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Energy Management Strategy of Fuel Cell Hybrid Electric Vehicle Based on Model Predictive Control

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Abstract:
The continuous high-speed growth of automobile ownership in China has led to increasing pressure on the environment from automobile exhaust emissions, thus new energy vehicles have been favored by government policies. In new energy vehicles, Fuel Cell Hybrid Electric Vehicles (FCHEV) are considered to have great potential due to their high efficiency, smooth power output, and short fuel replenishment time. The hybrid power system is one of the important parts of FCHEV. Such system is comprised of lithium-ion batteries and fuel cells. This study combined the vehicle speed and power demand of new energy vehicles to establish a fuel cell vehicle model, longitudinal dynamics model, drive motor model, and fuel cell/lithium-ion battery model. A model predictive control method was proposed to design an energy control tactic for FCHEV. In view of the three aspects of fuel cell effectiveness, economy, and lithium battery SOC maintenance, the optimized objective of energy control was determined, and a cost function for multi-objective optimization of fuel cell hybrid power mechanisms was created. On the grounds of the rule of rolling time domain optimization, a real-time FCHEV energy control tactic was devised. Through MATLAB simulation under combined operating conditions, the efficacy of the energy management tactic presented has been validated. It could ensure that lithium-ion batteries have sufficient power reserves, and enabled fuel cells to operate stably with higher efficiency, reducing durability losses and saving more hydrogen gas.

Keywords: SOC, model predictive control, energy, hybrid electric vehicle

INTRODUCTION

According to China's "dual carbon" goal and relevant policies, the demand for the development of new energy vehicle technology has reached an unprecedented level. Fuel Cell Hybrid Electric Vehicle (FCHEV) is considered one of the most promising new energy vehicles due to its advantages of zero emissions, high efficiency, and long-range [1-4]. The power system of FCHEV consists of two parts, a fuel cell and lithium-ion battery. Therefore, it is necessary to formulate a valid Energy Management Strategy (EMS) to allocate power between two energy sources.

In recent years, new energy vehicles have been favored by government policies. In 2020, the General Office of the State Council released the "Development Plan for the New Energy Vehicle Industry (2021-2035)", claiming that the sale volume of new energy vehicles would occupy roughly 20% of the whole sales of novel vehicles until 2025, pure electric vehicles will become the mainstream of new sales vehicles, and fuel cell vehicles will be fully commercialized until 2035. It can be foreseen that new energy vehicles will have broad market prospects in the future. Among various new energy vehicles, Fuel Cell Hybrid Electric Vehicles (FCHEV) are considered to have great potential due to their high efficiency, smooth power output, and short fuel replenishment time[5-8]. One of the important parts of FCHEV is the hybrid power system composed of fuel cells and lithium-ion batteries.

The design of energy management strategies is an important part of fuel cell vehicle technology. An effective energy control tactic can enhance the vehicle power performance and fuel efficiency, protect the power supply, and even reduce lifespan degradation. Therefore, scholars at home and abroad have extensively and in depth researched energy management tactic design for FCHEVs [9-12].

The energy management strategies of FCHEVs can be divided into two types: rule-based energy management strategies and optimization-based energy management strategies. The main difference between the two is whether there is an optimal control problem-solving step in the energy management strategy. The rule-based energy management strategy relies on established rules to allocate power between different power sources, which is characterized by simplicity, feasibility, and strong adaptability. The energy control tactic was to address the optimum control issue according to specific optimization objectives. This method obtains the optimal solution or local optimal solution, but requires a large amount of computation [13-19]. The principle based on energy control tactic is widely used and convenient to execute, but their output results are not optimal, so hybrid power systems are not at the optimal operating point. To address this issue and further improve the performance of hybrid power systems, more research is needed on optimization based energy management strategies. In order to thoroughly solve the problem that rules are often artificially formulated and enable the designed energy management strategies to obtain truly optimized solutions online, the design of energy control tactics on the grounds of Model Predictive Control (MPC) has begun to receive increasing attention from scholars.

There are generally limitations in the design process of energy management strategies, such as single objective optimization and SOC retention of power batteries. Based on this research, a multi-objective optimization strategy was designed for energy management using model predictive control, including power battery SOC, fuel cell efficiency, and economy. The optimal solution for energy allocation in system control was obtained, and the missing state information was supplemented using an online prediction model to achieve rolling optimization of information in the prediction time domain, overcoming the impact of uncertainty and disturbance on the system. A comparative analysis was conducted on the energy management strategy of FCHEV based on MPC and the energy management strategy based on CD-CS rules, and it was found that this strategy improved the maximum power and energy response speed of the vehicle.

