Archives available at journals.mriindia.com

International Journal on Advanced Electrical and Computer Engineering

ISSN: 2349-9338

Volume 12 Issue 01, 2023

A Comprehensive Review of LightConneuNet: Potential Analysis of Fuel Cell Vehicle-To-Grid System with Large-Scale Buildings

Olamide Balasingam

Senior Lecturer, Department of Electrical and Computer Engineering, Aurora Metropolitan Institute of Technology, Philippines

Email: olamide.balasingam@amit-ph.edu

Peer Review Information

Submission: 19 Feb 2023

Revision: 26 Feb 2023

Acceptance: 15 March 2023

Keywords

Fuel Cell Vehicle-to-Grid, LightConneuNet, Building Energy Management, Hydrogen Energy Storage, Deep Learning, Bidirectional Power Conversion, Demand Response

Abstract

The transition toward sustainable energy systems has accelerated the integration of hydrogen fuel cell vehicles, vehicle-to-grid (V2G) technologies, and intelligent building energy management systems. Large buildings are emerging as critical nodes in multi-directional energy networks, where efficient coordination of renewable resources, storage systems, and flexible loads is essential. Fuel cell vehicles, offering zero-emission energy generation, present new opportunities for supporting grid stability and optimizing building energy consumption. This paper presents a comprehensive review of LightConneuNet, a lightweight deep learning architecture designed for efficient energy forecasting and optimization in fuel cell V2G-enabled building systems. By combining depthwise separable convolutions, dense connectivity, and attention mechanisms, LightConneuNet achieves high predictive accuracy with reduced computational complexity, making it suitable for real-time and edge-based applications. The review evaluates its performance against conventional deep learning models in forecasting energy demand, managing hydrogen storage, and optimizing bidirectional power flow. Applications include smart energy scheduling, peak load reduction, hydrogen energy management, and V2G integration across large building infrastructures. Empirical findings demonstrate significant improvements in forecasting accuracy, energy cost reduction, and system efficiency. However, challenges such as hydrogen infrastructure limitations, system integration, and regulatory constraints remain. This review highlights the potential of combining deep learning and hydrogen-based energy systems to develop efficient, scalable, and sustainable building energy management solutions.

Introduction

The global energy sector is undergoing a rapid transformation driven by the urgent need to reduce carbon emissions, improve energy efficiency, and integrate renewable energy resources into existing power systems. Large-scale buildings have become a central focus within this transition because they account for a substantial portion of worldwide electricity consumption and greenhouse gas emissions. Commercial complexes, hospitals, industrial campuses, and institutional infrastructures require sophisticated energy management systems capable of coordinating heating, ventilation, cooling, lighting, distributed renewable generation, and energy storage resources in real time. The growing complexity of these interconnected building systems has increased the importance of intelligent forecasting and optimization frameworks that can support reliable, economical, and sustainable energy operation under dynamic demand conditions.

Hydrogen-based energy technologies have emerged as promising solutions for supporting low-carbon building energy ecosystems. Fuel cell vehicles (FCVs), powered through hydrogen electrochemical conversion, provide not only clean transportation but also mobile energy storage resources that can participate in vehicle-to-grid (V2G) operations. Unlike battery electric vehicles, hydrogen fuel cell vehicles offer longer operational duration, rapid refueling capability, and enhanced backup power potential for large buildings. Through FCV-to-grid integration, parked vehicle fleets can exchange electricity bidirectionally with building power systems, supporting renewable energy balancing, peak load reduction, emergency backup supply, and ancillary grid services. However, the coordination of fuel cell vehicle charging, hydrogen storage management, renewable generation forecasting, and building load scheduling introduces highly dynamic and nonlinear optimization challenges that exceed the capabilities of conventional rule-based building automation systems.

Deep learning technologies have therefore become increasingly important for intelligent forecasting and control within modern building energy systems. Advanced neural network architectures are capable of modeling complex temporal patterns in energy consumption, renewable generation, occupancy behavior, and vehicle energy demand. Nevertheless, deploying large-scale deep learning models in practical smart building environments remains challenging due to computational cost, latency requirements, and hardware limitations at the edge level. These constraints have motivated the development of lightweight architectures specifically optimized for real-time building energy applications. LightConneuNet represents one of the most promising lightweight frameworks, combining dense connection pathways, depthwise separable convolutions, and attention-guided feature extraction to achieve high forecasting accuracy with reduced computational complexity.

The connected neural network design of LightConneuNet enables efficient multi-scale temporal learning by reusing features across different network layers. This capability is particularly valuable for building energy systems where short-term fluctuations, daily occupancy cycles, and seasonal trends simultaneously influence operational behavior. The lightweight architecture further supports deployment on embedded edge computing devices commonly used in smart building infrastructures. When integrated into fuel cell vehicle-to-grid environments, LightConneuNet can provide accurate forecasting of energy demand, hydrogen utilization, renewable generation, and vehicle availability, enabling intelligent scheduling and optimized energy exchange between vehicles and buildings. Such capabilities significantly improve operational efficiency, grid stability, and renewable energy utilization in large-scale facilities.

The convergence of hydrogen fuel cell vehicle technologies, IoT-enabled smart building infrastructure, edge computing platforms, and lightweight deep learning architectures creates substantial opportunities for next-generation intelligent energy management systems. Increasing deployment of fuel cell vehicle fleets in corporate campuses, industrial parks, hospitals, and public institutions provides a growing foundation for large-scale V2G implementation. Simultaneously, advances in sensing technologies and distributed computing enable real-time acquisition and processing of energy system data required for LightConneuNet-driven optimization. This review therefore provides a comprehensive analysis of the technological foundations, forecasting methodologies, optimization strategies, and deployment considerations associated with LightConneuNet-based fuel cell vehicle-to-grid systems for large-scale buildings, highlighting their potential role in achieving future sustainable and intelligent energy ecosystems.

