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Review

Fuel Cell Hybrid Electric Vehicles: A Review of Topologies and Energy Management Strategies

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Abstract: With the development of the global economy, the automobile industry is also developing constantly. In recent years, due to the shortage of environmental energy and other problems, seeking clean energy as the power source of vehicles to replace traditional fossil energy could be one of the measures to reduce environmental pollution. Among them, fuel cell hybrid electric vehicles (FCHEVs) have been widely studied by researchers for their advantages of high energy efficiency, environmental protection, and long driving range. This paper first introduces the topology of common FCHEVs and then classifies and introduces the latest energy management strategies (EMSs) for FCHEVs. Finally, the future trends of EMSs for FCHEVs are discussed. This paper can be useful in helping researchers better understand the recent research progress of EMSs for FCHEVs.

Keywords: fuel cells; hybrid electric vehicles; energy management strategy; topologies

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1. Introduction

Currently, energy shortages and ecological protection are gaining widespread attention in various countries, and the massive use of fossil fuels is further worsening environmental problems. Among various energy sources and technologies to replace fossil fuels, hydrogen energy and fuel cells are considered promising solutions to achieve zero-pollution emissions [1]. The automobile industry is an important industry in many countries, and automobiles are also a necessity in people's daily lives. At present, traditional fuel vehicles still occupy a large share of the market, which will produce many air pollutants and greenhouse gases in the driving process. Replacing fossil fuels as power sources for vehicles with clean energy sources such as hydrogen and electricity can greatly reduce pollutant and greenhouse gas emissions [2].

The fuel cells discussed in this paper are proton exchange membrane fuel cells (PEMFCs), which use hydrogen energy as the energy source to generate electricity. The PEMFC directly converts the chemical energy contained in hydrogen into electricity, heat, and water [3]. The fuel cell suffers from a slow dynamic response [4] and is difficult to adapt to complex driving conditions [5]. The chemical reaction of the hydrogen in the fuel cell which supplies electrical energy is often smaller than the rate of change of the load. At the same time, rapid acceleration and deceleration and frequent start-stop operations during driving will affect the durability of the fuel cell. Based on these characteristics, fuel cells are often used in hybrid energy storage systems with other energy sources, such as batteries and ultracapacitors, for power applications [6,7]. Additionally, fuel cells are widely used in hybrid power systems with other energy sources. It is useful to reduce the consumption of hydrogen, reduce the size of fuel cells and increase the economy of hybrid power systems [8,9]. Fuel cell-based hybrid systems are widely used not only in fuel cell hybrid vehicles but also in other transportation equipment, such as unmanned aerial vehicles (UAVs) and trams [10]. This shows that hydrogen energy is playing an increasingly important role in the transportation industry.

Fuel cell hybrid vehicles usually use fuel cells as the main power source and are equipped with batteries or ultracapacitors as auxiliary energy sources. The working conditions of automobiles driving on the road are very complex. They often face various emergencies, and the required power demand will also have large fluctuations and sudden changes. However, if only fuel cells are used as the energy source, the output of large fluctuations in power can reduce the life of the fuel cell [11]. Therefore, the role of the auxiliary energy source is necessary. Batteries and ultracapacitors can play good roles in auxiliary energy sources. Batteries can recover excess energy and provide power to the system simultaneously with fuel cells when the load demand power is high. The ultracapacitor has the characteristics of a fast dynamic response, fast energy recovery, and high specific power, which can play the role of a timely response in the face of rapid changes in load demand [12]. At present, there are three main system structures of fuel cell hybrid vehicles. The first type is a hybrid system composed of fuel cells and batteries. The second is a hybrid system composed of fuel cells and ultracapacitors. The final type is a hybrid system composed of fuel cells, batteries, and ultracapacitors. The power system structure has been studied and analyzed for different types of fuel cell hybrid vehicles [13].

EMSs play a significant role in the performance and efficiency of fuel cell hybrid vehicles [14]. Its main objective is distributing power between different energy sources while achieving two goals: first, reducing hydrogen consumption or minimizing equivalent energy consumption [15]; and second, extending fuel cell life, which also means increasing the economy of the hybrid system [16]. A large number of energy management strategies are focused on these two optimization goals. The first type of EMSs is the rule-based method. This usually requires obtaining the power map of the fuel cell to obtain the highest efficiency operating point. It can also adjust the power distribution of the fuel cell and the energy storage system (battery or ultracapacitor), according to the power system state. However, it has many disadvantages, such as the parameters that are affected by the test operating conditions, lacking adaptability to different operating conditions, and the control results are not optimal. Optimization-based energy management strategies are some of the most studied types and can be divided into two categories: online optimization strategies; and offline optimization strategies. Among them, the real-time optimal energy management strategy based on model predictive control (MPC) has been widely discussed in the past two years. The third category are the learning-based energy management strategies. Its basic idea is to use large data sets of real-time and historical information to train the parameters of the strategy to obtain optimal control [17]. An energy management strategy based on intelligent vehicle interconnection technology has also been recently proposed by researchers and is discussed in this paper. The classification of common energy management strategies for fuel cell hybrids is shown in Figure 1. Regardless of the type of energy management strategy, the core of the optimization is represented by two aspects: optimizing energy consumption; and extending the life of fuel cells and other components [18].

This paper focuses on the following aspects. The first is to summarize the topologies commonly used in fuel cell hybrid vehicles. The fuel cell can form a hybrid power system with batteries or ultracapacitors, or with both batteries and ultracapacitors. These three types of hybrid power systems are commonly used in FCHEVs. Then, the latest energy management strategies for fuel cell hybrid vehicles are classified and summarized. The purpose of this paper is to provide a reference and help researchers study energy management strategies for fuel cell hybrid vehicles.

The rest of this paper is arranged as follows: The Section 2 gives the topology classification of fuel cell hybrid vehicle systems. Then, the Section 3 summarizes and concludes the energy management strategies. The Section 4 gives the conclusion and suggestions.

