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*Research Article*

# A GM-Based Energy Management Strategy of Hybrid Power System for Hydrogen Fuel Cell Buses

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Hydrogen energy is a clean, carbon-free, flexible, efficient, and widely used secondary energy source, which is an ideal alternative to promote the clean and efficient use of traditional fossil fuels. Hydrogen fuel cell bus has the advantages of a high-energy conversion rate, absolute pollution-free, sufficient raw materials, and convenient filling. The hybrid power system, composed of fuel cell and auxiliary energy source, is one of the key technologies to promote the development of hydrogen fuel cell vehicle. This study aims to propose an energy management strategy by analyzing the output characteristics and power allocation of fuel cell and power battery in the hybrid power mode with fuel cell as the main and battery as the auxiliary. A GM (1, $N$) power prediction strategy was proposed and compared with other strategies as an on-off control strategy and logical threshold value strategy in this study. The variation curves of the battery SOC and fuel cell output power under two working conditions of CCBC and real vehicle conditions were analyzed by using these three strategies, when the initial SOC of power battery is 30%, 70%, and 90%, respectively. Results showed that the power prediction strategy based on GM (1, $N$) has a better performance in output efficiency and fuel economy when compared to the other two strategies by analyzing the aspects of the battery in the SOC variation and equivalent hydrogen consumption and the fuel cell in the output power variation and hydrogen consumption. This research can be helpful to provide the suggested solution for energy management of the hybrid power system for hydrogen fuel cell buses.

## 1. Introduction

Faced with the increasingly severe environmental problems and energy crisis, hydrogen fuel cell vehicles use hydrogen as the only fuel, with a high energy conversion rate, no pollution, sufficient raw materials, convenient refueling, and other advantages, becoming one of the best choices for the vehicle industry to get rid of energy constraints and achieve carbon neutrality. Hydrogen fuel cells have some characteristics such as slow dynamic response, soft output characteristics, and external energy supply for cold start, which need to be controlled and optimized by the fuel cell system energy management strategies. In order to ensure the safe and reliable operation of hydrogen fuel cell system and improve the dynamic response performance, the research of the hydrogen fuel cell energy management strategy has become the key link in the process of developing hydrogen fuel cell vehicles. During the driving process, the energy management strategy calculates the required power according to the current working condition and the state of the vehicle and reasonably controls the coordinated operation of all components of the fuel cell vehicle to achieve dynamic power allocation. The fuel cell vehicle should adopt the required energy management strategy according to the actual situation and design objectives, in order to meet the optimal fuel economy, performance, and the cost requirements of the hybrid electric bus [1–4].

Research studies on the energy management strategy of fuel cell vehicles have been carried out recently including rule-based control strategies and optimization-based control strategies. The rule-based control strategy is to set a set of logical rules in advance, according to which the driving state is judged and the driving power is allocated. The main design goal is to make the fuel cell vehicle run at the high efficiency point or the low fuel consumption point as much as possible. It can be divided into the deterministic rule strategy and fuzzy rule strategy according to the certainty of logical rules, among which the strategy of deterministic rules is the most commonly used method including the on-off control strategy and the logical threshold value strategy. The on-off control strategy mainly determines the start and stop of fuel cell and the output power level by the SOC value of battery, while the logical threshold value strategy is to determine and control the rational distribution of energy among various components of the hybrid power system according to the steady-state efficiency map of key components so as to adapt to different states. Peng et al. [5] propose a recalibration method to improve the performance of the rule-based energy management through the results calculated by the dynamic programming algorithm, which reduces the fuel consumption significantly. The rule-based strategy method is simple, effective, and practical and is the basis of formulating an advanced energy management strategy. The operating points of the fuel cell and power battery system are determined according to the required power and battery SOC, and the operating limits of the hybrid power system components are considered. But this kind of methods has some limitations as to the rules and threshold values are set in advance; that is, they cannot be flexibly adapted to all driving conditions, and the fixed control law leads to the poor dynamic performance of the system.

To optimize the control objectives, constraint conditions are set and the lowest energy cost is calculated, based on the optimal energy management strategy by defining the energy cost function [6–9]. According to the calculation length, optimization-based control strategies can be divided into the global optimal energy management strategy and the instantaneous or local optimal energy management strategy [10–15]. The former usually takes the vehicle economy or power as the design objective and the system variables as the constraint conditions and then establishes the optimization model by the optimal control theory and optimization method to achieve the global optimal design objective. It is usually used for off-line simulation analysis and vehicle performance evaluation. By transforming the global optimization problem into a series of instantaneous optimization problems, the design objective of the objective function is changed to ensure the minimum energy consumption at the current moment, and the energy management optimization can be carried out according to the real-time state of the vehicle. Motapon et al. [16, 17] established a hybrid energy management system of fuel cell, lithium battery, and supercapacitor on Simulink and compared a variety of control methods, among which the optimal strategy is determined by comparing the SOC fluctuations, hydrogen consumption, and the overall efficiency. By combining the weighted coefficients to construct optimization functions for the net power of fuel cells and the fuel consumption rate, the global extreme value search (GES) algorithm was proposed as a real-time optimization strategy for multipeak optimized surfaces [18]. Song et al. [19] proposed a real-time approximate optimal energy management strategy based on the minimum principle of Pontriagin, which provides an online common state update method for an uncertain driving cycle, which can control the battery charging state within a certain range and determine the optimal hydrogen consumption. However, the global-based optimization strategy can only solve the energy allocation of hybrid electric vehicles with a known path and obtain the optimal energy allocation results under the path, which cannot be adjusted with the vehicle conditions, and the current vehicle single-chip microcomputer is difficult to meet the calculation requirements, as the amount of calculation and storage is very large when the number of iteration steps increases. In order to minimize the instantaneous equivalent fuel consumption at each calculation point, the instantaneous optimization strategy needs to build an accurate prediction model, which requires relatively high hardware requirements, and the instantaneous optimal is not necessarily optimal at the global level.

