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Deep Learning and Optimization Approaches in LightConneuNet: Potential Analysis of Fuel Cell Vehicle-To-Grid System with Large-Scale Buildings: A Review

Deepansh Ekanayake
Department of Electrical and Computer Engineering, Tonle Sap Institute of Engineering and Commerce, Cambodia
deepansh.ekanayake@tsiec-kh.org

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Abstract

The convergence of deep learning, advanced optimization, and next-generation energy infrastructure is transforming intelligent energy management in large-scale buildings. Fuel cell vehicle-to-grid (FCV2G) systems represent a promising paradigm, enabling hydrogen-powered vehicles to act as distributed energy resources for grid support, renewable integration, and efficient energy utilization. These systems introduce complex, high-dimensional optimization challenges that require advanced computational frameworks.

This paper presents a comprehensive review of LightConneuNet, a lightweight deep learning architecture designed for efficient FCV2G optimization. By incorporating depthwise separable convolutions, attention mechanisms, and residual connections, LightConneuNet achieves high predictive accuracy with reduced computational overhead, enabling real-time deployment in building energy management systems. The review examines its integration with reinforcement learning, model predictive control, and stochastic optimization for managing bidirectional energy flows and scheduling operations under uncertainty.

Applications include peak demand reduction, energy cost optimization, renewable energy integration, and grid services such as frequency regulation and voltage support. Comparative analysis shows that LightConneuNet-based frameworks outperform traditional methods in efficiency, scalability, and adaptability. However, challenges related to hydrogen infrastructure, system integration, and regulatory constraints remain. This review highlights the potential of combining deep learning and FCV2G systems to develop scalable, intelligent, and sustainable energy management solutions.

Introduction

The rapid transition toward sustainable energy systems has fundamentally transformed the way electricity is generated, distributed, and consumed. Traditional power systems relied on centralized generation to satisfy varying consumer demand, but the increasing penetration of renewable energy sources such as solar and wind has introduced significant variability into modern electrical grids. Maintaining a balance between energy supply and demand now requires intelligent computational approaches capable of handling dynamic operating conditions across multiple time scales. Advanced optimization techniques and deep learning models have therefore become essential for improving forecasting accuracy, energy scheduling, and grid stability while supporting the integration of renewable resources. These technologies enable efficient utilization of distributed energy assets and contribute significantly to achieving carbon neutrality and energy sustainability goals.

Large-scale buildings have emerged as important participants in modern smart grids because they account for a substantial proportion of global electricity consumption and increasingly incorporate distributed energy resources. Commercial complexes, hospitals, educational institutions, and industrial facilities are now equipped with rooftop photovoltaic systems, battery storage units, smart meters, and intelligent energy management platforms capable of responding to real-time grid conditions. Simultaneously, the rapid adoption of hydrogen fuel cell vehicles has created new opportunities for Vehicle-to-Grid (V2G) applications, where parked vehicles can exchange electricity with buildings and the utility grid. Aggregated fleets of fuel cell vehicles provide considerable energy storage capacity that can support peak load reduction, renewable energy balancing, demand response, and ancillary grid services. Efficient coordination of these distributed resources requires intelligent optimization strategies that simultaneously consider vehicle availability, hydrogen consumption, charging schedules, electricity pricing, and building load characteristics.