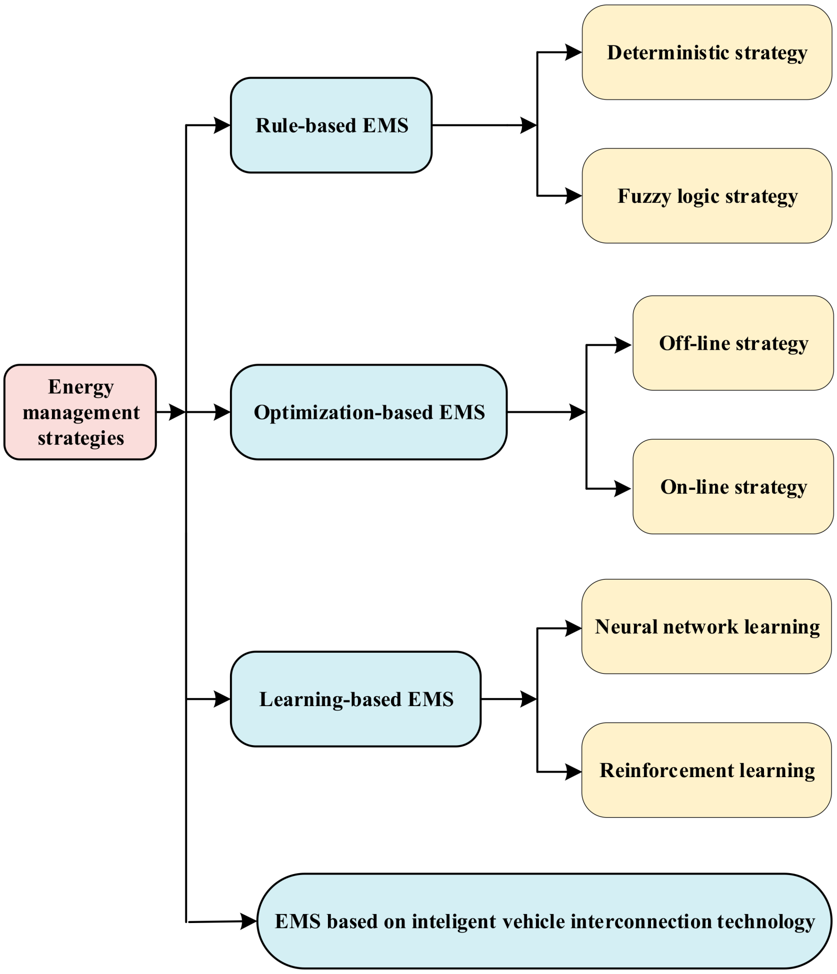


Figure 1. Classification of common energy management strategies.

2. Typical Topologies of FCHEVs

Fuel cells are often combined with other auxiliary energy sources to form a hybrid system to supply energy to hybrid electric vehicles. These auxiliary power sources are batteries, ultracapacitors (UCs), superconducting magnetic energy storage (SMES), solar photovoltaics (SPVs), and flywheels. The most commonly used auxiliary energy sources are batteries and ultracapacitors [19]. Batteries are easy to install, low maintenance, and low cost. Therefore, fuel cell/battery hybrid electric vehicles are widely used in production and are the most common topology. An ultracapacitor is a storage unit to enhance the dynamic response. It can be used to quickly provide load or recover energy when the load fluctuates rapidly [20]. Compared with batteries and ultracapacitors, the application of other auxiliary energy storage elements is not as extensive [21]. A SMES is an energy storage device with high power output and low energy density. The working conditions required by SMES are relatively severe. Due to the consideration of vehicle cost, the application in fuel cell hybrid vehicles is also relatively rare. SPV is a sustainable, nonpolluting power generation device, but its energy generation depends on sunlight irradiation with large uncertainty. Therefore, it is not a very ideal auxiliary energy for automobiles. When torque is applied to the flywheel, the flywheel will store energy in the form of mechanical energy. When the system requires greater power, the flywheel can release the mechanical energy and convert it into electrical energy to supply energy to the system. It requires high security and is often used in power grid systems.

Commonly, there are five topological classifications of FCHEVs: fully FC; FC + battery hybridization; FC + UC hybridization; FC + battery + UC hybridization; and FC + other hybridization. The advantages and disadvantages of common FCHEVs' topologies are listed in Table 1.

Table 1. Summary of common FCHEVs' topologies.

Topological Classifications	Main Advantages	Main Disadvantages
Fully FCEV	• Simple structure • Easy to implement control strategies	• Unable to recover energy
FC + Battery hybridization	• High energy density(battery) • Ability to recover energy	• Slow dynamic response
FC + UC hybridization	• Fast dynamic response • Ability to recover energy	• UC is more expensive than battery • Low energy density(UC)
FC + battery + UC hybridization	• High energy density(battery) • Fast dynamic response(UC) • Ability to recover energy	• Control strategies are complex and difficult to implement

2.1. Fully FCEV

Fuel cell electric vehicles only use fuel cells to power the transmission system, with no auxiliary energy source. This topology is simple, as seen in Figure 2, and consists only of a fuel cell stack, DC/DC converter, inverter, and electric motor. Because of its simple structure, it has the characteristics of being easy to control and realize. Commonly used applications are mainly in low-speed vehicles, such as forklifts, buses, aviation vehicles, trams, and marine vehicles [22].