MODEL ESTABLISHMENT OF FUEL CELL HYBRID ELECTRIC VEHICLE

In view of the different connection methods between energy sources and buses, the construction of hybrid power mechanisms was separated into four categories, and their characteristics were analyzed one by one to determine the observed hybrid structure studied. Based on the force situation, this research established one longitudinal dynamic model of the vehicle through a lookup table method to establish a drive motor model, and then separately established models for lithium-ion battery and fuel cell systems [20-24]. Finally, establish a control oriented FCHEV vehicle model to lay the foundation for the energy control tactic design.

Design of Active Fuel Cell Hybrid Power System

The requirements of the mobile vehicle are complex and varied. As the sole energy for fuel cell vehicles, fuel cells can not meet the requirements of dynamic energies. Moreover, PEMFC itself has the characteristics of time delay and nonlinearity, so the energy source of fuel cell vehicles often becomes a hybrid power system [25-29], namely, the structure of energy storage equipment and fuel cells. Energy storage equipment like lithium-ion batteries can play a role in recovering braking energy, increasing output peak, and improving response speed.

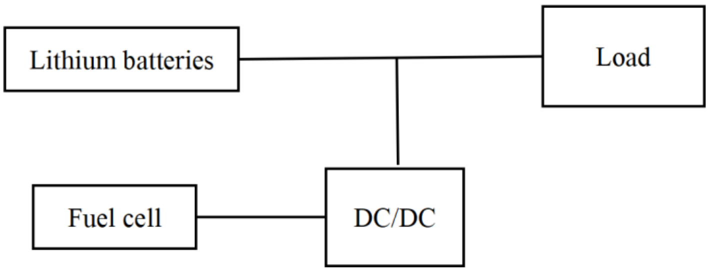

Figure 1. Structure of active fuel cell hybrid power system

As displayed in Figure 1, the structure of the active fuel cell hybrid power mechanism is the most common in engineering research. The output terminal of the fuel cell relates to a unidirectional DC-DC converter, which is linked with the vehicle. Lithium batteries are directly associated with the vehicle. Under this structure, terminal voltages of lithium batteries vary with the bus voltage, while terminal voltages and load current of fuel cells are handled by the DC-DC converter. Meanwhile, due to a unidirectional DC-DC converter, the harm of bus current backflow is also avoided. Due to the absence of intermediate components, lithium batteries can provide faster power response and higher energy utilization efficiency. From a feasibility perspective, the selection of DC-DC converters is simpler and only needs to allow for the power range of fuel cells. From an economic perspective, this structure only requires a monodirectional DC-DC converter as a transformer component, with low cost and good economy. Therefore, energy control strategies for fuel cell hybrid power mechanisms were researched based on this structure.

Establishment of Vehicle Dynamics Model

The longitudinal dynamics model was formulated on the grounds of dynamic differential equations of the vehicle during travel. Pursuant to Newton's second law, the force on vehicles related to the acceleration and vehicle mass during travel.

According to the force situation of the vehicle during driving, the driving force of the car is expressed as [30-32]:

$$F = fmg\cos\theta + \frac{A_f C_d u^2}{21.15} + mg\sin\theta + \delta m\frac{du}{dt} \quad (1)$$

Among them, F denotes the driving force provided by the driving motor, f denotes the tire rolling resistance coefficient, m denotes the whole vehicle mass, g denotes the acceleration from gravity, α denotes the road slope, set to be 0 in this article, fA denotes the equivalent windward region of the vehicle body, dC denotes the air resistance coefficient, u denotes the vehicle velocity, denotes the conversion coefficient of rotational mass, and t denotes time.

Establishment of Drive Motor Model

According to the vehicle dynamics, the driving torque and speed of the driving motor are [33, 34]:

$$T_m = \frac{T_w}{R_{tr}\eta_{tr}} \quad (2)$$

$$\omega_m = \omega_w R_{tr} \quad (3)$$

Among them, T_m represents the motor driving torque, T_w represents the driving torque at the center of the vehicle's driving wheels, R_{tr} represents the final transmission proportion, η_{tr} represents the transmission effectiveness, ω_m represents the driving motor velocity, and ω_w represents the rotational angular speed of the vehicle's driving wheels.