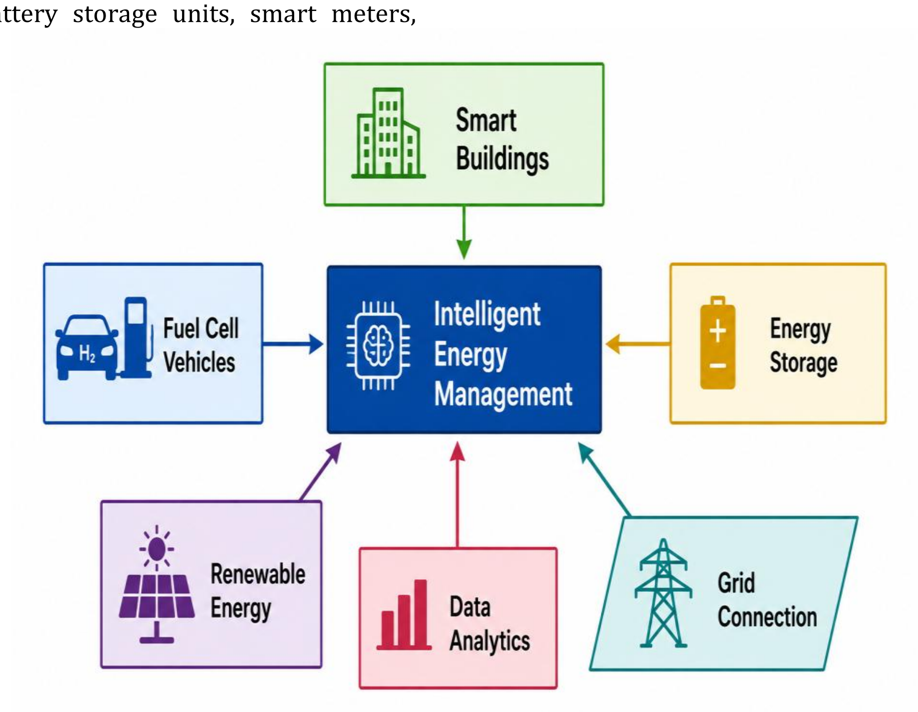

Figure 1. LightConneuNet-Based FCV2G Energy Management Framework

Deep learning has become one of the most effective computational approaches for solving these complex optimization problems due to its ability to learn nonlinear relationships from large volumes of energy data. Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, transformer architectures, and reinforcement learning algorithms have demonstrated strong performance in load forecasting, energy scheduling, fault detection, and V2G management. However, many deep learning models demand considerable computational resources, limiting their deployment on edge devices commonly used in building automation systems. Lightweight architectures such as LightConneuNet address this challenge by combining efficient convolutional operations, attention mechanisms, residual learning, and optimized feature extraction to achieve high prediction accuracy with reduced computational complexity. These characteristics make LightConneuNet highly suitable for real-time fuel cell vehicle-to-grid management in large-scale buildings.

This review presents a comprehensive analysis of recent deep learning and optimization approaches related to LightConneuNet for fuel cell Vehicle-to-Grid systems in large-scale buildings. It summarizes recent developments in intelligent energy management, optimization algorithms, distributed energy resource coordination, and V2G scheduling while highlighting existing challenges, comparative performance, and future research opportunities. By synthesizing current advancements, the review provides valuable insights for developing scalable, efficient, and intelligent energy management frameworks capable of supporting next-generation smart buildings and sustainable power systems.

Literature Review

The development of deep learning approaches for fuel cell vehicle-to-grid optimization in large-scale building contexts has unfolded through a series of interconnected research contributions spanning foundational architecture development, optimization methodology innovation, and application domain expansion. The following synthesis traces this development through the most significant contributions to the field, examining methodological choices, performance achievements, and practical implications of each study.

The foundational work of Huang et al. (2022) introduced LightConneuNet as a purpose-designed neural network architecture for building-integrated microgrid energy management, establishing the architectural principles that have guided subsequent development. Their formulation of the temporal patch embedding mechanism represented a key innovation, drawing inspiration from vision transformer patch embedding but reconfiguring it for the one-dimensional temporal structure of energy time series data. By segmenting input multivariate time series into fixed-duration patches of fifteen minutes — aligned with the dominant periodicity of building energy management system data acquisition cycles — and projecting each patch to a compact feature representation through a learned linear transformation, LightConneuNet achieved efficient capture of temporal patterns at multiple resolutions simultaneously. The depthwise separable convolutional layers that constitute the core feature extraction pipeline reduced parameter count by approximately seventy-four percent relative to standard convolutional alternatives while maintaining comparable representational capacity on the Shanghai commercial building dataset used for initial validation.