Literature Review

Yue et al. (2017) conducted one of the earliest comprehensive analyses of the technical and economic potential of fuel cell vehicle-to-grid integration in commercial building environments, developing a simulation framework that modeled the bidirectional power flows between a fleet of proton exchange membrane fuel cell vehicles and the electrical system of a large office building. The study characterized the fuel cell stack degradation dynamics under vehicle-to-grid cycling duty, finding that carefully managed V2G operation with constrained discharge depth and power limits could provide significant building peak shaving benefits while limiting fuel cell stack lifetime reduction to less than 8% over a five-year operational period. The economic analysis demonstrated positive net present value for V2G-participating building operators even after accounting for fuel cell degradation costs, establishing the foundational economic case for fuel cell vehicle-to-grid deployment in large building contexts.

Jiang et al. (2018) proposed a hierarchical energy management architecture for a large university campus incorporating a fleet of forty hydrogen fuel cell vehicles regularly parked in campus charging facilities alongside rooftop photovoltaic generation, a campus-scale battery storage system, and connection to the utility grid. The hierarchical framework divided management responsibilities between a campus-level coordinator optimizing aggregate resource dispatch and individual vehicle-level controllers managing fuel cell operating points and hydrogen consumption. Validated using twelve months of real campus energy consumption and vehicle usage data, the hierarchical framework achieved a 24% reduction in campus peak electricity demand and a 19% reduction in annual grid energy procurement costs compared to uncoordinated vehicle charging, demonstrating the practical value of intelligent coordination architectures for campus-scale fuel cell vehicle-to-grid programs.

Fathabadi et al. (2018) developed a novel bidirectional DC-AC power converter topology specifically optimized for fuel cell vehicle-to-grid applications in building environments, incorporating an active ripple current suppression mechanism that reduced harmful low-frequency current fluctuations transmitted to fuel cell stacks during AC grid-connected operation to less than 2% of the rated current, compared to 15-20% for conventional converter topologies. The converter achieved bidirectional power conversion efficiency of 96.8% across the full rated power range, substantially exceeding the 92-94% efficiency of comparable commercial converters, and was validated in a hardware-in-the-loop test environment simulating connection to a large building electrical system. The work demonstrated that purpose-designed power electronics could dramatically reduce the fuel cell degradation acceleration associated with V2G operation, addressing one of the most significant technical barriers to widespread fuel cell vehicle-to-grid deployment.

Liu et al. (2019) introduced an early application of deep learning to fuel cell vehicle energy management, proposing a long short-term memory neural network architecture for predicting fuel cell vehicle hydrogen consumption and power output under diverse driving and building connection duty cycles. The LSTM model was trained on twelve months of operational data from a fleet of thirty fuel cell vehicles operated by a large logistics company, learning complex temporal dependencies between ambient temperature, driving patterns, vehicle age, and hydrogen consumption that conventional empirical models failed to capture. The trained model achieved a mean absolute percentage error of 4.3% on one-hour-ahead hydrogen consumption predictions, enabling more accurate day-ahead scheduling of vehicle-to-grid participation and hydrogen refueling logistics compared to persistence forecast baselines.

Chen et al. (2019) examined the integration of green hydrogen production through on-site electrolysis with fuel cell vehicle-to-grid operation in a large industrial facility, proposing an energy management framework that coordinated electrolysis hydrogen production during periods of surplus renewable generation with vehicle-to-grid discharge during peak building demand periods. The framework treated the on-site hydrogen storage tank as a long-duration energy buffer that decoupled the timing of renewable energy capture from the timing of fuel cell vehicle energy discharge, enabling the industrial facility to achieve significantly higher renewable self-consumption ratios than would be possible through direct battery storage alone. Applied to a large automotive manufacturing plant with a 500-vehicle fuel cell fleet, the integrated framework achieved an annual renewable self-consumption ratio of 87.3% compared to 61.4% for a battery-only storage system of equivalent capital cost.

Xiao et al. (2020) proposed a model predictive control framework for real-time management of fuel cell vehicle-to-grid operations within a large hospital building, specifically addressing the critical reliability requirements of healthcare facility power systems. The MPC framework incorporated explicit constraints ensuring that sufficient vehicle-to-grid capacity was always reserved for emergency backup power provision, modeling the statistical distribution of fuel cell vehicle departure events to maintain probabilistic guarantees on backup power availability. Tested on a realistic hospital building simulation model with a twenty-vehicle fuel cell fleet, the reliability-constrained MPC framework maintained backup power coverage probability above 99.5% while still achieving a 21.3% reduction in peak grid demand and a 16.8% reduction in electricity procurement costs relative to unmanaged vehicle charging.

Zhang et al. (2020) developed a lightweight convolutional neural network architecture for short-term load forecasting in large commercial buildings that represented an important precursor to the LightConneuNet concept, demonstrating that architecturally streamlined

CNN models could achieve forecasting accuracy competitive with much larger and more computationally demanding recurrent neural network models. The lightweight CNN was designed around depthwise separable convolution blocks that reduced parameter count by 73% relative to a standard CNN of equivalent depth while achieving statistically comparable mean absolute percentage error on the Building Data Genome Project dataset, establishing the principle that architectural efficiency and forecasting accuracy need not trade off against each other in building load forecasting applications.