The mechanical power and electrical power of the driving motor can be expressed as:

$$P_m = \omega_m T_m \quad (4)$$

$$P_e = \begin{cases} P_m/\eta_m, & P_m \geq 0 \\ P_m\eta_m, & P_m < 0 \end{cases} \quad (5)$$

Among them, P_m means the mechanical power of the driving motor; P_e means the electrical power of the driving motor. $P_m < 0$ means when the vehicle falls into a braking state, the current flows from the drive motor to the power battery.

Establishment of FCHEV Vehicle Energy Demand Model

Based on the characteristics of the FCHEV vehicle energy control system, a control oriented FCHEV vehicle model was established, where the system input was the load current of fuel cells, and state variables were the power battery SOC and fuel cell system power [35-37]. The state space expression is:

$$\begin{cases} S\dot{O}C(t) = SOC(t) - \dfrac{h_1(SOC(t)) - \sqrt{h_1^2(SOC(t)) - 4h_2(SOC(t))(P_{re}(t) - P_{fc}(t)}}{2h_2(SOC(k))Q_c} \\ \dot{P}_{re}(t) = g(I_{st}(t)) \\ x^T(t) = \{SOC(t), P_{re}(t)\}, u(t) = I_{st}(t) \end{cases} \quad (6)$$

Among them, $P_{re}(t)$ signifies the required vehicle power, $P_{fc}(t)$ signifies the output power of fuel cell systems, which is the sum of the auxiliary equipment power and the driving motor power, $SOC(t)$ signifies the remaining power of lithium-ion batteries, I_{st} signifies the starting current, $u(t)$ $x^T(t)$ signifies the mechanism state quantity, and the mechanism input quantity.

MULTI OBJECTIVE ENERGY MANAGEMENT STRATEGY FOR FCHEV BASED ON MODEL PREDICTIVE CONTROL

The analysis on the FCHEV vehicle model showed that controllable energy allocation between lithium batteries and fuel cells could be fulfilled through the control system input, namely the fuel cell load current. This section describes an energy control tactic for FCHEV on the grounds of model predictive control. Firstly, determine the optimization objectives of energy management, and establish a cost function for multi-objective optimization of fuel cell hybrid power mechanisms from three aspects: economy, maintenance of lithium battery SOC, and effectiveness of fuel cells. Then, as per the rule of rolling time-region optimization, a real-time FCHEV energy control tactic was devised. Finally, the efficacy of the energy management tactic in this chapter was validated through MATLAB simulation under combined operating conditions.

Basic Principles of Model Predictive Control

As Generalized Predictive Control, Rolling Time Domain Control, Backward Time Domain Control, and Dynamic Matrix Control, Model Predictive Control (MPC) has been an extensive feedback control approach in the industrial sector recently. The principle of model predictive control serves to address a limited-time open-loop optimization issue online on the grounds of the established system state data at each sampling time point, attain the best control sequence, and subsequently apply the first sequence element to the actuator. During the next sampling period, repeating the actions above will generate a novel optimization problem with new state information, which can be solved again for a novel optimal control sequence. The characteristic of model predictive control serves to handle some open-loop optimization issues online and achieve a range of local optimum solutions.

The fundamental characteristics of MPC can be summarized as below: model-based prediction, rolling optimization, and feedforward control. In terms of predictive control, the model aims to forecast the follow-up state of the mechanism. Hence, the model is called one predictive model. The form of the prediction model is not important, it can be a system mechanism model, convolutional model, fuzzy model, neural network model, etc., as long as it can play a predictive role. The role of the predictive model is to refresh the open-loop optimization issue per sampling cycle. On account of the limited-time domain of the open-loop optimization issue and the possibility of disturbances and uncertainties in the system, resolving the open-loop optimization issue can not be used entirely in the system. Instead, the first element of the optimization solution is taken and the "prediction + optimization" step is continued in the next sampling period. Compared with traditional global optimization control algorithms, the biggest difference of MPC is that the optimization issue is repeatedly refreshed and solved online. Although each finite time domain optimization solution is a suboptimal solution, this rolling iteration approach can alter the optimization problem in real time as per the actual system state, overcoming the impact of uncertainty and disturbance on the system.