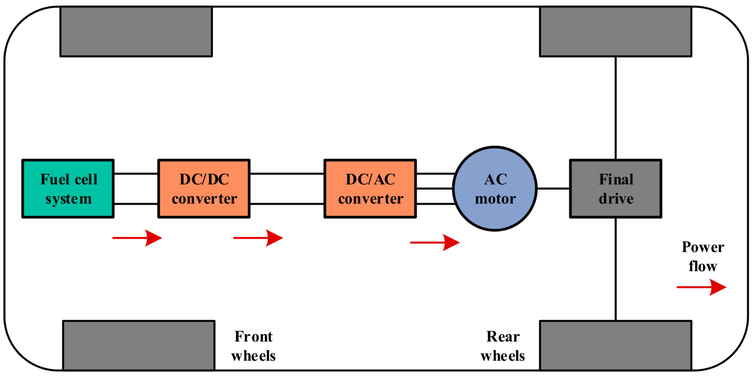
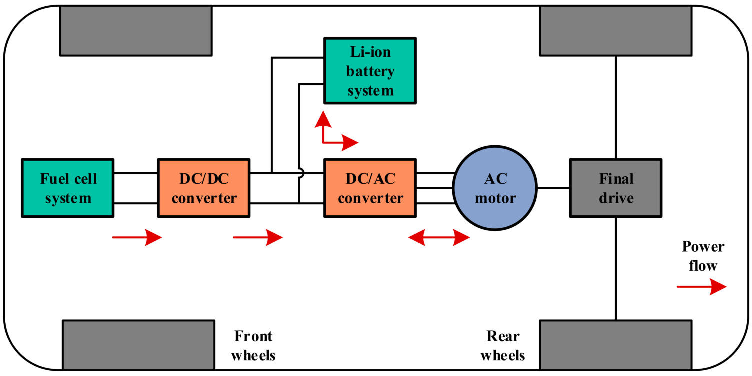


Figure 2. Full FCEV topology.

2.2. FC + Battery Hybridization

The hybrid power system composed of fuel cells and batteries is the most common topology. Batteries have the advantages of high energy density, low maintenance and low cost. The average life cycle of battery is 4–6 years. Therefore, this type of hybridization is widely used in production and are the most common topology [23]. There are two common topologies of FC + battery hybridization. The first is the battery directly connected to the DC bus. In addition, the other is the battery connected to the DC bus after the DC/DC converter, as shown in Figure 3. In this system, fuel cells are used as the main power source to provide most of the power for the load. This system has the advantages of recovering braking energy. However, its dynamic response is slower than FC + UC hybridization.



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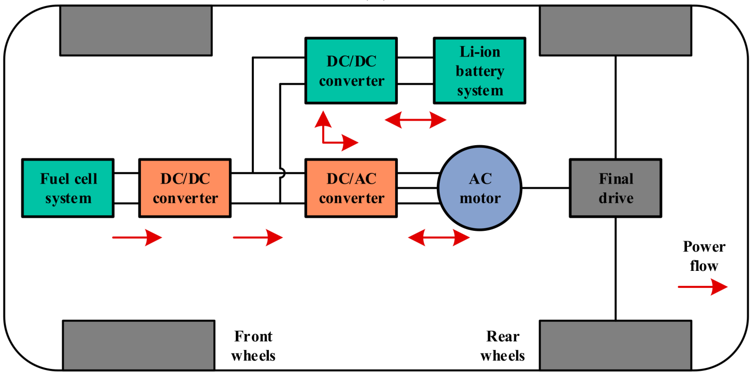

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Figure 3. Topologies of FC + battery: (**a**) batteries disconnected to the DC/DC converter; (**b**) batteries connected to the DC/DC converter.

2.3. FC + UC Hybridization

Compared with the disadvantages of batteries, such as low energy density, large size, and small instantaneous charge and discharge current, ultracapacitors have the advantages of fast charge and discharge, and of being able to be used more times. Additionally, the average life cycle of UC is 12–20 years [24]. According to whether the ultracapacitor is connected to the DC bus through a DC/DC converter, the hybrid system can also be divided into two types, as shown in Figure 4. Because the voltage fluctuation of the ultracapacitor is too large, a fully active topology, as shown in Figure 4b, is generally adopted. This system has the advantages of more efficient power recovery and better dynamic response to instantaneous high-power demand. It also has the disadvantages of high economic cost and low energy density; therefore, it is not as widely used as hybrid power systems with fuel cells and batteries.

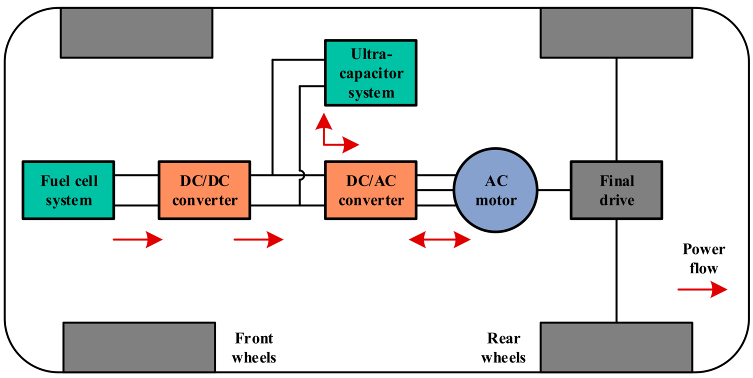

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Figure 4. *Cont.*

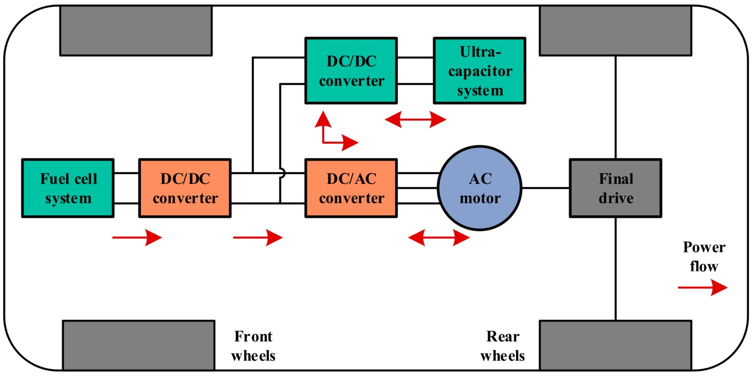

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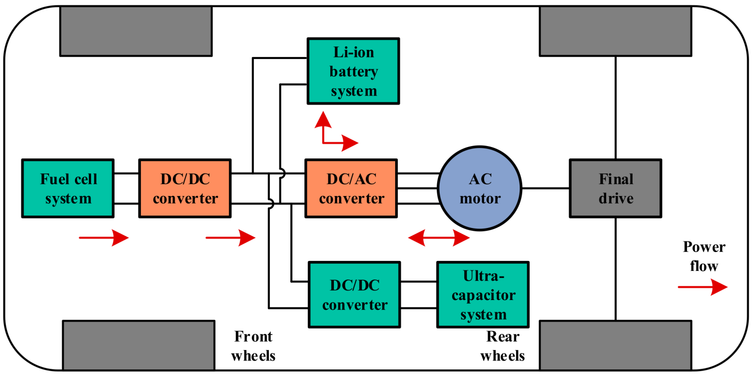
Figure 4. Topologies of FC + UC: (**a**) UC disconnected to the DC/DC converter; (**b**) UC connected to the DC/DC converter.

