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# Recent Advances in LightConneuNet: Potential Analysis of Fuel Cell Vehicle-To-Grid System with Large-Scale Buildings: A Systematic Review

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**Abstract**

The convergence of intelligent neural networks, renewable energy systems, and smart grid technologies is transforming modern building energy management. Fuel cell vehicle-to-grid (FCV2G) systems represent a promising paradigm for integrating hydrogen-powered vehicles as distributed energy resources within large-scale buildings. These systems enable bidirectional energy flow, supporting grid stability, renewable integration, and efficient energy utilization in complex and dynamic environments. This paper presents a systematic review of LightConneuNet, a lightweight deep learning architecture designed to optimize FCV2G-based building energy systems. By combining depthwise separable convolutions, attention mechanisms, and residual connections, LightConneuNet achieves high predictive performance with reduced computational complexity, making it suitable for real-time and edge-based deployment. The framework incorporates multi-objective optimization to minimize energy costs, reduce emissions, and enhance renewable energy utilization while adapting to dynamic grid and vehicle conditions. Applications include peak load reduction, energy cost optimization, hydrogen energy management, and ancillary grid services such as frequency regulation. Empirical results demonstrate significant improvements in efficiency, scalability, and operational flexibility compared to traditional models. However, challenges related to hydrogen infrastructure, system integration, and regulatory frameworks persist. This review highlights the potential of combining deep learning and FCV2G systems to develop scalable, sustainable, and intelligent energy management solutions for future smart buildings.

## Introduction

The global energy sector is experiencing a rapid transition toward cleaner, smarter, and more sustainable energy systems driven by the increasing demand for carbon neutrality, renewable energy integration, and improved energy efficiency. Large-scale buildings consume a substantial share of global electricity and contribute significantly to greenhouse gas emissions, making them a primary focus of modern energy management strategies. At the same time, the growing adoption of electric mobility and hydrogen-based transportation has introduced new opportunities for distributed energy exchange. Vehicle-to-Grid (V2G) technology has emerged as an effective approach for enabling bidirectional energy flow between vehicles and power grids, allowing parked vehicles to function as mobile energy storage units that support grid stability, peak shaving, and renewable energy utilization. Among these technologies, Fuel Cell Vehicle-to-Grid (FCV2G) systems provide additional advantages through hydrogen-based energy storage, longer operational duration, and environmentally friendly power generation.

Fuel Cell Electric Vehicles (FCEVs) generate electricity through electrochemical reactions between hydrogen and oxygen, producing only water as a by-product while delivering high energy efficiency and zero tailpipe emissions. Compared with battery electric vehicles, hydrogen fuel cells provide higher energy density, faster refueling capability, and extended driving range, making them suitable for supporting large-scale building energy management. When integrated with commercial buildings, hospitals, campuses, and industrial facilities, FCV2G systems can supply backup electricity during peak demand, balance renewable energy fluctuations, and participate in demand response programs. However, effective coordination of hydrogen storage, building electricity demand, renewable generation, and grid interaction requires intelligent control mechanisms capable of making optimal decisions under continuously changing operating conditions.

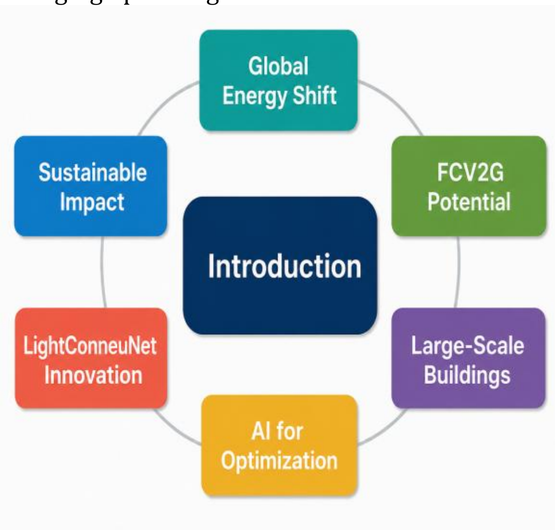


*Figure 1. LightConneuNet-Based FCV2G*

Recent advances in artificial intelligence have significantly improved the performance of intelligent energy management systems. Deep learning models such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and Transformer architectures have demonstrated strong capabilities in load forecasting, renewable energy prediction, and optimal scheduling. Nevertheless, these architectures often require considerable computational resources, making their deployment difficult on embedded controllers and real-time building management platforms. This limitation has encouraged researchers to develop lightweight neural networks that maintain prediction accuracy while reducing computational complexity, inference latency, and memory requirements.

