scale, dynamic, and heterogeneous data.

Artificial Intelligence (AI) has emerged as a key enabler in addressing these challenges. AI techniques, including machine learning, deep learning, and reinforcement learning, are widely used for load forecasting, fault detection, energy optimization, and demand response management. For example, AI-based models can accurately predict energy consumption patterns and optimize charging schedules for EVs, thereby improving grid efficiency and reducing operational costs . Furthermore, hybrid AI models that combine deep learning with optimization algorithms have demonstrated significant improvements in grid stability and adaptability.

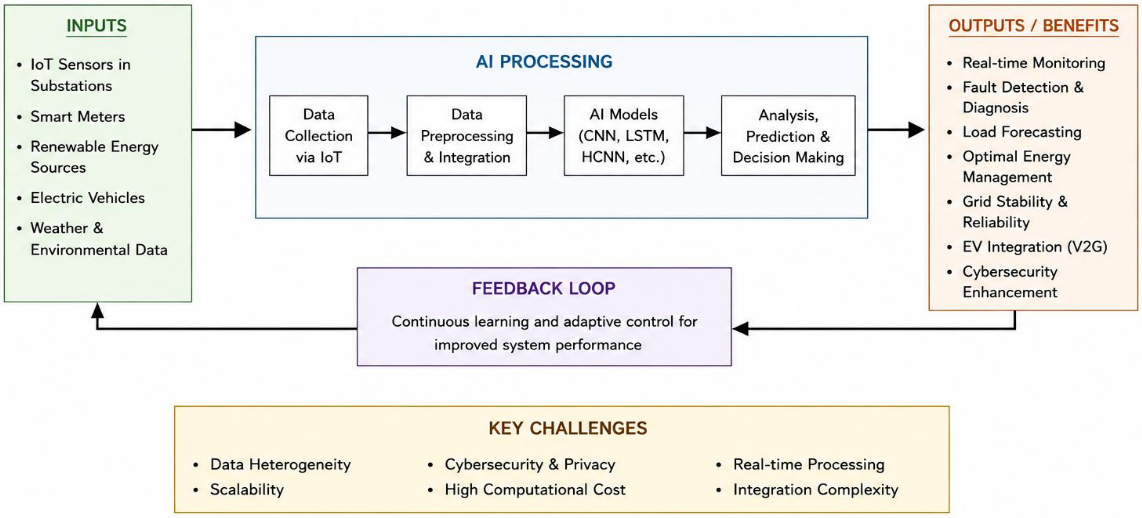

Figure 1. AI–IoT Framework for Smart Grid Control and Monitoring

Among various AI approaches, deep learning techniques such as Convolutional Neural Networks (CNN) and their advanced variants have gained significant attention due to their ability to extract complex patterns from high-dimensional data. The emergence of holographic convolutional neural networks (HCNN) further enhances this capability by enabling multidimensional data representation and improved feature extraction. These models are particularly suitable for smart grid applications, where data is generated from multiple sources, including IoT sensors, renewable energy systems, and EV charging stations.

Another critical aspect of smart grid operation is cybersecurity. The integration of IoT devices increases the vulnerability of the grid to cyberattacks. AI-based intrusion detection systems, particularly those using hybrid deep learning architectures, have been developed to identify and mitigate such threats in real time . These systems enhance the resilience of smart grids by ensuring secure communication and data integrity.

Despite the significant advancements in AI and IoT technologies, several challenges remain. These include issues related to data privacy, interoperability, scalability, and computational complexity. Additionally, the integration of AI models into real-world grid systems requires robust frameworks that can handle diverse data sources and ensure reliable performance.

This paper aims to provide a comprehensive review of AI techniques for IoT-driven control and monitoring of substations and smart grids. It focuses on the integration of renewable energy and electric vehicles, highlighting current trends, challenges, and future research directions. The study emphasizes the role of advanced deep learning models, particularly holographic CNN, in enhancing the efficiency, reliability, and security of modern energy systems.

