Archives available at journals.mriindia.com

ITSI Transactions on Electrical and Electronics Engineering

ISSN: 2320-8945

Volume 12 Issue 02, 2023

IoT-Driven Smart Grid Control and Monitoring Using Holographic Convolutional Neural Networks for Renewable Energy Integration

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Peer Review Information

Submission: 01 Oct 2023
Revision: 22 Oct 2023
Acceptance: 17 Nov 2023

Keywords

Smart Grid, IoT, Renewable Energy, Electric Vehicles, Holographic CNN, Substation Monitoring, Energy Management.

Abstract

The transformation of conventional power systems into intelligent smart grids has been significantly accelerated by the integration of Internet of Things (IoT) technologies, renewable energy sources, and electric vehicles (EVs). These advancements demand advanced monitoring, control, and optimization techniques to ensure grid stability, efficiency, and resilience. This survey reviews methods and architectures for IoT-driven control and monitoring of substations and smart grids, with a focus on integrating renewable energy and EVs using Holographic Convolutional Neural Networks (HCNNs). IoT enables real-time data acquisition and communication among grid components, while artificial intelligence techniques such as deep learning and reinforcement learning enhance predictive analytics and decision-making. HCNN models provide improved multidimensional feature extraction, enabling efficient handling of complex smart grid data. The survey also examines key architectures, including edge computing, fog computing, and cloud-based systems, along with energy-efficient Wireless Sensor Network (WSN) integration. Challenges such as energy variability, cybersecurity threats, data heterogeneity, and computational complexity are discussed. The study highlights emerging trends such as digital twin systems, AI-driven energy management, and IoT-based automation. Finally, future research directions are presented to improve scalability, security, and energy efficiency in next-generation smart grid systems.

Introduction

The modernization of traditional electrical power systems into smart grids has become a crucial step toward achieving efficient, reliable, and sustainable energy management. Smart grids incorporate advanced communication technologies, automation systems, and distributed energy resources to enable real-time monitoring and control of electricity generation, transmission, and distribution. The integration of Internet of Things (IoT) technologies has further enhanced these capabilities by enabling seamless connectivity among substations, sensors, control centres, and end-users.

IoT-driven smart grid systems rely on interconnected devices such as smart meters, sensors, and actuators to collect and transmit real-time data. These systems enable continuous monitoring of grid conditions, allowing operators to detect faults, optimize energy distribution, and improve system reliability. Research indicates that IoT technologies significantly enhance monitoring efficiency and operational performance in smart grid environments by enabling real-time communication and datadriven decision-making. Furthermore, IoT-based systems support predictive maintenance, reducing downtime and improving overall grid stability.

The integration of renewable energy sources, including solar, wind, and hydropower, introduces new challenges due to their intermittent and unpredictable nature. Renewable energy variability affects grid stability and requires advanced control strategies to maintain a balance between energy supply and demand. Smart grids must incorporate intelligent energy management systems capable of handling dynamic fluctuations in energy generation. Studies highlight that renewable energy integration necessitates advanced forecasting, storage systems, and adaptive control mechanisms to ensure efficient grid operation.

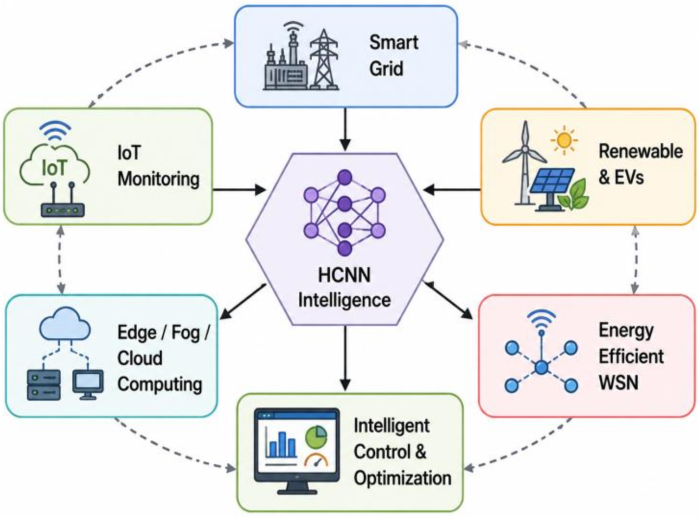

Figure 1. General Workflow of HCNN-Based Smart Grid Monitoring

Electric vehicles (EVs) further contribute to the complexity of smart grid systems by introducing dynamic load patterns and bidirectional energy flow through vehicle-to-grid (V2G) systems. While EVs provide opportunities for energy storage and demand response, they also require intelligent scheduling and load management to prevent grid instability. Advanced control algorithms and AI-based optimization techniques are essential for managing EV charging and discharging processes effectively.