The specific implementation steps of model predictive control are as follows. Let the prediction model of the system be:

$$\begin{cases} x(k+1) = f(x(k), u(k)), x(0) = x_0 \\ y(k) = h(x(k), u(k)) \end{cases} \tag{7}$$

Among them, $x(k)$ stands for the system state quantity at time k, $u(k)$ stands for the control system input quantity at time k, and $y(k)$ stands for the system output quantity at time k.

The MPC principle could be summed up as follows: updating the optimal control problem within each sampling period; solving the updated optimal control problem; and subsequently utilizing the first element of the obtained optimal control sequence in the system. The process above was repeated in the next sampling cycle until it ends. The three steps of model predictive control are:

(1) Using predictive models to update optimal control problems;

(2) Seeking analytical or numerical solutions for the optimal control problem;

(3) Take the first element of the optimal solution as the control input for the next moment.

Establishment of FCHEV Prediction Model

Based on the established control oriented FCHEV state space model, due to the rolling optimization characteristics of model predictive control, the predictive model of the controlled object must be time discrete. Therefore, the model is discretized as follows:

$$\begin{cases} x_1(k+1) = x_1(k) - \dfrac{h_1(x_1(k)) - \sqrt{h_1^2(x_1(k)) - 4h_2(x_1(k))(P_{re}(t) - P_{fc}(t)}}{2h_2(x_1(k))Q_c}\Delta t \\ x_2(k+1) = g(u(k) \\ y_1(k) = \eta_{fc}(x_2(k)) \\ y_2(k) = x_1(k) \\ y_3(k) = \dot{m}_{H_2}(x_2(k)) \end{cases} \tag{8}$$

Among them, t is the sampling period, the output $y(k)$ is a three-dimensional column vector, the first dimension output η_{fc} is the effectiveness of fuel cells, which means the $x_2(k)$ function, the second dimension output is the power $\dot{m}_{H_2}(x_2(k))$ cell SOC, and the third dimension output means the hydrogen consumption rate of fuel cells at time k.

FCHEV Energy Management Objective Function Design

In general, the energy control tactic design for FCHEVs was considered from an economic perspective, that is, to minimize hydrogen consumption during vehicle operation, such as ECMS. Power batteries were an auxiliary power origin for hybrid power systems. When the speed of the vehicle changed significantly, the power battery could compensate for the energy supply gap of fuel cells while improving the maximal power and energy response speed of the vehicle. At the same time, sustaining the SOC of power batteries within limits could reduce the quantity of deep charge and discharge circulations, which protected power batteries while extending their lifespan. If the fuel cell system operated at low efficiency for a long time, the energy usage ratio of the system will be very low. And due to the long-term high-power operation of the auxiliary equipment of the fuel cell system, its service life will also be affected. Therefore, when designing energy management strategies for FCHEVs, not only should economic considerations be taken into account, but also the maintenance of power battery SOC and effectiveness of fuel cells.

When operating in a hybrid power system, the operating efficacy of fuel cells was higher, the energy usage ratio of the system would be higher. In the design process of FCHEV energy control tactic, various constraints of hybrid power mechanism must be taken into account. Based on various constraints of the system, the goal function was formed as below:

In which, $J(k)$ means the economic cost function at time k, N means the length of the predicted time domain, and J_2 and J_3 are the weights. $P_{fc}(k)$ For the power of fuel cells, $P_{bat}(k)$ for the power of power cells, and $P_v(k)$ for the required system power.

$$\begin{cases} J(k)=\sum_{j=0}^{N-1}[\lambda_1 J_1(k+j)+\lambda_2 J_2(k+j)+\lambda_3 J_3(k+j)] \\ P_{re}(k)=P_{fc}(k)+P_b(k) \\ SOC_{\min}\le SOC(k)\le SOC_{\max} \\ P_{fc\min}<P_{fc}(k)<P_{fc\max} \\ \Delta P_{fc\min}<\Delta P_{fc}(k)<\Delta P_{fc\max} \end{cases} \tag{9}$$

Verification of MPC Energy Management Strategy under Typical Operating Conditions

To validate the MPC rationality and efficiency based FCHEV energy control tactic in this section, simulation verification will be designed and the results will be analyzed and discussed. The simulation environment is MATLAB R2016b, and all code is written in the m file. In the simulation, the hybrid power system topology of a certain vehicle model is adopted, which meant that the lithium batteries were directly associated with the vehicle, and fuel cell were indirectly linked with the vehicle. To confirm the efficiency of the energy control tactic for FCHEV on the grounds of MPC, this paper compares and validates the MPC strategy with a commonly used Charge Depletion Charge Sustainment (CD-CS) strategy in the industry.

