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Review

The Energy Management Strategies for Fuel Cell Electric Vehicles: An Overview and Future Directions

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Abstract

The rapid development of fuel cell electric vehicles (FCEVs) has highlighted the critical importance of optimizing energy management strategies to improve vehicle performance, energy efficiency, durability, and reduce hydrogen consumption and operational costs. However, existing approaches often face limitations in real-time applicability, adaptability to varying driving conditions, and computational efficiency. This paper aims to provide a comprehensive review of the current state of FCEV energy management strategies, systematically classifying methods and evaluating their technical principles, advantages, and practical limitations. Key techniques, including optimization-based methods (dynamic programming, model predictive control) and machine learning-based approaches (reinforcement learning, deep neural networks), are analyzed and compared in terms of energy distribution efficiency, computational demand, system complexity, and real-time performance. The review also addresses emerging technologies such as artificial intelligence, vehicle-to-everything (V2X) communication, and multi-energy collaborative control. The outcomes highlight the main bottlenecks in current strategies, their engineering applicability, and potential for improvement. This study provides theoretical guidance and practical reference for the design, implementation, and advancement of intelligent and adaptive energy management systems in FCEVs, contributing to the broader goal of efficient and low-carbon vehicle operation.

Keywords: energy management strategy; model predictive control; reinforcement learning; transfer learning

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1. Introduction

The development of new energy vehicles (NEVs) contributes significantly to reducing dependence on fossil fuels, enhancing energy diversity, lowering carbon emissions in the transportation sector, improving air quality, and promoting the transition toward a green and low-carbon society. At the same time, it facilitates the application of clean energy sources such as electricity and hydrogen, accelerating the deep integration between the transportation and energy systems, and thus holds substantial environmental, economic, and social significance [1–4]. Figure 1 systematically illustrates the relationships between various NEV technology pathways and their corresponding energy sources, reflecting a coordinated advancement in energy diversification, CO_2 emission reduction, and air quality improvement. The transition from conventional internal combustion engine vehicles

(ICEVs) to hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and finally to fuel cell electric vehicles (FCEVs) demonstrates a progressive electrification of the powertrain, which aligns with the fundamental logic of low-carbon transformation in the transport sector. Conventional ICEVs primarily rely on gasoline and diesel derived from petroleum, which are associated with high carbon emission intensities. In contrast, HEVs and PHEVs incorporate electric drive systems that significantly improve energy efficiency and reduce carbon emissions. BEVs rely entirely on electricity, and their environmental benefits are closely linked to the carbon intensity of the power generation mix. With the global energy transition underway and the growing emphasis on environmental sustainability, FCEVs, which make use of hydrogen as fuel to produce electricity through the electrochemical reaction of hydrogen and oxygen to drive the electric motor, have become one of the solutions to replace traditional internal combustion engine vehicles. FCEVs offer distinct advantages, including zero emissions, superior efficiency, and low noise levels, making them a promising option for reducing carbon emissions and promoting sustainable transportation development [5–12].

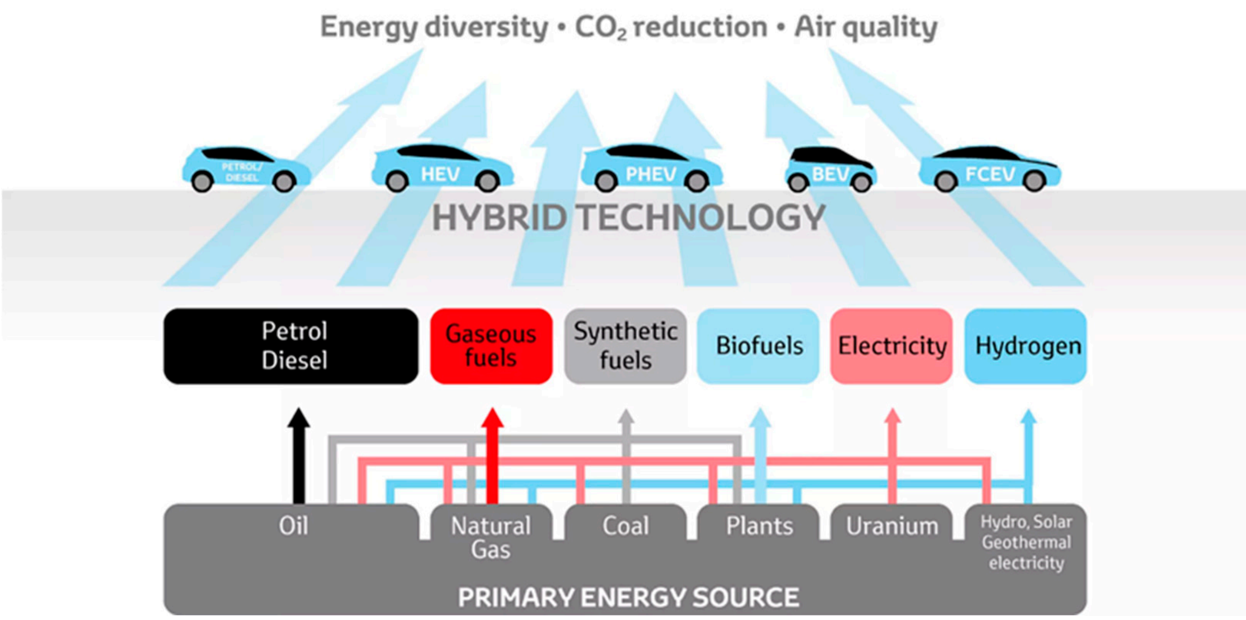

Figure 1. The relationships between various NEV technology pathways and their corresponding energy sources.

The Toyota Motor Corporation has proposed that the future of the automotive industry will be characterized by the coexistence and coordinated development of three technological pathways: battery electric vehicles, hybrid electric vehicles, and fuel cell electric vehicles. This vision emphasizes that different types of new energy vehicles will play distinct roles based on their respective advantages, as shown in Figure 2. For instance, BEVs are well-suited for short-distance urban travel, HEVs offer transitional benefits in improving fuel efficiency and reducing emissions, while FCEVs, with their fast-refueling capability and long driving range, are more appropriate for long-distance transportation and commercial vehicle applications. By establishing a diversified powertrain system, this approach not only better meets the complex and varied demands of the market but also contributes to the sustainable development of the automotive industry.

Fuel cell vehicles are typically equipped with energy storage units such as power batteries and supercapacitors. These auxiliary energy systems work together with the fuel cell power system. The key challenge for fuel cell vehicle control strategies is how to optimize the energy flow among the fuel cell power system, power battery, and supercapacitor through control strategies to achieve the hybrid power system's high performance [13–25].

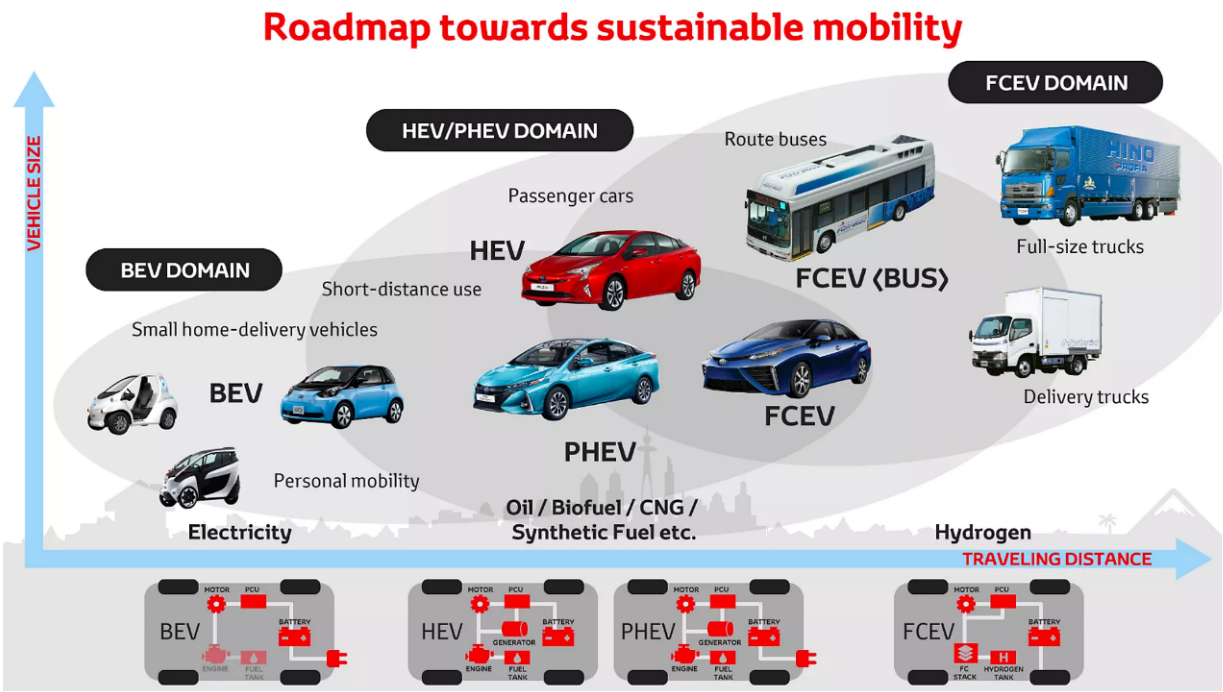

Figure 2. The future of the automotive industry from Toyota Motor Corporation's perspective.