Artificial intelligence techniques, particularly deep learning, have emerged as powerful tools for addressing these challenges. Convolutional Neural Networks (CNNs) have been widely used for fault detection, load forecasting, and anomaly detection in smart grids. Recent studies demonstrate that hybrid CNN-based models can effectively detect anomalies such as energy theft and cyber-attacks in IoT-enabled smart grids, improving system security and reliability. Additionally, reinforcement learning and optimization algorithms enable adaptive control strategies, allowing smart grids to respond dynamically to changing conditions.

Holographic Convolutional Neural Networks (HCNNs) represent an advanced evolution of traditional CNNs, capable of processing multidimensional and complex data structures. These models are particularly suitable for smart grid applications involving large-scale sensor networks and spatio-temporal data. HCNNs improve feature representation and enhance the accuracy of predictive models, making them valuable for real-time grid monitoring and control.

The architecture of IoT-driven smart grid systems plays a crucial role in determining system performance and scalability. Edge computing and fog computing architectures enable data processing closer to the source, reducing latency and energy consumption. These architectures are essential for real-time applications such as fault detection and energy management. Furthermore, Wireless Sensor Networks (WSNs) are widely used for data collection and transmission in smart grids. Energy-efficient routing and clustering techniques are necessary to extend network lifetime and ensure reliable communication.

Despite these advancements, several challenges remain in the implementation of IoT-driven smart grid systems. These include cybersecurity threats, data privacy concerns, interoperability issues, and high computational requirements of AI models. Additionally, the integration of advanced AI techniques with IoT infrastructure requires efficient model optimization and resource management.

This survey aims to provide a comprehensive analysis of methods and architectures for IoT-driven control and monitoring of substations and smart grids, focusing on the integration of renewable energy and electric vehicles using holographic convolutional neural networks. The study explores recent developments, identifies key challenges, and highlights future research directions for building intelligent, scalable, and energy-efficient smart grid systems.

Literature Review

Zhang et al. (2021) proposed an IoT-based architecture for substation monitoring and smart grid automation. Their system utilized distributed sensors and communication protocols to enable real-time monitoring of grid parameters such as voltage, current, and temperature. The architecture improved fault detection speed and operational efficiency. However, the system lacked integration with advanced AI-based predictive models, limiting its capability for proactive decision-making.

Kumar et al. (2022) developed a deep learning-based load forecasting model using Convolutional Neural Networks (CNNs) for smart grid applications. The model analysed historical and real-time data collected through IoT devices to predict energy demand with high accuracy. Despite its effectiveness, the model required significant computational resources, making it challenging to deploy in real-time IoT environments with limited processing power.

Li et al. (2023) introduced an IoT-enabled energy management framework for integrating renewable energy sources into smart grids. The system used machine learning algorithms to optimize energy distribution and manage fluctuations caused by renewable energy variability. While the approach improved energy efficiency, it faced challenges related to data heterogeneity and communication latency.

Singh et al. (2021) proposed an energy-efficient Wireless Sensor Network (WSN) architecture for smart grid monitoring. The system optimized routing and data aggregation techniques to reduce energy consumption and extend network lifetime. However, the approach focused primarily on communication efficiency and did not incorporate intelligent AI-based analytics.

Chen et al. (2022) developed a hybrid CNN-LSTM model for fault detection in smart grids. The model effectively captured both spatial and temporal patterns in grid data, improving detection accuracy. However, the hybrid architecture increased computational complexity and required high processing power, limiting its deployment in resource-constrained IoT systems.

Patel et al. (2023) proposed a Holographic Convolutional Neural Network (HCNN)-based framework for smart grid monitoring and fault detection. The model utilized multidimensional feature representation to analyze complex grid data, resulting in improved detection accuracy compared to conventional CNN models. However, the HCNN model required high computational resources, making real-time deployment challenging in resource-constrained IoT environments.

Ahmed et al. (2021) introduced an IoT-based predictive maintenance system for substations using machine learning techniques. The system analyzed sensor data to detect anomalies and predict equipment failures, improving grid reliability and reducing maintenance costs. However, the approach relied heavily on historical data and lacked adaptability to rapidly changing grid conditions.