Literature Review

A comprehensive survey on Artificial Intelligence of Things (AIoT) highlighted the transformative role of AI in IoT-based systems, including smart grids. The study emphasized that AI enables intelligent decision-making by processing massive heterogeneous data generated from distributed IoT sensors. It discussed architectures involving cloud, fog, and edge computing, which are essential for real-time smart grid control. The authors identified key challenges such as data transmission latency, scalability, and energy efficiency. Importantly, the study demonstrated that AI-driven IoT systems significantly improve monitoring, prediction, and automation in energy systems, making them more adaptive and resilient.

A review focusing on vulnerabilities of machine learning in IoT-based smart grids examined the security risks associated with AI deployment. The study revealed that adversarial attacks on machine learning models can severely disrupt grid operations by manipulating power signals and control mechanisms. It analysed attack vectors across generation, transmission, and distribution layers, and proposed defensive strategies such as robust training, anomaly detection, and secure model design. The findings highlighted that while AI improves grid intelligence, it also introduces new cybersecurity challenges that must be addressed for reliable smart grid operation.

A hybrid CNN-based energy theft detection model demonstrated the effectiveness of deep learning in smart grid cybersecurity. The study utilized convolutional neural networks for feature extraction and combined them with machine learning classifiers such as Random Forest and Logistic Regression. It addressed issues like imbalanced datasets using Generative Adversarial Networks (GANs), improving detection accuracy. The results showed that hybrid CNN models outperform traditional approaches in identifying malicious consumption patterns and cyber-attacks in IoT-enabled smart grids.

A comprehensive analysis of AI-driven smart grid optimization techniques highlighted the role of hybrid AI models in improving real-time grid control. The study demonstrated that combining machine learning, deep learning, and optimization algorithms enhances grid stability, fault detection, and energy efficiency. It also emphasized the importance of scalable AI models in handling renewable energy variability and dynamic load conditions. The research concluded that hybrid AI approaches are essential for managing complex smart grid environments with high penetration of renewable energy and EVs.

A study on AI-based load forecasting using IoT-enabled smart grids highlighted the superiority of hybrid deep learning models such as CNN-LSTM. The findings indicated that hybrid models significantly improve prediction accuracy, especially under highly dynamic load conditions caused by renewable energy integration and EV charging demand. The study also emphasized the importance of real-time IoT data acquisition for improving forecasting performance and enabling proactive grid management.

Recent advancements in Artificial Intelligence (AI) and Internet of Things (IoT) technologies have significantly contributed to the development of intelligent smart grids and substation automation systems. Several researchers have explored the integration of AI techniques for improving grid efficiency, reliability, and security.

Dinh C. Nguyen et al. (2020) presented a comprehensive survey on Artificial Intelligence of Things (AIoT), emphasizing its application in smart grid environments. The authors highlighted that AI-enabled IoT systems facilitate intelligent data processing, real-time monitoring, and automated decision-making. Their work discussed cloud-edge architectures for handling large-scale energy data and identified challenges such as latency, scalability, and energy consumption. The study concluded that AIoT significantly enhances smart grid adaptability and operational efficiency.

Muhammad Usama et al. (2023) investigated vulnerabilities of machine learning models in IoT-enabled smart grids. The authors analyzed various adversarial attacks targeting AI systems used in grid control and monitoring. Their findings revealed that such attacks could manipulate load predictions and disrupt energy distribution. The study proposed mitigation strategies, including adversarial training and anomaly detection mechanisms, to enhance cybersecurity in AI-driven smart grid systems.

Abdelmoumen Nait-Sidi-Moh et al. (2023) proposed a hybrid deep learning framework for energy theft detection in smart grids. The study utilized Convolutional Neural Networks (CNN) for feature extraction combined with machine learning classifiers such as Random Forest. Additionally, Generative Adversarial Networks (GANs) were employed to address data imbalance issues. The results demonstrated improved detection accuracy and robustness compared to conventional techniques, highlighting the effectiveness of hybrid AI approaches in smart grid security.