Based on the current driving condition, the predictive adaptive strategy calculates and adjusts parameters to adapt to the changing driving conditions and vehicle conditions in advance. The adaptive strategy method needs to calculate the next time demand parameters based on a large number of vehicle running data in real time according to a certain algorithm [20–22], which commonly includes the algorithm based on the neural network (NN) and the model predictive control (MPC). Zhang et al. [23] established a fuel cell water management system model by integrating the stack voltage model, water balance equation, and water transport process on the membrane. The predictive control mechanism based on the recursive neural network (RNN) optimization was implemented in the MATLAB/Simulink environment, and the simulation results show that this method can avoid the fluctuation of cathode water concentration and prolong the service life of the fuel cell stack. Ziogou et al. [24] conducted a set of comparative evaluation experiments to deploy different MPC strategies in an industrial automation system and found that the fuel cell system was in a stable and economic environment no matter how the conditions changed with dynamic models. The adaptive algorithm based on optimization can predict the parameters of the next time point, effectively alleviating the weakness of soft output characteristics of fuel cells, but it requires a large amount of calculation and is difficult to be applied in practice at present. The algorithm based on neural network, as an example, requires a large number of experimental samples for training, but it cannot be accurately predicted with a small size of sample.

Given previously, researchers have proved different methods to be effective in energy management strategies for fuel cell vehicles. But these methods mainly focus on a predetermined set of fixed rules or adaptive rules based on large data. It becomes difficult to conduct the evaluation of the efficiency of energy management optimization when facing a small amount of incomplete vehicle motion-related information provided. Therefore, this study is expected to propose a new grey model-based power predictive control strategy model in the hybrid power system of fuel cell, primarily aiming to improve the fuel economy of the vehicle under the typical Chinese city bus cycle (CCBC) and real vehicle conditions. The method presented in this study could contribute to the improvement of energy management strategies for hydrogen fuel cell buses.

## 2. Methodology

*2.1. Model Building.* The topology structure of fuel cell and power battery is selected in this study, controlled by the following three controllers: battery management system (BMS), fuel cell control unit (FCU), and vehicle control unit (VCU). BMS measures the parameters of the power battery, including SOC, voltage, current, and temperature and then sends the parameters to the vehicle controller in real time via CAN signal line. FCU receives sensor parameters connected to the fuel cell and DC/DC converter, including voltage and current of each single fuel cell, flow and pressure in the flow channel, temperature and humidity inside the fuel cell, and input and output voltages of the DC/DC converter. The parameters are transmitted to the vehicle controller in real time. After receiving the parameters detected by the battery management system and fuel cell controller, the vehicle controller determines the parameters by the internal energy management strategy and sends the commands to BMS and FCU, which executes the related operations according to the built-in program.

The fuel cell system is a nonlinear and strongly coupled system, especially in the case of high current and high power so that it is very difficult to accurately describe the behavior of fuel cells with its obvious nonlinear characteristics. The proton exchange membrane fuel cell modeling is the cornerstone of fuel cell bus modeling, and its accuracy directly affects the accuracy of vehicle modeling. In this study, a proton exchange membrane fuel cell model was established, combining the polarization characteristics of the equivalent circuit and the empirical formula of the Ballard 9SSL technical manual. The Simulink block diagram of the output characteristics of a proton exchange membrane fuel cell stack is shown in Figure 1. The input in the proton exchange membrane fuel cell module is hydrogen and air flow. It is default that the air flow is sufficient and there is no oxygen hunger. Then, the Nernst voltage and the activated polarization overpotential and the final output voltage, current, and efficiency of the fuel cell are calculated, respectively. In this study, the rated power of the hydrogen fuel cell stack is 42 kW.

As the auxiliary energy source of hydrogen fuel cell bus, power battery is one of the important components in the hybrid power system, which plays a key role in "peak-cutting and valley-filling" power and fuel cell start-up energy supply. In the Simulink model library, an improved power battery model was built by the equivalent R-int circuit model by regarding the battery as formed by the voltage source and internal resistance in series. In this model, the response time, dynamic and steady-state characteristics of the battery, the ability to preset the battery type, initial SOC, standard voltage, and rated capacity were considered. Current was input based on the states of charging and discharging. The current is positive with power battery charged, while it is negative in the discharged state. Therefore, when designing the fuel cell energy management strategy, it is necessary to ensure that the power battery SOC is within a certain range to avoid overcharging and overdischarging.

In this study, only the longitudinal dynamics was considered in vehicle motion modeling, that is, the motion state of the vehicle along the driving direction. The external forces acting on the driving direction of the vehicle are divided into driving force and driving resistance. The longitudinal dynamics model of the vehicle can be described according to the balance equation of these forces. Vehicle driving resistance actually represents the demand for the power of vehicles. According to different driving states, driving resistance can be divided into steady-state driving resistance and transient driving resistance. The former includes air resistance, rolling resistance, and slope resistance, while the latter refers to acceleration resistance. Vehicles are driving on the flat side of the road so that the road slope is set as 0 and the slope resistance is ignored. The driving force module model of the vehicle in Simulink is shown in Figure 2. The required power of the vehicle can be obtained from this driving force model by inputting the vehicle speed and acceleration curves under different working conditions.

*2.2. GM (1, N) Power Prediction Strategy.* Grey model (GM) is a kind of method that describes the evolution mechanism of uncertain system containing both known and unknown information, which has the advantages of a small amount of experimental data input needed, less computation, and high prediction accuracy. For the fuel cell bus energy management strategy, it can be treated as a grey system, which is composed of known parameters such as measurable speed, acceleration, steering angle, and some unknown parameters such as road conditions and emergencies. Therefore, GM is theoretically selected in this study to design a new energy management strategy by taking known parameters as dependent variables and the vehicle demand power at the next moment as an independent variable.

GM (1, $N$) represents a first-order grey model with one dependent variable and $N-1$ independent variables. It is assumed that there are $N$ sets of sequences composed of non-negative variables $x_i\,(i = 1, 2, \ldots, N)$, and each set of sequences has $m$ initial values:

$$x_i^{(0)} = \left\{x_i^{(0)}(1), x_i^{(0)}(2), \ldots x_i^{(0)}(m)\right\}. \tag{1}$$

A new first-order cumulative sequence $x_i^{(1)}$ is calculated when each value of the initial sequence accumulates all the values as follows:

$$x_i^{(1)} = \left\{x_i^{(1)}(1), x_i^{(1)}(2), \ldots, x_i^{(1)}(m)\right\}, \tag{2}$$

where

$$x_i^{(1)}(t) = \sum_{j=1}^{t} x_i^{(0)}(j) \quad t = 1, 2 \ldots, m. \tag{3}$$

The grey differential equation of GM (1, $N$) is defined as follows:

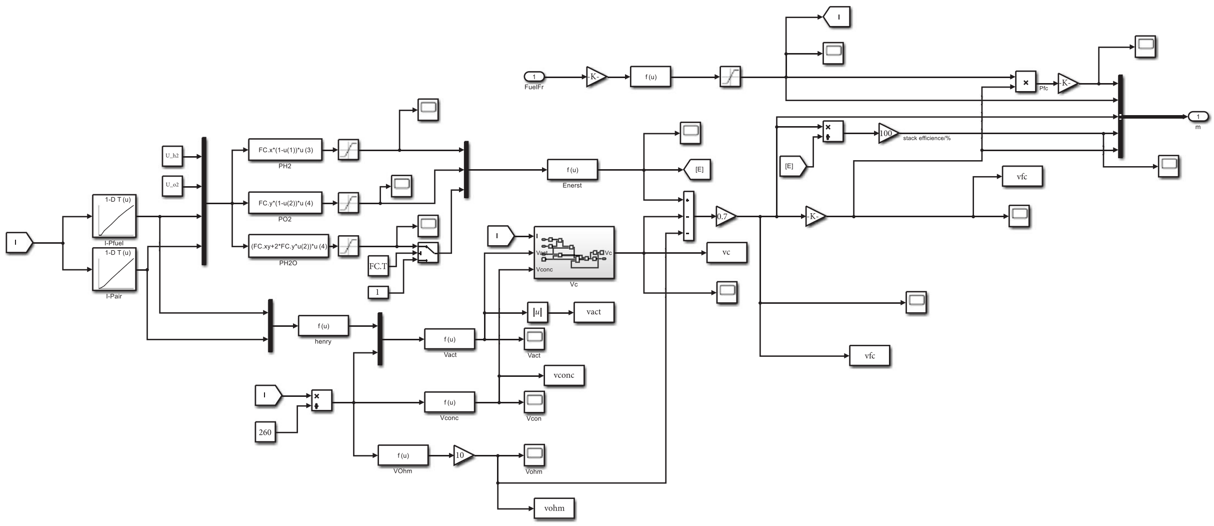



Figure 1: Simulink block diagram of the output characteristics of a proton exchange membrane fuel cell stack.

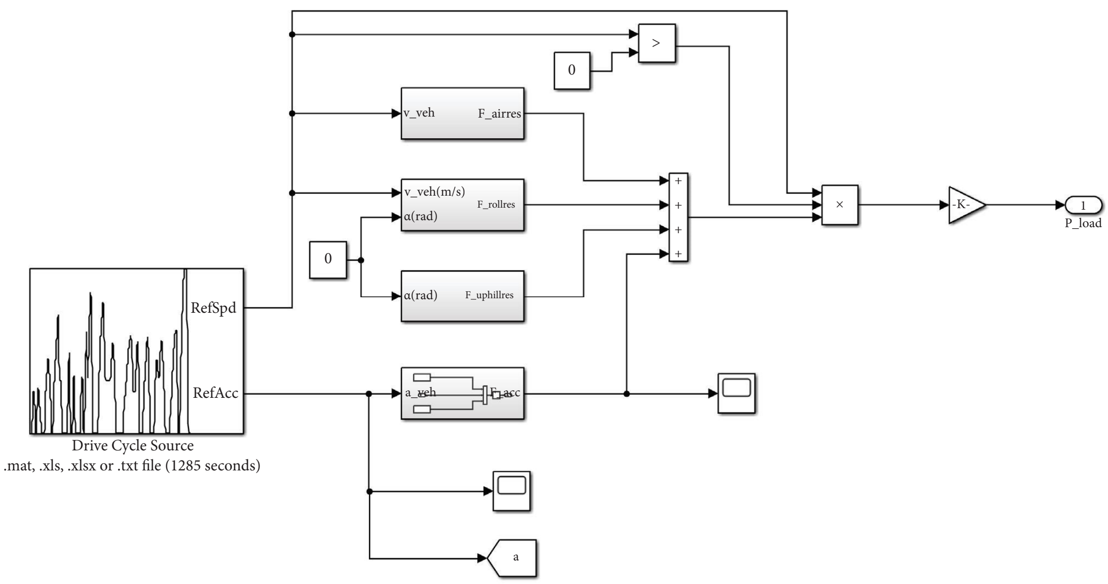



Figure 2: Simulink block diagram of the driving force module model of the vehicle.

$$\frac{dx_1^{(1)}(k)}{dt} + ax_1^{(1)}(k) = \sum_{i=2}^{n} b_i x_i^{(1)}(k), \quad (4)$$

where $a$ is the system development parameter and $b_i$ is the driving parameter, representing the influence degree and the polarity of the independent variable on the dependent variable. The dependent variable increases as the independent variable increases and vice versa. The grey differential equation can be defined as follows:

$$x_1^{(1)}(k) + az_1^{(1)}(k) = \sum_{i=2}^{n} b_i x_i^{(1)}(k), \quad (5)$$

where $z_1^{(1)}(k)$ is defined as follows:

$$z_1^{(1)}(k) = \frac{x_1^{(1)}(k) + x_1^{(1)}(k-1)}{2}. \quad (6)$$

The grey parameters of the grey model $P_N$ represent the vector set of system development parameters and driving parameters, which can be calculated as follows:

$$\begin{aligned} P_N &= (a, b_2, \ldots b_n)^T = B^{-1}Y_n (m = N+1), \\ P_N &= \left(B^T B\right)^{-1} B^T Y_n \quad (M > N+1), \\ P_N &= B^T\left(B^T B\right)^{-1} Y_n \quad (M > N+1), \end{aligned} \quad (7)$$

where:

$$B = \begin{bmatrix} -z_1^{(1)}(2) & -x_2^{(1)}(2) & \cdots & -x_i^{(1)}(2) \\ -z_1^{(1)}(3) & -x_2^{(1)}(3) & \cdots & -x_i^{(1)}(3) \\ \vdots & \vdots & \vdots & \vdots \\ -z_1^{(1)}(m) & -x_2^{(1)}(m) & \cdots & -x_i^{(1)}(m) \end{bmatrix},$$
$$Y_n = \begin{bmatrix} x_1^{(0)}(2) \\ x_1^{(0)}(3) \\ \vdots \\ x_1^{(0)}(m) \end{bmatrix}. \quad (8)$$

Then, the solution of equation (4) can be obtained as follows:

$$\hat{x}_1^{(1)}(k+1) = \left( x_1^{(0)}(1) - \sum_{i=2}^{n-1} \frac{b_i x_i^{(1)}(k+1)}{a} \right) e^{-at} + \sum_{i=2}^{n-1} \frac{b_i x_i^{(1)}(k+1)}{a}. \quad (9)$$

Finally, the predicted value of the initial sequence can be obtained as follows:

$$\hat{x}_1^{(0)}(k+1) = \hat{x}_1^{(1)}(k+1) - \hat{x}_1^{(1)}(k). \quad (10)$$

The basic idea of the GM (1, $N$) is to update the data series involved in the grey model every time new data information is obtained so that the established grey model has the "metabolic" function. At least 4 groups of historical data are needed to calculate the grey model. In this study, the historical vehicle demand power, power battery SOC, vehicle speed, and fuel cell output power are used as state variables obtained from the hybrid power system of fuel cell bus to predict the vehicle demand power at the next moment through this method of metabolism. State variables are, respectively, taken from three main core components of the hybrid power system of the fuel cell bus, namely, battery, vehicle, and fuel cell. The fuel cell bus energy management system will allocate the fuel cell and battery output power at the next moment in advance according to the predicted vehicle demand power to evaluate the power performance of the fuel cell output efficiency and fuel economy.