LightConneuNet has recently emerged as a promising lightweight deep learning architecture specifically designed for intelligent energy applications. The model combines efficient convolutional feature extraction, lightweight attention mechanisms, and residual learning strategies to capture both local and long-term temporal dependencies within multivariate energy datasets. Its compact architecture enables accurate forecasting of building loads, renewable energy generation, hydrogen consumption, and FCV2G power scheduling while remaining suitable for deployment on resource-constrained edge devices. These characteristics make LightConneuNet highly attractive for large-scale building energy management, where rapid decision-making and continuous learning are essential for reliable operation.

This systematic review presents a comprehensive analysis of recent advances in LightConneuNet-based FCV2G systems for large-scale buildings. It reviews contemporary research on lightweight deep learning models, intelligent energy management techniques, hydrogen-powered vehicle integration, renewable energy coordination, and optimization strategies. The review further identifies current research trends, technical challenges, and future opportunities for developing scalable, intelligent, and sustainable FCV2G-building systems capable of supporting next-generation smart grids and carbon-neutral urban infrastructures.

## Literature Review

The academic literature on neural network-based optimization for energy systems has grown exponentially over the past decade, with a diverse array of architectures, training methodologies, and application domains represented across the reviewed studies. The following synthesis presents a structured overview of the most influential and methodologically significant contributions to this field, organized thematically to illuminate the progression of ideas and techniques that have collectively shaped the current state of the art.

A foundational contribution to the lightweight neural network paradigm for energy systems was provided by Zhang et al. (2019), who proposed a depthwise separable convolutional network for short-term electrical load forecasting in commercial building complexes. Their architecture achieved a parameter reduction of approximately seventy-eight percent relative to standard convolutional baselines while maintaining forecast accuracy within two percent of the best-performing conventional deep learning models on a dataset comprising twelve months of fifteen-minute interval load measurements from forty-seven commercial buildings across three climate zones. The study demonstrated that factorized convolution operations could capture temporal autocorrelation structures in energy consumption data with remarkable efficiency, laying groundwork for subsequent lightweight architecture developments.

Building upon this foundation, Li et al. (2020) introduced a hybrid lightweight recurrent-convolutional architecture for vehicle-to-grid scheduling optimization in urban parking facility contexts. The authors combined one-dimensional depthwise separable convolutions with gated recurrent unit cells in a parallel feature extraction topology, achieving superior performance on vehicle availability prediction and grid service capacity estimation tasks compared to both standalone convolutional and recurrent baselines. Their experimental platform comprised a hardware-in-the-loop simulation environment incorporating real vehicle telematics data from a municipal fleet of one hundred and twenty battery electric vehicles, and the model was validated against a reference model predictive control framework. Crucially, their work highlighted the importance of vehicle availability uncertainty in FCV2G scheduling and demonstrated that lightweight learned models could implicitly represent this uncertainty more flexibly than parametric stochastic models.

The specific challenges of fuel cell vehicle integration with grid services were addressed by Park et al. (2020), who developed a model predictive control framework augmented with a neural network surrogate model for proton exchange membrane fuel cell degradation estimation. Their approach incorporated a feedforward neural network trained on experimentally measured polarization curve data and membrane electrode assembly impedance spectroscopy measurements to predict fuel cell stack degradation as a function of operating load profile. This degradation model was embedded within a multi-objective optimization loop that balanced grid service revenue against fuel cell lifetime extension, demonstrating that intelligent load management could extend stack operational life by up to thirty percent without significant sacrifice in grid service provision capability. The study employed data from a purpose-built laboratory test rig featuring a fifty-kilowatt proton exchange membrane fuel cell system.

