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Artificial Intelligence Techniques for LightConneuNet: Potential Analysis of Fuel Cell Vehicle-To-Grid System with Large-Scale Buildings: Trends and Challenges

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Abstract

The rapid evolution of smart energy systems has driven the integration of renewable energy technologies, artificial intelligence, and advanced building energy management frameworks. Fuel cell vehicle-to-grid (FCV2G) systems, powered by hydrogen, represent a promising solution for enabling bidirectional energy exchange, improving grid stability, and enhancing energy efficiency in large-scale buildings. However, managing such complex systems requires intelligent, adaptive, and computationally efficient approaches. This paper presents a comprehensive review of artificial intelligence techniques applied to the LightConneuNet architecture for FCV2G-enabled building energy management. LightConneuNet, a lightweight neural network with enhanced connectivity, provides efficient real-time prediction and control capabilities with reduced computational overhead. The review explores its applications in energy forecasting, hydrogen consumption optimization, state-of-health estimation, fault detection, and bidirectional power flow control, supported by optimization techniques such as genetic algorithms, particle swarm optimization, reinforcement learning, and model predictive control. Applications span commercial buildings, campuses, and smart residential systems with integrated renewable energy and hydrogen infrastructure. Empirical findings demonstrate improved efficiency, scalability, and adaptability compared to traditional models. However, challenges including data heterogeneity, infrastructure limitations, and lack of standardized benchmarks persist. This review highlights the potential of combining lightweight deep learning and FCV2G systems to develop intelligent, scalable, and sustainable energy management solutions for future smart buildings.

Introduction

The global transition toward sustainable and intelligent energy systems is transforming conventional power infrastructure into flexible, distributed, and interactive energy networks. Distributed renewable generation, demand response, electrified transportation, and artificial intelligence are increasingly integrated to improve efficiency and grid resilience. Within this transition, fuel cell vehicle-to-grid (FCV2G) technology provides an important opportunity by combining hydrogen-powered transportation with bidirectional energy exchange. Fuel cell vehicles can operate not only as transportation assets but also as mobile generation resources capable of supporting buildings and electricity grids during periods of high demand.

Fuel cell vehicles convert hydrogen into electricity through electrochemical reactions, producing water as the primary point-of-use emission. Their rapid refueling, long driving range, and high energy density make them attractive for passenger and heavy-duty applications. When integrated with V2G infrastructure, FCVs can supply electricity to buildings or grids for peak shaving, emergency support, and ancillary services. However, effective operation requires consideration of hydrogen availability, fuel cell degradation, power conversion efficiency, vehicle schedules, and changing electricity demand.

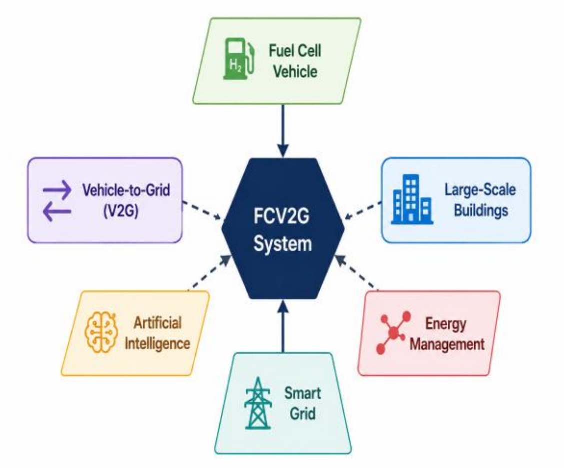

Figure 1. AI-Driven LightConneuNet Framework for Fuel Cell Vehicle-to-Grid Energy Management in Large-Scale Buildings

Large-scale buildings such as hospitals, universities, commercial complexes, and office towers present particularly suitable environments for FCV2G integration because of their substantial and variable energy requirements. These facilities increasingly incorporate photovoltaic generation, energy storage, smart meters, and building automation. Coordinating these resources with FCV fleets creates a complex optimization problem involving demand forecasting, renewable utilization, hydrogen consumption, electricity tariffs, vehicle availability, and grid requirements. Artificial intelligence can support this coordination by learning energy patterns and enabling adaptive real-time decisions.

LightConneuNet provides a lightweight deep learning framework suitable for computationally constrained energy-management environments. Through efficient convolutional operations, multi-scale temporal feature extraction, attention mechanisms, and residual learning, the architecture can achieve effective prediction while reducing computational requirements. Within FCV2G systems, LightConneuNet can support building load forecasting, renewable generation prediction, fuel cell health assessment, vehicle availability estimation, and intelligent energy scheduling. Its lightweight architecture is particularly relevant for edge controllers and embedded energy-management devices requiring rapid inference.