Additionally, the other two strategies as the on-off control strategy and logical threshold value strategy are also analyzed in this study and compared to the proposed GM-based strategy to examine their performance in fuel economy and output efficiency. The on-off control strategy is selected as a comparison because this strategy is also used in some fuel cell commercial vehicles currently. It is divided into five levels according to the SOC size of the power battery, and a fixed fuel cell power is set at each level. When the SOC is less than 60%, the SOC should be increased to an appropriate range so that the power battery can be charged as far as possible. When SOC > 90%, the power battery is sufficient so that only the power battery supplies energy to the vehicle and the fuel cell will be powered off. When the SOC is between 60% and 90%, the SOC is set at every 10% level and the fuel cell power varies with the level. The logical threshold energy manage system strategy is also established for fuel cell hybrid power systems in this study. The basic idea of the logical threshold strategy is to properly allocate the power between fuel cells and battery based on their steady-state efficiency so as to adapt to different states and maximize the system efficiency. When the battery SOC is normal or high, fuel cell will work at a lower power or even with power off and thus stop working. When SOC is low or the power required is high, the fuel cell operates at its maximum power. Moreover, the other states of the fuel cell power vary with the power demand within the optimal efficiency range.

## 3. Results and Discussion

The proposed strategies were analyzed and verified under the Chinese urban bus cycle (CCBC) and the actual road conditions. The duration of the typical Chinese urban bus cycle is 1314 seconds, and the total vehicle length is 6.048 km. The real vehicle operating conditions of a bus line were measured on the driving route of a hydrogen fuel bus in Wuhan in China in this study. Compared with CCBC, the speed and acceleration change more frequently in the real vehicle condition with longer travel time and driving distance, as shown in Table 1.

In this study, the on-off control strategy, logical threshold value strategy, and prediction strategy based on GM (1, $N$) are, respectively, simulated in the CCBC and real vehicle working conditions. These three strategies are verified by comparing output efficiency and fuel economy (e.g., the changes of battery SOC, fuel cell power variation, and vehicle hydrogen consumption) with different initial SOC under the same operating conditions. Among them, both the start-stops and the large variation of power output of the fuel cell will affect the durability and life of the fuel cell. The characteristics of the two working conditions were compared under different working conditions and the same strategy. The simulation is completed in a control system development and testing platform based on MATLAB/Simulink.

Table 1: Comparison of parameters under CCBC and real vehicle condition.

| Parameters | CCBC condition | Real vehicle condition |
|---|---|---|
| Driving distance (km) | 5.91 | 16.38 |
| Travel time (s) | 1385 | 2893 |
| Maximum required power (kW) | 55.00 | 58.13 |
| Average demand power (kW) | 18.74 | 20.96 |

The variables as the final SOC of battery, hydrogen consumption of fuel cells, equivalent hydrogen consumption of battery, and fuel economy were used to measure the energy utilization of different strategies. In this study, during the strategy design process, the SOC of the power battery is expected to be maintained at an appropriate value, such as 70%, during the operation of the vehicle. The equivalent hydrogen consumption of battery is the mass difference of energy equivalent hydrogen under the final SOC of the power battery and the initial SOC, defined as equation (12). The total hydrogen consumption $\mathrm{Sum}\Delta H_2$ is the sum of hydrogen consumption of the fuel cell $F\Delta H_2$ and equivalent hydrogen consumption of battery $B\Delta H_2$.

$$B\Delta H_2\,(g) = \frac{(SOC_H - SOC_0) \times 0.01 \times E_{\mathrm{batt}} \times 3600 \times 1000}{\mathrm{Heat}_{H_2} \times U_{H_2} \times \eta_{\mathrm{charge}} \times \eta_{DCDC} \times \eta_{FC}} \times 100\%, \tag{11}$$

where $\mathrm{SOC}_H$ is the final SOC, $\mathrm{SOC}_0$ is the initial SOC, $E_{\mathrm{batt}}$ is the battery capacity, $\mathrm{Heat}_{H_2}$ is the hydrogen calorific value, $U_{H_2}$ is hydrogen utilization, $\eta_{\mathrm{charge}}$ is the battery charging efficiency, $\eta_{\mathrm{DCDC}}$ is the DC/DC converter efficiency, and $\eta_{\mathrm{FC}}$ is the fuel cell efficiency.

The fuel economy was measured with the on-off control strategy as the control group (i.e., the economy is set as 100%). The fuel economy calculation formula of the other two energy management strategies is expressed as equation (12). The smaller the fuel economy is, the lower the hydrogen consumption is compared with the on-off control strategy.