Control strategies for fuel cell vehicles are currently classified into three main types: rule-based, optimization-based, and machine learning-based approaches. These control methods have progressed from static control approaches to dynamic adjustments of power distribution between the fuel cell and energy storage units, tailored to real-time vehicle driving cycle and driving demands, thereby greatly strengthening the fuel cell vehicle's energy management for better performance and efficiency.

To provide a comprehensive understanding of current research in fuel cell electric vehicle (FCEV) energy management, a systematic literature search was conducted using Web of Science, Scopus, and IEEE Xplore with keywords such as "Fuel Cell Electric Vehicle", "Energy Management Strategy", and "Reinforcement Learning" for the period 2015–2025. Peer-reviewed articles directly related to FCEV energy management were included, while non-English, unrelated, or duplicate studies were excluded. This approach ensures a structured and comprehensive coverage of existing methods and challenges.

Building on this literature foundation, this paper aims to promote the further development of energy management technology by reviewing existing studies and summarizing key technologies. The specific tasks include: (1) providing an overview of the topological structure, advantages, and disadvantages of FCEV powertrain systems; (2) classifying existing energy management methods based on theoretical foundations, with a systematic review of the latest research progress, including the control principles, technical advantages, and limitations of each method; and (3) discussing future research directions in energy management technology, with a focus on multi-energy coordination, data-driven approaches, and artificial intelligence technologies [26–35].

2. The Structural Design of Fuel Cell Hybrid Powertrain System

Fuel cell electric vehicles can be classified into four distinct architectures based on the integration of fuel cells with auxiliary energy systems: fuel cell standalone powertrain systems, fuel cell–battery hybrid powertrain systems, fuel cell–supercapacitor hybrid powertrain systems, and fuel cell–battery–supercapacitor hybrid powertrain systems. Each of these configurations exhibits distinct characteristics in terms of energy efficiency, power density, and dynamic performance, and is selected according to specific application requirements and operating conditions [36–38].

2.1. The Fuel Cell Standalone Powertrain System

Figure 3a shows the fuel cell standalone powertrain system, where electricity is produced directly by the electrochemical reaction of hydrogen and oxygen, which in turn powers the electric motor that drives the fuel cell hybrid vehicle.

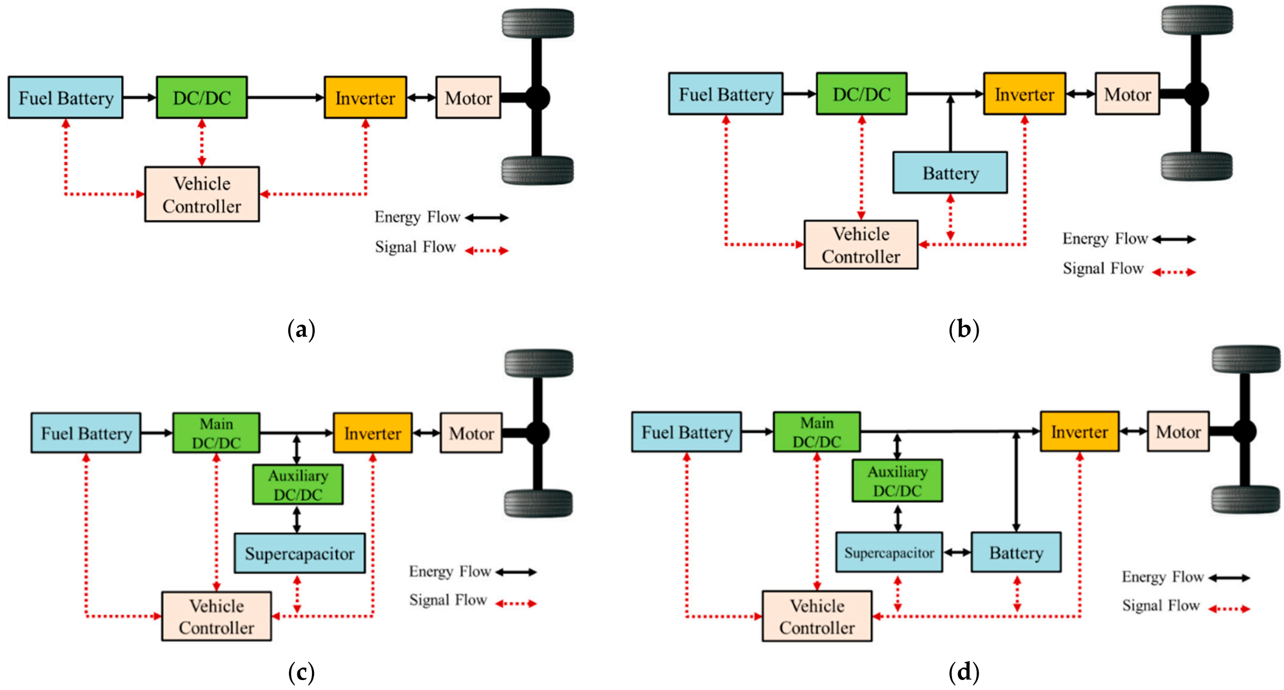

Figure 3. Structure diagram of fuel cell powertrain system. (**a**) The fuel cell standalone powertrain system; (**b**) The fuel cell–battery hybrid powertrain system; (**c**) The fuel cell–supercapacitor hybrid powertrain system; (**d**) The fuel cell-battery-supercapacitor hybrid powertrain system.

This system does not rely on additional energy storage devices or is equipped with only a small amount of energy storage to maintain short-term stability. As a result, it has advantages such as a simple structure, low cost, and light weight. In parallel, the fuel cell, functioning as an environmentally friendly power source, offers high energy conversion efficiency. However, fuel cells have high requirements for instantaneous power response, making it difficult to meet high power demands such as acceleration and climbing. When there is frequent gear shifting or large load fluctuations, the fuel cell may have limited responsiveness to rapid load changes, leading to efficiency reduction and affecting the system's lifespan. Therefore, this system is suitable for applications with relatively stable operating conditions and lower dynamic performance requirements, and is rarely used in actual vehicle applications.

It should be emphasized that the relatively slow dynamic response of fuel cells is not inherently disadvantageous in all applications. For instance, in long-haul buses or logistics vehicles, where the power demand is relatively stable, the fuel cell can operate under near steady-state conditions with high efficiency and durability. In contrast, in urban buses or passenger vehicles with frequent load fluctuations, the limited transient response becomes more significant, often requiring hybridization with batteries or supercapacitors to meet acceleration and braking demands. This distinction clarifies the suitability of standalone fuel cell systems for stable-load applications.

2.2. The Fuel Cell-Battery Hybrid Powertrain System

The fuel cell–battery hybrid powertrain system is illustrated in Figure 3b, where the fuel cell and power battery operate in a coordinated manner. The fuel cell serves as the primary source of continuous power, primarily supplying energy to the vehicle's driving electric motor, whereas the power battery functions to mitigate power fluctuations and support transient load demands, recover energy, and assist in power output during acceleration. During deceleration or braking, the power battery recovers energy and stores it.

This system optimizes control strategies to ensure the fuel cell always operates within its optimal efficiency range, thereby reducing hydrogen consumption. In addition, the power battery helps enhance the system's dynamic response, allowing it to adapt to various complex operating conditions. However, the system is more complex and costlier, and the power battery adds weight and occupies more space. Therefore, this system is more suitable for applications that require frequent start-stop operations, such as urban passenger cars and logistics vehicles.

2.3. The Fuel Cell-Supercapacitor Hybrid Powertrain System

The fuel cell–supercapacitor hybrid powertrain system is depicted in Figure 3c, where the fuel cell and supercapacitor collaboratively work. In this configuration, the fuel cell is primarily responsible for supplying power, while the supercapacitor is responsible for rapid energy storage and release, effectively supporting transient power demands and enhancing dynamic performance. During the vehicle acceleration, the supercapacitor discharges quickly to provide additional power; during deceleration or braking, the supercapacitor recovers braking energy and stores it. This system optimizes energy use to improve overall efficiency.

Supercapacitors have high power density and excellent transient performance, making them effective in supporting short-term high-power demands. At the same time, the fuel cell can focus on providing stable power, thereby extending its lifespan. However, supercapacitors have a low energy density and cannot meet long-term high-load demands. The system is also costlier and has a limited range of applications. Therefore, this system is primarily used in vehicles that require frequent start-stop operations, such as short-distance buses and logistics vehicles.

2.4. The Fuel Cell-Battery-Supercapacitor Hybrid Powertrain System

The fuel cell-battery-supercapacitor hybrid powertrain system is shown in Figure 3d. In this system, the fuel cell, power battery, and supercapacitor function in harmony to achieve a balance between long-range endurance, high power output, and energy recovery. The fuel cell serves as the primary power source, the battery stores and delivers energy for moderate power demands, while the supercapacitor handles instantaneous power requirements. The subsystems are dynamically optimized through an energy management system, which intelligently schedules power distribution to maximize the overall system performance.

The main advantages of this system lie in its excellent dynamic response capability, enabling it to adapt to various complex driving cycles. It also maximizes the fuel cell efficiency, extends the system's lifespan, and improves overall energy utilization. However, the system has a complex structure and has stricter development and maintenance requirements. Therefore, this system is suitable for applications with extremely high-performance requirements, such as long-distance buses, heavy-duty trucks, and military vehicles.

2.5. Comparative Summary of Powertrain Architectures

To support system-level design decisions, Table 1 summarizes the key trade-offs among the four fuel cell powertrain architectures discussed above, with a focus on energy efficiency, cost, size/weight, and dynamic performance [39,40].

Table 1. The key trade-offs among the four fuel cell powertrain architectures.

