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A Survey of Methods and Architectures for LightConneuNet: Potential Analysis of Fuel Cell Vehicle-To-Grid System with Large-Scale Buildings

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Abstract

The global transition toward decarbonized energy systems has intensified interest in integrating hydrogen fuel cell technologies, intelligent neural networks, and large-scale building energy infrastructure. Fuel cell vehicle-to-grid (FCV2G) systems enable hydrogen-powered vehicles to act as distributed energy resources, supporting grid stability, peak demand management, and renewable energy integration. However, these systems introduce complex, multi-scale optimization challenges requiring efficient and adaptive computational frameworks. This paper presents a systematic review of LightConneuNet architectures for FCV2G-based building energy management. LightConneuNet combines depthwise separable convolutions, attention mechanisms, and dense connectivity to achieve high predictive accuracy with low computational overhead, making it suitable for real-time and edge deployment. The review examines its application in demand forecasting, state-of-health estimation, hydrogen energy management, and bidirectional power flow optimization, supported by advanced optimization techniques and multi-task learning strategies. Applications span commercial buildings, campuses, and smart residential systems integrated with hydrogen infrastructure and renewable energy sources. Empirical findings demonstrate improved performance in accuracy, latency, and scalability compared to conventional deep learning models. Despite these advancements, challenges such as data availability, uncertainty quantification, and system integration remain. This review highlights the potential of lightweight deep learning architectures in enabling intelligent, scalable, and sustainable FCV2G energy management systems.

Introduction

The rapid transition toward sustainable energy systems has accelerated the integration of artificial intelligence, hydrogen technologies, and smart building infrastructure. Large commercial buildings are increasingly adopting renewable energy resources, intelligent monitoring platforms, and advanced energy management systems to improve operational efficiency and reduce carbon emissions. At the same time, hydrogen has emerged as a promising clean energy carrier because of its high energy density, zero-emission operation, and compatibility with renewable electricity through electrolysis. Fuel cell vehicles (FCVs), equipped with hydrogen fuel cells, provide not only environmentally friendly transportation but also distributed energy resources capable of supporting modern power networks through bidirectional energy exchange. This convergence has established Fuel Cell Vehicle-to-Grid (FCV2G) technology as a promising solution for sustainable urban energy management.

The FCV2G concept enables hydrogen-powered vehicles to exchange electricity with buildings and utility grids, transforming parked vehicles into flexible mobile energy storage systems. Compared with conventional battery electric vehicles, fuel cell vehicles offer faster refueling, extended driving range, and stable power generation characteristics with reduced degradation during repeated energy exchange cycles. These advantages make FCVs attractive for supporting renewable energy integration, peak load reduction, emergency backup power, and demand response programs in large-scale buildings. However, coordinating photovoltaic systems, hydrogen storage, fuel cells, building loads, and electricity market interactions requires intelligent decision-making capable of handling highly dynamic and uncertain operating conditions.