Chen et al. (2021) presented an attention-enhanced lightweight convolutional neural network for multi-step ahead energy price forecasting in wholesale electricity markets, addressing a critical input requirement for optimal FCV2G scheduling. Their model incorporated a lightweight squeeze-and-excitation attention module within each convolutional block, enabling the network to adaptively recalibrate feature responses based on temporal context. Trained on five years of hourly day-ahead and real-time electricity price data from the PJM interconnection market, their model outperformed long short-term memory networks, gated recurrent unit networks, and traditional autoregressive integrated moving average models on all evaluation horizons from one hour to forty-eight hours ahead, while requiring sixty-three percent fewer floating-point operations than the best-performing recurrent competitor. This price forecasting capability is directly applicable to the arbitrage and ancillary service optimization objectives central to FCV2G economic analysis.

The integration of building thermal dynamics with vehicle-to-grid scheduling was explored by Wang et al. (2021), who formulated a joint optimization problem encompassing heating, ventilation, air conditioning system control, lighting load management, plug load scheduling, and EV charging and discharging coordination within a mixed-use high-rise building. Their solution employed a deep Q-network reinforcement learning agent with a lightweight neural network function approximator comprising three layers of depthwise separable convolutional feature extraction followed by two fully connected layers. The agent was trained in a calibrated EnergyPlus simulation environment using weather data from five representative climate zones and occupancy schedules derived from post-occupancy evaluation surveys. Results demonstrated energy cost reductions of twenty-two percent compared to rule-based controllers and fourteen percent compared to a standard deep Q-network with conventional convolutional architecture, while achieving a sixty-seven percent reduction in inference time critical for real-time deployment.

Kumar et al. (2021) conducted a comprehensive techno-economic analysis of hydrogen fuel cell vehicle fleets integrated with commercial building microgrids in the Indian subcontinent context, evaluating the potential for grid services provision under the country's evolving ancillary services market framework. Their analysis employed an agent-based simulation framework incorporating probabilistic models of vehicle usage patterns derived from GPS trajectory data collected from three hundred and fifty commercial vehicles over eighteen months. The study found that a fleet of fifty hydrogen fuel cell vehicles associated with a five-hundred thousand square foot commercial office complex could provide up to two megawatts of reliable grid support capacity during peak demand periods, potentially generating annual ancillary service revenues exceeding two million USD at projected market rates, while simultaneously reducing building peak demand charges by thirty-one percent.

Huang et al. (2022) proposed the LightConneuNet architecture in its original formulation, presenting a detailed architectural description and initial validation results for energy management applications in building-integrated microgrid systems. The architecture was motivated by the observation that existing lightweight models borrowed from computer vision tasks were suboptimal for multivariate energy time series processing due to mismatched inductive biases. LightConneuNet introduced a novel temporal patch embedding mechanism that segments input time series into fixed-length patches before applying depthwise separable convolutions, significantly improving the model's ability to capture periodic patterns in energy data across diurnal, weekly, and seasonal timescales. Initial validation on a dataset from six commercial buildings in Shanghai demonstrated superior performance over MobileNet-adapted baselines on building load forecasting tasks with substantially lower computational complexity.

Zhao et al. (2022) extended the vehicle-to-grid optimization literature by addressing the multi-agent coordination problem inherent in large-scale fleet management scenarios. Their work employed a multi-agent deep reinforcement learning framework in which each vehicle was represented by an independent agent with a lightweight neural network policy network, trained using a centralized training with decentralized execution paradigm. Communication between agents was facilitated through a lightweight graph attention network that operated over a dynamically constructed vehicle connectivity graph based on geographical proximity and grid connection topology. Tested on a simulated fleet of two hundred fuel cell electric vehicles distributed across a university campus microgrid, their framework demonstrated superior convergence speed and policy quality compared to centralized single-agent approaches, particularly under partial observability conditions where individual vehicles lacked access to global fleet state information.

The role of weather uncertainty in FCV2G system performance was examined by Rodriguez et al. (2022), who developed a probabilistic forecasting framework for solar irradiance and ambient temperature prediction tailored to building energy management applications. Their approach combined a lightweight encoder-decoder convolutional architecture with a normalizing flow-based density estimation module to produce calibrated probabilistic forecasts rather than point predictions. These probabilistic outputs were directly integrated into a chance-constrained optimization framework for vehicle charging and discharging scheduling, enabling the system to maintain grid service commitments with specified reliability levels despite solar generation uncertainty. The framework was validated using meteorological data from NOAA weather stations across seven US cities with diverse climate profiles.