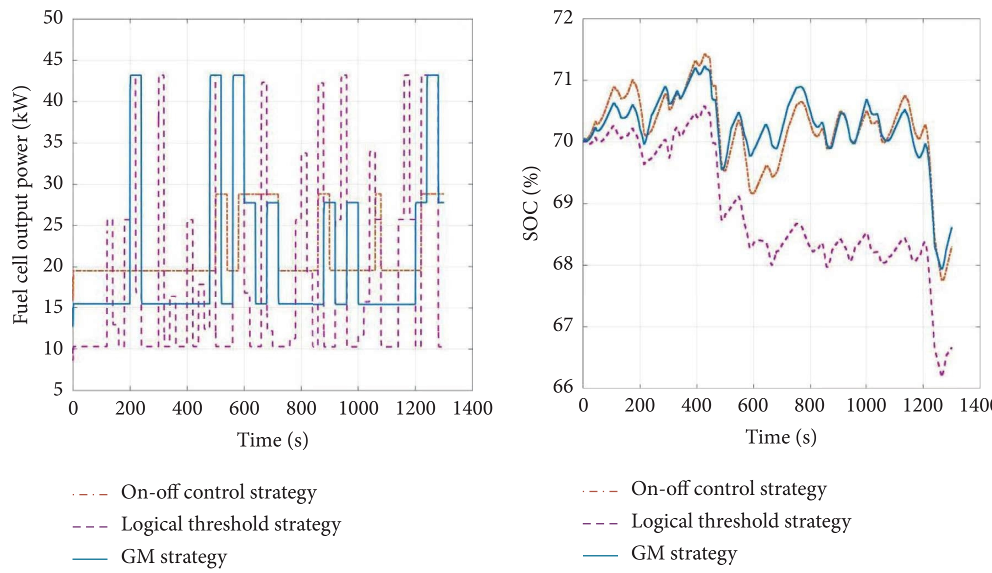
$$\eta_{H_2} = \frac{m_{H_2}}{m_{H_2\mathrm{switch}}} \times 100\%, \tag{12}$$

where $m_{H_2}$ is the amount of hydrogen consumed.

*3.1. CCBC Condition.* Under the CCBC condition, when the initial SOC of the battery is 70%, it is found that these three energy management strategies perform differently, as shown in Figure 3. It is observed that when compared to the logical threshold strategy, the GM and the on-off control strategy can better maintain the SOC of power cells at around 70% and fuel cells have less power regulation, which is more conducive to the fuel cell life. Figures 4 and 5 show the battery SOC changes and fuel cell output power changes when the initial SOC of the battery is set at 30% and 90%, corresponding to the performance of the fuel cell energy management system under the extreme conditions of low SOC and high SOC. For the 30% initial SOC, the GM and on-off control strategies can adjust the power of the fuel cell to a large value, so as to increase the SOC of battery to the expected level as soon as possible, while meeting the dynamic requirements of the vehicle. In contrast, for the 90% initial SOC, GM and on-off control strategies reduced the fuel cell power to consume the battery power, thus reducing the SOC. In addition, in the condition of the 90% initial SOC with the on-off control strategy, the fuel cell is not started for a long time in the early stage, and the fuel cell is switched on and off twice in the late stage, which is not a good choice for vehicle dynamics and the durability of the fuel cell. The logical threshold strategy performed poorly in terms of maintaining battery SOC and fuel cell durability at the conditions of initial SOC at 30% and 90%.

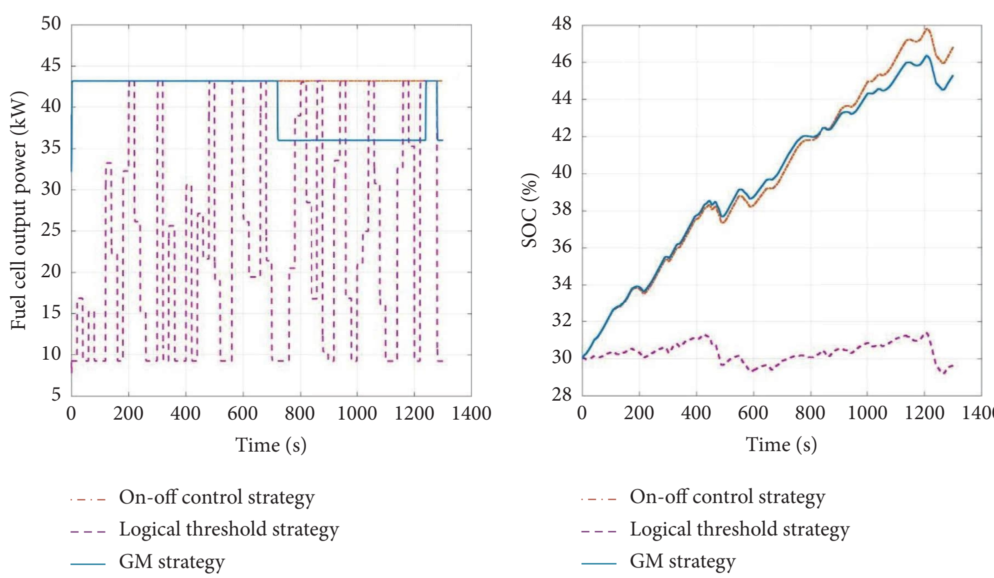
Measurements as final SOC, fuel cell hydrogen consumption, battery equivalent hydrogen consumption, total hydrogen consumption, and fuel economy were calculated under CCBC condition with three energy management strategies at 30%, 70% and 90% initial SOC, shown in Table 2. With 70% initial SOC, highest fuel economy was found with the GM predicted energy management strategy, indicated by saving 7.17% and 7.47% hydrogen compared with the logical threshold strategy and on-off control strategy, respectively. Under low initial SOC condition, efficiency was higher with the GM strategy than the on-off control one but lower than the logical threshold strategy. While with 90% initial SOC, fuel economy of the GM strategy is similar to that of the on-off control strategy, indicated by about 30% less hydrogen than the logical threshold strategy. Combing considering the battery SOC variation, fuel cell power variation, and vehicle hydrogen consumption, the GM strategy is comparable to the on-off control strategy in maintenance of SOC and fuel cell running life, and both of these two are superior to the logical threshold one. In terms of fuel economy, the GM strategy performs better than the on-off controlled one.

*3.2. Real Vehicle Condition.* As to the real vehicle working condition, battery SOC variation curves and fuel cell output power variation curves of these three strategies under the normal, low, and high initial SOC conditions of 70%, 30%, and 90% battery are shown in Figures 6–8, respectively. Overall, the results of real vehicle condition are similar to CCBC condition. Logical threshold strategy cannot maintain the SOC of battery to the expected value well in real vehicle




(a) (b)

Figure 3: Curves of three strategies under CCBC condition with 70% initial SOC. (a) Fuel cell output power variation. (b) Battery SOC variation.