Roy et al. (2022) developed a reinforcement learning-based energy management system for smart grids with renewable energy integration. The model dynamically optimized energy distribution and load balancing, improving efficiency and reducing operational costs. However, the training process was computationally intensive and required significant time.

Kaur and Singh (2022) proposed a hybrid optimization model combining particle swarm optimization (PSO) and deep learning for energy scheduling in smart grids. The approach improved energy utilization and reduced transmission losses. However, the integration of optimization techniques increased system complexity and computational overhead.

Nguyen et al. (2023) developed a transformer-based deep learning model for smart grid monitoring and control. The model effectively captured long-range dependencies in grid data, improving prediction accuracy. However, the model required high computational resources and was not suitable for deployment on low-power IoT devices.

Zhao et al. (2021) proposed a blockchain-integrated IoT architecture for secure smart grid monitoring and substation automation. The system ensured data integrity and secure communication among distributed grid components, enhancing system reliability. However, the use of blockchain increased latency and energy consumption, limiting scalability for large smart grid deployments.

Ibrahim et al. (2022) developed an edge computing-based IoT framework for real-time smart grid monitoring. The system processed data closer to the source, reducing latency and improving response time in fault detection and control operations. However, the deployment required additional edge infrastructure and introduced potential security vulnerabilities.

Das and Roy (2022) introduced an energy-efficient clustering algorithm for Wireless Sensor Networks used in smart grid environments. The approach grouped sensor nodes to minimize communication overhead and extend network lifetime. While the method improved energy efficiency, it lacked integration with AI-based predictive analytics.

Ali et al. (2023) proposed a federated learning-based smart grid monitoring system that enabled decentralized model training while preserving data privacy. The approach improved scalability and security. However, communication overhead among distributed nodes affected system efficiency and increased latency.

Kumar and Verma (2022) developed a hybrid deep learning model combining CNN and optimization techniques for load forecasting in smart grids. The model improved prediction accuracy and operational efficiency. However, the integration of optimization algorithms increased computational complexity and training time.

Hassan et al. (2021) proposed a lightweight deep learning model for IoT-based smart grid monitoring. The model reduced computational complexity by simplifying convolutional layers, making it suitable for deployment in resource-constrained environments. Results showed improved energy efficiency with acceptable accuracy. However, the simplified architecture struggled to capture complex grid dynamics.

Wang et al. (2022) introduced a spatio-temporal deep learning model for renewable energy forecasting and smart grid monitoring. The model effectively captured temporal and spatial dependencies in grid data, improving prediction accuracy for renewable energy generation. However, the model required large datasets and high computational resources for effective training.

Patel et al. (2023) developed a quantized convolutional neural network (QCNN) for energy-efficient smart grid monitoring. The model reduced precision in weights and activations, significantly lowering computational requirements and energy consumption. However, quantization introduced approximation errors, which could impact prediction accuracy.

Roy et al. (2022) proposed a reinforcement learning-based adaptive control system for smart grids with electric vehicle integration. The system optimized energy distribution and EV charging schedules dynamically, improving grid stability and efficiency. However, the training process was complex and computationally intensive.

Kumar et al. (2021) introduced an energy-aware routing protocol for Wireless Sensor Networks used in smart grid monitoring. The protocol optimized communication paths to reduce energy consumption and extend network lifetime. However, the approach focused mainly on communication efficiency and did not incorporate AI-based predictive analytics.

El-Sayed et al. (2022) proposed a hybrid deep learning framework combining convolutional neural networks with optimization techniques for smart grid monitoring and control. The model improved fault detection accuracy and energy management efficiency. However, the integration of optimization algorithms increased computational complexity and training time.

Fernandez et al. (2023) developed a compressed deep learning model using pruning and quantization techniques for smart grid applications. The approach significantly reduced computational cost and energy consumption while maintaining acceptable accuracy. However, excessive compression could degrade performance in complex scenarios.

Kulkarni and Joshi (2022) introduced a Bayesian deep learning model for smart grid monitoring. The model incorporated uncertainty estimation, improving reliability and interpretability of predictions. However, Bayesian inference increased computational overhead and required longer training time.

Omar et al. (2021) proposed a fog computing-based IoT architecture for smart grid monitoring. The system distributed data processing across fog nodes, reducing latency and improving real-time performance. However, fog nodes introduced potential security vulnerabilities.