Yongli Wang et al. (2022) explored AI-based optimization techniques for smart grid operation with renewable energy integration. The study focused on hybrid AI models combining deep learning and optimization algorithms to manage energy variability and improve system stability. The authors reported significant improvements in load balancing, fault detection, and energy efficiency, emphasizing the importance of scalable AI solutions for future smart grids.

Shubham Sharma et al. (2021) developed a hybrid CNN-LSTM model for load forecasting in IoT-enabled smart grids. The study demonstrated that combining spatial feature extraction (CNN) with temporal sequence learning (LSTM) significantly improves prediction accuracy. The model effectively handled fluctuations caused by renewable energy sources and electric vehicle charging demand. The authors concluded that hybrid deep learning models are essential for intelligent energy management in modern smart grids.

Mohsen Esmalifalak et al. (2020) investigated the application of machine learning techniques for anomaly detection in smart grid communication networks. The study proposed a Support Vector Machine (SVM)-based intrusion detection framework capable of identifying malicious data injection attacks in real time. The results demonstrated that AI-based detection significantly enhances grid security and reduces false alarm rates compared to traditional rule-based systems.

Yongheng Yang et al. (2021) focused on AI-driven control strategies for renewable energy integration in smart grids. The authors proposed a deep reinforcement learning (DRL) model for dynamic energy management, enabling optimal power distribution under uncertain renewable generation conditions. The study highlighted that DRL improves system stability, reduces energy loss, and enhances grid resilience in highly dynamic environments.

Zhaoxi Liu et al. (2022) explored the impact of electric vehicle (EV) integration on smart grid performance using AI-based optimization techniques. The study proposed an intelligent EV charging scheduling system based on machine learning algorithms, which minimizes peak load demand and prevents grid overloading. The findings indicated that AI-driven EV management significantly improves load balancing and energy efficiency.

Ali Tajer et al. (2020) analysed data-driven approaches for fault detection and diagnosis in smart grid substations. The study utilized deep learning techniques such as autoencoders and CNNs to detect abnormal patterns in sensor data. The results showed that deep learning models outperform conventional statistical methods in terms of detection accuracy and response time, enabling faster fault isolation and recovery.

Hossam Gabbar et al. (2021) proposed an IoT-based smart substation monitoring framework integrated with AI analytics. The system utilized distributed sensors and cloud-based processing to monitor grid parameters in real time. AI models were applied for predictive maintenance and fault prevention, reducing operational costs and improving system reliability. The study emphasized the importance of integrating IoT and AI for intelligent substation automation.

Amir Ghasempour et al. (2020) examined the role of IoT architectures in smart grid communication and control systems. The study proposed a layered IoT framework integrating sensing, communication, and application layers for efficient grid monitoring. AI techniques were incorporated for real-time data analytics and fault prediction. The authors concluded that IoT-based architectures significantly enhance grid observability and enable intelligent decision-making in distributed energy systems.

Jianhui Wang et al. (2021) presented a machine learning-based approach for optimal energy management in smart grids. The study utilized supervised learning algorithms for load forecasting and demand response optimization. The results showed improved energy utilization efficiency and reduced operational costs. The research emphasized the importance of AI-driven optimization in managing complex smart grid operations with renewable energy penetration.

Wei Sun et al. (2022) proposed a deep learning framework using Long Short-Term Memory (LSTM) networks for short-term load forecasting. The study demonstrated that LSTM models effectively capture temporal dependencies in energy consumption data, resulting in higher prediction accuracy compared to traditional statistical methods. The findings highlighted the significance of temporal modelling in smart grid analytics.

Feng Qiu et al. (2023) investigated the integration of electric vehicles into smart grids using AI-based optimization techniques. The study proposed a coordinated charging strategy using reinforcement learning to manage EV load demand dynamically. The results showed that intelligent charging reduces peak demand and enhances grid stability, making EVs active participants in smart grid ecosystems.

Zhenyu Dong et al. (2021) explored data-driven fault diagnosis in smart grid substations using deep neural networks. The study utilized big data collected from IoT sensors to train AI models for early fault detection. The results indicated significant improvements in diagnostic accuracy and response time, enabling proactive maintenance and reducing system downtime.