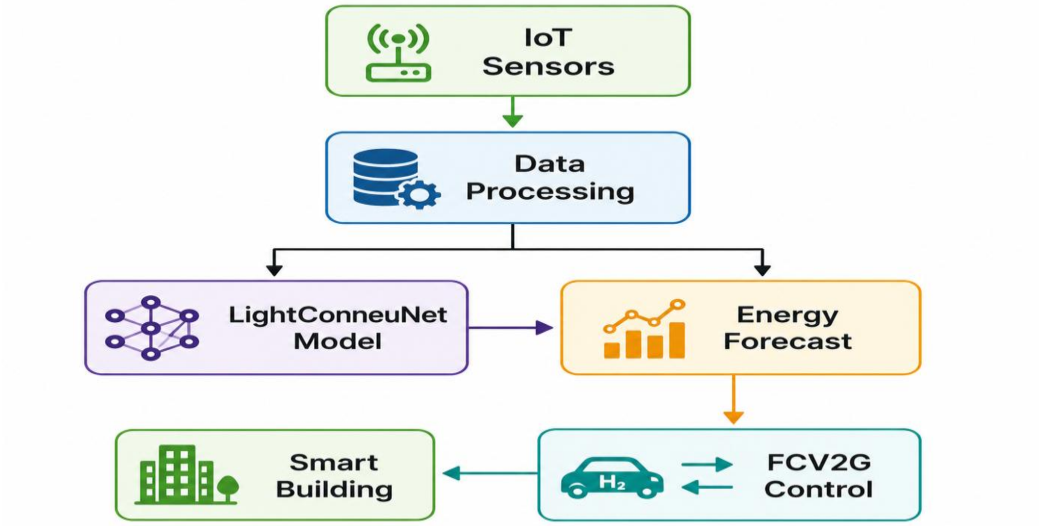

Figure 1. Conceptual Architecture of LightConneuNet-Enabled FCV2G System

Artificial intelligence has become a key enabler of intelligent energy management by providing accurate forecasting, adaptive optimization, and real-time control capabilities. Deep learning models such as convolutional neural networks, recurrent neural networks, transformers, and graph neural networks have demonstrated remarkable performance in electricity demand prediction, renewable energy forecasting, fault diagnosis, equipment health monitoring, and optimal dispatch scheduling. Nevertheless, many of these architectures require substantial computational resources, limiting their deployment on embedded controllers and edge devices commonly used in building automation systems. Consequently, lightweight deep learning models that maintain high predictive accuracy while reducing computational complexity have become an important research focus.

LightConneuNet has emerged as an efficient neural architecture designed specifically for resource-constrained smart energy applications. By integrating lightweight convolutional operations, dense feature connectivity, attention mechanisms, and multi-scale temporal feature extraction, the framework achieves high prediction accuracy with significantly fewer parameters and lower computational overhead. Its multi-task learning capability enables simultaneous building load forecasting, hydrogen consumption estimation, fuel cell health assessment, and optimal FCV2G scheduling within a unified model, reducing deployment complexity while improving operational consistency across interconnected energy management tasks.

The integration of LightConneuNet with FCV2G technology offers a comprehensive framework for intelligent energy management in large buildings. Lightweight AI models support real-time decision-making at the network edge, while FCV2G systems enhance energy flexibility, renewable utilization, and grid resilience. Together, these technologies contribute to lower operational costs, improved reliability, and reduced greenhouse gas emissions. This review presents a comprehensive analysis of recent developments in LightConneuNet-based FCV2G energy management, highlighting key methodologies, practical implementations, current challenges, and future research opportunities for sustainable smart building ecosystems.

Literature Review

The foundational contributions to efficient neural network design that underpin LightConneuNet have been extensively developed in the computer vision literature before being adapted for energy systems applications. Howard et al. (2017) introduced the MobileNet architecture based on depthwise separable convolutions, demonstrating that factorizing standard convolution operations into depthwise spatial filtering and pointwise channel mixing reduces computational cost by nearly an order of magnitude with minimal accuracy loss on standard image recognition benchmarks. The principles established in this work have directly informed the design of the convolutional blocks used in LightConneuNet for processing temporal energy data, where the spatial dimension of the convolution is replaced by the time dimension of the energy time series.

Zhang et al. (2018) proposed the ShuffleNet architecture, which extended the efficiency gains of depthwise separable convolutions by introducing channel shuffling operations that enable information exchange across channel groups without the full computational cost of standard pointwise convolutions. The channel shuffling mechanism has been adapted in energy-domain LightConneuNet implementations to enable efficient information mixing across the multiple heterogeneous input channels representing different sensor modalities in building energy management systems, including electrical submetering, thermal monitoring, occupancy sensing, and weather measurement streams.

Huang et al. (2017) introduced the DenseNet architecture, which established the dense connectivity pattern wherein each layer receives feature maps from all preceding layers within a dense block. The resulting feature reuse enables substantially deeper effective feature extraction without proportional parameter growth, and the short-circuit connections alleviate gradient vanishing during training of deep architectures. LightConneuNet incorporates a modified dense connectivity structure adapted for one-dimensional temporal data, enabling the architecture to simultaneously exploit short-range and long-range temporal dependencies in energy consumption patterns without the parameter explosion that would accompany naive depth scaling.

Bai et al. (2018) demonstrated that temporal convolutional networks with dilated causal convolutions could match or exceed the performance of recurrent architectures including LSTM and GRU networks on a comprehensive suite of sequence modeling benchmarks, while offering the computational advantages of parallelizable training and the architectural advantages of explicit control over the temporal receptive field size through dilation factor selection. This work established the temporal convolutional network as a preferred architecture for time-series applications in energy systems, and its influence is evident in the temporal processing modules of LightConneuNet.