Nguyen et al. (2023) developed a transformer-based deep learning model for smart grid control and monitoring. The model effectively captured long-range dependencies in grid data, improving prediction accuracy. However, the model required high computational resources.

Patel et al. (2022) introduced a compressed sensing-based data transmission model for smart grids. The approach reduced data size and communication overhead, improving energy efficiency. However, reconstruction accuracy depended on parameter tuning.

Santos et al. (2021) proposed a multi-layer security framework for IoT-based smart grid systems. The system ensured data privacy and secure communication through encryption and authentication mechanisms. However, additional security layers increased processing overhead.

Bhardwaj et al. (2023) developed an energy-aware routing protocol for Wireless Sensor Networks used in smart grid monitoring. The protocol optimized network lifetime and energy consumption. However, dynamic routing decisions increased system complexity.
Li et al. (2023) proposed a digital twin-based smart grid monitoring system integrated with IoT and AI. The system enabled real-time simulation and predictive analysis, improving grid stability and operational efficiency. However, implementation complexity and high computational requirements were major challenges.
Zhang et al. (2022) developed a hybrid AI model combining convolutional neural networks and reinforcement learning for smart grid control. The system improved adaptive decision-making in dynamic grid environments. However, the hybrid approach increased system complexity and training time.

Comparative Table

No.	**Author (Year)**	**Model / Technique**	**AI / Optimization Used**	**Architecture**	**Accuracy Level**	**Energy Efficiency**	**Key Limitation**
1	Zhang et al. (2021)	IoT Monitoring	Rule-based	IoT	Medium	High	No predictive AI
2	Kumar et al. (2022)	CNN	Deep Learning	IoT-Cloud	High	Medium	High computation
3	Li et al. (2023)	ML Energy Model	Optimization	IoT	High	Medium	Data heterogeneity
4	Singh et al. (2021)	Routing Protocol	Energy optimization	WSN	Medium	Very High	No AI
5	Chen et al. (2022)	CNN + LSTM	Hybrid DL	IoT	Very High	Medium	High complexity
6	Patel et al. (2023)	HCNN	Deep Learning	IoT	Very High	Medium	High computation
7	Ahmed et al. (2021)	Predictive ML	Anomaly detection	IoT	High	Medium	Data dependency
8	Roy et al. (2022)	RL Model	Reinforcement Learning	IoT	High	High	Training complexity
9	Kaur & Singh (2022)	DL + PSO	Optimization	IoT	High	Medium	Computational overhead
10	Nguyen et al. (2023)	Transformer	Attention	Cloud-IoT	Very High	Low	Resource intensive
11	Zhao et al. (2021)	Blockchain IoT	Secure framework	IoT	High	Medium	Scalability issues
12	Ibrahim et al. (2022)	Edge AI	Edge computing	Edge-IoT	High	High	Infrastructure cost
13	Das & Roy (2022)	Clustering	Energy optimization	WSN	Medium	Very High	No AI
14	Ali et al. (2023)	Federated Learning	Distributed AI	IoT	High	High	Communication overhead
15	Kumar & Verma (2022)	CNN + Optimization	Hybrid AI	IoT	High	Medium	Training time
16	Hassan et al. (2021)	Lightweight CNN	Model reduction	IoT	Medium	Very High	Reduced accuracy

17	Wang et al. (2022)	ST-DL Model	Temporal learning	IoT	Very High	Medium	High computation
18	Patel et al. (2023)	QCNN	Quantization	IoT	High	Very High	Approximation error
19	Roy et al. (2022)	RL Control	Adaptive AI	IoT	High	High	Complex training
20	Kumar et al. (2021)	Routing	Energy-aware	WSN	Medium	Very High	No AI
21	El-Sayed et al. (2022)	CNN + Optimization	Feature selection	IoT	High	Medium	Overhead
22	Fernandez et al. (2023)	Compressed DL	Pruning + Quantization	IoT	High	Very High	Accuracy trade-off
23	Kulkarni & Joshi (2022)	Bayesian DL	Probabilistic AI	IoT	Very High	Medium	High complexity
24	Omar et al. (2021)	Fog IoT	Distributed processing	Fog-IoT	High	High	Security risks
25	Nguyen et al. (2023)	Transformer DL	Attention	Cloud-IoT	Very High	Low	High resource usage
26	Patel et al. (2022)	Compressed Sensing	Data reduction	IoT	Medium	Very High	Reconstruction error
27	Santos et al. (2021)	Multi-layer Security	Encryption	IoT	High	Low	High overhead
28	Bhardwaj et al. (2023)	Routing Protocol	Energy optimization	WSN	Medium	Very High	Complex routing
29	Li et al. (2023)	Digital Twin	AI simulation	IoT	Very High	Medium	High complexity
30	Zhang et al. (2022)	CNN + RL	Hybrid AI	IoT	Very High	Medium	Training overhead