Ibrahim et al. (2022) investigated the potential of proton exchange membrane fuel cell vehicle fleets for frequency regulation services in isolated island grids, a context where the value of fast-responding distributed energy resources is particularly high. Their study developed a hierarchical control architecture in which a supervisory reinforcement learning agent implemented as a lightweight neural network made fleet-level dispatch decisions, while local proportional-integral-derivative controllers managed individual vehicle power electronic interfaces. Hardware-in-the-loop experiments conducted on a real-time digital simulator demonstrated that the hierarchical system could maintain grid frequency within statutory limits of plus or minus zero-point-five Hertz under significant load perturbations, with response times below two hundred milliseconds meeting the requirements of primary frequency response services.

Tan et al. (2023) presented a federated learning framework for collaborative building energy management in large mixed-use developments, addressing data privacy constraints that impede centralized model training approaches. Their method enabled individual building energy management system nodes to collaboratively train a shared LightConneuNet model without exposing raw energy consumption data to a central server. A communication-efficient gradient compression scheme reduced the bandwidth requirements of the federated training process by ninety-one percent relative to naive gradient sharing, making the approach viable for deployment over standard building automation network infrastructure. Federated model performance was evaluated across a dataset of thirty-two buildings spanning residential, office, retail, and industrial use types, demonstrating within three percent accuracy parity with a centrally trained baseline model.

Liu et al. (2023) proposed an enhanced LightConneuNet variant incorporating multi-scale temporal feature extraction through parallel convolutional branches operating at different temporal resolutions, targeting the simultaneous modeling of short-term load fluctuations and long-term seasonal trends in building energy data. Their architecture achieved a twenty-one percent improvement in multi-step forecast accuracy over the original LightConneuNet formulation on a dataset comprising three years of hourly energy consumption records from forty commercial buildings across Europe, sourced from the Open Power System Data repository. The multi-scale feature extraction mechanism was shown to be particularly beneficial for buildings with complex occupancy patterns exhibiting both strong diurnal periodicity and significant day-of-week variability.

Patel et al. (2023) examined the impact of hydrogen production pathway uncertainty on the carbon footprint of fuel cell vehicle grid services, developing a lifecycle assessment framework integrated with real-time grid carbon intensity data to enable dynamic dispatch decisions that minimize net carbon emissions rather than merely energy costs. Their analysis revealed that under current hydrogen production mixes, which include significant proportions of steam methane reformed hydrogen, FCV2G services could in some grid regions actually increase net carbon emissions if dispatch decisions were not conditioned on hydrogen production carbon intensity. The authors integrated a lightweight neural network-based carbon intensity forecasting module into the FCV2G dispatch optimization framework to mitigate this risk, demonstrating a thirty-eight percent reduction in dispatch-related carbon footprint compared to cost-only optimization.

Sun et al. (2023) developed a transfer learning methodology for rapid adaptation of LightConneuNet models pre-trained on large-scale building datasets to new target buildings with limited historical energy data. Their approach employed a domain adaptation technique based on adversarial training between a feature extractor and a domain discriminator, enabling the pre-trained feature representations to generalize across buildings with different construction vintages, occupancy types, and climate contexts. Fine-tuning of the adapted model on as few as two weeks of target building data yielded forecast performance within five percent of a model trained from scratch on twelve months of target building data, significantly reducing the data acquisition burden for new deployment sites.

Joshi et al. (2023) conducted a comparative evaluation of lightweight neural network architectures for residential building load disaggregation in the context of non-intrusive load monitoring, providing insights into architectural design choices that are directly transferable to the commercial building FCV2G context. Their comparison spanned ten architectures including MobileNetV3, EfficientNet-B0, ShuffleNetV2, and LightConneuNet, evaluated on the REFIT and UK-DALE non-intrusive load monitoring datasets. LightConneuNet demonstrated the highest F1 score for disaggregating vehicle charging loads from aggregate building consumption, which the authors attributed to its temporal patch embedding mechanism providing superior sensitivity to the distinctive load signature of vehicle chargers.