Architecture Type	Energy Efficiency	Cost (USD/kW)	Size/Weight (kg/kW)	Dynamic Performance	Typical Applications
Standalone Fuel Cell	40–55% (sensitive to load fluctuations)	800–1200	8–12	Poor	Low-speed, stable-load vehicles
Fuel Cell–Battery Hybrid	45–60% (optimized FC operation)	500–800	10–15	Good	Urban buses, logistics vehicles
Fuel Cell–Supercapacitor Hybrid	45–58% (effective transient support)	600–900	9–13	Excellent	Short-distance buses, delivery vans
Fuel Cell–Battery–Supercapacitor Hybrid	50–65% (full-range optimization)	900–1500	12–18	Excellent	Long-haul buses, heavy-duty trucks

The results indicate that standalone fuel cell systems exhibit relatively low efficiency (40–55%) and poor dynamic performance, but remain attractive in low-speed, steady-load applications due to their lowest cost (800–1200 USD/kW) and lightest weight (8–12 kg/kW). In contrast, the fuel cell–battery hybrid raises efficiency to 45–60% by buffering energy fluctuations, with moderate cost (500–800 USD/kW) and weight (10–15 kg/kW), making it widely adopted in urban buses and logistics vehicles. The fuel cell–supercapacitor hybrid achieves 45–58% efficiency and outstanding transient response, at a cost of 600–900 USD/kW and weight of 9–13 kg/kW, which is advantageous for short-distance and stop-and-go operations. The three-source hybrid demonstrates the highest efficiency (50–65%) and dynamic adaptability, but with significantly higher cost (900–1500 USD/kW) and weight (12–18 kg/kW), making it more suitable for long-haul buses and heavy-duty trucks. Overall, hybrid configurations clearly outperform standalone fuel cells in efficiency and adaptability, although the trade-offs in cost and system complexity remain critical considerations for practical deployment.

3. Research Progress on Energy Management Strategies

Approaches for optimizing energy consumption in fuel cell electric vehicles are commonly classified into three primary approaches: rule-based control, which relies on predefined logic and conditions; optimization-based control, which aims to maximize performance through mathematical modeling and solution techniques; and machine learning-based control, which adapts and improves based on data-driven insights and real-time vehicle performance (Figure 4).

In practical applications, there are also hybrid control strategies that combine multiple control methods [41–57]. Among these, rule-based control is straightforward and simple to execute, but it lacks the ability to achieve global optimization, limiting its effectiveness in handling complex and dynamic driving environments; optimization-based control can improve fuel economy but has high computational demands; machine learning-based control has adaptive capabilities but is complex to train and difficult to interpret. Different strategies are suitable for different application scenarios, and the specific choice needs to comprehensively consider vehicle requirements, computational resources, and operating environments to optimize the economic efficiency, dynamic performance, and operational lifespan of the fuel cell or battery within the power system. Therefore, it is essential to develop advanced control strategies and improve energy management techniques to ensure optimal performance under varying operational driving environments [58–64].

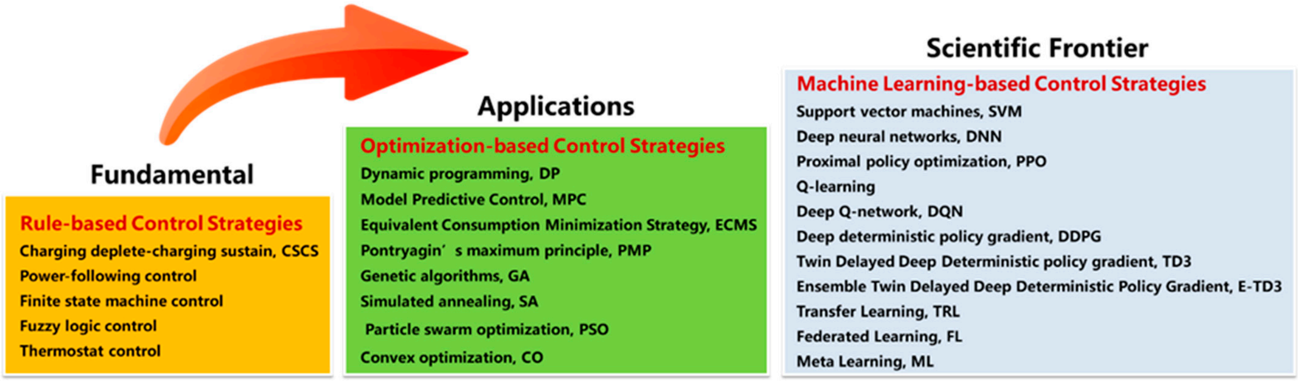

Figure 4. The classification of energy management strategies.

3.1. The Rule-Based Energy Management Strategy

The rule-based energy management strategy regulates the power allocation between the fuel cell power system and auxiliary energy storage components—such as the power battery and supercapacitor—through a predefined set of deterministic control rules, typically derived from expert knowledge or empirical observations. For example, the classic rule-based strategy is the Charging Deplete-Charging Sustain (CD-CS) strategy, which determines whether the powertrain operates in pure fuel cell, pure electric, or hybrid mode based solely on the battery's State of Charge (SOC). Another common strategy is the power-following control strategy, which typically bases its decisions on driving conditions (such as acceleration, constant speed, braking, etc.) and vehicle load requirements to determine the output power of each energy source [65–69].

For instance, a power-following control strategy proposed by Zhang et al. [70], illustrated in the flowchart in Figure 5, employs fixed upper and lower thresholds for the power battery (set at 30% and 70%, respectively). When the SOC drops below the limit, the fuel cell operates at its maximum power output; conversely, when it exceeds the upper limit, the fuel cell reduces its output or ceases operation. While strategies such as the Charge Depleting–Charge Sustaining (CD-CS) approach, thermostat control, and finite state machine control offer simplicity and ease of implementation, their reliance on fixed rules may limit adaptability under varying driving conditions. Consequently, although these methods contribute to improved system efficiency and operational stability, their effectiveness may be constrained in complex or highly dynamic scenarios.

Although the aforementioned methods are simple to implement and have relatively low computational burden, they suffer from poor adaptability and flexibility, making them unsuitable for complex driving environments and dynamic operating conditions. To address these limitations, fuzzy logic control strategies based on non-deterministic rules have been further developed. These strategies use fuzzy inference systems to handle complex, nonlinear energy management issues.

In this approach, system input variables (such as accelerator pedal position, vehicle speed, SOC, etc.) are transformed into fuzzy sets and then processed through a rule base to derive the appropriate output power (as shown in Figure 6). Fuzzy control methods do not require precise mathematical models and can address uncertainty and nonlinearity within the system. As a result, they perform well under conditions of incomplete information and exhibit good adaptability [71,72]. The main advantages of this method are its strong flexibility and good real-time performance, making it suitable for driving environments with high uncertainty.

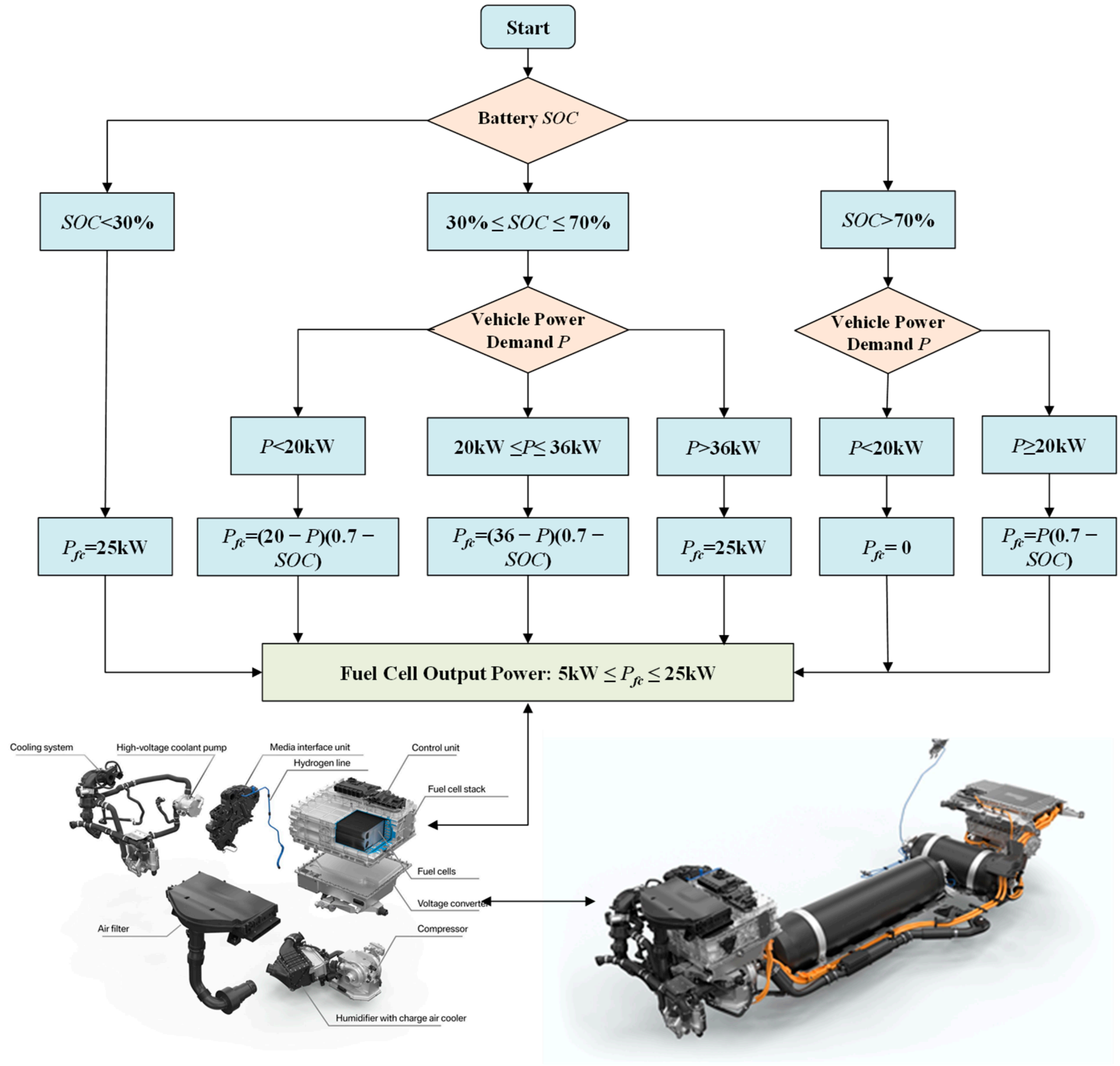

Figure 5. The flowchart of the power-following control strategy algorithm.