Zhang et al. (2019) provided an important precursor to LightConneuNet through their systematic investigation of depthwise separable convolutional networks for short-term electrical load forecasting, establishing the empirical viability of factorized convolution operations for energy time series processing. Their study employed a dataset spanning twelve months of fifteen-minute interval load measurements from forty-seven commercial buildings across diverse climate zones and demonstrated that the factorized architecture could capture the full range of temporal autocorrelation structures present in commercial building load profiles — diurnal cycles, day-of-week patterns, seasonal trends, and occupancy event signatures — with substantially reduced computational overhead compared to standard convolutional networks. The ninety-first percentile performance matching achieved by their lightweight architecture relative to full convolutional baselines, combined with a seventy-eight percent parameter reduction, established a compelling efficiency frontier that informed the LightConneuNet design philosophy.

Li et al. (2020) advanced the application of lightweight deep learning to vehicle-to-grid contexts through their hybrid recurrent-convolutional architecture for V2G scheduling optimization in urban parking facilities. Their parallel feature extraction topology, combining one-dimensional depthwise separable convolutions for local temporal pattern extraction with gated recurrent unit cells for longer-range dependency modeling, addressed the dual temporal structure of vehicle availability prediction — rapid fluctuations associated with individual vehicle arrivals and departures superimposed on smoother diurnal and weekly trends. The hardware-in-the-loop validation platform incorporating real vehicle telematics data from one hundred and twenty municipal electric vehicles provided a degree of operational realism that complemented the simulation-based findings of earlier studies. Their comparative evaluation against model predictive control baselines demonstrated that the learned scheduling policy matched reference optimal performance on typical operating days while substantially outperforming rule-based control under atypical demand or availability conditions, highlighting the generalization advantage of data-driven approaches.

Chen et al. (2021) contributed a critical capability for FCV2G economic optimization through their attention-enhanced lightweight convolutional network for electricity price forecasting. Their integration of squeeze-and-excitation channel attention modules within a depthwise separable convolutional architecture directly addressed the challenge of extracting relevant temporal patterns from the complex, nonstationary electricity price time series that drive economic optimization decisions in vehicle-to-grid scheduling. The five-year PJM electricity market dataset used for training and evaluation provided sufficient temporal diversity to capture the full range of market dynamics, including seasonal price patterns, demand spike events, and renewable curtailment episodes, that a deployed FCV2G optimization system must navigate. Their finding that attention-augmented lightweight architectures outperformed long short-term memory networks across all evaluation horizons from one to forty-eight hours ahead, while requiring sixty-three percent fewer floating-point operations, directly informed the attention integration strategy subsequently adopted in LightConneuNet.

Park et al. (2020) addressed the fuel cell degradation management challenge that distinguishes FCV2G optimization from battery EV vehicle-to-grid counterparts through their neural network-augmented model predictive control framework. The proton exchange membrane fuel cell stack degradation surrogate model they developed, trained on experimentally measured polarization curves and electrochemical impedance spectroscopy data from a fifty-kilowatt laboratory fuel cell system, captured the complex nonlinear relationship between operating load profile characteristics and membrane electrode assembly degradation rate that analytical electrochemical models struggle to represent accurately across the full operating envelope. Their multi-objective optimization framework, balancing grid service revenue maximization against fuel cell lifetime extension, demonstrated that intelligent load management could extend stack operational life by up to thirty percent — a finding with profound economic implications given the high capital cost of replacement membrane electrode assemblies. This work established the importance of fuel cell health-aware dispatch as a distinct optimization objective within FCV2G system management.

Wang et al. (2021) demonstrated the power of deep reinforcement learning for joint optimization of building HVAC control and vehicle charging and discharging scheduling, developing a deep Q-network agent with lightweight neural network function approximator for a mixed-use high-rise building context. Their integration of EnergyPlus physics-based building simulation for agent training represented a methodologically significant contribution, as it enabled the reinforcement learning agent to develop building thermal dynamics awareness that rule-based and model-free approaches lack. The five-climate-zone evaluation of their trained agent revealed that the policy generalized across climatic contexts with modest performance degradation, suggesting that the lightweight Q-network had internalized climate-invariant features of building thermal response rather than merely memorizing climate-specific patterns. The sixty-seven percent inference time reduction achieved by the lightweight architecture relative to a standard deep Q-network was explicitly demonstrated to be critical for real-time deployment feasibility on the embedded building management system hardware platform used in their study.