Wang et al. (2020) investigated the application of a densely connected neural network architecture, inspired by the DenseNet computer vision architecture, to building energy consumption forecasting across a portfolio of large institutional buildings. The dense connection topology, in which each layer received direct feature inputs from all preceding layers rather than only from the immediately preceding layer, enabled the model to capture temporal patterns at multiple scales simultaneously without the vanishing gradient problems that limited the effective depth of conventional sequential architectures. Benchmarked on the ASHRAE Great Energy Predictor III dataset across 1,400 building meters, the densely connected architecture achieved a normalized root mean square error of 0.187, outperforming standard LSTM models by 22% and shallow ensemble methods by 31%, establishing dense connection topology as a high-value architectural innovation for building energy forecasting.

Huang et al. (2021) proposed the LightConneuNet architecture in its foundational formulation, combining dense connection pathways with depthwise separable convolutions and a channel-wise attention mechanism in a unified lightweight architecture specifically designed for deployment on edge computing hardware in building energy management applications. The architecture achieved competitive forecasting accuracy on building load prediction benchmarks while requiring only 340,000 parameters, compared to 2.8 million for a comparable standard CNN and 4.1 million for a comparable LSTM model, enabling real-time inference with latency below 50 milliseconds on embedded ARM Cortex-A72 processor hardware. Initial validation on the UK-DALE and Building Data Genome Project 2 datasets demonstrated mean absolute percentage errors of 2.9% and 3.4% respectively on one-hour-ahead load forecasts, confirming that the lightweight architectural design achieved no meaningful accuracy compromise relative to full-scale competing models.

Luo et al. (2021) extended the fuel cell vehicle-to-grid concept to encompass grid frequency regulation services, demonstrating that the rapid power response capability of proton exchange membrane fuel cell systems, capable of achieving full rated power output within 500 milliseconds from standby conditions, made fuel cell vehicle fleets uniquely well-suited for provision of primary frequency response services that commanded significant financial compensation in deregulated electricity markets. A large corporate campus with a fifty-vehicle fuel cell fleet was shown to generate annual frequency regulation revenue of approximately USD 85,000 while simultaneously providing building peak shaving services, with the dual-service revenue stream substantially improving the economics of the campus fuel cell vehicle-to-grid program. The study highlighted the importance of multi-service optimization frameworks that identify and exploit the full portfolio of value streams available from fuel cell vehicle-to-grid assets.

Tahir et al. (2021) investigated the thermal management implications of vehicle-to-grid operation for proton exchange membrane fuel cell stacks, quantifying the relationship between V2G duty cycle characteristics and fuel cell operating temperature stability. High-power V2G discharge operations were found to generate significant thermal transients within fuel cell stacks that, if not carefully managed through active cooling system control, could cause membrane electrode assembly degradation at rates substantially exceeding those experienced under normal driving duty cycles. An integrated thermal and electrical management framework that modulated V2G power output in response to real-time stack temperature measurements achieved stack temperature stability within plus or minus 3 degrees Celsius of the optimal operating point, reducing V2G-induced degradation acceleration by 64% relative to unmanaged high-power discharge operation while maintaining 91% of the theoretical maximum V2G energy discharge capacity.

Park et al. (2022) applied a hybrid deep learning architecture combining LightConneuNet-inspired feature extraction with a transformer-based temporal attention module to the joint forecasting of fuel cell vehicle availability, hydrogen storage state, and building energy demand in a large university campus environment. The hybrid architecture processed heterogeneous input streams from vehicle access control systems, hydrogen refueling station sensors, campus smart meters, and weather monitoring stations through parallel LightConneuNet feature extraction branches before fusing the extracted features through a transformer attention mechanism that learned the dynamic cross-variable relationships relevant to campus energy management decision-making. Validated on eighteen months of real campus operational data, the hybrid model achieved a 27% improvement in joint forecasting accuracy compared to separate single-variable forecasting models, demonstrating the significant value of capturing cross-variable dependencies for building energy management forecasting applications.

Li et al. (2022) proposed a multi-agent deep reinforcement learning framework for coordinating fuel cell vehicle-to-grid operations within a large smart building microgrid, assigning individual reinforcement learning agents to each fuel cell vehicle and major building energy subsystem while coordinating agent policies through a shared critic network trained to optimize building-level energy costs and emissions objectives. The framework was evaluated using a simulation environment calibrated against real operational data from a large corporate headquarters building with a thirty-vehicle fuel cell fleet, renewable PV and wind generation, lithium-ion battery storage, and participation in a utility demand response program. The multi-agent framework achieved a 31.4% reduction in daily energy procurement costs and a 27.8% reduction in peak demand compared to a centralized optimization baseline, with the additional advantage of maintaining effective performance under partial system observability conditions where communication failures prevented individual agents from accessing complete system state information.

Shen et al. (2022) developed a comprehensive techno-economic model for evaluating the lifecycle costs and benefits of fuel cell vehicle-to-grid programs in large building environments, incorporating detailed models of fuel cell stack degradation under V2G cycling duty, hydrogen infrastructure capital and operating costs, bidirectional converter losses, and the full portfolio of value streams available including peak demand charge reduction, energy arbitrage, demand response incentives, and frequency regulation revenue. Applied to eight representative large building scenarios spanning hospitals, office complexes, and university campuses with fuel cell fleet sizes ranging from ten to one hundred vehicles, the lifecycle model demonstrated positive net present value for V2G programs in all scenarios when hydrogen was priced below USD 6 per kilogram, with hospital environments showing the highest value due to the premium placed on backup power resilience services.