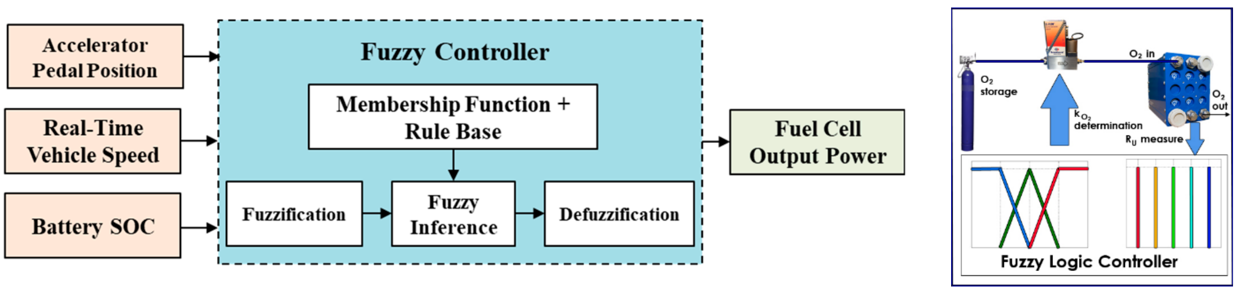

Figure 6. The fuzzy logic-based control strategy.

3.2. The Optimization-Based Energy Management Strategy

The optimization-based control strategy uses mathematical optimization algorithms to determine the energy allocation scheme, typically aiming to minimize fuel consumption, improve dynamic response, or extend system lifespan. It is generally classified into two main categories: global optimization methods, which aim to determine the optimal control strategy over a complete driving cycle with prior knowledge of driving conditions, and real-time optimization methods, which seek to make near-optimal decisions dynamically based on current and predicted vehicle states.

3.2.1. The Global Optimization Control Strategy

The global optimization control strategy generally seeks to minimize energy consumption, assuming that the global driving cycle are known and that the powertrain's operating range serves as the boundary conditions. The objective is to optimize the distribution of multiple energy sources using various optimization algorithms. Global optimization methods commonly employed in energy management systems include: Dynamic Programming (DP), which exhaustively evaluates all possible state-action combinations to identify the globally optimal control strategy over a predefined driving cycle, is widely used for its accuracy in finding optimal solutions; Pontryagin's Maximum Principle (PMP), considering the alternative, converts the optimization problem into a boundary-value problem by applying necessary optimality conditions, ensuring an efficient determination of the optimal solution; Genetic Algorithms (GA) mimic evolutionary processes, utilizing selection, crossover, and mutation to explore complex and nonlinear solution spaces, providing robust performance in uncertain environments; Simulated Annealing (SA) adopts a probabilistic approach to accept suboptimal solutions, enabling the algorithm to escape local optima and converge toward a global solution; Particle Swarm Optimization (PSO) simulates social behavior among particles, iteratively refining candidate solutions based on both individual and collective experiences; with convex objective functions and constraints, the Convex Optimization (CO) offers a robust mathematical framework for solving optimization problems, ensuring the problem is tractable and has a unique global solution [73–84].

Among these approaches, dynamic programming is frequently regarded as the most classical method. It is grounded in Bellman's Principle of Optimality, which involves dividing the overall problem into smaller subproblems, solving each optimally, and then using these solutions to construct the global optimum. Therefore, DP can find the global optimum and is less likely to become stuck in local optima. However, its state space size grows exponentially with increasing dimensions, leading to a dramatic increase in computational complexity, making it difficult to apply online. It is typically used for offline optimization to generate reference trajectories or theoretical benchmarks.

Approximate Dynamic Programming (ADP) addresses the "curse of dimensionality" by introducing function approximation (e.g., value function fitting or neural networks). This significantly reduces computational requirements, enabling online or real-time applications, while still achieving near-optimal results in many practical use cases.

In contrast, Stochastic Dynamic Programming (SDP) incorporates randomness into state transitions or control effects, making it suitable for systems operating under uncertainty, such as real-world traffic and variable driver behavior. By computing the expected value of the cost function, SDP achieves optimality in probabilistic terms but often requires longer convergence time due to the complexity of sampling-based evaluation.

A detailed comparison is provided in Table 2, which includes both algorithmic features and practical performance metrics based on reported values from literature and typical experimental setups.

As shown in Table 2, dynamic programming offers the highest theoretical performance but suffers from an extremely high computational burden, which makes it impractical for real-time vehicle control. ADP, by simplifying the value function and policy representation, reduces runtime by an order of magnitude while maintaining over 90% of the fuel-saving benefit compared to DP. SDP is effective in uncertain or stochastic environments but requires more iterations and careful design of probability models. From an engineering standpoint, ADP is currently the most promising trade-off method, balancing optimization quality, real-time feasibility, and deployment complexity.

Table 2. Comparative analysis of DP, ADP, and SDP in energy management applications.

Feature/Metric	DP (Dynamic Programming)	ADP (Approximate DP)	SDP (Stochastic DP)
Applicable Problem	Deterministic Optimization	Deterministic with Complexity	Optimization under Uncertainty
State Transition	$x_{k+1} = f(x_k, u_k)$	$x_{k+1} \approx f_{\text{approx}}(x_k, u_k)$	$x_{k+1} = f(x_k, u_k, w_k)$
Objective Function	$min \sum g_k(x_k, u_k)$	$J_{\text{policy}} = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^k g_k(x_k, u_k)\right]$	$J_{\text{policy}} = \mathbb{E}\left[\sum_{k=0}^{T} \gamma^k g_k(x_k, u_k)\right]$
Optimality	Global Optimum	Near-Optimal (Approximate)	Expected Value Optimum
Computational Complexity	Very High (offline only)	Medium (online feasible)	High (longer convergence)
Typical Runtime [85,86]	>1000 s (UDDS, MATLAB R2021b, I7-10750H)	10–100 s (WLTC, MATLAB R2021b, I7-10750H)	60–300 s (UDDS, MATLAB R2021b, I7-10750H)
Fuel Economy Improvement (vs. Rule) [87]	About 18–20% UDDS, WLTC (SOC∈(30, 70))	About 12–15% WLTC (SOC∈(30, 70))	About 10–13% UDDS (SOC∈(30, 70))
Real-Time Applicability	No	Yes	Partial (depends on modeling)
Representative Use Case	Offline benchmark generation	Embedded control in EV/FCV	Adaptive strategies under traffic

3.2.2. The Real-Time Optimization Control Strategy

Recent studies on real-time optimization control strategies for energy management predominantly explore two major methods: the Equivalent Consumption Minimization Strategy (ECMS), which aims to reduce fuel consumption by efficiently distributing energy between various power sources, and Model Predictive Control (MPC), which utilizes system models to predict future behaviors and optimize control actions over a defined time window, both being widely adopted approaches in energy management systems.

The ECMS is derived from the optimal fuel consumption control strategy originally developed for Hybrid Electric Vehicles (HEVs), but has since been adapted and enhanced for use in fuel cell vehicle power systems. The core of this strategy lies in establishing an equivalent relationship between the fuel cell output power and the battery power draw. This relationship converts the battery's energy usage into an equivalent amount of hydrogen consumption, which allows for the optimization of energy balancing between the fuel cell power system and the power battery to ensure efficient energy consumption. One of the key benefits of ECMS is its strong real-time performance, allowing for quick adjustments to energy distribution, while also maintaining low computational complexity, making it an attractive choice for real-time applications.

Despite these advantages, ECMS does have its limitations. One significant drawback is its reliance on a single equivalent factor, which may not be sufficient to adapt to varying and complex driving conditions, such as steep slopes or high-speed driving. Under these circumstances, a fixed equivalent factor might lead to suboptimal performance, either overusing the battery or underutilizing the fuel cell. To overcome this limitation, numerous researchers have proposed the Adaptive ECMS (A-ECMS), an advanced version of the traditional ECMS that dynamically adjusts the equivalent factor in response to real-time driving cycle and system performance. This adjustment allows for more precise control over energy distribution, ensuring that power is managed efficiently under varying driving scenarios. As a result, A-ECMS offers a more adaptable and optimized energy management solution, improving the overall performance, fuel efficiency, and lifespan of fuel cell electric vehicles, particularly in environments with fluctuating demands. For example, Gao et al. [88] introduced an innovative approach by proposing a variable equivalent factor that adapts according to the battery's SOC. This dynamic adjustment mechanism enhances the control strategy, enabling the fuel cell electric vehicle to maintain an optimal SOC while effectively harnessing the surplus energy of the power battery. The reported simulation outcomes featuring a transient deviation of no more than 1.2% and a steady-state deviation of no more than 0.2% demonstrate the method's high precision and robustness. Compared to conventional ECMS, this strategy significantly improves the adaptability of energy management across varying driving environments.