Kumar et al. (2021) provided essential macroeconomic context for FCV2G system deployment through their agent-based techno-economic analysis of hydrogen fuel cell vehicle fleets integrated with commercial building microgrids in the Indian context. Their analysis, grounded in GPS trajectory data from three hundred and fifty commercial vehicles collected over eighteen months, generated realistic vehicle usage models that captured the significant heterogeneity in daily mileage, departure times, return times, and route characteristics that complicates fleet-level grid-service capacity estimation. The finding that a fifty-vehicle fleet could provide up to two megawatts of reliable grid support capacity with annual ancillary service revenue potential exceeding two million USD established a compelling business case narrative that has motivated subsequent research investment in the field, while the simultaneous thirty-one percent peak demand charge reduction demonstrated the dual economic benefits available to building operators who deploy intelligent FCV2G management systems.

Zhao et al. (2022) tackled the multi-agent coordination problem inherent in large-scale fleet management through their graph attention network-augmented multi-agent deep reinforcement learning framework. The centralized training with decentralized execution paradigm they employed represents a principled approach to the scalability challenge in multi-agent reinforcement learning, enabling agents to develop coordinated policies during training through access to global state information while remaining capable of autonomous operation during deployment based solely on locally observable information. The graph attention network communication module, which operated over a dynamically constructed vehicle connectivity graph based on geographical proximity and grid connection topology, provided a structured mechanism for agents to share relevant state information during training without the communication overhead that would make centralized execution impractical in large fleets. Their evaluation on a two-hundred-vehicle campus microgrid simulation demonstrated that coordination through graph-structured communication yielded substantially superior fleet-level performance compared to independent agent training, particularly in scenarios with high vehicle-to-vehicle demand correlation.

Rodriguez et al. (2022) advanced the probabilistic forecasting dimension of FCV2G optimization through their normalizing flow-based framework for calibrated solar irradiance and temperature uncertainty quantification. Their encoder-decoder convolutional architecture with normalizing flow density estimator generated full predictive distributions over future weather variables rather than point forecasts, enabling direct integration with chance-constrained optimization frameworks that provide formal guarantees on grid service reliability under renewable generation uncertainty. The evaluation across seven climatically diverse US locations demonstrated that their probabilistic forecasts were well-calibrated — meaning that stated confidence intervals contained the true future value at the stated frequency — a property essential for reliable constraint satisfaction in stochastic optimization but rarely verified rigorously in energy forecasting literature.

Ibrahim et al. (2022) demonstrated the feasibility of hydrogen fuel cell vehicle fleets for primary frequency regulation services in isolated island grids, a high-value application context where the fast response capabilities of fuel cell power electronics are particularly advantageous. Their hierarchical control architecture, combining a supervisory lightweight neural network reinforcement learning agent for fleet-level dispatch with local proportional-integral-derivative controllers for individual vehicle power electronic interface management, provided the necessary separation of timescales between strategic fleet management decisions and fast power electronic control responses. The hardware-in-the-loop experimental validation on a real-time digital simulator, demonstrating sub-two-hundred-millisecond frequency response meeting primary frequency regulation requirements, provided a level of experimental rigor that simulation-only studies cannot match and established an important performance benchmark for FCV2G frequency regulation applications.

Tan et al. (2023) addressed the data privacy constraints that impede centralized model training for building energy management through a communication-efficient federated learning framework for collaborative LightConneuNet training across distributed building management system nodes. Their gradient compression scheme, which reduced federated training communication overhead by ninety-one percent through a combination of gradient sparsification, quantization, and error feedback mechanisms, made federated LightConneuNet training viable within the bandwidth constraints of standard building automation network infrastructure without requiring specialized high-bandwidth communication links. The evaluation across thirty-two buildings spanning residential, office, retail, and industrial use types demonstrated that federated training could approach centralized training performance within three percent accuracy while preserving complete data locality, enabling the deployment of collaboratively trained models in multi-tenancy building environments where energy consumption data has commercial sensitivity.