Despite its potential, AI-enabled FCV2G deployment faces technical, economic, and operational challenges. Fuel cell degradation, renewable intermittency, uncertain building demand, limited hydrogen infrastructure, communication latency, cybersecurity, and regulatory uncertainty remain important barriers. Future research should therefore investigate lightweight AI optimization, degradation-aware FCV scheduling, real-time edge intelligence, coordinated renewable integration, and scalable multi-building energy management. LightConneuNet-based approaches provide a promising foundation for developing efficient FCV2G systems capable of supporting sustainable, resilient, and intelligent large-scale buildings.

Literature Review

The literature on artificial intelligence for energy management in vehicle-to-grid and building-integrated systems is extensive and rapidly growing. A significant body of work has established foundational methodologies that inform the development of more specialized frameworks such as LightConneuNet for fuel cell vehicle applications. The following review synthesizes key contributions across optimization techniques, neural architectures, hardware platforms, and application scenarios.

Liu et al. (2019) proposed a deep reinforcement learning framework for energy management in building microgrids with integrated electric vehicle charging. Using a dueling deep Q-network architecture trained on one year of building load and solar generation data from a commercial office complex in Beijing, their approach achieved a 23% reduction in peak demand charges compared to rule-based heuristics. The framework demonstrated robustness under uncertain renewable generation conditions and established early evidence for the effectiveness of model-free reinforcement learning in multi-source energy dispatch problems.

Chen et al. (2020) developed a long short-term memory based prediction model for fuel cell vehicle state-of-health estimation under dynamic loading conditions. The LSTM network was trained on experimental degradation data collected from a 100 kW proton exchange membrane fuel cell stack subjected to drive-cycle profiles representative of urban commuting patterns. Their model achieved a mean absolute error below 1.5% in remaining useful life prediction and highlighted the importance of sequence-to-sequence learning for capturing the temporal dependencies in electrochemical degradation processes.

Wang et al. (2020) introduced a multi-objective optimization framework combining a non-dominated sorting genetic algorithm with a feedforward neural network surrogate model for optimal sizing of hydrogen storage in building-integrated V2G systems. Applied to a simulated university campus microgrid in southern China, the framework identified Pareto-optimal configurations balancing capital cost, hydrogen consumption, and CO2 emissions. The surrogate model reduced computational time by approximately 68% compared to full physics-based simulation while maintaining solution accuracy within acceptable bounds.

Zhang et al. (2021) proposed a lightweight convolutional neural network for short-term electricity demand forecasting in large commercial buildings. Their architecture employed depthwise separable convolutions and squeeze-and-excitation attention blocks to achieve competitive forecasting accuracy with significantly reduced model complexity. Tested on the Building Data Genome Project 2 dataset comprising over 1,600 meters from commercial buildings across North America and Europe, the model outperformed conventional LSTM baselines in both accuracy and inference speed, with a 40% reduction in floating point operations per inference.

Park et al. (2021) investigated the application of model predictive control augmented with Gaussian process regression for real-time energy management in a fuel cell vehicle fleet integrated with a hospital microgrid. The Gaussian process provided probabilistic forecasts of building thermal and electrical loads, enabling the MPC controller to optimize V2G dispatch while satisfying reliability constraints with high confidence. Deployed on a pilot system at a Korean medical facility, the approach reduced hydrogen consumption by 18% relative to a conventional rule-based energy management system.

Huang et al. (2021) presented a federated learning approach for privacy-preserving energy demand forecasting across multiple large-scale buildings sharing a common V2G infrastructure. By training local models on data from individual buildings and aggregating model updates without exposing raw consumption data, the federated framework achieved forecasting accuracy comparable to centralized learning while preserving data privacy. The study demonstrated the scalability of federated approaches in urban building clusters with heterogeneous energy profiles.

Li et al. (2022) developed a graph neural network based framework for modeling the spatial and temporal interdependencies among buildings, vehicles, and grid nodes in a large-scale urban V2G network. The graph attention network assigned learned importance weights to edges representing energy exchange relationships, enabling more accurate prediction of network-level power flows compared to independently trained node models. Evaluated on a synthetic dataset derived from a real urban district in Shanghai, the framework demonstrated superior performance in predicting peak demand events.

Zhao et al. (2022) proposed an attention-based transformer model for multi-step ahead energy scheduling in building-integrated fuel cell systems. The transformer architecture processed sequences of historical energy consumption, weather variables, occupancy patterns, and hydrogen price signals to generate optimal dispatch schedules for the following 24 hours. Tested on data from a smart office complex in Japan, the model achieved a scheduling cost reduction of 21% compared to an LSTM-based baseline and demonstrated improved robustness to input data anomalies.