2.4. FC + Battery + UC Hybridization

The topology of the fuel cell + battery + UC hybrid power system is shown in Figure 5. The hybrid system still uses fuel cells as the main energy source to provide the average power demand of the load. The characteristics of batteries and ultracapacitors are considered comprehensively so that they can work in different states. Ultracapacitors have the characteristics that can charge and discharge rapidly with high current but have small energy storage. Ultracapacitors can be used to provide instantaneous power or energy recovery when the power required by the load has large sudden changes. However, due to the complex structure of the hybrid system and the strong coupling between the power sources, the control strategy of this system is complicated.



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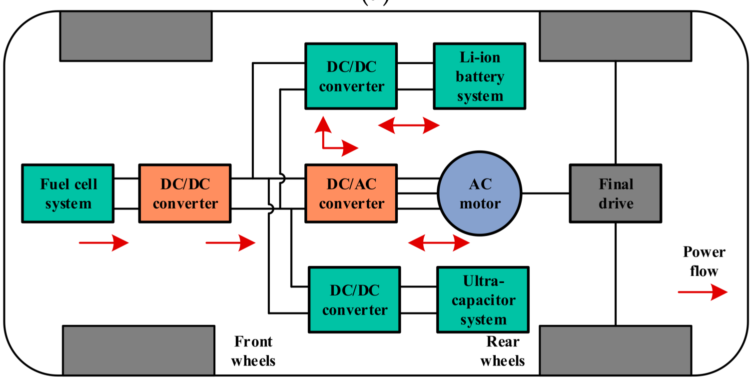

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Figure 5. Topologies of FC + battery + UC: (**a**) battery disconnected to the DC/DC converter; (**b**) battery connected to the DC/DC converter.

2.5. FC + Other Hybridization

Hybrid power systems composed of fuel cells and other auxiliary energy sources are still applied in a small range in the field of hybrid vehicles. Flywheels can replace batteries as auxiliary energy sources. The energy stored in the flywheel is high-speed mechanical energy, which is converted into electrical energy when the motor needs power. However, because flywheel operation requires a high level of security, it is not widely used. Similarly, SMES is not used on a large scale due to its high cost. SPVs are also not widely used because of their dependence on solar energy and the large uncertainty of the energy supply. This paper mainly focuses on hybrid power systems composed of fuel cells, batteries, and ultracapacitors, and does not elaborate too much on other auxiliary energy sources.

3. Energy Management Strategies

To improve the performance of fuel cell hybrids, designing and developing efficient energy management strategies is an urgent need for current automotive manufacturers. Mainstream energy management strategies are currently used to improve the performance of hybrid vehicles from both the energy consumption perspective and the durability of the components. From the perspective of energy consumption, the main work is to reduce hydrogen consumption. From the perspective of improving component durability, it focuses on preventing the degradation of fuel cells, batteries, and ultracapacitors. Mainstream energy management strategies can be divided into rule-based energy management strategies, optimization-based energy management strategies, and learning-based energy management strategies. In recent years, energy management strategies based on intelligent connected vehicle technology have also received extensive attention from researchers. The advantages and disadvantages of common EMS are listed in Table 2.

Table 2. EMS summary.

EMS Type	Main Advantages	Main Disadvantages
Rule-based strategies	• Simple to realize • Good adaptability	• Deviate from the optimal solution • Less effective in reducing hydrogen consumption
Optimization-based strategies (offline)	• The optimal solution can be obtained to provide reference for other strategies	• The amount of calculation is large and cannot be applied online
Optimization-based strategies (online)	• Good effective in reducing hydrogen consumption • Accurate estimation on energy source status	• Complex mathematical operations • High computing power requirements
Learning-based strategies	• Close to the optimal solution • Suitable for multi-objective optimization problems	• Requires a large amount of real data to train • Large amount of calculation
EMS based on intelligent vehicle interconnection technology	• High accuracy of speed prediction • High Accuracy in Driving Pattern Recognition	• Difficulty in obtaining real-time road and surrounding environment information

3.1. Rule-Based Energy Management Strategies

Rule-based energy management strategies have the advantage of facilitating integration in embedded controllers, which means that they can be more widely used in engineering [25]. It has also been shown that sometimes simple rule-based controllers can provide good control effects. For example, they can suppress the fuel cell stack and battery degradation to minimize the cost [26,27]. They and can also play useful roles in reducing hydrogen consumption [28,29]. Researchers have conducted many studies on the effect of different rule-based energy management strategies on the fuel economy of FCHEVs [30].

In recent years, researchers have combined rule-based methods with other methods to form energy management strategies for FCHEVs [31]. Farrokhifar et al. [32] proposed a rule-based online multilevel energy management system, which divided the vehicle operation state into five states and the fuel cell operation mode into six. Then, different energy management strategies were adopted according to different vehicle operation states, which had a good control effect. Liu et al. [33] first used the Pontryagin minimum principle to derive the optimal fuel cell power control sequence and the charging trajectory state of the lithium-ion battery pack during driving. Then, they used repeated incremental pruning to produce an error reduction algorithm. It can be used to learn and classify the underlying rules to obtain an energy management strategy. This EMS can reduce energy consumption and improve the economy. Wang et al. [10] proposed finite state machine strategies with nine and nineteen states for energy management for the FC+B and FC+B+UC systems, respectively. Li et al. [15] proposed a state machine strategy based on droop control, which has shown good results in reducing hydrogen consumption. Rule-based energy management strategies are easy to understand; however, these approaches do not always lead to optimal goals [34].

