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ENERGY MANAGEMENT STRATEGY OF FUEL CELL/BATTERY HYBRID VEHICLE BASED ON SERIES FUZZY CONTROL

Hekun Jia[1)], Jiexu Tang[1)], Yingxiao Yu[1)*], Yan Sun[1)], Bifeng Yin[1)] and Chao Zhang[2)]

[1)]School of Automotive and Traffic Engineering, Jiangsu University, Zhenjiang 212013, China
[2)]Technique Center, Foresight Energy Co., Ltd., Shansong Road, National High-tech Zone, Suzhou 215000, China

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ABSTRACT–Fuel cell durability and vehicle operating cost are the main optimization goals of energy management strategy (EMS) for fuel cell hybrid electric vehicles (FCHEV). In this paper, a series fuzzy control strategy (SFCS) is proposed to decrease the load changing rate of fuel cell system (FCs). The test bench is used to obtain the output characteristics and load changing capacity of FCs. In order to increase the driving mileage and to eliminate the uncertainty of manual experience in fuzzy controller, particle swarm optimization (PSO) is used to optimize the subjection function distribution and rule weights of fuzzy control, and the evaluation function is constructed by operating cost. Based on the experiment data of FC and battery, the model of the vehicle and strategy are constructed in the software environment, and the optimization result is obtained through simulation. The results show that the FCs load changing rate is reduced and limited to the range of change capacity through the SFCS, while the durability of the fuel cell is optimized. The SFCS optimized by PSO (PSFCS) increases the driving mileage. Under WLTC and UDDS conditions, mileage has been increased by 11.2 % and 8.79 % respectively.

KEY WORDS : FCHEV, Energy management strategy, Series Fuzzy control, PSO, Fuel cell durability

SUBSCRIPTS

A : windward area
a : vehicle acceleration rate
C_r : rolling resistance coefficient
C_d : Wind bound coefficient
C_{bat} : battery capacity
C_{fc} : the price of fuel cell system
C_{ele} : the price of electricity
C_{H_2} : the price of hydrogen
con_{H_2} : hydrogen capacity
SFCS : series fuzzy control strategy
D_{fc} : the degradation of fuel cell
D_{fc}^* : the degradation of fuel cell system in this paper
F_t : traction force
F : faraday constant
FCS : fuzzy control strategy
I_{fc} : the output current of fuel cell system
I_{cell} : the output current of single cell
I_{req} : current demand
m_{fc} : system instantaneous hydrogen consumption rate
M_{H_2} : hydrogen molar mass
N : the number of single cells
N_{com} : torque command
P_{req} : power demand
P_{mec} : mechanical power
P_{ele} : electric power
P_{fc} : the output power of fuel cell system
P_{bat} : the output power of battery
P_{lost} : the lost power of motor
PSO : particle swarm optimization
$PSFCS$: the SFCS optimized by PSO
Q_{LHV} : hydrogen low heating value
Q_{bat} : the capacity of battery
R_{bat} : the internal resistance of battery
S_{inl} : the evaluation index of PSO
SOC : the state of charge of battery
U_{oc} : the open voltage of battery
V_{mot} : the rotary velocity of motor
V : vehicle speed
θ : road slope
δ_m : rotary mass coefficient
η_{fc} : the efficiency of fuel cell system
η_{mat} : the efficiency of motor
ρ : air density

1. INTRODUCTION

Energy crisis and global climate issues are the main factors limiting the development of internal combustion engine vehicles (Teng *et al*., 2020; Sulaiman *et al*., 2018; Lü *et al*.,

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**Corresponding author*. e-mail: yyx@ujs.edu.cn

2020; Yu and Ahn, 2020a). With the maturity of hydrogen technology, proton exchange membrane fuel cells (PEMFC) are gradually being used in automotive power systems (Ezzat and Dincer, 2020; Caux *et al*., 2017; Jin *et al*., 2021). PEMFC has the advantages of high energy density and high conversion efficiency. However, the physical and chemical properties determine the poor dynamic characteristics of PEMFC, that cannot adapt to frequent load changing conditions (Liu *et al*., 2020; Hu *et al*., 2018; Zhang *et al*., 2019). Therefore, power battery or super capacitor are often used to mix with PEMFC and are applied in fuel cell hybrid electric vehicles (FCHEV) (Wang *et al*., 2019). In this way, the vehicle equipped with fuel cell not only has a longer life, but also can adapt to complex driving conditions. So, hybrid power is beneficial to the energy saving and the service life of the components (Xu *et al*., 2020).

The rational design of energy management strategy (EMS) is the guarantee of vehicle dynamic performance, economy and durability (Fletcher *et al*., 2016; Yu and Ahn, 2019). The main objects of the EMS are to distribute the demand power, then each power source supplies energy according to a certain rule (Li *et al*., 2012; Yu and Ahn, 2020b). In a fuel cell/battery hybrid system, fuel cell is the main and battery is the auxiliary power source.