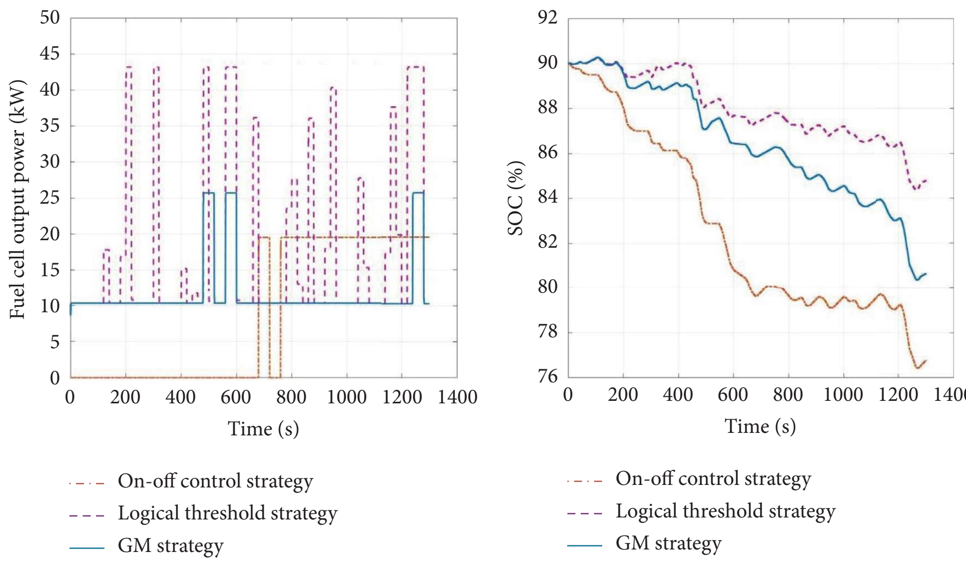



(a) (b)

Figure 4: Curves of three strategies under CCBC condition with 30% initial SOC. (a) Fuel cell output power variation. (b) Battery SOC variation.

condition, and the power regulation of fuel cell changes more dramatically than that in CCBC condition, which is extremely unfavorable to the running life of fuel cell, while GM and on-off control strategies perform better in this aspect of fuel cell output power regulation. Additionally, when the initial SOC is high at 90%, it was found that fuel cell still stayed off for a long time with the on-off control strategy.

Table 3 listed the comparison of fuel economy of three strategies under real vehicle conditions. It can be seen from Table 3 that, at the 70% initial SOC, GM has the best fuel economy performance with a reduction of 11.05% and 6.50% compared correspondingly with the on-off control and logical threshold strategy. At 30% initial SOC, the value of fuel economy of the GM strategy (80.06%) is slightly larger than the logical threshold one (73.65%) but much smaller than the on-off control one with a reduction of almost 20%. At 90% initial SOC, fuel economy of the GM strategy is roughly equivalent to the on-off control one but significantly better than the logical threshold one. Overall, GM shows good economy among these three strategies.

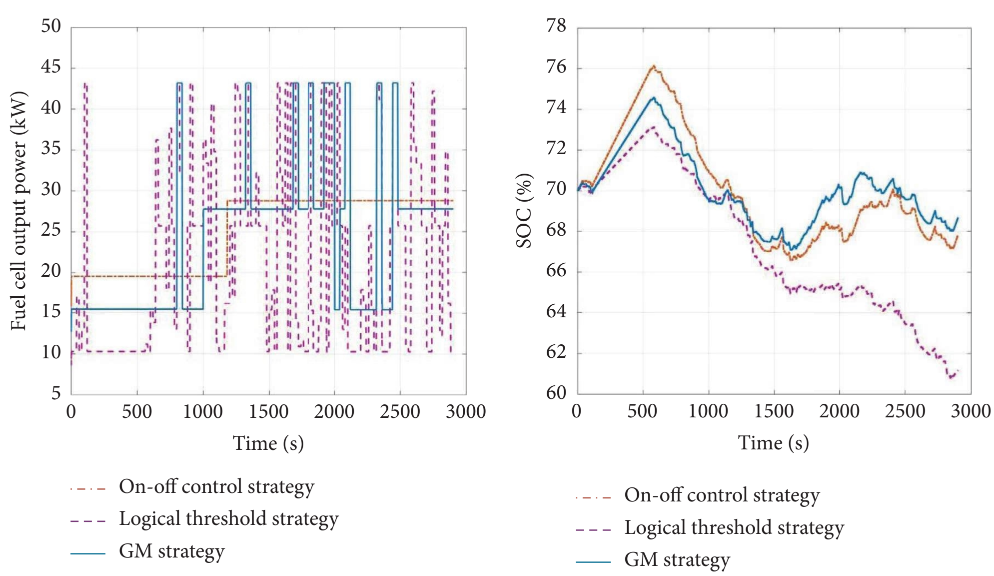



(a) (b)

Figure 5: Curves of three strategies under CCBC condition with 90% initial SOC. (a) Fuel cell output power variation. (b) Battery SOC variation.

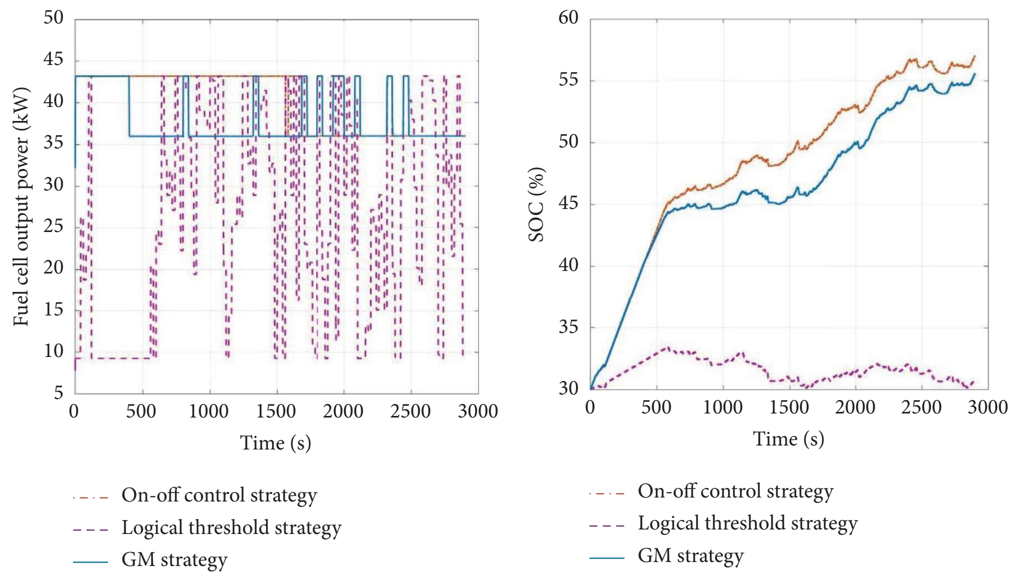
Table 2: Comparison of fuel economy of three strategies under CCBC condition.