In order to verify the MPC flexibility based on FCHEV energy control tactic in discrepant driving settings, this paper divides the vehicle driving scenarios into three categories: urban, suburban, and highway scenarios. Each category selects a set of standard cycle conditions as the test cycle, and the algorithm is validated under three different representative test cycles. Among them, the MANHATTAN working condition is selected as a typical urban working condition, the UDDS working condition is selected as a typical suburban working condition, and the HWFET working condition is selected as a typical highway working condition. The following article will compare and analyze the energy management strategies of FCHEV based on MPC and energy management strategy based on CD-CS rules from the perspectives of fuel cell output, hydrogen consumption, fuel cell efficiency, fuel cell durability, and lithium-ion battery SOC for each typical operating condition.

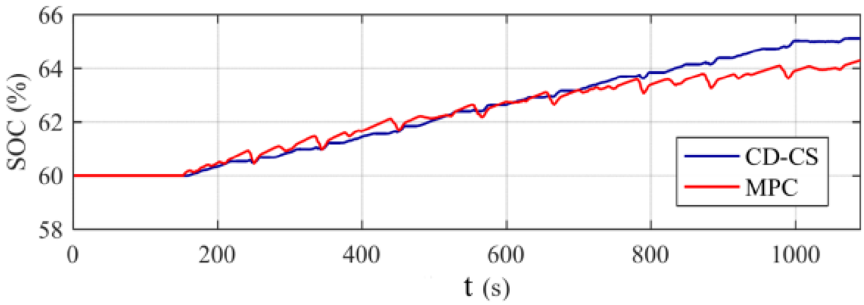

Figure 2. SOC trajectory under urban working conditions

From the perspective of SOC maintenance, the SOC of lithium-ion batteries under both strategies is stable near the reference value, with an error of 0.7% under MPC strategy control. Figure 2 shows the SOC trajectory under urban conditions, where the blue curve stands for the SOC trajectory under CD-CS strategy control and the red curve stands for the SOC trajectory under MPC strategy control. The SOC trajectory can reflect the working state of the hybrid power mechanism. For example, during the time period of 335s-344s, the vehicle is in a state of rapid acceleration, and the required power for the driving motor is high. Relying solely on the fuel cell output was not enough. Therefore, under the regulation of the MPC strategy, the lithium-ion battery acts as an auxiliary power source, transitioning from a charging state to a discharging state, corresponding to the decrease in the lithium-ion battery SOC represented by the red curve during this time period. However, under the CD-CS strategy control, the lithium-ion battery did not provide sufficient support due to inadequate fuel cell output power, leading to the fuel cell output being not smooth enough under the CD-CS strategy control.

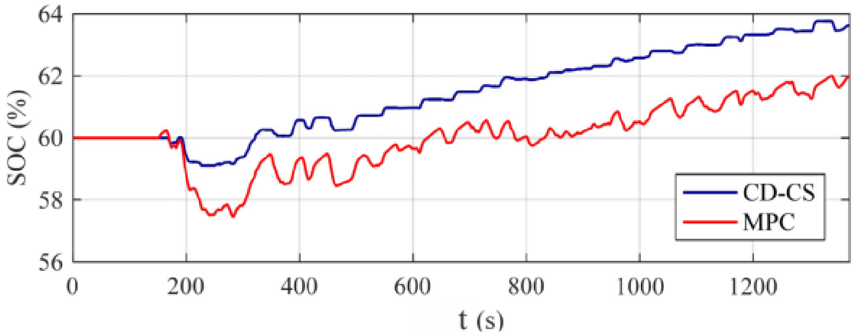

Figure 3. SOC trajectory under suburban operating conditions

Figure 3 shows the SOC trajectory of lithium-ion batteries in suburban testing. According to the maintenance of lithium-ion battery SOC, under suburban conditions, the error between the lithium-ion battery SOC controlled by MPC strategy and the given value is 2%. Compared with the test results of urban working conditions, the SOC error of suburban working conditions test results is relatively large. This is because the MPC strategy does not use SOC error as the sole evaluation indicator, and the power demand of vehicles in suburban conditions is relatively high. Considering fuel economy, reducing the charging current of lithium-ion batteries is also a way to save hydrogen. Due to the reference value of the lithium-ion battery SOC in this simulation being set to 0.65, the lithium-ion battery under MPC strategy control, although charging speed is slow, is still in a charging state. This also indirectly reflects the advantages of MPC multi-objective optimization.