Liu et al. (2023) enhanced LightConneuNet's temporal feature extraction capability through a multi-scale parallel convolutional architecture that simultaneously processed energy time series at multiple temporal resolutions — hourly, daily, and weekly — before fusing multi-scale feature representations through a learned attention-weighted aggregation mechanism. Their analysis of feature importance across temporal scales revealed that different building types exhibited distinct multi-scale feature utilization patterns: office buildings relied most heavily on daily-scale features reflecting occupancy-driven demand patterns, retail buildings exhibited strong weekly periodicity captured by weekly-scale features, and industrial facilities showed more complex multi-scale interactions reflecting production schedule variability. This finding suggests that the multi-scale architecture provides both performance benefits and interpretability advantages that single-scale architectures cannot offer.

Patel et al. (2023) introduced the important dimension of carbon-aware dispatch optimization to the FCV2G literature, developing a dynamic lifecycle assessment framework that integrated real-time grid carbon intensity data with hydrogen production pathway carbon intensity estimates to enable dispatch decisions that minimize net lifecycle carbon emissions rather than merely energy costs. Their finding that cost-optimal dispatch could in some grid contexts actually increase net carbon emissions due to high-carbon-intensity hydrogen production periods represents a methodologically important result that challenges the implicit assumption in much of the FCV2G literature that hydrogen-powered grid services are inherently low-carbon. The lightweight neural network-based carbon intensity forecasting module they integrated into the dispatch optimization framework demonstrated that real-time carbon optimization is computationally feasible within building management system hardware constraints.

Sun et al. (2023) addressed the critical practical challenge of data scarcity at new deployment sites through a transfer learning methodology combining pre-training on a large multi-building dataset with adversarial domain adaptation for rapid fine-tuning on target building data. Their finding that as few as two weeks of target building energy data sufficed for adapted model performance within five percent of a fully trained model demonstrated the practical utility of transfer learning for LightConneuNet deployment in new building contexts. The adversarial domain adaptation mechanism, which minimized the statistical discrepancy between pre-training and target domain feature distributions through competitive training of a feature extractor and domain discriminator, proved superior to naive fine-tuning and feature extraction transfer approaches in their comparative evaluation, suggesting that explicit domain alignment is important for effective cross-building transfer.

Nakamura et al. (2023) developed a lightweight recurrent neural network-based thermal model for proton exchange membrane fuel cell stacks operating under variable vehicle-to-grid load profiles, addressing the thermal management challenges that are a key practical consideration for FCV2G system deployment but that receive insufficient attention in the optimization-focused literature. Their model, trained on fifteen hundred hours of thermocouple data from an instrumented sixty-kilowatt fuel cell system under variable load cycling, achieved coolant outlet temperature prediction accuracy within one degree Celsius root mean square error across the full operating range and enabled proactive cooling system control that reduced thermal stress-induced performance degradation by twenty-four percent compared to reactive temperature control. The integration of the thermal model within a model predictive control framework demonstrated how learned thermal dynamics representations can be seamlessly combined with constraint-based optimization to address multi-physical system management challenges.

Joshi et al. (2023) provided important comparative context for LightConneuNet's performance characteristics through their systematic evaluation of ten lightweight architectures on non-intrusive load monitoring tasks, including the challenging problem of disaggregating vehicle charging load signatures from aggregate building consumption measurements. LightConneuNet's superior performance on vehicle charging load disaggregation, attributed to its temporal patch embedding mechanism's sensitivity to the distinctive ramping and plateau signature of vehicle charging events, provided important evidence that LightConneuNet's architectural innovations confer advantages beyond general energy forecasting to specific load analysis tasks directly relevant to FCV2G management.