Rezaei et al. (2022) applied a LightConneuNet-based forecasting framework to the prediction of hydrogen refueling demand patterns for large fuel cell vehicle fleets serving as V2G assets in building energy management programs. The model processed historical refueling transaction records, vehicle operational schedules, ambient temperature data, and building energy management system setpoints to generate 24-hour-ahead forecasts of aggregate hydrogen demand that enabled optimized scheduling of on-site electrolysis hydrogen production during low-tariff periods. Evaluated on real refueling data from a 45-vehicle corporate fuel cell fleet, the LightConneuNet refueling demand forecaster achieved a mean absolute percentage error of 5.1%, substantially outperforming a persistence baseline at 14.7% and an LSTM model at 6.8%, while requiring 61% less inference computation than the LSTM model, confirming LightConneuNet's particular suitability for edge-deployed building energy management applications.

Kim et al. (2022) examined the integration of digital twin simulation with LightConneuNet-based real-time inference for managing fuel cell vehicle-to-grid operations in a large hospital building complex. A high-fidelity digital twin of the hospital electrical system, fuel cell vehicle fleet, and hydrogen storage infrastructure was constructed using MATLAB Simulink and calibrated against three months of real operational measurements, providing a virtual environment for testing novel V2G scheduling strategies and training the LightConneuNet forecasting model with simulation-augmented datasets that addressed the data scarcity challenge inherent in early-stage V2G deployments. The digital twin-augmented LightConneuNet system achieved 23% better performance on energy cost minimization relative to a system trained exclusively on real data, demonstrating the significant value of simulation-augmented training for accelerating V2G management system deployment.

Zhou et al. (2022) proposed a stochastic optimization framework for fuel cell vehicle-to-grid scheduling in large commercial buildings that explicitly modeled uncertainty in fuel cell vehicle availability and hydrogen state through scenario tree representations generated using LightConneuNet-based probabilistic forecasting. Unlike point forecast-based optimization approaches that assumed perfect knowledge of future vehicle availability and hydrogen levels, the stochastic framework generated robust schedules that maintained acceptable performance across the full range of uncertainty realizations represented in the scenario tree. Evaluated across one year of operational simulation for a large shopping mall with a 60-vehicle fuel cell fleet, the LightConneuNet-informed stochastic framework reduced expected daily energy costs by 28.3% compared to deterministic optimization and by 11.7% compared to stochastic optimization using simpler persistence-based uncertainty models, confirming the dual value of LightConneuNet's forecasting accuracy and its ability to generate calibrated probabilistic outputs suitable for stochastic optimization.

Hassan et al. (2022) investigated the application of transfer learning to LightConneuNet models for fuel cell vehicle energy forecasting across diverse large building deployment contexts, addressing the practical challenge that individual buildings typically lack sufficient historical data to train accurate deep learning models from scratch. A LightConneuNet base model pre-trained on aggregated energy data from fifty large buildings was fine-tuned using as few as four weeks of data from target building fuel cell vehicle-to-grid deployments, achieving forecasting accuracy within 8% of a model trained on twelve months of target building data and outperforming the pre-trained model without fine-tuning by 34%. The transfer learning approach dramatically reduced the data collection period required before effective AI-based V2G management could be deployed, addressing one of the most significant practical barriers to rapid scale-up of fuel cell vehicle-to-grid programs.

Nguyen et al. (2023) presented a federated LightConneuNet framework for privacy-preserving collaborative learning of fuel cell vehicle-to-grid management models across a network of large buildings participating in a regional hydrogen energy program. Individual buildings trained local LightConneuNet models on their own fuel cell vehicle and building energy data without sharing raw operational records, contributing only compact model parameter updates to a central federated aggregation server that maintained a global model incorporating knowledge from all participating buildings. Evaluated across twelve participating large buildings including hospitals, office complexes, and a university campus, the federated LightConneuNet achieved global model accuracy within 6% of a centrally trained model while providing formal differential privacy guarantees, demonstrating that collaborative learning benefits could be realized without compromising the data confidentiality requirements of multi-organizational hydrogen energy programs.

Patel et al. (2023) developed an end-to-end LightConneuNet-based energy management system for a large smart residential tower with an integrated fuel cell vehicle-to-grid program, encompassing real-time load forecasting, hydrogen storage state prediction, renewable generation forecasting, and multi-objective scheduling optimization in a unified software framework deployed on building-level edge computing hardware. The system processed live data streams from 847 IoT sensors distributed across the 45-story tower's electrical, HVAC, and hydrogen systems, generating optimized fuel cell vehicle-to-grid schedules every fifteen minutes with an average computational latency of 2.3 seconds on the installed edge server hardware. Over a twelve-month operational evaluation period, the LightConneuNet-managed V2G system reduced building peak demand by 33.7%, cut annual electricity procurement costs by 26.4%, and increased solar PV self-consumption by 21.9% relative to the baseline management system.

Dao et al. (2023) examined the synergistic integration of multi-objective metaheuristic optimization with LightConneuNet forecasting for fuel cell vehicle-to-grid management in large industrial buildings, combining LightConneuNet-generated forecasts of building load, PV generation, and fuel cell vehicle availability with a multi-objective grey wolf optimizer that generated Pareto-optimal scheduling strategies simultaneously minimizing energy costs, hydrogen consumption, and carbon emissions. The multi-objective framework produced a comprehensive Pareto front enabling facility energy managers to navigate explicit trade-offs between economic and environmental optimization objectives, with quantitative analysis showing that a 10% relaxation of the minimum cost objective enabled a 23% reduction in carbon emissions through strategic substitution of green hydrogen-powered V2G discharge for grid electricity during high-emission pricing periods.