Additionally, the MPC operates by formulating a mathematical model of the system to predict its future behavior over a specified time horizon. At each control cycle, it optimizes the control inputs to meet predefined objectives, such as reducing hydrogen consumption or prolonging battery life.

Its core feature is rolling optimization, which involves optimizing the control inputs for a future period at each sampling moment, but implements only the first control action of the optimized input sequence at each sampling instant before recalculating the control sequence in the subsequent control cycle.

As a result, obtaining sufficiently accurate predictions of future driving cycles has become a key area of research in MPC. The prediction methods employed include various techniques such as the Markov Transition Matrix (MTM), the Exponential Forecasting (EF), the Neural Networks (NN), the Auto-Regressive Integrated Moving Average (ARIMA), the Support Vector Machine (SVM), the Tensor Padding (tensor padding refers to the process of adding artificial values to tensors to ensure consistent dimensionality for neural network operations), and the Deep Q-Network (DQN) algorithms et al. [9,10,89–92].

Among these, the MTM is a probability-based prediction method, which mainly includes three steps: speed state discretization, Markov transition matrix construction, and speed prediction [64,93]. Since the vehicle speed transition characteristics vary for different driving modes (such as urban, highway, and suburban), later studies introduced a driving mode recognition process after speed state discretization, improving the prediction accuracy. For example, Lin et al. [94] employed the K-means clustering algorithm to categorize segments of the driving condition based on their characteristic features and incorporated a neural network-based driving mode recognition before constructing the Markov matrix, and by leveraging this clustering technique, the predictive capability for future vehicle velocity is notably enhanced.

Currently, there is considerable research on short-term vehicle speed prediction based on neural networks, with common types including the Back Propagation Neural Networks (BPNN), the Radial Basis Function Neural Networks (RBFNN), the Convolutional Neural Networks (CNN), and the Long Short-Term Memory (LSTM) [95,96]. For instance, Lin et al. [97] adopted a thoughtful data preparation strategy by randomly reordering multiple typical operating conditions and merging them into a comprehensive training dataset comprising 7031 samples. This approach enriched the diversity of training scenarios, enhancing the robustness of the model. Furthermore, the use of the Levenberg–Marquardt algorithm for iterative training of the neural network demonstrates a deliberate emphasis on convergence speed and fitting accuracy. The results showed the best performance within a 5 s prediction range, improving by 12.5% compared to the Markov method. Li et al. [98] effectively integrated traffic information into their modeling framework and proposed a hybrid vehicle speed prediction model combining CNN and bidirectional long short-term memory (Bi-LSTM) networks. This integrated architecture leverages the strengths of spatial feature extraction and temporal sequence learning, resulting in a notable improvement in the accuracy of future speed predictions.

Driven by recent advancements in Vehicle-to-Everything (V2X) communication, the real-time acquisition of traffic information has become a reality, and many researchers have integrated traffic information into vehicle speed prediction [99–103]. For example, Liu et al. [104] utilized real-time location and traffic signal information in a Vehicle-to-Infrastructure (V2I) scenario to plan vehicle speed and proposed a model predictive control method with variable weights for vehicle speed control. He et al. [105] introduced an innovative dynamic driving cycle construction method that incorporates a real-time traffic information tensor model (Figure 7), utilizing a speed segment database and a traffic tensor model database. By enabling the real-time generation and dynamic updating of global driving cycles in response to current traffic conditions, this technique provides a substantial improvement in the accuracy and responsiveness when constructing global driving cycles. The method demonstrates strong potential for improving the adaptability of vehicle control strategies under complex and evolving traffic environments. Guo et al. [106] proposed a speed planning method tailored to the specific driving characteristics of buses, aiming to generate appropriate speed reference intervals. By aligning bus operation with traffic signal timing, this approach effectively reduces idling at intersections and has a considerable impact on reducing the total energy consumption throughout the journey. The method demonstrates a practical and targeted strategy for enhancing the energy efficiency of public transportation systems.

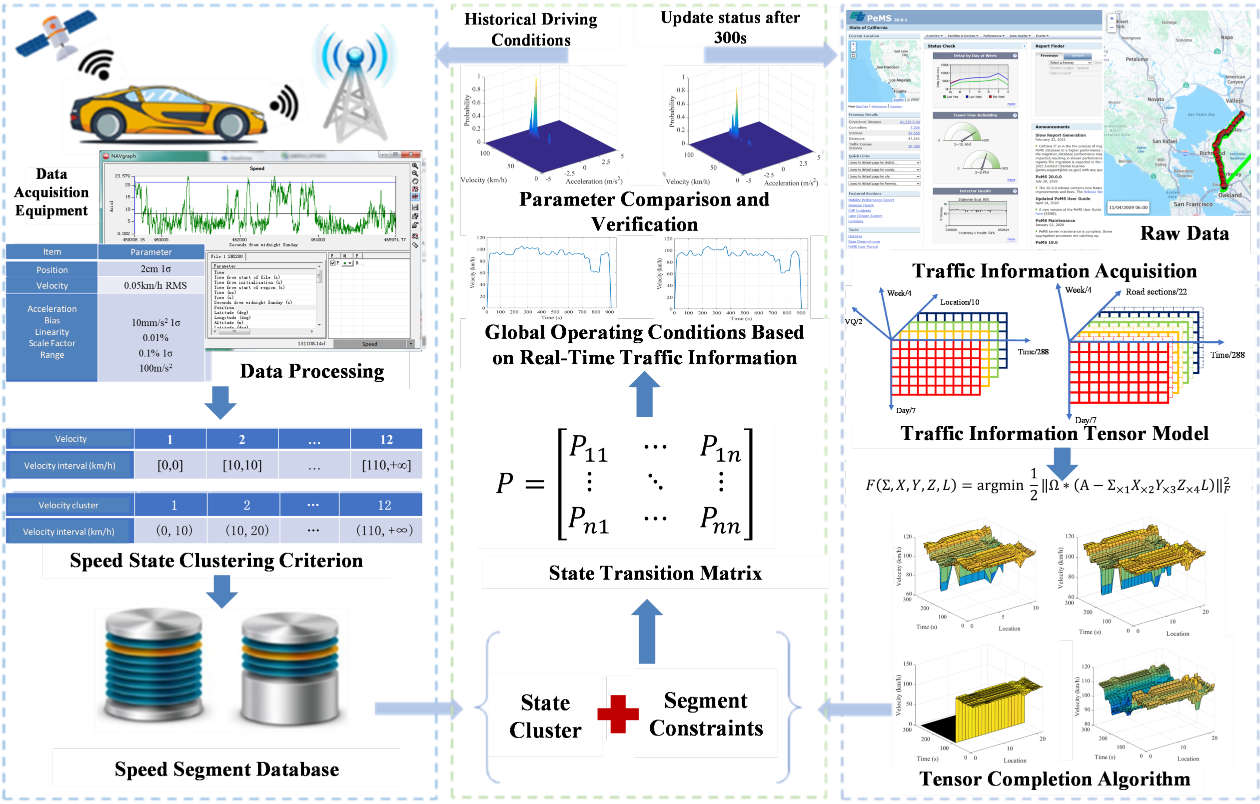

Figure 7. The driving cycle dynamic construction method based on the tensor model.

In addition, the control strategies for fuel cell electric vehicles have developed target functions that balance dynamic response and service life, based on optimizing overall vehicle energy consumption [107,108]. For example, Lin et al. [109] innovatively incorporated the open-circuit voltage degradation of the fuel cell into the energy management evaluation function as an equivalent hydrogen consumption term. This integration enables the energy management strategy to account for both immediate fuel efficiency and long-term system durability. In comparison with traditional rule-based strategies, the proposed method achieved a 2.6% reduction in hydrogen consumption and a 4.1% decrease in open-circuit voltage degradation, highlighting its effectiveness in balancing energy efficiency with fuel cell longevity. Wang et al. [110] introduced a new factor, the rate of change in fuel cell power, into the energy management strategy, with constraints on power rate of change, start-stop cycles, and maximum power. They analyzed the impact of different weight coefficients on overall vehicle energy consumption and proposed an adaptive optimization energy management strategy that considers performance degradation.

3.3. *The Machine Learning-Based Energy Management Strategy*

With the rapid advancement of computational intelligence technologies, machine learning based energy management strategies have garnered growing attention in recent years. These approaches leverage data-driven models to capture complex system dynamics and user behaviors, offering improved adaptability and optimization capabilities compared to conventional rule-based or model-based methods. Machine learning methods analyze a significant volume of historical data (such as driver behavior, road condition information, traffic patterns, etc.) and use intelligent algorithms for model training. This enables driver demand recognition, future road condition prediction, and the integration of multi-source information, such as weather and traffic accidents, with control strategies, enhancing the overall vehicle intelligence. Currently, machine learning-based energy management strategies can be broadly categorized into four main paradigms: supervised and unsupervised learning, reinforcement learning, transfer learning, and federated learning [111–118]. Each of these approaches offers distinct advantages in terms of data utilization, adaptability, and scalability, enabling more intelligent and context-aware energy management solutions in complex and dynamic vehicular environments.