Geng et al. [35] proposed an optimal on/off fuzzy power following an energy management strategy by combining various algorithms. The experimental results showed that the strategy ensured the dynamic performance of the fuel cell vehicle. It also obtained a good cruising range. Badji et al. [36] proposed a filtering-type strategy to decompose the load power into high-frequency power and low-frequency power. The low-frequency power was provided by the fuel cell, and the high-frequency power was provided by the ultracapacitor. Decomposing the load power into high-frequency power and low-frequency power enabled better output power distribution among energy sources.

Many researchers also use genetic algorithms to optimize rule-based energy management strategies. Genetic algorithms are often used for optimization and search problems. In the process of evolution, fitness is used to evaluate the objective function, which has a prominent advantage in the iterative optimization of energy management strategies [37]. Fu et al. [20] proposed a fuzzy logic-controlled energy management strategy. It used a genetic algorithm to optimize the fuzzy controller under multiple constraints. Multiple constraints considered fuel cell power fluctuations and hydrogen consumption. The simulation and experimental results obtained show that it can limit fuel cell power fluctuations to within 300 W/s. Limiting fuel cell power fluctuations can prolong fuel cell life. Yue et al. [38] proposed online fuzzy rules and used a genetic algorithm to optimize the fuzzy controller under different degradation states. This method can also effectively reduce hydrogen consumption and make a FC lifetime improvement of 56%. Genetic algorithms have good convergence and reach good results in some application scenarios. However, Liu et al. [39] found that the application of the teaching learning-based optimization method gives better results to the optimization of the rule parameters. Additionally, this optimization algorithm converges faster compared to the genetic algorithm.

Dynamic programming methods are one of the most effective strategies for solving global optimization problems. Some researchers have combined dynamic programming methods with rule-based methods to propose new energy management strategies. He et al. [40] applied a dynamic programming approach to improve the rule-based energy management strategy. Du et al. [41] proposed a method to combine dynamic programming with the rule-based energy management strategy. They added a limit on the rate of change of fuel cells' output power to the rule. It can prevent sudden changes of the power output of fuel cells and improve the durability of the fuel cells. Liu et al. [42] analyzed the optimal control method using dynamic programming and extracted the three-segment control rule from it. A functional relationship is established between the power splitting parameters and load statistics. The proposed strategy has a stronger capability of battery protection and energy savings under unknown load patterns. Dynamic programming methods can obtain globally optimal solutions; however, this method is computationally intensive. It is difficult to implement real-time applications.

From the previous paper, it is clear that a rule-based energy management strategy can no longer meet the needs of increasingly complex fuel cell hybrid systems. Researchers used neural networks or genetic algorithms to optimize parameters for fuzzy rule control [21]. Additionally, the dynamic programming approach was used to obtain power allocation schemes to improve the rule-based strategy [41]. In this way, researchers can form a better rule-based energy management strategy.

3.2. Optimization-Based Energy Management Strategy

Optimization-based energy management strategies are one of the most studied types of FCHEVs. Optimization-based energy management strategies can be divided into two categories: online optimization strategies; and offline optimization strategies. The optimization objectives selected by these strategies can often be quantified by a cost function representing fuel economy and component durability. Common optimization strategies include the dynamic programming algorithm, genetic algorithm, equivalent consumption minimum strategy, the Pontryagin minimum principle, and model predictive control, etc. To adapt to complex driving conditions, the real-time performance of the energy management strategy is also an indicator that must be considered.

3.2.1. Offline Optimization-Based EMS

The most common optimization-based offline energy management strategies are the dynamic programming method, and the Pontryagin minimum principle. They both rely on pre-knowledge of the operating conditions, are computationally intensive to solve, and can only be used offline.

Dynamic programming algorithms are mainly applied to solve optimal solutions and are also often used in energy management strategies for FCHEVs to find the optimal energy allocation method. Chen et al. [43] used dynamic programming to optimize the fuel cell current to save hydrogen consumption and prolong the life of the fuel cell. Zhou et al. [44] used a dynamic programming approach to derive the optimal power allocation strategy for different degradation stages of fuel cells. They found that this strategy resulted in an average reduction in operating cost of 14.17% and an average increase in fuel cell lifetime of 8.48%, compared to the rule-based strategy. However, this approach only considered the minimization of economic costs; it did not achieve the best results in terms of the reduction of hydrogen consumption in fuel cells.

The Pontryagin minimum principle exists in the form of a set of optimization conditions that constrain the state variables to a finite boundary. The optimization results obtained are close to dynamic programming algorithms [45,46]. Song et al. [47] developed a degradation model for fuel cells and lithium batteries. They added a fuel cell power change limiting factor to the Pontryagin minimum principle to suppress sudden changes in fuel cell power. They used this method to prolong the lives of fuel cells. Huangfu et al. [48] proposed an improved energy management strategy based on the Pontryagin minimum principle. They limited the fluctuation of fuel cell power and controlled the state of charge (SOC) of the lithium battery within a certain range (0.4–0.8). This strategy reduced the FC operating stress by 38.3% compared with the finite state machine strategy. The effectiveness of the strategy was verified by hardware-in-the-loop tests. Unlike simulation experiments that are performed only in the software, hardware-in-the-loop tests are more reflective of the confidence of the control strategy.

Although offline optimization strategies can obtain global optimal solutions in most cases, designing online energy management strategies that can be applied in real time is a hot topic for researchers.

3.2.2. Online Optimization-Based EMS

The adaptive control method has been widely studied by researchers in recent years. The adaptive control method can adjust the control strategy with changes in external parameters, such as changes in driver behavior, changes in vehicle driving conditions, and changes in the degradation state of hybrid power systems [49]. Adaptive algorithms have been widely studied by researchers for reducing fuel cell hydrogen consumption and improving fuel cell durability. Combining adaptive methods with other methods into hybrid energy management techniques has also been investigated [50].