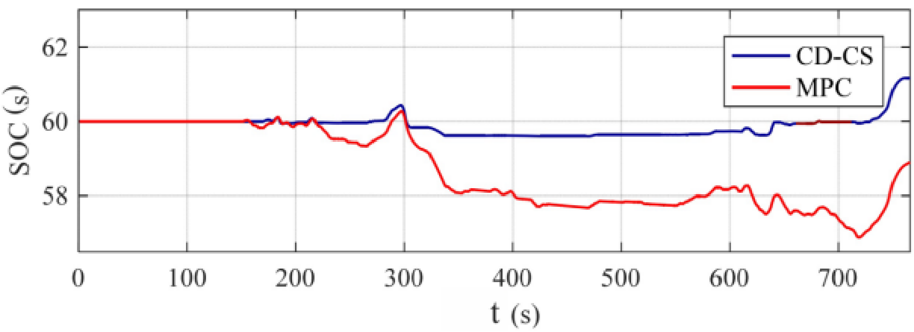

Figure 4. SOC trajectory under highway conditions

The SOC trajectory of lithium-ion batteries during highway condition testing is shown in Figure 4. From the perspective of SOC maintenance, the MPC strategy has a SOC error of 7% in highway condition testing, which is larger compared to the results of the other two typical condition tests. However, the SOC of the lithium-ion battery remains above 0.55 throughout the cycling process. Due to the high power demand of vehicles under highway conditions, the power consumption of lithium-ion batteries will be relatively higher.

Overall, from the perspectives of SOC maintenance, fuel cell efficiency, fuel cell durability, and economy, the MPC strategy remains effective and reliable in suburban testing conditions. From the test results of the three typical operating conditions mentioned above, the MPC tactic designed in this chapter has good adaptability to all operating conditions. Compared with the commonly used CD-CS strategy in industry, the MPC strategy can more effectively stabilize the fuel cell output, maintain the SOC of lithium-ion batteries, save fuel, and reduce the durability degradation of fuel cells.

CONCLUSION

With the increasing consumption of fossil fuels and the worsening environmental problems, the demand for the development of new energy vehicle technology is becoming more and more urgent. PEMFC has the advantages of zero emissions, elevated effectiveness, and a wide operating temperature range, therefore FCHEV has great potential for development. The driving motor of FCHEV is jointly powered by fuel cells and lithium-ion batteries. As a result, it is necessary to devise effective energy control tactics to distribute the output power of lithium-ion batteries and fuel cells for FCHEV performance.

This study establishes a multi-objective energy control tactic for FCHEV hybrid power system on the grounds of MPC. Firstly, when designing energy management strategies, three optimization indicators should be considered: fuel economy, stability of lithium-ion battery SOC maintenance, and high efficiency of fuel cell operation. Then, in view of the aforementioned optimization targets, this research designed the objective function of MPC and introduced the multiple shooting method to reduce the solution time of open-loop optimization problems within each sampling period. To confirm the efficiency and reliability of MPC energy management tactic, daily driving scenarios of vehicles are divided into three categories: urban, suburban, and highway. The control effect of the MPC strategy is verified under these three typical working conditions, and simulation results of the MPC strategy were contrasted with the common CD-CS strategy in the industry. The results show that the MPC strategy can always maintain sufficient power reserves for lithium-ion batteries. In comparison to the CD-CS tactic, the MPC tactic could remarkably enhance fuel economy and reduce hydrogen consumption. In addition, MPC strategy can make the fuel cell output smoother while decelerating the degradation of fuel cell durability. This article proposes multiple optimization objectives for the energy management problem of FCHEV, and adjusts the weights between the objectives with different weights. This article only verifies the rationality of multi-objective setting, and future work can focus on finding the optimal weight combination to better improve the performance of fuel cell hybrid power systems.

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