3.3.1. Supervised/Unsupervised Learning-Based Energy Management Strategy

Supervised learning is a method of training models based on existing input-output sample data and is often used in conjunction with optimization-based energy management strategies. In supervised learning, labeled data is essential for training, whereas unsupervised learning is independent of labeled data [119,120].

Supervised learning is typically used in energy management strategies to learn patterns from historical data, thereby predicting future power demands or optimal energy distribution strategies. For example, Deep Neural Networks (DNN) can be used to predict power demand under different driving modes by training on historical driving data; Support Vector Machines (SVM) can be used to identify driving modes and adjust the energy management strategy accordingly; and decision tree models can be trained using historical labeled data with Random Forest (RF) algorithms to identify the optimal energy distribution strategy under different driving conditions [9,93].

Unsupervised learning is used to automatically discover patterns from data. Common methods include group formation algorithms, including K-Means and density-based spatial clustering with noise, which are used to identify different driving modes (e.g., city driving, highway driving) and driving styles (e.g., aggressive driving, economical driving, balanced driving), applying different energy management strategies for each mode. Autoencoders and Principal Component Analysis (PCA) algorithms are commonly utilized for dimensionality reduction and feature extraction, enabling the identification of key variables that significantly impact energy management performance [10,94]. By effectively filtering redundant or less informative data, these techniques enhance model interpretability and computational efficiency, thereby supporting the development of more accurate and responsive energy management strategies.

3.3.2. The Reinforcement Learning-Based Energy Management Strategy

As a significant component of machine learning, the Reinforcement Learning (RL) has experienced rapid development and has been extensively applied to energy management in recent years. Its ability to learn optimal control policies through interaction with dynamic environments makes it particularly well-suited for addressing the complexity and uncertainty inherent in real-time energy management scenarios. It primarily involves training an agent within a given environment to optimize cumulative rewards, thereby deriving an optimal control strategy. The RL-based energy management encompasses various approaches, including value function-based methods, Deep Deterministic Policy Gradient (DDPG), Proximal Policy Optimization (PPO), and other advanced reinforcement learning techniques [121,122]. These methods leverage deep learning architectures to handle high-dimensional state spaces and improve the stability and convergence of policy learning, leading to improved effectiveness of energy management strategies, particularly in dynamic and complex driving scenarios.

1. Value Function-based Method

Q-learning operates by learning the optimal action-value function, which predicts the expected cumulative reward for each state-action pair, thereby guiding the agent toward optimal decision-making. By quantifying the expected return of an action in a specific state, the Q-value directs the agent's policy toward maximizing long-term rewards. As a model-free approach, Q-learning operates without the need for a predefined model of the environment, and it is proven to converge to the optimal Q-value within a finite state-action space, making it highly effective for sequential decision-making problems, such as energy management. However, it faces challenges when dealing with large state spaces, as it becomes difficult to store all the Q-values, and it also struggles with continuous action spaces. Therefore, Q-learning in energy management typically assumes discrete actions and cannot be directly applied to complex environments [123].

To address the aforementioned issues, the Deep Q-Network (DQN) algorithm has been gradually developed. It combines Q-learning with deep neural networks to achieve optimal energy management without relying on historical data (Figure 8). DQN is suitable for optimizing problems with nonlinear, high-dimensional state spaces [124,125]. For example, Zheng et al. [126] employed the Deep Q-Network (DQN) algorithm, optimizing for both economy and durability, and compared the performance improvements of various algorithms under an identical driving environment. The equivalent hydrogen consumption using the DQN algorithm was only 3.09% higher than the globally optimal DP algorithm. This small deviation illustrates a favorable trade-off between performance and computational efficiency, highlighting the practical applicability of DQN for real-time energy management.

2. Deep Deterministic Policy Gradient-based Method

The DDPG is a reinforcement learning algorithm based on Policy Gradient (PG) methods, designed specifically for continuous action spaces. By leveraging the discrete-action learning capability of DQN and the continuous-action optimization of DPG, DDPG provides a robust framework for tackling complex control tasks, such as those encountered in autonomous systems and robotics. The algorithm directly outputs actions through a policy network, which enhances decision-making efficiency and facilitates real-time control in environments with continuous, high-dimensional action spaces [127].

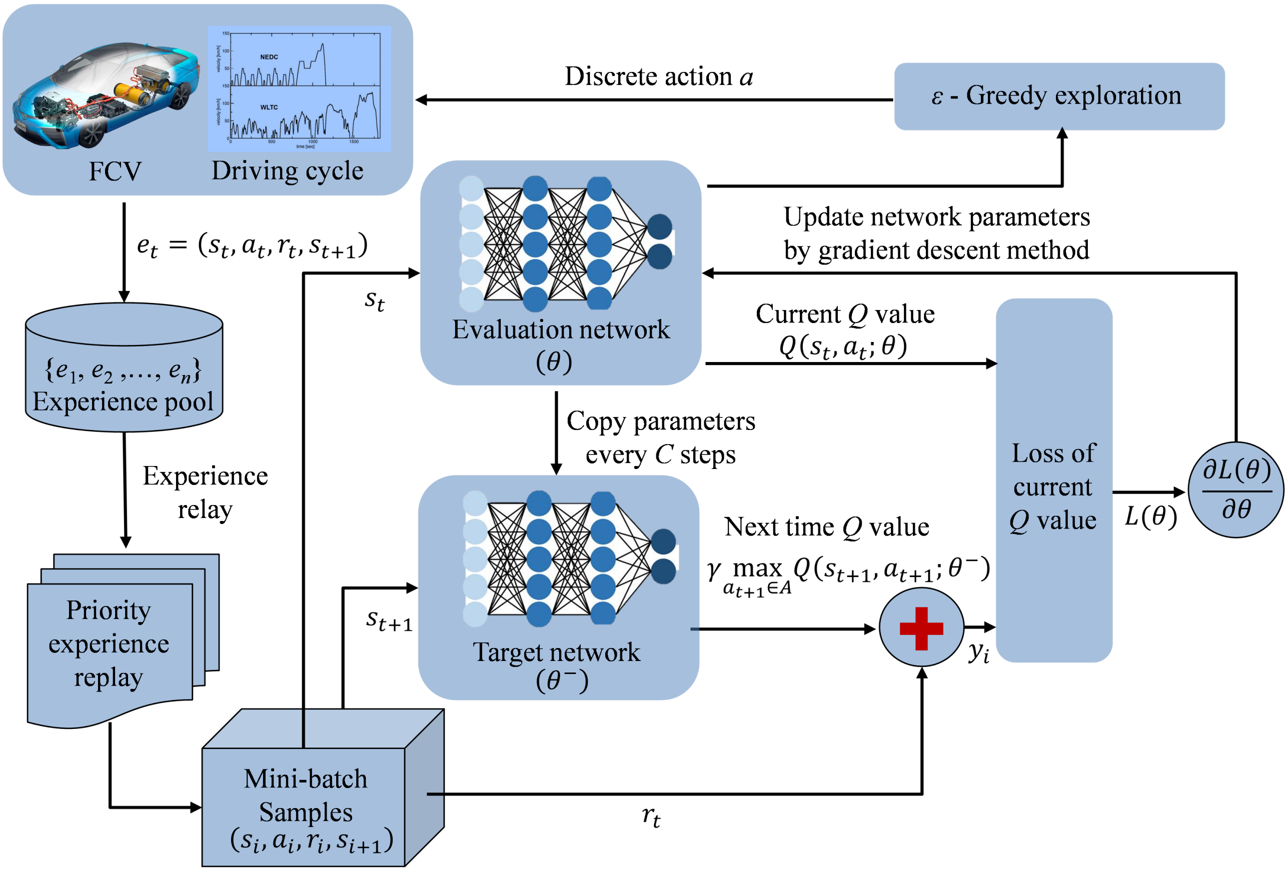

Figure 8. Energy management strategy framework based on DQN.

Twin Delayed Deep Deterministic Policy Gradient (TD3) builds upon the DDPG algorithm, incorporating additional mechanisms to mitigate issues like overestimation bias and instability in reinforcement learning. and designed to address some of the challenges associated with DDPG, such as instability and overestimation of Q-values. It addresses critical issues such as Q-value estimation bias, unstable policy updates, and inefficient exploration, which are prevalent in DDPG. These improvements enhance its suitability for energy management strategies in fuel cell electric vehicles, where the control tasks are continuous, stochastic, and inherently complex [128].

Ensemble/Enhanced Twin Delayed Deep Deterministic Policy Gradient (E-TD3) is an advanced reinforcement learning algorithm that builds upon the TD3 optimization framework. It further improves the stability, robustness, and iterative exploration efficiency of control strategies. For example, Huang et al. [129] proposed an enhanced version of the TD3 algorithm, referred to as E-TD3, which incorporates several improvements aimed at enhancing learning stability and policy performance. The computational framework of the proposed E-TD3 algorithm is illustrated in Figure 9, detailing the modifications introduced to the original TD3 architecture.

3. Proximal Policy Optimization-based Method

Proximal Policy Optimization (PPO) builds upon traditional policy gradient methods by introducing mechanisms that ensure more stable and efficient policy updates during reinforcement learning. By using a surrogate objective function and incorporating a trust region approach, PPO strikes a balance between exploration and exploitation, making it particularly effective for solving complex control tasks in dynamic environments, specifically designed for continuous control tasks in high-dimensional, complex environments [130,131].