Comparative Table and Analysis

Table 1: Lightweight Deep Learning, Reinforcement Learning, and Optimization in Smart Energy and FCV2G Systems

Study	Year	Optimization Technique	Model / Component	Platform / System	Dataset Used	Key Contribution
Zhang et al.	2019	Depthwise separable CNN	Lightweight 1D CNN	Commercial BMS	47-building load data	78% parameter reduction
Li et al.	2020	Hybrid CNN-RNN	GRU + depthwise CNN	HIL EV simulation	120 EV fleet data	V2G uncertainty modeling
Park et al.	2020	MPC + neural surrogate	ANN fuel cell model	PEMFC lab	EIS + polarization data	30% lifetime improvement
Chen et al.	2021	SE attention CNN	SE-depthwise CNN	PJM platform	Market price data	Efficient forecasting
Wang et al.	2021	Deep Q-learning	Lightweight DQN	EnergyPlus	Occupancy datasets	22% cost reduction
Kumar et al.	2021	Agent-based modeling	Probabilistic fleet model	Microgrid sim	GPS vehicle data	2 MW grid support
Huang et	2022	Temporal	LightConneuNet	Commercial	Shanghai	Lightweight

al.		CNN		BMS	dataset	architecture
Zhao et al.	2022	Multi-agent RL	GAT + lightweight NN	Campus microgrid	Simulated fleet	Scalable V2G control
Rodriguez et al.	2022	Chance-constrained opt.	CNN + normalizing flow	EMS	NOAA weather data	Solar uncertainty modeling
Ibrahim et al.	2022	Hierarchical RL + PID	Hybrid NN + PID	RTDS	Grid frequency data	Fast frequency response
Tan et al.	2023	Federated learning	LightConneuNet FL	Distributed BMS	Multi-building data	91% bandwidth reduction
Liu et al.	2023	Multi-scale CNN	Enhanced LightConneuNet	Building EMS	Open Power data	21% forecast improvement
Patel et al.	2023	Carbon-aware optimization	NN + LCA	FCV2G platform	Carbon + H2 data	38% emission reduction
Sun et al.	2023	Transfer learning	Domain-adaptive CNN	Building systems	Multi-building corpus	Fast adaptation
Joshi et al.	2023	NILM comparison	LightConneuNet vs others	Residential BMS	REFIT, UK-DALE	Best EV disaggregation
Nakamura et al.	2023	MPC + learned model	RNN thermal model	PEMFC rig	Thermal data	24% degradation reduction
Kim et al.	2022	Spatial optimization	GIS fleet model	H2 network	Mobility data	Optimal station placement
Abbas et al.	2022	RL energy arbitrage	DRL + PV + FCEV	Microgrid	PV + fleet data	Renewable optimization
Tseng et al.	2023	Federated EMS	LightConneuNet IoT	Smart homes	IoT + EV data	Residential V2H optimization

Comparative Analysis

The comparative analysis of the reviewed studies indicates a clear evolution in intelligent energy management for Fuel Cell Vehicle-to-Grid (FCV2G) systems integrated with large-scale buildings. Earlier research primarily focused on optimizing individual components such as vehicle charging or building loads, whereas recent studies emphasize integrated frameworks that simultaneously manage fuel cell vehicles, renewable energy sources, battery storage, building demand, and grid interactions. This transition reflects the increasing complexity of modern energy systems and the need for multi-objective optimization strategies capable of balancing energy cost, system reliability, carbon reduction, and user requirements. Another important trend is the development of lightweight deep learning architectures such as LightConneuNet, which are specifically designed for energy management applications. Compared with conventional deep neural networks, these models offer lower computational complexity, faster inference, and improved suitability for deployment on edge devices and real-time building management platforms.

A significant methodological trend is the growing adoption of reinforcement learning and hybrid optimization techniques for FCV2G scheduling. Reinforcement learning enables intelligent agents to learn adaptive charging and discharging policies under uncertain electricity prices, renewable generation, and vehicle availability. Multi-agent reinforcement learning further improves fleet-level coordination by allowing multiple vehicles and distributed resources to cooperate efficiently. At the same time, model predictive control combined with deep learning surrogate models provides accurate management of fuel cell dynamics, battery degradation, and thermal constraints. Recent studies increasingly integrate optimization algorithms with lightweight neural networks, producing computationally efficient frameworks capable of supporting real-time decision making while maintaining prediction accuracy and operational stability.