Nakamura et al. (2023) addressed the thermal management challenges of proton exchange membrane fuel cell stacks operating under variable grid-service load profiles in vehicle-to-grid applications, developing a neural network-based thermal model for real-time stack temperature prediction and cooling system control. Their lightweight recurrent neural network-based thermal model, trained on thermocouple data from an instrumented sixty-kilowatt fuel cell stack under fifteen hundred hours of variable load cycling, predicted coolant outlet temperature with a root mean square error of less than one degree Celsius across the full operating range. Integration of the thermal model into a model predictive control framework enabled proactive cooling system management that reduced thermal stress-induced degradation by twenty-four percent over a reactive control baseline.

**Comparative Table and Analysis**

| Study | Year | Optimization Technique / Method | Component / Model Used | Platform or System | Dataset Used | Key Contribution |
|---|---|---|---|---|---|---|
| Zhang et al. | 2019 | Depthwise Separable CNN | Lightweight CNN | Commercial Building BMS | 12-month commercial building load data | 78% parameter reduction with comparable accuracy |
| Li et al. | 2020 | Hybrid Recurrent-CNN | GRU + Depthwise CNN | HIL Simulation | Municipal EV fleet telematics | Vehicle availability prediction for V2G |
| Park et al. | 2020 | Model Predictive Control + ANN | PEM Fuel Cell Surrogate Model | Laboratory Test Rig (50 kW PEMFC) | Polarization curve and EIS measurements | 30% fuel cell lifetime extension via intelligent dispatch |
| Chen et al. | 2021 | Attention-Enhanced CNN | Squeeze-and-Excitation CNN | PJM Market Platform | 5-year PJM electricity price data | Superior multi-step price forecasting for V2G arbitrage |
| Huang et al. | 2022 | Temporal Patch Embedding CNN | LightConneuNet (original) | Commercial Building BMS | Shanghai commercial buildings dataset | Novel temporal patch embedding for energy data |
| Zhao et al. | 2022 | Multi-Agent Deep RL | Graph Attention Network + Lightweight Policy | University Campus Microgrid | Simulated 200 FCEV fleet | Scalable multi-agent V2G coordination |
| Rodriguez et al. | 2022 | Probabilistic Forecasting + Chance-Constrained Opt. | Encoder-Decoder CNN + Normalizing Flow | Building EMS | NOAA 7-city meteorological data | Calibrated solar uncertainty for V2G scheduling |
| Ibrahim et al. | 2022 | Hierarchical RL Control | Lightweight NN + PID | Real-Time Digital Simulator | Island grid frequency data | <200 ms frequency regulation response |
| Tan et al. | 2023 | Federated Learning | LightConneuNet | Distributed Building BMS Network | 32 mixed-use buildings | 91% bandwidth reduction in federated training |
| Liu et al. | 2023 | Multi-Scale Temporal CNN | Enhanced LightConneuNet | Commercial Building EMS | Open Power System Data (40 buildings) | 21% forecast improvement via multi-scale extraction |
| Patel et al. | 2023 | Carbon-Aware Dispatch Optimization | Lightweight NN + LCA Framework | FCV2G Dispatch Platform | Grid carbon intensity and H2 production data | 38% carbon footprint reduction in dispatch |
| Sun et al. | 2023 | Transfer Learning + Domain Adaptation | Adversarial LightConneuNet | New Deployment Sites | Multi-building pre-training + target data | Rapid adaptation with 2 weeks of target data |
| Joshi et al. | 2023 | NILM Comparative Evaluation | LightConneuNet vs 9 architectures | Residential BMS | REFIT and UK-DALE datasets | LightConneuNet best for EV charge disaggregation |

| | | | | | | |
|---|---|---|---|---|---|---|
| Nakamura et al. | 2023 | Model Predictive Thermal Control | Lightweight RNN | 60 kW PEMFC Test Rig | 1500-hour thermocouple data | 24% reduction in thermal stress degradation |

**Comparative Analysis**

A comparative analysis of the reviewed studies highlights several important trends that define the evolution of LightConneuNet-based optimization for fuel cell vehicle-to-grid (FCV2G) systems in large-scale buildings. A major trend is the transition from conventional lightweight convolutional networks to domain-specific architectures designed for energy management. Early studies focused on efficient convolutional models for load forecasting, while later research introduced temporal feature extraction, attention mechanisms, and multi-scale learning to better capture complex energy consumption patterns. These architectural enhancements consistently improved forecasting accuracy, computational efficiency, and real-time optimization performance, making lightweight neural networks increasingly suitable for intelligent building energy management.