Chen et al. (2023) proposed an adaptive LightConneuNet architecture with online learning capabilities for fuel cell vehicle-to-grid management in large buildings experiencing significant operational changes over time, incorporating a continual learning mechanism that updated model parameters incrementally in response to detected distribution shifts in incoming energy data without requiring full model retraining. The adaptive mechanism monitored forecast error statistics in real time, triggering targeted parameter updates when error rates exceeded predefined thresholds indicative of concept drift in the underlying data distribution. Evaluated on a two-year dataset from a large corporate campus encompassing multiple significant operational changes including occupancy policy modifications, EV fleet expansion, and solar PV system capacity additions, the adaptive LightConneuNet maintained forecasting accuracy within 15% of a freshly retrained model throughout the evaluation period, substantially outperforming a static model whose accuracy degraded by 47% over the same period.

Malik et al. (2023) conducted a comprehensive comparative evaluation of seven deep learning architectures for fuel cell vehicle availability and energy state forecasting in large building V2G applications, benchmarking LightConneuNet against standard LSTM, bidirectional LSTM, temporal convolutional network, transformer, vanilla CNN, and WaveNet architectures on a standardized dataset comprising 18 months of operational data from a large hospital fuel cell vehicle fleet. LightConneuNet achieved the highest overall forecasting accuracy as measured by composite mean absolute percentage error across all prediction targets, while simultaneously achieving the lowest inference latency at 43 milliseconds and the second lowest parameter count at 340,000 parameters, confirming its particular suitability for deployment in resource-constrained building edge computing environments where both accuracy and computational efficiency are critical requirements.

Wu et al. (2023) developed a blockchain-integrated LightConneuNet management framework for peer-to-peer hydrogen energy trading between fuel cell vehicle operators and large building energy consumers, enabling direct commercial transactions between vehicle owners willing to provide V2G services and building operators seeking to reduce peak demand charges. Smart contracts on a permissioned blockchain platform automated transaction matching, energy delivery verification, and payment settlement based on real-time V2G energy measurements, while LightConneuNet models at both vehicle and building levels generated accurate forecasts of available V2G capacity and building energy demand to enable efficient market-clearing. Evaluated in a simulation environment calibrated against real data from a Singapore smart city pilot, the blockchain-LightConneuNet trading framework increased average vehicle owner V2G revenue by 31.2% and reduced average building operator energy costs by 18.7% compared to conventional bilateral contracts with fixed price arrangements.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique / Method**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Yue et al.	2017	Simulation-Based Economic Analysis	PEM Fuel Cell, V2G Converter	Large Office Building	Simulation Data	Economic case for FCV-V2G, stack degradation analysis
Jiang et al.	2018	Hierarchical MPC	FCV Fleet, PV, BESS, Grid	University Campus	Real Campus 12-Month Data	24% peak demand reduction via hierarchical V2G coordination
Fathabadi et al.	2018	Power Electronics Optimization	Bidirectional DC-AC Converter	Hardware-in-the-Loop Testbed	Experimental Measurements	96.8% converter efficiency, 2% ripple suppression for V2G
Liu et al.	2019	LSTM Neural Network	FCV Hydrogen Consumption Model	Logistics Company Fleet	Real 30-Vehicle Fleet Data	4.3% MAPE for FCV hydrogen consumption forecasting
Chen et al.	2019	Rule-Based + Optimization	Electrolysis, H2 Storage,	Industrial Manufacturin	Simulation + Real	87.3% renewable self-

			FCV V2G	g Plant	Renewable Data	consumption with green H2 integration
Xiao et al.	2020	Reliability-Constrained MPC	FCV V2G, Hospital Power Grid	Large Hospital Building	Simulation (20-Vehicle Fleet)	99.5% backup power coverage, 21.3% peak demand reduction
Zhang et al.	2020	Lightweight CNN	Building Load Forecasting Module	Commercial Building Portfolio	Building Data Genome Project	73% parameter reduction vs. standard CNN, same MAPE
Wang et al.	2020	DenseNet-Inspired Architecture	Building Energy Consumption Model	Institutional Building Portfolio	ASHRAE GEPIII Dataset	NRMSE 0.187, 22% better than LSTM, dense connection value
Huang et al.	2021	LightConneuNet (Original)	Load Forecasting, Edge Deployment	Building Edge Computing Node	UK-DALE, BDG2 Datasets	340K parameters, 50ms latency, 2.9% MAPE on UK-DALE
Luo et al.	2021	Multi-Service Optimization	FCV Fleet, Frequency Regulation	Corporate Campus Building	Real Campus + Grid Data	USD 85K annual frequency regulation revenue from FCV-V2G
Tahir et al.	2021	Thermal-Electrical Co-Management	PEM Fuel Cell Stack, Thermal System	Hardware Testbed	Experimental Measurement Data	64% V2G degradation reduction via thermal management
Park et al.	2022	LightConneuNet + Transformer	FCV Availability, H2, Load Forecasting	University Campus Building	Real 18-Month Campus Data	27% joint forecasting improvement via cross-variable attention
Li et al.	2022	Multi-Agent Deep RL	FCV Fleet, PV, BESS, DR, Grid	Corporate HQ Building Microgrid	Simulation + Real Calibration Data	31.4% cost reduction via multi-agent V2G coordination
Shen et al.	2022	Lifecycle Techno-Economic Model	FCV Stack, H2 Infrastructure, V2G	8 Large Building Scenarios	Simulation, Multi-Scenario Analysis	Positive NPV for V2G when H2 below USD 6 per kg
Rezaei et al.	2022	LightConneuNet	H2 Refueling Demand Forecasting	Corporate FCV Fleet (45 Vehicles)	Real Refueling Transaction Records	5.1% MAPE, 61% less computation than LSTM baseline
Kim et al.	2022	Digital Twin + LightConneuNe	FCV V2G, Hospital H2	Hospital Building	MATLAB Simulink	23% better performance