| Energy management strategies | $SOC_0$ (%) | $SOC_H$ (%) | $F\Delta H_2$ (g) | $B\Delta H_2$ (g) | $Sum\Delta H_2$ (g) | $\eta_{H2}$ (%) |
|---|---|---|---|---|---|---|
| On-off control strategy | 30 | 49.26 | 935.69 | −195.36 | 740.32 | 100 |
| | 70 | 69.18 | 411.70 | 8.37 | 420.07 | 100 |
| | 90 | 77.14 | 167.36 | 130.39 | 297.75 | 100 |
| Logical threshold | 30 | 31.85 | 492.35 | −18.74 | 473.61 | 64.0 |
| | 70 | 68.13 | 399.92 | 18.95 | 418.87 | 99.7 |
| | 90 | 86.12 | 352.30 | 39.38 | 391.68 | 131.55 |
| GM (1, *N*) | 30 | 40.37 | 684.07 | −106.25 | 577.82 | 78.05 |
| | 70 | 68.06 | 365.60 | 23.10 | 388.70 | 92.53 |
| | 90 | 80.98 | 211.50 | 91.50 | 303.00 | 101.76 |



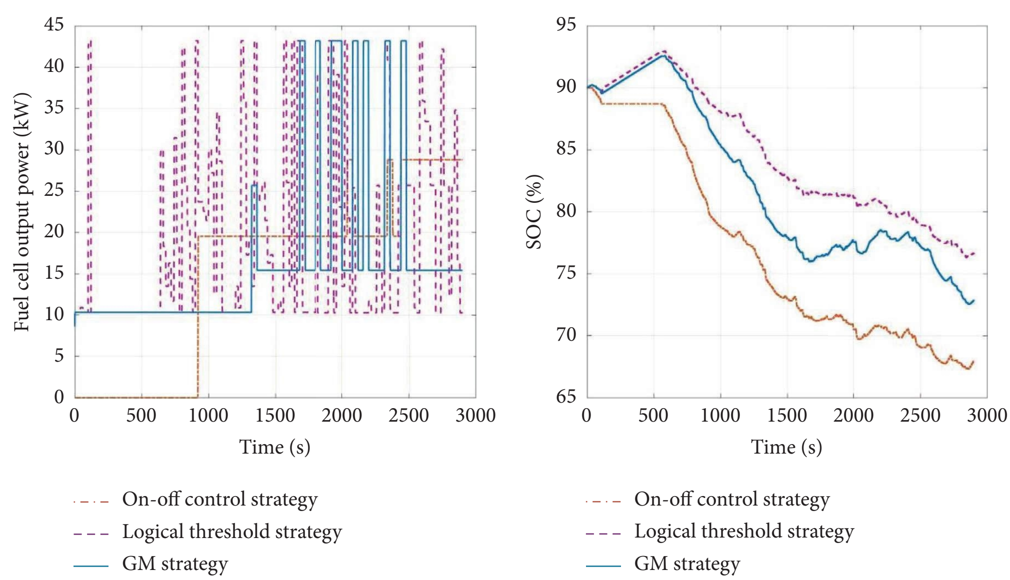

(a) (b)

Figure 6: Curves of three strategies under real vehicle condition with 70% initial SOC. (a) Fuel cell output power variation. (b) Battery SOC variation.




(a) (b)

Figure 7: Curves of three strategies under real vehicle condition with 30% initial SOC. (a) Fuel cell output power variation. (b) Battery SOC variation.




(a) (b)

Figure 8: Curves of three strategies under real vehicle condition with 90% initial SOC. (a) Fuel cell output power variation. (b) Battery SOC variation.

Table 3: Comparison of fuel economy of three strategies under real vehicle conditions.

| Energy management strategies | $SOC_0$ (%) | $SOC_H$ (%) | $F\Delta H_2$ (g) | $B\Delta H_2$ (g) | $Sum\Delta H_2$ (g) | $\eta_{H2}$ (%) |
|---|---|---|---|---|---|---|
| On-off control strategy | 30 | 57.05 | 1763.20 | −274.38 | 1488.82 | 100 |
| | 70 | 67.85 | 1003.31 | 21.82 | 1025.14 | 100 |
| | 90 | 68.03 | 594.77 | 222.87 | 817.64 | 100 |
| Logical threshold | 30 | 30.71 | 1103.77 | −7.19 | 1096.58 | 73.65 |
| | 70 | 61.17 | 885.69 | 89.53 | 975.22 | 95.13 |
| | 90 | 76.69 | 787.58 | 135.07 | 922.65 | 112.77 |
| GM (1, *N*) | 30 | 40.34 | 1296.38 | −104.87 | 1191.5 | 80.06 |
| | 70 | 60.96 | 820.13 | 91.72 | 911.86 | 88.95 |
| | 90 | 74.16 | 674.94 | 160.70 | 835.64 | 102.20 |

## 4. Conclusions

Hydrogen fuel cell energy management strategies play an important role in improving the dynamic response performance and contributing safe and reliable operation of hydrogen fuel cell system. There are limitations of the existing energy management startegy such as poor real-time performance and large amount of calculation. This study proposed an energy management strategy of the hybrid power system based on GM (1, $N$) power prediction which is applicable in the condition of a limited small amount of experimental data and low requirements on data distribution. Three kinds of energy management strategies including the on-off control strategy, logical threshold strategy, and GM (1, $N$) power prediction strategy were compared under two different working conditions of CCBC and real vehicle with different initial SOC. Among them, the on-off control strategy determines the system state by battery SOC, while the logical threshold strategy is based on the vehicle demand power and battery SOC. All the simulations are completed in a control system development and testing platform based on MATLAB/Simulink. Comparisons were mainly made between three strategies in the aspects of output efficiency and fuel economy by measurements of battery SOC variation, fuel cell output power variation, the hydrogen consumption of fuel cell, and equivalent hydrogen consumption of battery. Based on the research results of CCBC and real vehicle conditions of three different values of initial SOC, the GM strategy shows good performance in the hybrid power system for hydrogen fuel cell vehicles. Specifically, the GM strategy has better fuel economy when compared with the on-off control strategy and is more conducive to fuel cell life and vehicle power battery charging state maintenance when compared with the logical threshold one. Comprehensive considering the aspects of vehicle battery, fuel economy, and output efficiency, it is concluded that the GM predictive energy management strategy performs the best among the three control strategies in this study, which can contribute improvement in energy management of the hybrid power system for hydrogen fuel cell vehicles.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

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## References

[1] C. M. Martinez, X. Hu, D. Cao, E. Velenis, B. Gao, and M. Wellers, “Energy management in plug-in hybrid electric vehicles: recent progress and a connected vehicles perspective,” *IEEE Transactions on Vehicular Technology*, vol. 66, no. 6, pp. 4534–4549, 2017.