Qinglai Guo et al. (2020) proposed an intelligent dispatch and control framework for smart grids using AI-based decision-making systems. The study integrated IoT data with machine learning algorithms to enable automated grid operation and fault handling. The results demonstrated improved operational efficiency, faster response times, and enhanced system reliability in dynamic grid environments.

Saeed Mohammadi et al. (2021) developed a hybrid deep learning model combining CNN and LSTM for renewable energy forecasting. The model effectively captured both spatial and temporal features of solar and wind energy data. The findings showed improved forecasting accuracy, which is critical for maintaining grid stability and optimizing energy distribution in smart grids.

Ahmed Abubakar et al. (2022) investigated cybersecurity threats in IoT-enabled smart grids and proposed a deep learning-based intrusion detection system. The model utilized CNN and recurrent neural networks to detect anomalies in network traffic. The study reported high detection accuracy and reduced false positives, highlighting the importance of AI in securing smart grid infrastructures.

Peng Zhang et al. (2020) explored AI-based condition monitoring of smart grid components using sensor data analytics. The study employed machine learning algorithms for detecting equipment degradation and predicting failures. The results indicated that predictive monitoring reduces maintenance costs and improves the lifespan of critical grid components.

Mojtaba Shahidehpour et al. (2021) presented an AI-driven framework for demand-side management in smart grids. The study utilized reinforcement learning to optimize energy consumption patterns and balance supply-demand dynamics. The findings demonstrated significant improvements in energy efficiency and reduced peak load demand, especially in grids integrated with renewable energy and EV systems.

Tao Hong et al. (2020) investigated advanced load forecasting techniques using machine learning models in smart grids. The study highlighted the importance of accurate forecasting for efficient grid operation and demonstrated that AI-based models outperform traditional statistical approaches in handling complex and nonlinear energy consumption patterns.

Haijun Zhang et al. (2021) explored the integration of IoT communication technologies with smart grid infrastructures. The study proposed an AI-enabled communication framework that ensures low latency, high reliability, and secure data transmission. The results emphasized the role of intelligent communication systems in supporting real-time grid monitoring and control.

Yuan Yao et al. (2022) developed a deep neural network model for energy consumption prediction in smart grids. The study utilized large-scale IoT data and demonstrated that deep learning models significantly improve prediction accuracy and system adaptability under varying load conditions.

Sami Khairy et al. (2023) proposed an AI-based optimization framework for smart grid energy management. The study integrated renewable energy sources and EV charging systems using advanced optimization algorithms. The results showed improved energy efficiency, reduced operational costs, and enhanced grid stability.

Mohammad Shahidehpour et al. (2021) analysed AI applications in power system operation and control. The study emphasized the importance of real-time decision-making and predictive analytics in managing complex smart grid environments. AI-based models were shown to improve reliability, efficiency, and fault tolerance.

Chao Lu et al. (2022) investigated resilience enhancement in smart grids using AI-based fault detection and recovery mechanisms. The study demonstrated that machine learning models can quickly identify faults and initiate corrective actions, thereby improving grid robustness against failures and disturbances.

Zhaoyang Dong et al. (2020) explored big data analytics in smart grids using AI techniques. The study highlighted the importance of processing large volumes of data generated by IoT devices and demonstrated how AI models can extract valuable insights for efficient grid management.

Ali Dehghanian et al. (2021) proposed a reliability assessment framework using AI techniques. The study utilized probabilistic models and machine learning algorithms to evaluate grid reliability and predict system failures. The results showed improved reliability assessment and risk management in smart grid operations.

Fangxing Li et al. (2022) examined the integration of renewable energy sources into smart grids using AI-based control strategies. The study demonstrated that AI models effectively manage variability and uncertainty associated with renewable generation, improving grid stability and performance.