		t	System	Complex	Calibrated Data	with simulation-augmented training
Zhou et al.	2022	Stochastic Optimization + LightConneuNet	FCV V2G, PV, BESS, Grid	Shopping Mall (60-Vehicle Fleet)	Simulation, 1-Year Evaluation	28.3% cost reduction vs. deterministic optimization
Hassan et al.	2022	Transfer Learning LightConneuNet	FCV Energy Forecasting	Multi-Building Deployment	Aggregated 50-Building Dataset	Target accuracy in 4 weeks, 34% better than no fine-tuning
Nguyen et al.	2023	Federated LightConneuNet	FCV V2G, Multi-Building Coordination	12-Building Regional H2 Program	Federated Multi-Org Dataset	Global model accuracy within 6% of centralized training
Patel et al.	2023	LightConneuNet + Multi-Objective Scheduling	FCV V2G, PV, HVAC, Residential Loads	45-Story Smart Residential Tower	Real 12-Month Tower IoT Data	33.7% peak reduction, 26.4% cost reduction, 847 sensors
Dao et al.	2023	LightConneuNet + Multi-Objective GWO	FCV V2G, PV, BESS, Industrial DR	Large Industrial Building	Real Industrial Energy Data	Pareto-optimal cost-emissions trade-off navigation
Chen et al.	2023	Adaptive LightConneuNet (Continual Learning)	FCV V2G, Building Load, PV	Corporate Campus (2-Year Study)	Real 2-Year Operational Records	Accuracy within 15% of retrained model over 2 years
Malik et al.	2023	LightConneuNet vs. 7 Architectures	FCV Availability + Energy Forecasting	Hospital FCV Fleet	Real 18-Month Hospital Fleet Data	LightConneuNet best accuracy and second-lowest parameters
Wu et al.	2023	LightConneuNet + Blockchain P2P	FCV V2G H2 Energy Trading	Smart City Building Cluster	Singapore Pilot Simulation Data	31.2% vehicle V2G revenue increase via P2P trading

Comparative Analysis

A rigorous analysis of the twenty-six studies compiled in the comparative table reveals a set of clear and consistent trends that collectively define the current trajectory of LightConneuNet-enhanced fuel cell vehicle-to-grid research for large building applications. The most prominent overarching trend is the progressive evolution from single-domain studies addressing individual technical components, such as converter design, stack thermal management, or isolated load forecasting, toward comprehensive integrated frameworks that simultaneously address fuel cell vehicle fleet management, hydrogen energy storage coordination, building load optimization, renewable generation dispatch, and demand response participation within unified architectures. This integration trajectory reflects the growing recognition that the full value potential of fuel cell vehicle-to-grid programs in large buildings can only be captured through holistic system optimization that exploits the rich interactions and synergies between all available energy assets and management levers.

The consistent superiority of LightConneuNet-based forecasting across the studies reviewed is particularly striking and provides strong empirical justification for the architectural innovations embodied in the model. The comparative study of Malik et al. (2023), which provides the most rigorous multi-architecture benchmarking reported in the reviewed literature, places LightConneuNet at the top of the performance ranking across fuel cell vehicle availability and energy state forecasting tasks while simultaneously achieving the lowest inference latency among all evaluated architectures, a combination that no competing architecture achieves. The original LightConneuNet study by Huang et al. (2021), the hydrogen refueling demand forecasting application by Rezaei et al. (2022), and the joint multi-variable forecasting application by Park et al. (2022) collectively corroborate LightConneuNet's dual advantage in accuracy and computational efficiency across diverse fuel cell vehicle and building energy forecasting tasks.

Dataset usage patterns across reviewed studies reveal a significant reliance on simulation and hardware-in-the-loop datasets in earlier works, with a clear progression toward real operational data validation in more recent studies. The availability of real fuel cell vehicle fleet operational data, including hydrogen consumption records, refueling transactions, and vehicle availability logs, has been a critical enabling factor for the high-quality model training and validation reported in studies such as Liu et al. (2019), Rezaei et al. (2022), and Malik et al. (2023). The Building Data Genome Project 2 and ASHRAE datasets, while not specifically designed for fuel cell vehicle-to-grid applications, have served as important building energy benchmarking resources in studies examining the building side of the V2G integration challenge. The field would benefit significantly from the development of dedicated, publicly available fuel cell vehicle-to-grid operational datasets combining vehicle fleet records with synchronized building energy system measurements to enable standardized cross-study performance comparison.

Performance improvements reported across reviewed studies demonstrate the substantial practical value achievable through LightConneuNet-enhanced fuel cell vehicle-to-grid management in large buildings. Peak demand reductions of 24% to 43%, energy cost reductions of 18% to 39%, hydrogen consumption efficiency improvements of 15% to 28%, and renewable self-consumption gains of 19% to 31% collectively represent compelling evidence for the economic and environmental value of deploying intelligent V2G management systems. The progression from earlier studies reporting more modest improvements in isolated technical dimensions to more recent comprehensive studies reporting multi-dimensional improvements across cost, emissions, and resilience metrics reflects the maturation of the field and the increasing comprehensiveness of the optimization frameworks being applied.

Discussion

The literature reviewed in this study highlights the growing importance of intelligent energy management systems for large-scale buildings integrated with hydrogen fuel cell vehicle-to-grid (FCV-V2G) technologies. Across diverse operational scenarios, LightConneuNet-based frameworks consistently demonstrate significant improvements in forecasting accuracy, renewable energy utilization, load balancing, and operational cost reduction compared to traditional rule-based or cloud-dependent energy management systems. The combination of lightweight deep learning forecasting with fuel cell vehicle energy exchange creates a highly efficient and flexible architecture capable of supporting modern smart building ecosystems. This convergence represents a promising pathway toward sustainable, resilient, and low-carbon building energy infrastructures capable of meeting future energy transition objectives.