[2] Y. Wu, H. Tan, J. Peng, H. Zhang, and H. He, “Deep reinforcement learning of energy management with continuous control strategy and traffic information for a series-parallel plug-in hybrid electric bus,” *Applied Energy*, vol. 247, pp. 454–466, 2019.

[3] F. Zhang, X. Hu, R. Langari, and D. Cao, “Energy management strategies of connected HEVs and PHEVs: recent progress and outlook,” *Progress in Energy and Combustion Science*, vol. 73, pp. 235–256, 2019.

[4] J. Hu, D. Liu, C. Du, F. Yan, and C. Lv, “Intelligent energy management strategy of hybrid energy storage system for electric vehicle based on driving pattern recognition,” *Inside Energy*, vol. 198, Article ID 117298, 2020.

[5] J. Peng, H. He, and R. Xiong, “Rule based energy management strategy for a series–parallel plug-in hybrid electric bus optimized by dynamic programming,” *Applied Energy*, vol. 185, pp. 1633–1643, 2017.

[6] T. Fletcher, R. Thring, and M. Watkinson, “An Energy Management Strategy to concurrently optimise fuel consumption and PEM fuel cell lifetime in a hybrid vehicle,” *International Journal of Hydrogen Energy*, vol. 41, no. 46, pp. 21503–21515, 2016.

[7] H. Li, A. Ravey, A. N’Diaye, and A. Djerdir, “A novel equivalent consumption minimization strategy for hybrid electric vehicle powered by fuel cell, battery and supercapacitor,” *Journal of Power Sources*, vol. 395, pp. 262–270, 2018.

[8] Y. Balali and S. Stegen, “Review of energy storage systems for vehicles based on technology, environmental impacts, and costs,” *Renewable and Sustainable Energy Reviews*, vol. 135, Article ID 110185, 2021.

[9] A. Al-Othman, M. Tawalbeh, R. Martis et al., “Artificial intelligence and numerical models in hybrid renewable energy systems with fuel cells: advances and prospects,” *Energy Conversion and Management*, vol. 253, Article ID 115154, 2022.

[10] J. Ko, S. Ko, H. Son, B. Yoo, J. Cheon, and H. Kim, “Development of brake system and regenerative braking cooperative control algorithm for automatic-transmission-based hybrid electric vehicles,” *IEEE Transactions on Vehicular Technology*, vol. 64, no. 2, pp. 431–440, 2015.

[11] N. Denis, M. R. Dubois, and A. Desrochers, “Fuzzy-based blended control for the energy management of a parallel plug-in hybrid electric vehicle,” *IET Intelligent Transport Systems*, vol. 9, no. 1, pp. 30–37, 2015.

[12] X. Qi, G. Wu, K. Boriboonsomsin, M. J. Barth, and J. Gonder, “Data-driven reinforcement learning–based real-time energy management system for plug-in hybrid electric vehicles,” *Transportation Research Record*, vol. 2572, no. 1, pp. 1–8, 2016.

[13] C. K. Sundarabalan and K. Selvi, “Real coded GA optimized fuzzy logic controlled PEMFC based Dynamic Voltage Restorer for reparation of voltage disturbances in distribution system,” *International Journal of Hydrogen Energy*, vol. 42, no. 1, pp. 603–613, 2017.

[14] H. Tian, X. Wang, Z. Lu, Y. Huang, and G. Tian, “Adaptive fuzzy logic energy management strategy based on reasonable SOC reference curve for online control of plug-in hybrid

electric city bus," *IEEE Transactions on Intelligent Transportation Systems*, vol. 19, no. 5, pp. 1607–1617, 2018.

[15] I. López, E. Ibarra, A. Matallana, J. Andreu, and I. Kortabarria, "Next generation electric drives for HEV/EV propulsion systems: technology, trends and challenges," *Renewable and Sustainable Energy Reviews*, vol. 114, Article ID 109336, 2019.

[16] S. N. Motapon, L. A. Dessaint, and K. Al-Haddad, "A comparative study of energy management schemes for a fuel-cell hybrid emergency power system of more-electric aircraft," *IEEE Transactions on Industrial Electronics*, vol. 61, no. 3, pp. 1320–1334, 2013.

[17] S. N. Motapon, A. Lupien-Bedard, L. A. Dessaint, H. Fortin-Blanchette, and K. Al-Haddad, "A generic electrothermal Li-ion battery model for rapid evaluation of cell temperature temporal evolution," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 2, pp. 998–1008, 2017.

[18] N. Bizon, "Real-time optimization strategy for fuel cell hybrid power sources with load-following control of the fuel or air flow," *Energy Conversion and Management*, vol. 157, pp. 13–27, 2018.

[19] K. Song, X. Wang, F. Li, M. Sorrentino, and B. Zheng, "Pontryagin's minimum principle-based real-time energy management strategy for fuel cell hybrid electric vehicle considering both fuel economy and power source durability," *Inside Energy*, vol. 205, Article ID 118064, 2020.

[20] Y. Zhou, A. Ravey, and M. C. Péra, "Multi-objective energy management for fuel cell electric vehicles using online-learning enhanced Markov speed predictor," *Energy Conversion and Management*, vol. 213, Article ID 112821, 2020.

[21] S. Li, C. Gu, P. Zhao, and S. Cheng, "Adaptive energy management for hybrid power system considering fuel economy and battery longevity," *Energy Conversion and Management*, vol. 235, Article ID 114004, 2021.

[22] Z. Chen, Y. Liu, Y. Zhang, Z. Lei, Z. Chen, and G. Li, "A neural network-based ECMS for optimized energy management of plug-in hybrid electric vehicles," *Inside Energy*, vol. 243, Article ID 122727, 2022.

[23] L. Zhang, M. Pan, and S. Quan, "Model predictive control of water management in PEMFC," *Journal of Power Sources*, vol. 180, no. 1, pp. 322–329, 2008.

[24] C. Ziogou, S. Voutetakis, M. C. Georgiadis, and S. Papadopoulou, "Model predictive control (MPC) strategies for PEM fuel cell systems–A comparative experimental demonstration," *Chemical Engineering Research and Design*, vol. 131, pp. 656–670, 2018.