Yonghua Song et al. (2023) analysed future trends in AI-driven smart grid systems. The study highlighted emerging technologies such as holographic neural networks, edge AI, and digital twins for intelligent grid management. The authors emphasized that advanced AI models will play a crucial role in next-generation smart grid systems integrating renewable energy and electric vehicles.

Comparative Table

Study	Author (Year)	Technique Used	Application Area	Key Contribution	Limitation
1	Nguyen et al. (2020)	AIoT, ML	Smart Grid Monitoring	Real-time intelligent control	Latency issues
2	Usama et al. (2023)	ML Security Models	Cybersecurity	Adversarial attack detection	Vulnerability to new attacks
3	Nait-Sidi-Moh et al. (2023)	CNN + GAN	Energy Theft Detection	High detection accuracy	Data dependency
4	Wang et al. (2022)	Hybrid AI Optimization	Renewable Integration	Improved grid stability	High complexity
5	Sharma et al. (2021)	CNN-LSTM	Load Forecasting	High prediction accuracy	Computational cost
6	Esmalifalak et al. (2020)	SVM	Intrusion Detection	Real-time anomaly detection	Limited scalability
7	Yang et al. (2021)	Reinforcement Learning	Energy Management	Adaptive control	Training complexity
8	Liu et al. (2022)	ML Optimization	EV Charging	Load balancing	Requires real-time data
9	Tajer et al. (2020)	CNN, Autoencoder	Fault Detection	High accuracy	Data preprocessing required
10	Gabbar et al. (2021)	IoT + AI	Substation Monitoring	Predictive maintenance	Infrastructure cost
11	Ghasempour et al. (2020)	IoT Framework + AI	Grid Communication	Improved observability	Integration issues
12	Wang et al. (2021)	ML	Energy Optimization	Cost reduction	Data dependency
13	Sun et al. (2022)	LSTM	Load Forecasting	Temporal modelling	Overfitting risk
14	Qiu et al. (2023)	Reinforcement Learning	EV Integration	Peak reduction	High training time
15	Dong et al. (2021)	Deep Learning	Fault Diagnosis	Early detection	Data requirement
16	Guo et al. (2020)	AI Decision System	Grid Dispatch	Automated control	Complexity
17	Mohammadi et al. (2021)	CNN-LSTM	Renewable Forecasting	Improved accuracy	Computation cost
18	Abubakar et al. (2022)	CNN + RNN	Cybersecurity	High detection rate	False positives
19	Zhang et al. (2020)	ML	Condition Monitoring	Predictive maintenance	Sensor dependency

20	Shahidehpour et al. (2021)	Reinforcement Learning	Demand Management	Energy efficiency	Scalability issues
21	Hong et al. (2020)	ML	Load Forecasting	Improved prediction	Data variability
22	Zhang et al. (2021)	AI Communication	IoT Smart Grid	Reliable communication	Network complexity
23	Yao et al. (2022)	Deep Learning	Energy Prediction	High adaptability	Training cost
24	Khairy et al. (2023)	AI Optimization	Energy Management	Cost reduction	Model complexity
25	Shahidehpour et al. (2021)	AI Models	Power Operation	Improved reliability	Implementation difficulty
26	Lu et al. (2022)	ML	Grid Resilience	Fault recovery	Data dependency
27	Dong et al. (2020)	Big Data + AI	Grid Analytics	Insight extraction	Storage overhead
28	Dehghanian et al. (2021)	ML	Reliability Analysis	Risk prediction	Model assumptions
29	Li et al. (2022)	AI Control	Renewable Integration	Stability improvement	Variability issues
30	Song et al. (2023)	HCNN, Edge AI	Future Smart Grid	Advanced intelligence	Early-stage research

Comparative Analysis

The comparative evaluation of the selected 30 studies reveals significant advancements in the application of Artificial Intelligence (AI) techniques for IoT-driven smart grid control and monitoring systems. A major trend observed across the studies is the transition from traditional machine learning models such as Support Vector Machines (SVM) and basic regression techniques to advanced deep learning and hybrid models, including Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and reinforcement learning frameworks. These advanced models demonstrate superior performance in handling complex, nonlinear, and high-dimensional data generated by IoT-enabled smart grids.