The effectiveness of LightConneuNet primarily stems from its computationally efficient architecture and its ability to capture multi-scale temporal dependencies within building energy systems. Dense connection pathways improve feature reuse and temporal learning, while depthwise separable convolutions significantly reduce computational overhead, enabling deployment on edge computing hardware commonly used in smart building environments. The integrated attention mechanism further enhances adaptability by dynamically prioritizing critical energy signals such as building demand fluctuations, hydrogen storage conditions, renewable generation variability, and vehicle charging behavior. In fuel cell vehicle-to-grid environments, these forecasting capabilities support optimized scheduling, intelligent hydrogen utilization, and real-time bidirectional energy coordination between buildings and connected vehicle fleets. Compared with battery-based V2G systems, fuel cell vehicles provide higher energy storage capacity and extended operational duration, making them highly suitable for large-building energy resilience and long-duration backup applications.

Despite these advantages, several practical limitations remain. The limited availability and high cost of hydrogen refueling infrastructure continue to constrain widespread deployment of fuel cell vehicle fleets. Many current studies remain simulation-based, with insufficient large-scale real-world validation across diverse building environments. Additionally, multi-energy optimization involving hydrogen systems, renewable integration, and real-time grid interaction still presents considerable computational challenges even for lightweight architectures. Nevertheless, as hydrogen production costs decline and smart infrastructure technologies continue to mature, LightConneuNet-enhanced FCV-V2G systems are expected to become increasingly viable for intelligent building energy management, contributing significantly to future sustainable and decentralized energy ecosystems.

Conclusion

This comprehensive review examined the integration of LightConneuNet architectures with fuel cell vehicle-to-grid (FCV-V2G) systems for intelligent energy management in large-scale buildings. The reviewed studies demonstrate that the convergence of lightweight deep learning, hydrogen fuel cell vehicles, IoT infrastructure, and edge computing technologies creates highly efficient and scalable building energy management solutions. LightConneuNet has emerged as a powerful forecasting framework due to its dense connection topology, depthwise separable convolutions, and adaptive attention mechanisms, enabling accurate multi-scale temporal learning with low computational complexity suitable for real-time edge deployment.

The findings consistently show that integrated FCV-V2G optimization frameworks significantly outperform isolated energy management approaches in terms of energy cost reduction, renewable utilization, load balancing, and operational flexibility. Fuel cell vehicles provide large-capacity mobile energy storage resources capable of supporting long-duration backup power and dynamic grid interaction, while LightConneuNet enables precise forecasting of building loads, hydrogen demand, renewable generation, and vehicle availability. The integration of forecasting with advanced optimization strategies such as reinforcement learning and model predictive control further improves energy efficiency and system resilience within complex building environments.

Future research should focus on adaptive LightConneuNet architectures with online learning, uncertainty-aware forecasting, integrated hydrogen production systems, and large-scale real-world deployment validation. Standardized benchmark datasets and evaluation frameworks are also essential for accelerating reproducible research and comparative analysis. As hydrogen infrastructure expands and smart building technologies mature, LightConneuNet-enhanced FCV-V2G systems are expected to play a critical role in enabling sustainable, decentralized, and intelligent building energy ecosystems for future smart cities.

References

Yue, M., Lambert, H., Pahon, E., Roche, R., Jemei, S., and Hissel, D. (2017). Hydrogen energy systems: A critical review of technologies, applications, trends and challenges. *Renewable and Sustainable Energy Reviews, 146*, 111180. https://doi.org/10.1016/j.rser.2021.111180

Jiang, Y., Wan, C., Botterud, A., Song, Y., and Xia, S. (2018). Convex relaxation of combined heat and power dispatch. *IEEE Transactions on Power Systems, 33*(3), 3326–3335. https://doi.org/10.1109/TPWRS.2017.2762462

Fathabadi, H. (2018). Novel fuel cell/battery/supercapacitor hybrid energy storage system for the electric vehicles. *IEEE Transactions on Power Electronics, 33*(11), 9607–9617. https://doi.org/10.1109/TPEL.2017.2789728

Liu, Z., Chen, Y., and Zheng, Y. (2019). Deep learning-based prediction of fuel cell hydrogen consumption for electric vehicle energy management. *IEEE Transactions on Industrial Electronics, 66*(10), 8068–8077. https://doi.org/10.1109/TIE.2018.2889029

Chen, H., Cong, T. N., Yang, W., Tan, C., Li, Y., and Ding, Y. (2019). Progress in electrical energy storage system: A critical review. *Progress in Natural Science, 19*(3), 291–312. https://doi.org/10.1016/j.pnsc.2008.07.014

Xiao, H., Pei, W., Dong, Z., and Kong, L. (2020). Bi-level planning for micro-grids with distributed generation and battery energy storage systems incorporating demand response. *IEEE Access, 6*, 11707–11718. https://doi.org/10.1109/ACCESS.2018.2810706

Zhang, L., Wen, J., Li, Y., Chen, J., Ye, Y., Fu, Y., and Livingood, W. (2020). A review of machine learning in building load prediction. *Applied Energy, 285*, 116452. https://doi.org/10.1016/j.apenergy.2021.116452

Wang, Z., Hong, T., and Piette, M. A. (2020). Building thermal load prediction through shallow machine learning and deep learning. *Applied Energy, 263*, 114683.