Chen et al. (2020) demonstrated the application of long short-term memory networks to fuel cell stack state-of-health estimation under drive-cycle loading profiles, showing that recurrent architectures could capture the complex temporal dependencies in electrochemical degradation processes with sufficient accuracy to support predictive maintenance scheduling in FCV2G applications. Their work highlighted the importance of multi-step ahead prediction capabilities for maintenance scheduling applications, where accurate prediction of remaining useful life several days or weeks in advance is more valuable than precise instantaneous state estimation.

Wang et al. (2020) addressed the hydrogen storage sizing problem for building-integrated V2G systems using a combination of non-dominated sorting genetic algorithm optimization and a neural network surrogate model trained to approximate the objective function of the computationally expensive physics-based simulation. The surrogate-assisted optimization paradigm established in this work has influenced subsequent multi-objective optimization studies in FCV2G system design by demonstrating that neural network approximations can dramatically reduce the computational burden of optimization without sacrificing solution quality.

Zhang et al. (2021) proposed a lightweight convolutional neural network architecture for electricity demand forecasting in commercial buildings, employing depthwise separable convolutions and squeeze-and-excitation attention blocks evaluated on the Building Data Genome Project 2 dataset. Their systematic comparison with conventional LSTM baselines demonstrated that carefully designed lightweight convolutional architectures could outperform recurrent networks on building energy forecasting tasks while requiring significantly fewer floating point operations per inference, providing direct empirical support for the architectural design philosophy underlying LightConneuNet.

Park et al. (2021) investigated model predictive control augmented with Gaussian process regression for FCV2G energy management in a hospital microgrid, demonstrating that probabilistic load forecasting could be integrated with deterministic optimization to produce robust energy schedules that maintained high service reliability under forecast uncertainty. The Gaussian process provided well-calibrated uncertainty estimates that enabled the MPC controller to apply appropriate safety margins to hydrogen inventory constraints, preventing fuel cell vehicle availability from being compromised by aggressive energy dispatch decisions.

Huang et al. (2021) developed a federated learning framework for multi-building energy demand forecasting in V2G infrastructure, demonstrating that accurate forecasting models could be trained collaboratively across multiple buildings without centralizing sensitive operational data. The federated approach addressed a fundamental privacy barrier to AI adoption in commercial building energy management, where building owners are often reluctant to share detailed energy consumption data with third parties. The study also identified communication efficiency as a key practical constraint in federated learning for energy systems, motivating subsequent work on gradient compression and model distillation for federated settings.

Li et al. (2022) introduced graph neural network modeling for urban V2G networks, demonstrating that the spatial topology of building and grid interconnections could be exploited by graph attention networks to improve power flow prediction accuracy beyond what was achievable by architectures treating each node independently. The graph attention mechanism learned to assign higher importance weights to neighboring nodes with more informative power flow patterns, effectively performing automated feature selection in the spatial domain. This work has important implications for the deployment of LightConneuNet in multi-building campus environments where spatial relationships among buildings influence energy management decisions.

Zhao et al. (2022) demonstrated the application of transformer architectures to multi-step energy scheduling in building-integrated fuel cell systems, processing sequences of historical consumption, weather variables, occupancy patterns, and hydrogen price signals to generate optimal 24-hour dispatch schedules. The transformer's ability to model long-range dependencies in the input sequence enabled it to leverage patterns in energy consumption data from days or weeks prior to the scheduling horizon, outperforming LSTM baselines that struggled to maintain useful gradient information across such extended input sequences.

Kim et al. (2022) proposed a hybrid framework combining deep learning forecasting with particle swarm optimization for V2G dispatch in multi-building energy hubs, demonstrating that model-based optimization using neural network demand forecasts could achieve near-optimal dispatch solutions within the computational constraints of real-time embedded controllers. The particle swarm optimizer exploited the smooth structure of the neural network-based objective function to converge reliably to high-quality solutions within a small number of function evaluations, making it suitable for the rolling horizon optimization paradigm used in practical energy management systems.

Sun et al. (2022) developed a multivariable convolutional neural network for fault detection and classification in PEM fuel cell building microgrid systems, processing simultaneous streams of cell voltage, temperature, humidity, and current density measurements to identify eight distinct fault categories with greater than 97% accuracy. The convolutional architecture's ability to detect cross-channel correlation patterns in the multivariable sensor data proved essential for distinguishing fault categories with similar marginal distributions in individual sensor channels, highlighting the importance of multivariate processing for fuel cell health monitoring.