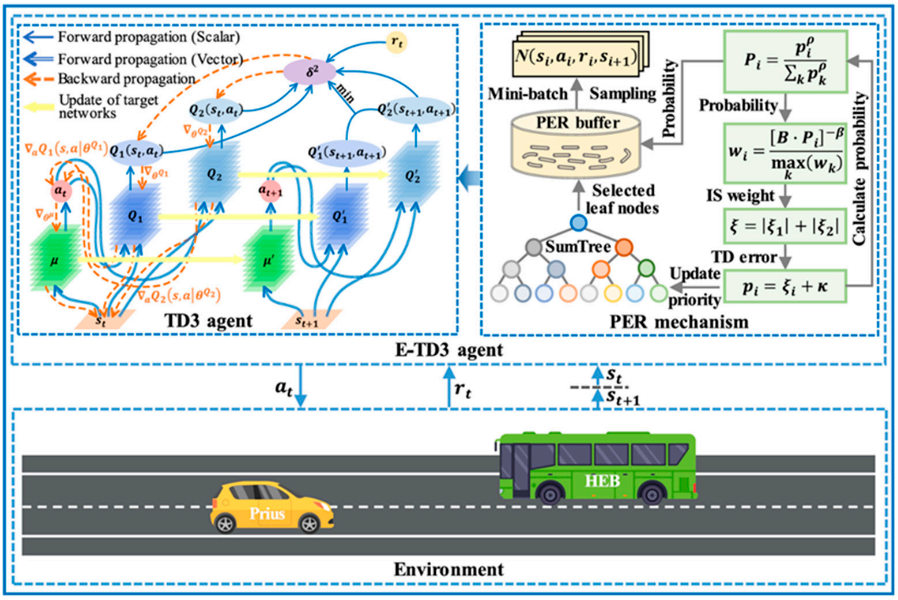

Figure 9. Energy management strategy framework based on E-TD3.

PPO mainly improves upon traditional policy gradient methods, making them more stable, efficient, and easier to implement. For example, Li et al. [132] proposed an energy management strategy based on PPO and compared it with DQN and TD3 (Figure 10). Performance metrics included algorithmic convergence behavior, energy consumption optimization, and fuel cell lifespan. The results demonstrated that, under both training and validation conditions, PPO, DQN, and TD3 exhibited varying hydrogen consumption levels, highlighting their respective efficiencies in energy management, relative to the DP baseline scheme, which were 3.79%, 8.45%, and 6.86%, respectively. These findings indicate the relative efficiency of each algorithm in reducing hydrogen consumption, with PPO showing the closest performance to the globally optimal DP scheme. Additionally, compared to DQN and TD3, PPO reduced fuel cell degradation by 2.51% and 0.12%, respectively. The convergence speed of PPO was 93.55% and 97.17% faster than DQN and TD3, respectively, demonstrating superior learning efficiency and optimization capability.

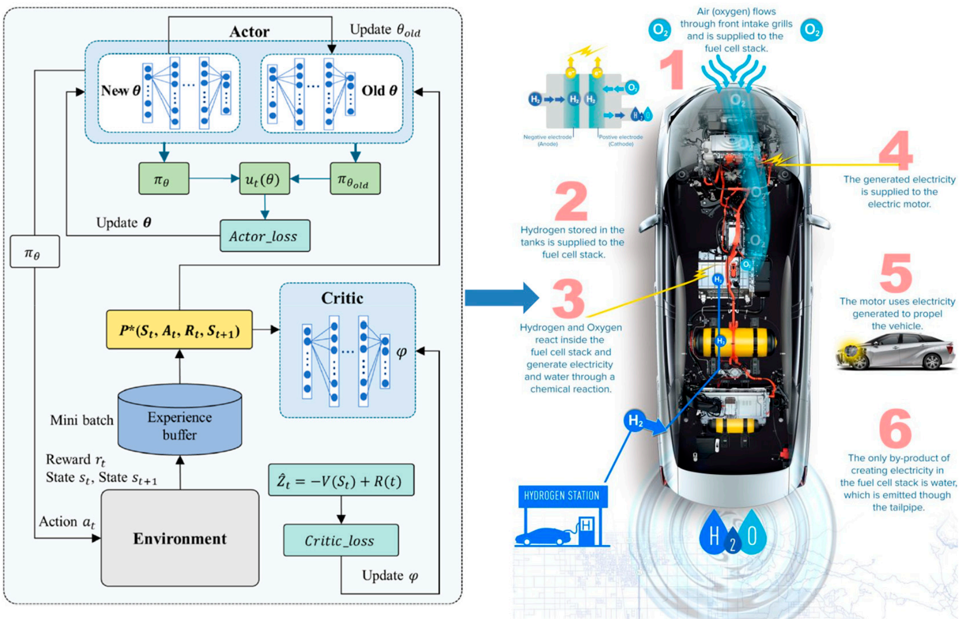

Figure 10. Energy management strategy framework based on PPO.

4. Real-Time Deployability and Embedded Inference Analysis of DRL Methods

While Deep Reinforcement Learning (DRL) algorithms such as DQN, DDPG, PPO, and TD3 have demonstrated notable performance improvements in fuel cell hybrid vehicle control (e.g., up to 3.09% energy saving compared to DP), their practical deployment requires careful evaluation of onboard computational constraints. The inference efficiency comparison of RL algorithms for onboard FCEV applications is shown in Table 3.

Table 3. Inference efficiency comparison of RL algorithms for onboard FCEV applications.

Algorithm	Typical Model Size	Inference Latency (on Jetson/ARM)	Control Frequency	Deployment Feasibility
DQN [133]	About 0.5–2 M	10–30 ms @ Jetson Xavier NX, FP32, batch = 1	Low (1–10 Hz)	Moderate (needs pruning)
DDPG [134]	About 1–3 M	15–40 ms Jetson TX2, FP16, batch = 1	Medium (5–20 Hz)	Feasible
PPO [135]	About 1–2 M	20–50 ms @ ARM Cortex-A72, PyTorch 1.8, FP32	Medium (5–12 Hz)	Computationally heavier
TD3/E TD3 [136]	About 2–4 M	25–60 ms Jetson Xavier, FP32, batch = 1	Medium (5–10 Hz)	Needs optimization

For instance, DQN and TD3 involve fully connected deep Q-networks with thousands to millions of parameters, depending on input dimensionality and network depth. On embedded automotive platforms such as NVIDIA Jetson Xavier NX, inference latency typically ranges between 5 and 30 ms per decision, which is acceptable for low-frequency control (e.g., 10 Hz), but might be limiting for high-speed dynamics or fine-grained energy management [137].

Moreover, algorithms like PPO and TD3 require multiple policy rollouts and gradient updates during training, which can be computationally expensive. While these processes are often offloaded to cloud or desktop training environments, runtime inference must be lightweight enough for deployment on automotive-grade ECUs (e.g., ARM Cortex-A series) [138]. Model quantization and network pruning techniques can help reduce the model size and inference delay, albeit potentially at the cost of performance degradation.

Therefore, although DRL-based strategies offer promising improvements, their integration into real-time fuel cell vehicle control systems remains constrained by hardware resources, memory bandwidth, and latency budgets. Balancing model complexity with onboard feasibility is crucial for practical implementation.

3.3.3. Transfer Learning-Based Energy Management Strategy

In the development of energy management strategies for vehicles, a key challenge lies in efficiently adapting pre-trained models to varying driving conditions, vehicle configurations, or geographic environments. Traditional methods typically require extensive retraining with large-scale new datasets, which is both time-consuming and computationally expensive. To address this issue, Transfer Learning (TRL) has emerged as a promising paradigm for enhancing the adaptability and generalization of control strategies with limited data and computational resources. This method is particularly suitable for energy management applications, where rapid deployment and robustness across diverse scenarios are essential.

Transfer learning refers to the process of fine-tuning an already trained model for a new task. The primary goal is to minimize reliance on large-scale training data while enhancing the generalization capability of energy management strategies. This is especially beneficial in scenarios where data availability is limited or computational resources are constrained, enabling effective adaptation of models to new, unseen environments with minimal additional training.

The underlying principle of transfer learning involves transferring knowledge, including models, features, and parameters, learned from one or more source domains to one or more target domains, thereby improving learning performance. This is particularly advantageous for knowledge transfer between different vehicle models or driving environments, enhancing the model's flexibility and robustness.

For example, Huang et al. [129] integrated transfer learning into deep reinforcement learning algorithms, building upon the E-TD3 framework. They proposed a Deep Transfer Reinforcement Learning (DTRL) method tailored for hybrid powertrain energy management (Figure 11). This approach enables an energy management strategy trained in one city to be effectively transferred to another, thereby improving model scalability and adaptability. Simulation results demonstrated that, under the proposed transfer learning framework, development time was reduced by 90.38%, and fuel efficiency improved by 6.07% in fuel cell hybrid vehicles.