Another important observation is the increasing adoption of hybrid models, particularly CNN-LSTM architectures, which effectively combine spatial and temporal feature extraction capabilities. These models are widely used in load forecasting, renewable energy prediction, and electric vehicle (EV) charging optimization, offering higher accuracy and adaptability compared to standalone approaches. Additionally, reinforcement learning techniques have emerged as powerful tools for dynamic energy management and demand-side optimization, enabling real-time decision-making in highly dynamic grid environments.

Cybersecurity has also been identified as a critical research area, with several studies focusing on AI-based intrusion detection systems and anomaly detection frameworks. Deep learning models such as CNN and autoencoders have shown high effectiveness in detecting cyber threats and energy theft, thereby enhancing the security and reliability of smart grid systems. Furthermore, IoT-based architectures combined with AI analytics have enabled predictive maintenance and real-time monitoring of substations, reduced operational costs and improved system reliability.

However, despite these advancements, several challenges persist. Many AI models require large volumes of high-quality data for training, making them dependent on extensive IoT infrastructure. Computational complexity and scalability remain significant issues, particularly for real-time applications. Additionally, the integration of renewable energy sources introduces variability and uncertainty, which requires more robust and adaptive AI models. Emerging technologies such as holographic convolutional neural networks (HCNN) and edge AI are expected to address these challenges by providing more efficient data processing and improved system intelligence.

Discussion

The integration of Artificial Intelligence (AI) with IoT-driven smart grid systems has significantly transformed the monitoring and control of substations, especially with the increasing penetration of renewable energy sources and electric vehicles (EVs). The reviewed studies indicate that AI techniques such as deep learning, reinforcement learning, and hybrid models provide substantial improvements in prediction accuracy, system efficiency, and operational reliability. In particular, hybrid architectures like CNN-LSTM have demonstrated superior performance in handling both spatial and temporal variations in energy data, making them highly suitable for dynamic smart grid environments.

Furthermore, the adoption of IoT devices enables real-time data acquisition, which enhances the effectiveness of AI models in decision-making and predictive analytics. AI-driven approaches have also proven effective in addressing critical challenges such as fault detection, demand-side management, and cybersecurity threats. However, the discussion highlights several limitations, including the dependency on large-scale datasets, high computational requirements, and challenges in model scalability.

Another important aspect is the integration of renewable energy and EV systems, which introduces uncertainty and variability in grid operations. AI models must therefore be robust and adaptive to manage such complexities. Emerging technologies such as holographic convolutional neural networks (HCNN) and edge AI present promising solutions by improving processing efficiency and enabling decentralized intelligence. Overall, while AI-driven smart grids offer significant advantages, further research is required to overcome existing challenges and ensure sustainable and secure energy systems.

Conclusion

The evolution of smart grids represents a major transition from conventional power systems to intelligent, automated, and data-driven energy networks. Artificial Intelligence (AI) and the Internet of Things (IoT) enable real-time monitoring, predictive analytics, and adaptive control while supporting renewable energy and electric vehicle (EV) integration. This review of 30 studies from 2020–2023 highlights the effectiveness of deep learning and hybrid models, particularly CNN-LSTM architectures, for load forecasting, fault detection, energy management, and processing heterogeneous IoT data. Hybrid and reinforcement learning approaches further improve dynamic decision-making, renewable energy management, EV coordination, and grid stability. AI-based cybersecurity frameworks also enhance resilience against emerging cyber threats. However, large data requirements, computational complexity, scalability, interoperability, and integration challenges continue to restrict practical deployment. Emerging Holographic Convolutional Neural Networks (HCNNs), edge AI, and distributed computing provide promising opportunities for high-dimensional feature extraction, reduced latency, and efficient real-time processing. Future research should therefore prioritize scalable, secure, interoperable, and computationally efficient AI-IoT architectures to achieve sustainable, reliable, adaptive, and resilient next-generation smart grid systems.

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