In terms of improving fuel cell life, Yue et al. [51] proposed an online health management strategy for FCHEVs based on adaptive prediction. By monitoring the health status of the fuel cell online, they proposed a prediction-based health management state to improve the durability of the fuel cell. The strategy reached the best performance with the fuel cell durability improved by 95.4%. compared with EMS without prognostics. Zhou et al. [52] divided the driving modes into three by a Markov pattern recognizer. Then, they obtained the ideal control strategy by a multimode predictive controller. Compared to the single-mode benchmark strategy, the proposed multimode strategy can significantly reduce over 87.00% fuel cell power transients. Li et al. [53] proposed an online adaptive equivalent consumption minimization strategy, as well as a method for the online estimation of fuel cell and battery health states. Then, they designed an adaptive energy management strategy. It can adjust the equivalence factor and fuel cell dynamic current change rate with the change in their health status. This strategy is verified to serve the purpose of reducing hydrogen consumption and inhibiting fuel cell and battery degradation. There are many advantages of adaptive strategies, however, sometimes the simple fuzzy processing of information by the adaptive strategy will lead to a reduction in the control accuracy of the system.

Adaptive energy management strategies are often associated with the Pontryagin minimum principle [54]. Fu et al. [55] proposed a hierarchical energy management strategy. The strategy incorporated adaptive regulation and optimization based on the Pontryagin minimum principle. Li et al. [56] proposed an adaptive environmental control system based on the Pontryagin minimum principle. The system used a particle swarm optimization algorithm for online identification of drive modes. The simulation on a combined driving cycle showed good results in reducing fuel cell hydrogen consumption. Iqbal et al. [57] proposed an adaptive energy management strategy that minimizes the integrated cost instantaneously and improves the economy of FCHEVs.

The idea of model predictive control is to transform the global optimization problem into a series of local optimization problems. It is good at handling optimization problems with multiple constraints, especially for systems with many internal coupling relationships. Additionally, it can predict future changes by passing current values, dynamic states, and process variables, etc. Its basic principle is shown in Figure 6.

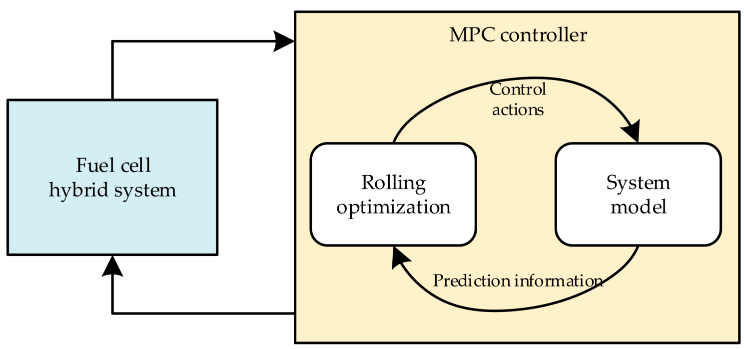

Figure 6. Basic principles of model predictive control.

The fuel cell hybrid vehicle system is a complex system with strong internal coupling relationships, which is suitable for its control by model predictive control. Additionally, the model predictive control-based approach is suitable for application in real-time application scenarios [58]. Ma et al. [59] proposed a multi-objective predictive energy management strategy with model predictive control. It can avoid frequent fuel cell start-stop. Additionally, it can limit the fluctuation of fuel cell output power during rapid load changes and suppresses fuel cell degradation. Yazdani et al. [60] investigated the effect of the prediction horizon length of model predictive control on controller performance. They found that model predictive control was comparable to dynamic programming methods in its ability to reduce hydrogen consumption when prediction horizon lengths greater than seven seconds. The multi-objective function designed by Anbarasu et al. [61] considered the factors of hydrogen consumption, rate of change of fuel cell power, battery power, and fuel cell efficiency, etc., to dynamically adjust each component's weight online. This model predictive control strategy plays a good role in extending the service life of each component. Fu et al. [62] used neural networks to predict the power demand of hybrid vehicles in a short period of time. Then, the local optimization problem was solved for each prediction domain. This model predictive control strategy achieved good results in saving hydrogen consumption in both World Light Vehicle Test Cycle (WLTC) conditions as well as China light-duty vehicle test cycle (CLTC) conditions. Zhou et al. [63] used the Markov method for speed prediction of vehicles. They designed a model predictive control-based energy management strategy based on the predicted travel time and the predicted speed. The simulation showed this strategy has good performance in reducing hydrogen consumption. Although the energy management strategy based on model predictive control has achieved good results, its prediction accuracy is affected by various parameters, such as road conditions, dynamic traffic conditions, vehicle passing speed, and predicted speed. To improve the prediction accuracy, additional information input is often needed, which leads to an increase in computational cost and deteriorates the performance of real-time control.

Yuan et al. [64] proposed a globally optimal energy management strategy that first predicts the long-term average speed for each future trip. Then, they used a model averaging method for short-term speed prediction. The method was validated using the collected real driving conditions. This energy management strategy can reduce hydrogen consumption and the number of fuel cell starts and stops. However, this method is computationally intensive and requires accurate road information.

The extremum seeking method is mainly applied to improve fuel cell durability and to make the operating point of a controlled PEMFC stack system in its maximum efficiency region [65]. Zhou et al. [66] designed an extremum seeking controller to save hydrogen consumption by maintaining the operating point of the fuel cell system in a high-efficiency region. The experimental comparison results show that the performance of the proposed extremum seeking controller is close to the offline benchmark dynamic programming. However, the extremum seeking method has the disadvantage that the given results are often not optimal solutions.