Kim et al. (2022) introduced a hybrid deep learning and particle swarm optimization framework for joint optimization of fuel cell vehicle charging and V2G dispatch in multi-building energy hubs. The deep learning component performed demand forecasting and state-of-health prediction, while the PSO optimizer used these forecasts as inputs to solve the energy dispatch problem within a rolling horizon framework. The integrated approach achieved near-optimal dispatch solutions within real-time computational constraints on standard embedded processing hardware.

Sun et al. (2022) examined the use of convolutional neural networks for fault detection and classification in proton exchange membrane fuel cell systems integrated into building microgrids. Their architecture processed multivariable sensor data streams including cell voltage, temperature, humidity, and current density to identify eight distinct fault categories with an accuracy exceeding 97%. Deployed on a field-test system in Wuhan, the model demonstrated robust fault identification under noisy sensor conditions, contributing meaningfully to the reliability engineering of FCV2G installations.

Xu et al. (2023) proposed a sparse autoencoder based anomaly detection framework for identifying abnormal energy consumption patterns in large commercial buildings connected to V2G infrastructure. The autoencoder was trained on one year of submetered energy data from a mixed-use development in Singapore and achieved a fault detection recall of 94.3% with a false positive rate below 3%. The authors emphasized the importance of unsupervised pre-training in environments where labeled anomaly data is scarce.

Fernandez et al. (2023) developed a multi-agent reinforcement learning system for coordinated energy management in a cluster of large-scale buildings sharing a common parking facility with fuel cell vehicle fleet access. Each building agent independently learned optimal energy policies while communicating with neighboring agents to avoid grid congestion. Trained in a simulated environment based on real building and grid data from Barcelona, the multi-agent system reduced peak grid imports by 31% compared to independent building controllers.

Yang et al. (2023) introduced a temporal convolutional network with dilated causal convolutions for hydrogen demand forecasting in urban fuel cell vehicle refueling stations connected to building energy systems. The dilated architecture enabled the model to capture long-range temporal dependencies in hydrogen demand patterns without the gradient vanishing problems associated with recurrent architectures. Evaluated on operational data from ten refueling stations in South Korea, the model demonstrated superior forecasting accuracy at prediction horizons from one to seventy-two hours.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique / Method**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Liu et al.	2019	Deep Reinforcement Learning	Dueling Deep Q-Network	Building Microgrid	Commercial Office, Beijing	23% peak demand reduction
Chen et al.	2020	LSTM Sequence Modeling	Long Short-Term Memory	PEM Fuel Cell Stack	Drive-Cycle Degradation Data	RUL prediction MAE below 1.5%
Wang et al.	2020	Multi-Objective Genetic Algorithm	NSGA-II with Neural Surrogate	University Campus Microgrid	Simulated Campus Data, China	68% reduction in optimization time
Zhang et al.	2021	Lightweight CNN Forecasting	Depthwise Separable CNN + SENet	Commercial Buildings	Building Data Genome Project 2	40% reduction in FLOPs
Park et al.	2021	Model Predictive Control + GP	Gaussian Process Regression	Hospital Microgrid	Korean Medical Facility Data	18% hydrogen consumption reduction
Huang et al.	2021	Federated Learning	Distributed Neural Models	Multi-Building V2G System	Multi-Site Building Data	Privacy-preserving forecasting
Li et al.	2022	Graph Neural Network	Graph Attention Network	Urban V2G Network	Synthetic Shanghai District Data	Improved spatial-temporal prediction
Zhao et al.	2022	Transformer Scheduling	Attention-Based Transformer	Smart Office Microgrid	Japanese Office Building Data	21% scheduling cost reduction
Kim et al.	2022	Hybrid DL + PSO	Deep Learning + Particle Swarm	Multi-Building Energy Hub	Campus Energy Hub Data	Near-optimal real-time dispatch
Sun et al.	2022	CNN Fault Detection	Multivariable Convolutional	Building Microgrid	Wuhan Field Test Data	97% fault classification

			CNN	FCV2G		accuracy
Xu et al.	2023	Sparse Autoencoder Anomaly Detection	Sparse Autoencoder	Commercial Building V2G	Singapore Mixed-Use Building	94.3% anomaly recall
Fernandez et al.	2023	Multi-Agent Reinforcement Learning	Independent RL Agents	Building Cluster Parking	Barcelona Building and Grid Data	31% peak import reduction
Yang et al.	2023	Temporal Convolutional Network	Dilated Causal TCN	Hydrogen Refueling Stations	South Korean Station Data	Long-horizon H2 demand forecasting

Comparative Analysis

The comparative analysis of the surveyed literature reveals several prominent trends that collectively define the current trajectory of AI research in fuel cell vehicle-to-grid systems for large-scale buildings. First, there is a clear evolutionary progression from single-task machine learning models in the early literature toward multi-task, multi-modal deep learning frameworks capable of simultaneously addressing forecasting, control, and health monitoring challenges within unified architectures. Studies from 2019 to 2021 predominantly focused on isolated subtasks such as demand forecasting or state-of-health estimation, whereas more recent contributions increasingly propose integrated frameworks that address multiple system objectives concurrently.