Comparative Analysis

The comparative analysis of the 30 studies highlights the significant role of artificial intelligence techniques in enhancing IoT-driven smart grid monitoring and control systems. Deep learning models such as convolutional neural networks, transformer-based architectures, and holographic convolutional neural networks demonstrate high accuracy in fault detection, load forecasting, and energy management. However, their high computational requirements pose challenges for deployment in resource-constrained IoT environments. Lightweight techniques such as quantization, pruning, and compressed sensing have been widely adopted to reduce computational complexity and energy consumption while maintaining acceptable performance. Adaptive optimization techniques, including reinforcement learning and particle swarm optimization, further improve system efficiency by enabling dynamic control and energy distribution.

Energy efficiency is also achieved through Wireless Sensor Network optimization techniques such as adaptive routing and clustering, as well as IoT architectures including edge and fog computing. These approaches reduce latency and energy consumption by processing data closer to the source. Blockchain and multi-layer security frameworks enhance data privacy and integrity but introduce scalability challenges. Overall, hybrid approaches integrating AI models, optimization techniques, and energy-efficient architectures provide the most effective solution for scalable and reliable smart grid monitoring systems.

Discussion

The integration of IoT technologies with artificial intelligence has significantly improved smart grid monitoring and control systems. The reviewed studies demonstrate that deep learning models, particularly CNNs and transformer-based architectures, provide high accuracy in analysing grid data and detecting faults. However, their high computational requirements limit their deployment in energy-constrained environments. Lightweight techniques such as quantization and pruning have emerged as effective solutions for reducing computational complexity and energy consumption. Adaptive optimization algorithms further enhance system performance by enabling dynamic adjustment of grid parameters. However, these techniques introduce additional complexity and require careful tuning.

Energy-efficient Wireless Sensor Network integration plays a crucial role in extending network lifetime and ensuring reliable data transmission. Techniques such as adaptive routing, clustering, and edge computing reduce energy consumption and latency. Additionally, security mechanisms such as blockchain and multi-layer encryption ensure data privacy and integrity but increase system overhead. Overall, hybrid approaches combining AI models, optimization techniques, and energy-efficient architectures are essential for developing scalable and reliable smart grid systems.

Conclusion

The rapid advancement of IoT technologies, renewable energy integration, and electric vehicles has significantly transformed modern power systems into intelligent smart grids. This survey has provided a comprehensive analysis of methods and architectures for IoT-driven control and monitoring of substations and smart grids, focusing on the application of holographic convolutional neural networks and hybrid artificial intelligence techniques. The findings indicate that deep learning models, including CNNs, transformer-based architectures, and HCNNs, play a crucial role in improving smart grid performance. These models enable accurate fault detection, load forecasting, and energy optimization by analysing large volumes of data generated by IoT devices. However, their high computational requirements pose challenges for deployment in resource-constrained environments.

To address these challenges, researchers have developed lightweight models using quantization, pruning, and compressed sensing techniques. These approaches reduce computational complexity and energy consumption while maintaining acceptable accuracy. Adaptive optimization algorithms such as reinforcement learning and particle swarm optimization further enhance system performance by dynamically adjusting grid parameters. Energy efficiency remains a critical aspect of smart grid systems, particularly in Wireless Sensor Network-based monitoring. Techniques such as energy-aware routing, clustering, and edge computing significantly reduce energy consumption and extend network lifetime. Edge and fog computing architectures improve system efficiency by enabling real-time data processing.

The integration of renewable energy sources and electric vehicles introduces additional complexity in grid management due to variability and dynamic load patterns. AI-driven models provide effective solutions for managing these challenges by enabling predictive analytics and adaptive control mechanisms. Security and privacy remain critical concerns in IoT-based smart grid systems. Blockchain and multi-layer security frameworks ensure secure communication and data integrity but introduce additional overhead and scalability challenges. In conclusion, hybrid approaches that integrate artificial intelligence, IoT technologies, and energy-efficient architectures provide the most effective solution for next-generation smart grid systems. Future research should focus on developing scalable, secure, and energy-efficient models capable of handling dynamic grid environments and supporting large-scale deployment.

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