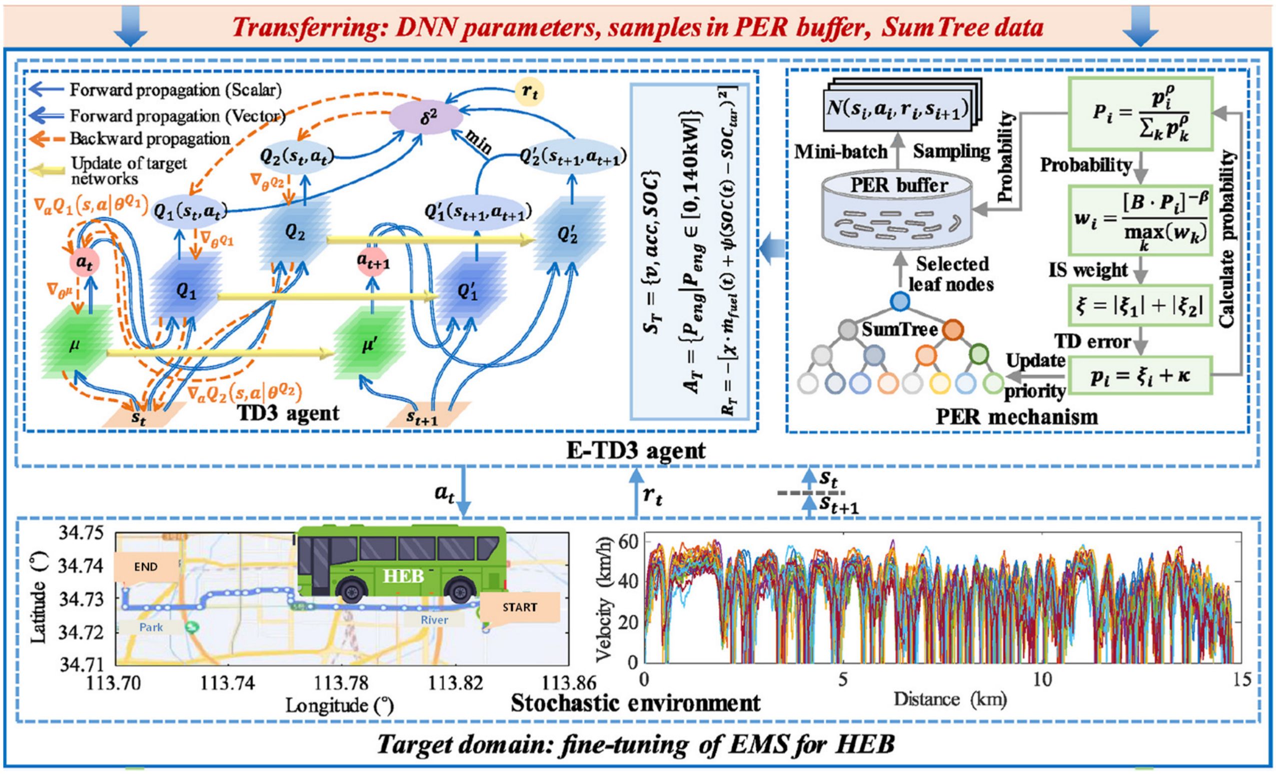

Figure 11. Energy management strategy framework based on transfer learning.

Despite its advantages, transfer learning faces several challenges in practical applications. One issue is the heterogeneity between domains, such as differences in vehicle configurations, environmental conditions, and sensor modalities, which may lead to domain shifts and performance degradation. Additionally, if the knowledge from the source domain is not sufficiently relevant to the target task, negative transfer may occur, adversely affecting the model's performance.

To address these limitations, researchers have explored domain adaptation techniques such as feature alignment and model fine-tuning. Nevertheless, ensuring robust generalization across domains and validating the effectiveness of transfer learning under real-world conditions remain crucial directions for future research.

3.3.4. Federated Learning-Based Energy Management Strategy

While transfer learning enables knowledge reuse across domains to accelerate convergence and reduce data dependence, it often relies on access to labeled data from source and target environments. In contrast, federated learning (FL) complements TL by enabling collaborative model training across multiple vehicle nodes without requiring centralized data collection. This decentralized learning paradigm is particularly advantageous for energy management applications, where data privacy, system scalability, and distributed computation are critical considerations.

Given the distributed nature of vehicle fleets and the privacy sensitivity of onboard data, FL offers a promising solution for intelligent energy optimization in connected transportation systems. By facilitating model updates through encrypted gradient or weight exchanges instead of raw data transfer, FL ensures privacy preservation while minimizing communication costs (Figure 12) [139].

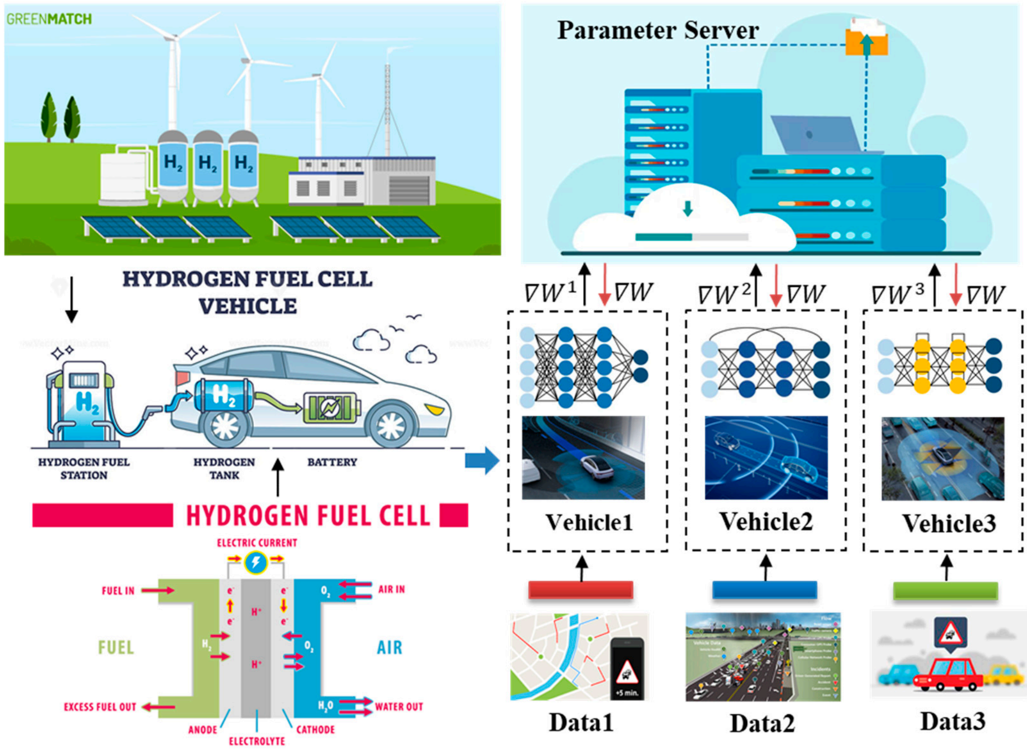

Figure 12. Energy management strategy framework based on federated learning.

However, several challenges hinder large-scale deployment. Communication overhead, caused by frequent parameter synchronization between vehicles and central servers, demands high-bandwidth, low-latency infrastructure. Techniques such as gradient sparsification and asynchronous updates have been proposed to reduce this burden, though often at the expense of model convergence and stability.

Furthermore, statistical heterogeneity among clients-resulting from varying vehicle usage patterns, traffic conditions, and environmental contexts-can impair global model generalization. This non-IID nature of vehicular data has motivated the development of personalized FL and cluster-wise aggregation approaches.

Robustness is also essential for real-world deployment. Issues such as intermittent connectivity, client dropout, and heterogeneous computing capabilities pose nontrivial obstacles. Despite promising results in simulated environments, comprehensive field trials are needed to validate FL's performance, reliability, and energy-saving potential under real driving conditions [140].

4. Conclusions

The energy management strategy for FCEVs is a critical enabling technology to enhance system efficiency, extend component lifespan, and optimize overall vehicle performance. With the continuous advancement of power electronics, control theory, and artificial intelligence, FCEV energy management strategies are gradually evolving from simple rule-based approaches and global optimization methods toward adaptive optimization, data-driven control, and intelligent decision-making frameworks.

This review first analyzed the topological structure of FCEV power systems, highlighting the advantages and disadvantages of different multi-source architectures. Based on this, a systematic comparison of energy management strategies was provided, ranging from fuzzy control, optimization-based methods such as DP and MPC, to emerging AI-driven approaches. While fuzzy logic offers robustness to uncertainty, its optimization effect is limited. Optimization-based methods can deliver near-optimal energy allocation through accurate modeling, but suffer from high computational cost. AI-based strategies, especially reinforcement learning, have shown promise in capturing system nonlinearity and improving real-time adaptability.

Looking ahead, three development directions can be identified. (1) AI-based energy management, leveraging machine learning and reinforcement learning to improve real-time control and adapt to dynamic driving conditions. These methods are particularly suitable for on-board implementation in the near term. (2) V2X-enabled cooperative optimization, which will integrate FCEVs with intelligent transportation infrastructure, allowing anticipatory scheduling and coordinated energy allocation under external factors such as traffic flow and road gradient. This represents a medium-term research focus, dependent on infrastructure maturity. (3) Cloud-based monitoring and fleet management, where large-scale vehicle-cloud collaboration can enable predictive maintenance, fault diagnosis, and route-level optimization, especially for buses and logistics fleets. This long-term approach supports system-level coordination but requires reliable communication and data security.

In addition to control strategies, it must also be recognized that the deployment of FCEVs is constrained by the technological bottlenecks of the fuel cell itself, including durability, cost, and hydrogen storage limitations. More importantly, achieving true zero-emission requires that hydrogen fuel be produced from renewable or low-carbon sources, not fossil-based pathways. Although these issues fall beyond the immediate scope of this review, they will fundamentally determine the sustainability and scalability of future FCEV energy management solutions.

By prioritizing on-board AI solutions in the short term, while progressively incorporating V2X and cloud-based approaches, a scalable, adaptive, and intelligent energy management ecosystem for FCEVs can be realized, ultimately supporting the transition toward zero-emission transportation.

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