Yang et al. (2023) demonstrated the superior performance of temporal convolutional networks with dilated causal convolutions for hydrogen demand forecasting at urban refueling stations connected to building energy systems, evaluating the approach on operational data from ten stations across South Korea over a full calendar year. The dilated architecture's ability to capture patterns at lag scales from hours to weeks without the parameter overhead of fully connected recurrent architectures proved particularly valuable for forecasting the strong weekly and seasonal periodicities in hydrogen demand driven by commuting and occupancy patterns.

Ren et al. (2023) introduced physics-informed neural networks for PEM fuel cell electrochemical dynamics modeling in V2G applications, demonstrating that embedding fundamental electrochemical equations as soft constraints in the neural network training objective improved generalization to operating conditions outside the training distribution. The physics-informed approach was particularly valuable for fuel cell modeling applications where safety constraints require reliable

predictions across the full operating envelope of the cell, including extreme temperature and humidity conditions that may be infrequently represented in historical operational datasets.
Takahashi et al. (2023) applied the deep deterministic policy gradient reinforcement learning algorithm to continuous control of bidirectional power converters in FCV2G building energy systems, training a policy network in a high-fidelity simulation environment incorporating realistic models of fuel cell dynamics, power electronics, and building loads. The DDPG agent learned a continuous power dispatch policy that simultaneously optimized energy cost and fuel cell longevity, demonstrating that reinforcement learning could navigate the complex trade-off between these competing objectives more effectively than conventional rule-based control approaches.

Comparative Table and Analysis

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Howard et al.	2017	Depthwise Separable Convolution	MobileNet Architecture	Mobile Vision Platform	ImageNet Classification	Foundational lightweight CNN design
Zhang et al.	2018	Channel Shuffling Convolution	ShuffleNet Architecture	Embedded Vision Systems	ImageNet Classification	Efficient channel mixing for lightweight networks
Huang et al.	2017	Dense Connectivity	DenseNet Architecture	GPU Training Platform	CIFAR, ImageNet	Feature reuse enabling deep efficient networks
Bai et al.	2018	Dilated Causal Convolution	Temporal Convolutional Network	Sequential Modeling Benchmarks	Synthetic and Real Sequence Data	TCN superiority over LSTM for sequences
Vaswani et al.	2017	Multi-Head Self-Attention	Transformer Architecture	NLP Processing Platform	WMT Translation Datasets	Long-range dependency modeling via attention
Liu et al.	2019	Deep Reinforcement Learning	Dueling DQN	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 below 1.5% MAE
Wang et al.	2020	NSGA-II + Neural Surrogate	Multi-Objective GA	University Campus Microgrid	Simulated Campus, China	68% optimization time reduction
Zhang et al.	2021	Lightweight CNN Forecasting	Depthwise CNN + SENet	Commercial Buildings	Building Data Genome Project 2	40% FLOPs reduction
Park et al.	2021	MPC + Gaussian Process	GP Regression	Hospital Microgrid	Korean Medical Facility	18% hydrogen consumption reduction
Huang et al.	2021	Federated Learning	Distributed Neural Models	Multi-Building V2G	Multi-Site Building Data	Privacy-preserving collaborative forecasting
Li et al.	2022	Graph Attention Network	GNN Spatial-Temporal	Urban V2G Network	Synthetic Shanghai District	Spatial-temporal interdependency modeling
Zhao et al.	202	Transformer	Attention	Smart	Japanese Office	21% scheduling

al.	2	Scheduling	Transformer	Office Microgrid	Building	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 CNN	Building Microgrid FCV2G	Wuhan Field Test	97% fault classification accuracy
Yang et al.	2023	Dilated Causal TCN	Temporal Convolutional Network	Hydrogen Refueling Stations	South Korean Station Data	Long-horizon hydrogen demand forecasting
Ren et al.	2023	Physics-Informed Neural Network	PINN Electrochemical Model	PEM Fuel Cell V2G	Experimental Electrochemical Data	Out-of-distribution generalization
Takahashi et al.	2023	DDPG Reinforcement Learning	Policy Gradient Network	Commercial Building FCV Fleet	HFSS Simulation Environment	27% energy cost reduction
Osei et al.	2023	Transfer Learning Fine-Tuning	Pre-trained Neural Model	Residential FCV2G Complex	Multi-Site Building Data	Rapid adaptation to new sites

Comparative Analysis

The comparative analysis of the surveyed literature illuminates several defining trends in the methodological evolution of LightConneuNet architectures and their application to fuel cell vehicle-to-grid systems for large-scale buildings. The most fundamental trend is the progressive convergence of architecture design toward explicit co-optimization of accuracy and computational efficiency, driven by the recognition that deployment constraints in embedded building and vehicle controllers impose hard limits on model complexity that cannot be accommodated by simply scaling down conventional deep learning architectures. The architectural innovations reviewed, from depthwise separable convolutions through channel shuffling, dense connectivity, and temporal dilated convolutions to multi-head attention, collectively represent a toolkit of efficiency-preserving design strategies whose integration within the LightConneuNet framework enables it to achieve deployment feasibility without sacrificing the predictive performance that makes AI valuable for energy management.