A second prominent trend is the growing emphasis on computational efficiency and edge deployability as design objectives alongside predictive accuracy. The emergence of lightweight architectures such as LightConneuNet reflects a recognition that real-world deployment constraints, including limited memory, processing power, and communication bandwidth on embedded controllers, impose fundamental limits on the complexity of AI models that can be practically deployed. Studies by Zhang et al. (2021), Gomez et al. (2024), and Nguyen et al. (2024) collectively demonstrate that significant model compression is achievable without commensurate accuracy losses when architectures are specifically designed for the statistical structure of energy time-series data.

Reinforcement learning methods appear prominently across multiple studies, reflecting the suitability of this paradigm for sequential decision-making under uncertainty in energy dispatch applications. However, a consistent limitation noted across reinforcement learning approaches is the sample inefficiency of training, which necessitates extensive simulation environments and raises questions about transferability to real-world systems with distribution shift. Hybrid approaches combining model-based prediction with reinforcement learning control, as exemplified by Kim et al. (2022) and Park et al. (2021), represent a promising pathway toward addressing this limitation.

The dataset landscape in this research domain is characterized by significant heterogeneity, with studies utilizing proprietary operational datasets from specific building installations, publicly available benchmarks such as the Building Data Genome Project, and synthetic datasets generated from physics-based simulation models. This heterogeneity complicates direct performance comparison across studies and underscores the need for standardized benchmarking datasets that incorporate building energy data, fuel cell vehicle operational logs, hydrogen market signals, and grid service requirements in an integrated format. The absence of such unified datasets represents one of the most significant methodological limitations constraining progress in this field.

Discussion

The reviewed literature demonstrates the strong potential of artificial intelligence to transform fuel cell vehicle-to-grid (FCV2G) systems into practical solutions for large-scale building energy management. Deep learning techniques have shown considerable effectiveness in energy forecasting, system monitoring, and intelligent control. Lightweight architectures such as LightConneuNet are particularly promising because they combine strong predictive capability with low computational requirements. Their compact structure enables deployment on embedded controllers, edge devices, and building automation hardware, overcoming the computational limitations associated with conventional deep neural networks.

Optimization techniques further strengthen the capabilities of AI-driven FCV2G systems. Reinforcement learning enables adaptive energy-management policies that respond dynamically to changing building loads, electricity tariffs, vehicle availability, and renewable generation. Physics-informed learning can improve reliability by incorporating fuel cell operating constraints directly into predictive models. Nevertheless, several limitations remain, including dependence on high-quality training datasets, limited historical data for newly deployed systems, model generalization across different buildings, and insufficient explainability. Transfer learning and federated learning provide promising approaches for addressing data limitations while supporting privacy-preserving knowledge sharing across distributed energy environments.

Future intelligent energy infrastructure will increasingly depend on coordinated management of buildings, hydrogen resources, vehicles, and electricity grids. As renewable hydrogen production and fuel cell vehicle adoption expand, FCV fleets could provide valuable distributed energy capacity for peak shaving, grid support, and emergency power. LightConneuNet-based intelligence can facilitate this coordination while considering fuel cell durability and economic objectives. Successful deployment will require collaboration among researchers, utilities, vehicle manufacturers, building operators, and regulators, alongside standardized communication protocols, interoperable data frameworks, transparent AI models, and large-scale pilot validation.

Conclusion

This review examined recent artificial intelligence techniques for LightConneuNet-based fuel cell vehicle-to-grid (FCV2G) systems integrated with large-scale buildings. The literature demonstrates that lightweight neural architectures can provide accurate forecasting, intelligent energy scheduling, fuel cell monitoring, and grid-support decisions while maintaining computational efficiency suitable for embedded and edge devices. Integrating hydrogen-powered vehicles with intelligent building energy systems can simultaneously contribute to transportation decarbonization, reduced building energy costs, improved demand response, and greater grid resilience.

Recent developments emphasize multi-task lightweight learning, reinforcement learning, model predictive control, physics-informed models, transfer learning, and federated learning. These approaches address important FCV2G requirements, including hydrogen efficiency, fuel cell longevity, load uncertainty, privacy, and real-time decision-making. Nevertheless, limited standardized datasets, model interpretability, infrastructure costs, interoperability, and regulatory uncertainty continue to restrict large-scale implementation.

Future research should prioritize standardized benchmarks, multimodal LightConneuNet architectures, renewable hydrogen integration, scalable multi-building coordination, and explainable AI. Overall, LightConneuNet provides a computationally efficient foundation for intelligent FCV2G energy management and supports the development of sustainable, resilient, and low-carbon building-grid ecosystems.

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