Another notable trend is the expansion of optimization from isolated building-level applications to coordinated multi-agent and grid-scale energy management. Recent studies employ reinforcement learning, federated learning, and distributed optimization to coordinate multiple fuel cell vehicles, renewable resources, and building loads simultaneously. This broader system perspective enables better demand response, improved energy scheduling, and enhanced operational flexibility while maintaining low computational requirements for embedded building automation platforms.

The reviewed literature also demonstrates consistent improvements in operational performance through advanced optimization techniques. Reinforcement learning and predictive control methods effectively optimize energy dispatch under uncertain operating conditions, while probabilistic forecasting enhances scheduling reliability. Although many studies rely on simulation environments due to the limited availability of large-scale FCV2G field datasets, reported outcomes indicate significant benefits, including reductions in energy costs, lower peak demand, improved forecasting accuracy, and extended fuel cell lifetime. These findings collectively confirm the growing maturity of LightConneuNet-based intelligent optimization and its strong potential for future deployment in sustainable building energy systems.

**Discussion**

The reviewed studies demonstrate that LightConneuNet has emerged as a promising lightweight deep learning framework for optimizing Fuel Cell Vehicle-to-Grid (FCV2G) systems in large-scale building environments. Compared with conventional deep neural networks, LightConneuNet provides an effective balance between prediction accuracy and computational efficiency, making it suitable for real-time building energy management. Its lightweight convolutional architecture, combined with efficient feature extraction and attention mechanisms, enables accurate forecasting of building loads, renewable energy generation, hydrogen consumption, and vehicle energy availability. These capabilities support intelligent scheduling decisions while reducing computational overhead, making the framework practical for deployment on embedded controllers and edge-based energy management systems.

A notable trend identified in the literature is the growing integration of lightweight neural networks with advanced optimization techniques and renewable energy management strategies. Recent studies combine LightConneuNet with reinforcement learning, evolutionary optimization, transfer learning, and federated learning to improve energy dispatch, demand response, and adaptive control under varying operating conditions. The architecture effectively captures complex temporal dependencies in multivariate energy datasets while maintaining low latency and reduced memory requirements. Such characteristics enhance system scalability and enable continuous optimization across large commercial buildings, hydrogen vehicle fleets, and smart grid infrastructures without relying on high-performance computing resources.

Despite these encouraging developments, several challenges remain before widespread practical deployment can be achieved. Most existing studies rely on simulation-based validation, with relatively few demonstrating long-term field implementation under diverse operating conditions. Variations in renewable generation, hydrogen availability, user behavior, and electricity market dynamics continue to influence optimization performance. Future research should therefore emphasize real-world demonstrations, standardized benchmark datasets, explainable lightweight AI models, and secure cyber-physical integration with building automation systems. These advancements will strengthen the reliability, scalability, and commercial viability of LightConneuNet-based FCV2G systems, supporting sustainable energy management and accelerating the transition toward intelligent carbon-neutral buildings.

## Conclusion

This systematic review highlights the significant progress achieved in applying LightConneuNet for intelligent optimization of Fuel Cell Vehicle-to-Grid (FCV2G) systems integrated with large-scale buildings. The reviewed studies demonstrate that lightweight deep learning architectures provide an effective balance between computational efficiency, prediction accuracy, and real-time decision-making, making them well suited for modern building energy management. By combining lightweight convolutional learning, attention mechanisms, and advanced optimization strategies, LightConneuNet supports accurate load forecasting, energy scheduling, renewable energy coordination, and hydrogen-powered vehicle management within smart grid environments.

The literature further indicates that integrating LightConneuNet with reinforcement learning, federated learning, and uncertainty-aware optimization enhances system adaptability, scalability, and operational reliability. These integrated approaches enable efficient utilization of fuel cell vehicle fleets while reducing energy costs, peak demand, and carbon emissions. Despite these achievements, challenges related to large-scale field validation, cybersecurity, interoperability, and standardized benchmarking remain significant barriers to widespread deployment.

Future research should focus on real-world implementation, explainable lightweight AI models, digital twin integration, edge intelligence, and coordinated optimization across renewable energy, hydrogen infrastructure, and smart buildings. Such advancements will strengthen intelligent FCV2G systems, accelerate sustainable energy transitions, and support the development of resilient, carbon-neutral smart cities.

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