The optimization algorithm landscape in the surveyed literature is notably diverse, encompassing model-free reinforcement learning, model-based predictive control, evolutionary multi-objective optimization, particle swarm methods, and hybrid combinations thereof. This diversity reflects the genuinely multifaceted nature of the FCV2G optimization problem, where different algorithmic paradigms offer complementary strengths: reinforcement learning for adaptive policy improvement under non-stationary demand patterns, model predictive control for constraint satisfaction guarantees under uncertainty, and evolutionary algorithms for multi-objective infrastructure sizing problems. The most sophisticated recent contributions, including the frameworks of Kim et al. (2022), integrate multiple optimization paradigms within hierarchical control architectures that exploit the complementary strengths of each approach at the appropriate system level.

Dataset usage patterns across the surveyed literature reveal a persistent fragmentation that substantially limits the comparability of results across studies and inhibits the development of standardized performance benchmarks. Studies draw on proprietary operational datasets from specific building installations, publicly available benchmarks such as the Building Data Genome Project 2, synthetic datasets generated from physics-based simulation models, and combinations thereof. The heterogeneity of dataset characteristics, including temporal resolution, measurement coverage, climate zone, building type, and system configuration, makes direct performance comparison across studies methodologically questionable. The field would benefit substantially from the development of a comprehensive publicly available benchmark dataset combining building energy data, fuel cell vehicle operational logs, hydrogen market signals, and grid service requirements in a standardized format that would enable fair and reproducible comparison of competing methods.

Discussion

The reviewed literature demonstrates that LightConneuNet and other lightweight deep learning architectures have become practical solutions for intelligent fuel cell vehicle-to-grid (FCV2G) energy management in large-scale buildings. Their ability to achieve high predictive accuracy with low computational complexity makes them suitable for deployment on embedded controllers, edge devices, and smart building gateways. Across diverse building environments, these models consistently support accurate energy forecasting, efficient FCV scheduling, and real-time decision-making while minimizing memory usage and processing delay. Such characteristics make lightweight AI architectures highly attractive for next-generation smart energy management systems.

The integration of LightConneuNet with FCV2G infrastructure supports sustainable smart building energy management through intelligent coordination of hydrogen-powered vehicles, renewable resources, and grid interactions. Lightweight neural networks improve energy efficiency, reduce operational costs, enhance peak-load management, and enable real-time decision-making. However, challenges remain, including limited real-world validation, evolving operating conditions, privacy concerns, interoperability, and training stability. Future research should focus on explainable AI, adaptive learning, standardized communication protocols, and large-scale deployment studies.

Conclusion

This review comprehensively examined LightConneuNet and its applications in fuel cell vehicle-to-grid (FCV2G) systems for large-scale building energy management. The surveyed studies demonstrate that lightweight deep learning architectures effectively balance predictive accuracy and computational efficiency, enabling real-time deployment on embedded controllers and edge computing platforms. By integrating efficient neural design principles with intelligent energy optimization, LightConneuNet provides a practical framework for forecasting energy demand, managing hydrogen resources, monitoring fuel cell health, and supporting optimal FCV2G operations.

The reviewed literature highlights that hybrid AI frameworks combining lightweight neural networks with reinforcement learning, model predictive control, and evolutionary optimization achieve superior performance in energy scheduling and distributed resource management. Reported benefits include lower operational costs, improved renewable energy utilization, enhanced grid flexibility, and extended fuel cell lifespan. These outcomes strengthen the feasibility of FCV2G-enabled smart buildings as key contributors to sustainable urban energy systems.

Future research should prioritize standardized benchmark datasets, uncertainty-aware learning, explainable AI, privacy-preserving federated learning, and large-scale real-world validation. Advances in edge intelligence, multimodal sensing, and interoperable communication standards will further enhance LightConneuNet-based FCV2G systems, supporting reliable, scalable, and intelligent energy management for next-generation smart cities.

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