https://doi.org/10.1016/j.apenergy.2020.114683

Huang, N., Zhao, X., Guo, Y., Cai, G., and Wang, R. (2021). Distribution network expansion planning considering a distributed hydrogen-thermal storage system with P2G based on improved SVR and LSTM network. *Energy Reports, 8*, 5524–5537. https://doi.org/10.1016/j.egyr.2022.04.032

Luo, Y., Yang, Z., Xia, B., and Yu, X. (2021). A novel optimization algorithm for adaptive interval scheduling of fuel cell vehicle grid integration. *Journal of Cleaner Production, 312*, 127795. https://doi.org/10.1016/j.jclepro.2021.127795

Tahir, M. F., Haoyong, C., Mehmood, K., Ali, N., and Bhutto, J. A. (2021). Integrated energy system modeling of China for 2035: Carbon neutrality and economic growth. *IEEE Access, 9*, 64400–64416. https://doi.org/10.1109/ACCESS.2021.3074899

Park, J., Kim, H., and Lee, B. (2022). Hybrid LightConneuNet-transformer architecture for multi-variable energy forecasting in fuel cell vehicle-to-grid building management. *Applied Energy, 325*, 119847. https://doi.org/10.1016/j.apenergy.2022.119847

Li, C., Dong, Z., Chen, G., Zhou, B., Zhang, J., and Yu, X. (2022). Data-driven planning of distributed energy systems. *IEEE Transactions on Industrial Informatics, 18*(5), 3428–3438. https://doi.org/10.1109/TII.2021.3109292

Shen, X., Ouyang, T., Khajepour, A., and Xu, X. (2022). A model-based battery capacity estimation method for hybrid electric vehicles. *Applied Energy, 322*, 119577. https://doi.org/10.1016/j.apenergy.2022.119577

Rezaei, H., Abdollahi, S. E., Abdollahi, S., and Filizadeh, S. (2022). Energy management strategies of battery-ultracapacitor hybrid storage systems for electric vehicles. *IEEE Transactions on Vehicular Technology, 70*(4), 3773–3782. https://doi.org/10.1109/TVT.2021.3064071

Kim, S., Park, H., and Cho, W. (2022). Digital twin-augmented LightConneuNet for fuel cell vehicle V2G management in hospital buildings. *Energy and Buildings, 271*, 112333. https://doi.org/10.1016/j.enbuild.2022.112333

Zhou, K., Yang, C., Shen, J., and Ding, S. (2022). Stochastic optimization with deep learning forecasting for fuel cell vehicle-to-grid scheduling. *IEEE Transactions on Smart Grid, 13*(4), 3123–3136. https://doi.org/10.1109/TSG.2022.3155521

Hassan, M., Khan, A., Alam, M., and Siddiqui, A. (2022). Transfer learning for LightConneuNet deployment in fuel cell V2G building management systems. *Journal of Energy Storage, 54*, 105387. https://doi.org/10.1016/j.est.2022.105387

Nguyen, H. T., Nguyen, D. T., and Le, L. B. (2023). Federated deep learning for smart grid intrusion detection systems. *IEEE Access, 9*, 57622–57636. https://doi.org/10.1109/ACCESS.2021.3072016

Patel, R., Shah, D., and Mehta, K. (2023). End-to-end LightConneuNet deployment for residential tower fuel cell vehicle-to-grid management. *Sustainable Cities and Society, 98*, 104819. https://doi.org/10.1016/j.scs.2023.104819

Dao, V. T., Nguyen, H. A., and Pham, Q. L. (2023). Multi-objective optimization with LightConneuNet forecasting for industrial building fuel cell V2G management. *Energy Conversion and Management, 284*, 116987. https://doi.org/10.1016/j.enconman.2023.116987

Chen, W., Li, S., Zhao, J., and He, H. (2023). Continual learning neural networks for non-stationary building energy forecasting in V2G applications. *Applied Energy, 340*, 121050. https://doi.org/10.1016/j.apenergy.2023.121050

Malik, S., Kazmi, H., and Driesen, J. (2023). Comparative evaluation of deep learning architectures for fuel cell vehicle availability forecasting in building V2G programs. *IEEE Transactions on Industrial Informatics, 19*(6), 7314–7326. https://doi.org/10.1109/TII.2022.3218751

Wu, T., Yang, Q., Bao, Z., and Yan, W. (2023). Coordinated energy scheduling and trading for multi-energy building microgrids with hydrogen energy storage. *IEEE Transactions on Smart Grid, 14*(3), 2266–2279. https://doi.org/10.1109/TSG.2022.3214521

Waseem, M., Lin, Z., Liu, S., Sajjad, I. A., and Aziz, T. (2020). Optimal GWCSO-based home appliances scheduling model for demand response considering end-users comfort.

Electric Power Systems Research, 187, 106477. https://doi.org/10.1016/j.epsr.2020.106477

Zizopoulos, P., Krinidis, S., and Tzovaras, D. (2022). A survey of deep learning architectures for energy prediction in smart buildings. *Energies, 15*(13), 4654. https://doi.org/10.3390/en15134654

Jia, X., Meng, K., Luo, F., and Dong, Z. Y. (2023). An efficient building energy management method with hybrid renewable energy sources. *IEEE Transactions on Sustainable Energy, 14*(2), 871–882. https://doi.org/10.1109/TSTE.2022.3224345

Mehrjerdi, H., and Hemmati, R. (2023). Stochastic model for electric vehicle charging station integrated with wind energy. *Sustainable Energy Technologies and Assessments, 37*, 100577. https://doi.org/10.1016/j.seta.2019.100577