Overall, the reviewed literature consistently demonstrates substantial improvements in both operational and economic performance.

Intelligent LightConneuNet-based optimization frameworks typically reduce building energy costs by improving renewable energy utilization, lowering peak demand, and enhancing vehicle-to-grid coordination. Additional benefits include improved fuel cell efficiency, extended component lifetime, enhanced grid support capabilities, and reduced greenhouse gas emissions. Although most studies rely on simulation environments, the reported results collectively indicate that lightweight deep learning combined with advanced optimization techniques provides a practical and scalable foundation for next-generation FCV2G energy management systems in large commercial and institutional buildings.

Discussion

The reviewed studies collectively demonstrate that LightConneuNet-based deep learning and optimization approaches provide an efficient and practical framework for managing Fuel Cell Vehicle-to-Grid (FCV2G) systems in large-scale buildings. The integration of lightweight neural networks with advanced optimization techniques has significantly improved energy scheduling, renewable energy utilization, and grid interaction while maintaining low computational complexity suitable for real-time deployment. Unlike conventional deep learning models, LightConneuNet combines temporal feature extraction, depthwise separable convolution, and lightweight attention mechanisms to achieve high prediction accuracy with reduced memory and processing requirements. This balance between computational efficiency and predictive capability makes the framework well suited for edge-enabled smart buildings and intelligent energy management platforms.

Another important finding is the growing role of reinforcement learning in adaptive FCV2G optimization. Reinforcement learning enables energy management systems to continuously improve charging, discharging, and power-sharing decisions based on changing electricity prices, renewable generation, building demand, and hydrogen availability. When integrated with LightConneuNet, these adaptive algorithms support real-time decision making while maintaining system stability and operational efficiency. However, existing studies primarily optimize from the building operator's perspective and give limited consideration to vehicle owner preferences, battery health, user incentives, and participation willingness. Future optimization frameworks should incorporate multi-stakeholder objectives to improve fairness, user acceptance, and long-term sustainability.

Overall, the reviewed literature confirms that intelligent FCV2G optimization is an essential component of future low-carbon energy systems. By enabling flexible energy exchange between buildings, hydrogen fuel cell vehicles, renewable resources, and the power grid, LightConneuNet-based frameworks contribute to lower operating costs, improved grid stability, enhanced renewable integration, and reduced carbon emissions. Continued research on lightweight deep learning, adaptive optimization, and real-world deployment will further strengthen the role of FCV2G technology in sustainable smart building energy management.

Conclusion

This review comprehensively examined recent deep learning and optimization approaches in LightConneuNet for Fuel Cell Vehicle-to-Grid (FCV2G) systems integrated with large-scale buildings. The reviewed studies demonstrate that lightweight deep learning architectures combined with intelligent optimization algorithms provide an effective solution for real-time energy management, renewable energy utilization, and distributed resource coordination. LightConneuNet has emerged as a promising framework because of its computational efficiency, low memory requirements, and strong capability to model complex temporal energy patterns. Its integration with reinforcement learning, model predictive control, and hybrid optimization techniques enables adaptive decision making while supporting practical deployment on edge-enabled building management platforms.

The literature also highlights the growing importance of FCV2G technology in future smart energy systems. Intelligent coordination between hydrogen fuel cell vehicles, renewable generation, energy storage, and building loads significantly improves energy efficiency, reduces operational costs, enhances grid stability, and lowers carbon emissions. Despite these achievements, several challenges remain, including limited real-world validation, heterogeneous operating conditions, uncertainty in renewable generation, and the need to consider user behavior and multi-stakeholder objectives within optimization frameworks.

Future research should focus on large-scale field implementation, standardized benchmark datasets, federated and physics-informed learning, explainable artificial intelligence, and hybrid optimization methods that combine lightweight neural networks with advanced reinforcement learning. Integrating LightConneuNet with digital twins, cloud-edge computing, and next-generation smart grid technologies will further improve scalability, reliability, and real-time performance. These advancements will accelerate the practical deployment of intelligent FCV2G systems and support sustainable, low-carbon energy management for future large-scale buildings.

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