Zhou et al. [67] used a probabilistic support vector machine to classify the online driving conditions. They calculated the final parameters of the online fuzzy controller using a Dempster-Shafer evidence theory approach. This strategy can achieve stable operation of the fuel cell hybrid system. Jia et al. [68] proposed an energy management strategy to minimize the operating cost. It also reduces the energy management problem of a fuel cell vehicle to a mixed integer nonlinear optimization problem. The optimal current output of each energy source was obtained by solving this optimization problem online. The simulation results show its good effect on reducing the operating cost. Other methods, such as the game theory approach, believe that in actual vehicle driving it is impossible to make a completely accurate prediction of future road conditions. It is better to use the controller and future driving conditions as the two sides of the game, through game theory, to achieve energy allocation between hybrid systems [69,70]. However, in the presence of multiple information inputs, the game theory-based strategy does not necessarily lead to better control results compared to other strategies.

In addition to hydrogen consumption and system durability, the robustness of energy management strategies under uncertain conditions is also a key performance criterion. Koubaa et al. [71] proposed an energy management strategy based on robust optimization for the uncertain events that may occur during the operation of the fuel cell hybrid electric vehicle system. This algorithm adds uncertainty to the cost function and constraint set. It protects system performance from feasibility and optimality issues. Wu et al. [72] proposed a robust online energy management strategy, considering that the conventional optimization-based energy management strategy ignores the uncertainty of driving cycles due to various chance accidents. This strategy improves the robustness of the system. It also has good performance in fuel economy and load change control of the fuel cell. The robust optimization-based energy management strategy enhances the robustness of the system. However, the enhanced robustness comes at the cost of weakening some of the control effects.

3.3. Learning-Based EMS

Most of the current energy management strategy methods are based on prediction algorithms or predefined rules. However, they have poor adaptability to real-time driving conditions and they cannot provide the real optimal solution for real-time driving conditions. The learning-based energy management strategy can make up for these deficiencies. It also has the advantages of being model-free and being able to learn the optimal strategy autonomously in real time [73]. The basic idea of this method is that according to the current state S_t and reward R_t, the reinforcement learning controller gives the action a_t, and after controlling the target, it obtains the state S_{t+1} and reward R_{t+1} for the next moment and adjusts the action a_{t+1} for the next moment according to the size of the reward to continuously optimize the control effect. The basic principle of the method is shown in Figure 7. Additionally, its computation time is greatly reduced compared to the dynamic programming algorithm [74].

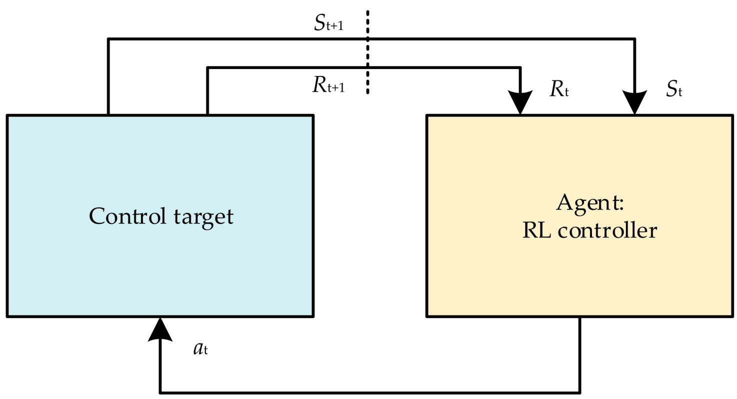

Figure 7. Basic principles of RL controller.

As a reinforcement learning method, q-learning has been extensively studied by researchers on the energy management strategy of FCHEVs. The basic idea is to initialize a q-table and continuously reward or punish the learned actions through the subsequent learning process. To obtain a perfect q-table, this method helps to make the best decision. Tao et al. [75] proposed a fuzzy energy management strategy based on improved q-learning and a genetic algorithm for the power distribution between fuel cells and ultracapacitors in FCHEVs. This method does not need to know the driving mode in advance. After comparison with the adaptive strategy, it is found that this method reduces the current fluctuation of the fuel cell and reduces the hydrogen consumption. For FCHEVs consisting of fuel cells and lithium batteries, Guo et al. [76] used a q-learning approach to learn an energy management strategy. It can be used to minimize hydrogen consumption and extend the battery lifetime. Lin et al. [77] proposed an online correction predictive energy management strategy. It used q-learning to optimize the parameters of the neural network.

Then, they predicted the velocity through the neural network. It served to reduce hydrogen consumption. Tang et al. [78] applied a deep Q-Network approach to incorporate the degradation of the fuel cell hybrid power system energy source into the objective function. Simulation results showed that the strategy can effectively improve the FCS lifetime with a slight increase in fuel economy. It achieved 91.04% of the fuel economy based on the DP benchmark in combined driving cycle. Zhang et al. [79] optimized the energy management strategy through a q-learning approach, which can effectively improve the energy efficiency of the system and slow down the degradation of the fuel cell. Q-learning also has these disadvantages; it needs a Q table. In the case of many states, the Q table will be very large, which consumes a lot of time and space to find and store.

Sun et al. [80] proposed an equivalent consumption minimization strategy based on reinforcement learning. It used experimental data for reinforcement learning to obtain a scheme for power allocation between the fuel cell, the cell, and the ultracapacitor. The results showed that it allowed the fuel cells to maintain high efficiency, as well as low hydrogen consumption. Fu et al. [81] used a similar idea but adopted a constraint on the rapid fluctuation of fuel cell power to protect the fuel cell while improving the hydrogen economy. Zhou et al. [82] proposed a long-term energy management strategy (LTEMS) dedicated to the optimal distribution of power among the energy sources, while ensuring the health of the hybrid system. This strategy obtained the state of the charge boundary of the lithium battery due to decay by reinforcement learning. It achieved the control of the fuel cell current based on the obtained state of the charge boundary. Compared with thermostat EMS and power following EMS, LTEMS can reduce fuel cell voltage degradation by 66.7% and 13.6%, respectively. Traditional reinforcement learning has the disadvantages of high computational cost and long computation time. Li et al. [83] proposed a speedy reinforcement learning method that can approach the optimal result with a fast convergence rate. It can overcome these disadvantages, however, it requires a trained and initialized framework. The simulation results of driving conditions show that it ensures good fuel economy and is suitable for real-time applications. Kim et al. [84] considered the prediction of short-time speed and power output without knowledge of future driving cycles as one of the worthy research directions. However, most of the reinforcement learning algorithms studied have the shortcomings of overestimating battery SOC and inappropriate ways of limiting battery SOC. These shortcomings lead to poor control performance.

Neural network methods have received extensive attention from researchers in many fields. Neural networks can be used to solve optimal problems for complex multi-variable problems due to their unique nonlinear adaptive information processing capabilities [85]. Li et al. [86] proposed a neural network-based equivalence factor predictor. It can predict the equivalence factor in real time considering various operating conditions and vehicle states. They designed a novel equivalence consumption minimization strategy. The strategy was found to lead to a significant reduction in computation time. Min et al. [87] used a genetic algorithm to train the neural network specifically. The trained neural network can make the fuel cell avoid specific output to avoid unnecessary start and stop under the condition of rapid fluctuation of load power. This energy management strategy effectively protects the fuel cell. Zhang et al. [88] utilized a long- and short-term memory network to predict the short-term future speed of a fuel cell hybrid vehicle. The specific method is to use the image captured by the camera as the information of the environment. Additionally, the historical speed of the vehicle operation is used as the motion information. The short-term future speed of the vehicle is predicted by these two types of information through the neural network. This method effectively improves the prediction accuracy and achieves lower hydrogen consumption. However, the effect of neural network methods largely depends on the amount of data, as well as the depth and complexity of the network. Sometimes, it takes weeks to successfully train a neural network.

3.4. EMS Based on Intelligent Vehicle Interconnection Technology

With the rapid development of vehicle networking, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) information interactions have become possible with the help of global positioning systems and intelligent transportation systems. The basic schematic is shown in Figure 8. With the input of external environmental information, these data can be used to develop advanced energy management. It also can improve vehicle operating characteristics and provide strong support for energy management strategies for FCHEVs. Recently, researchers have used additional environmental information input to improve the accuracy of speed prediction of FCHEVs. It also can plan the speed more rationally and obtain a better energy management strategy.

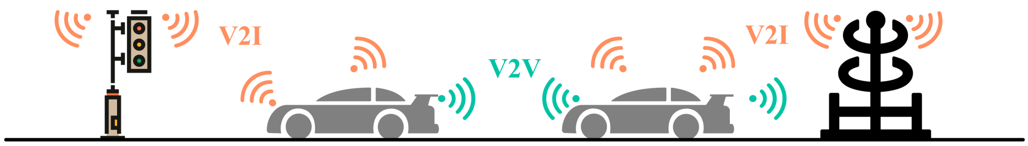

Figure 8. Schematic of the intelligent vehicle interconnection technology.

Liu et al. [89] investigated the problem of FCHEVs through multiple signalized intersections and proposed a bi-level optimization method. The nonlinear traffic light waiting time was transformed into a time-varying linear state constraint on the upper level. Additionally, the optimal future speed plan was derived, while the energy management problem was optimized at the lower level. Experimental results showed that obtaining real-time information of the traffic system can lead to better speed planning and energy management strategies for vehicles. Nie et al. [90] used future driving conditions and signal status information to derive the real-time safety optimal speed. They also designed an energy management strategy based on MPC (considering both hydrogen consumption and hybrid system durability) to achieve power distribution among hybrid power sources. The same can be done by considering information about future travel conditions and the real-time status of the vehicles in front and behind to plan the speed sequence [91]. Zhu et al. [92] proposed an optimal following distance algorithm considering driving safety and traffic throughput based on vehicle-to-vehicle and vehicle-to-infrastructure information. Based on this, an energy management strategy based on the minimization of equivalent consumption is proposed.

Taking traffic information into account in speed planning is a future trend in the development of energy management strategies, but achieving V2V, V2I, and vehicle-to-everything (V2X) information interaction, is a problem that needs to be solved.

4. Conclusions and Suggestions

This paper summarizes and concludes various energy management strategies at the current stage and analyses the advantages and disadvantages, as well as the main roles of various energy management strategies. A brief introduction to the latest energy management strategies based on intelligent vehicle interconnection technology is provided. In the complex urban traffic environment, there are a variety of unexpected situations, such as vehicle collisions, road gradients, dynamic changes in road coefficients, and traffic congestion that occur at signalized intersections. If V2V and V2I interconnection technologies can be utilized, information about the current driving status of the vehicle can be more accurately predicted. This leads to better optimization of the energy distribution of the hybrid powertrain. Although researchers have conducted some research on fuel cell hybrid power system structures and their energy management strategies, there is still much research work to be carried out. The following is a discussion of future trends in energy management strategies for FCHEVs:

- To achieve a synergistic optimization of hydrogen consumption as well as durability of hybrid powertrain components, using a combination of multiple algorithms for energy management strategies, will be helpful. The multi-algorithm combination of energy management strategies has outstanding advantages over single-method energy management strategies in terms of real-time performance and level of optimization. For example, genetic algorithms are used to optimize rule-based energy management policies. The resulting new energy management strategy has the advantage of real-time and optimization. Researchers extensively combine various algorithms to develop better energy management strategies, which is a worthy research direction;

- Current V2V, V2I, and vehicle-to-everything (V2X) interconnected technologies, are developing rapidly. V2V communication enables vehicles to wirelessly exchange information about their speed, position, and heading, making vehicle speed predictions more accurate. At the same time, the current road information can be obtained in real time through V2I communication to make a more accurate judgment on the driving state and driving mode recognition of the vehicle. With the additional input of environmental information, the energy management strategy provides better real-time and optimization performance for FCHEVs;
- An energy management strategy is the core issue of a fuel cell hybrid power system. It is meaningful to ensure the efficiency of the energy management strategy in the whole life cycle scale of the system. Energy management strategies that can coordinate changes in internal parameters of energy storage components, and external multiple load scenarios in different use phases, will be an important direction. It is of great importance in the future health and safety of power battery systems, as well as efficient management aspects.

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