The working conditions are changing in real time when the vehicle is operating, and the control signal transmission has a certain hysteresis. As a result, for complex and changeable working conditions, traditional control methods are often ineffective, such as thermostat control strategy (TCS). Fuzzy control can fuzz up the accuracy of the system and use expert experience for nonlinear controlled objects (Chen *et al*., 2012; Shen *et al*., 2020; Mohammadzadeh and Rathinasamy, 2020). Fuzzy control does not require quantified reference variables and has simple logic. This kind of control strategy Provides a better solution for the complex and changeable control environment. In FCHEV, fuzzy control needs to combine different requirements and component states to update the fuel cell output power in real time. The requirements and component states refer to the power demand, the state of charge (SOC) of the lithium battery, and the discharge rate of the battery. With the consideration of these state information, not only the battery can be protected under high current demand, but also the system can avoid low power anxiety (Punov and Gechev, 2020). According to the research of Wu *et al*. (2012), a fuzzy EMS based on driving cycle recognition is proposed to improve the fuel economy of a parallel hybrid electric vehicle. Based on the study of Saib *et al* (2017), the demand power, demand power error and battery SOC are used as input parameters of the fuzzy controller to control the output power of the fuel cell, and the FC dynamic response was improved. In order to solve the shortcomings, such as slow response rate of the fuel cell system, Gao *et al*. (2008) Optimized system power distribution using fuzzy controller. The effectiveness of the method was verified by the experiment. Therefore, fuzzy control has a great application prospect.

Fuzzy control has good real-time performance and can be well applied in engineering. But for now, the operating cost of fuel cells has become the main factor limiting the well development of fuzzy control (Rezk *et al*., 2019; Wang *et al*., 2019). The operating cost mainly refers to the durability. Due to the particularity of the stack structure and operating principle, the stack is very easy to be affected by changing working conditions when it is operating, leading to corrosion of internal reaction materials and affecting service life (Sun *et al*., 2020). The changing working conditions mainly include variable load, start-stop, etc. Song *et al*. (2020) Optimized the energy consumption of vehicles by using the Pontryagin's minimum principle (PMP). In order to reduce the durability loss caused by the load changing, a fuel cell durability model was constructed to reduce the total operating cost of the system. Based on the research of Zhang *et al*. (2019), three sub-fuel cells are configured as a fuel cell system so as to reduce the load changing rate of fuel cell. Each sub-fuel cell works in a fixed working condition, and realizes power classification by starting and stopping. In the study of Wu *et al*. (2020), a robust online EMS is proposed to deal with uncertain driving cycle, and a penalty coefficient to modify the output power of the fuel cell was introduced to reduce the load changing rate of the fuel cell. As a result, the changing load is easier to accelerate the corrosion of the catalyst. For the fuzzy control used in the FCHEV system, fuel cell is always considered as the controlled object. Under the condition of high-frequency changing demand power, fuel cell output is prone to excessive load change, which will cause irreversible and durable damage. In addition, the ability of the air compressor in the actual working process is directly related to the variable load rate.

Hence, to govern the output of fuel cell and battery, optimization of fuzzy control is necessary. According to de research of Yin *et al*. (2019), the membership function distribution of the fuzzy controller and the system energy consumption was optimized. Dayeni *et al*. (2017) presents a novel real-time fuzzy logic control (FLC) configuration for energy management of a fuel cell/battery vehicle. The parallel fuzzy controller was optimized to adapt the variational condition. The current research showed that the fuel economy of vehicle was improved with optimization of fuzzy control. However, the vast majority of existing fuzzy rules are based on expert experience, which could limit the adaptability of control strategy. On the other hand, most scholars have not considered the optimization of fuel cell durability in the process of fuzzy optimization. As a result, fuel economy and fuel cell durability need to be considered to eliminate the affection of manual experience and improve the durability of fuel cell simultaneously.

In this paper， a series fuzzy control strategy is proposed, which considers the impact of changing working conditions on the durability loss of fuel cells. In addition, the particle swarm optimization (PSO) is used to find the best combination of membership functions and fuzzy rule weights offline, in which the affection of manual experience is eliminated and the durability of fuel cell is improved Simultaneously. In section 2, the system topology and various component models are constructed, including the volt-ampere characteristic curve of FCs and the system load changing capacity obtained by the testing bench. In section 3, EMS based on series fuzzy control is proposed and the fuzzy control optimization process is analyzed in detail. In section 4, the efficiency of FCs and battery are tested. The results of the proposed strategy are obtained through the simulation analysis. Finally, the conclusions are provided in section 5.

2. SYSTEM STRUCTURE AND MODEL

The power system and vehicle model are based on Zotye® X5 compact SUV in this paper. The vehicle topology is shown in Figure 1.

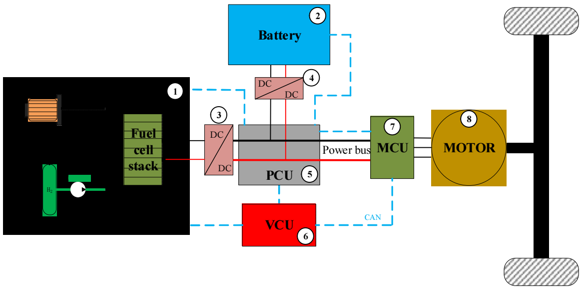


Figure 1. System topology.

Table 1. Dynamic system parameters.

	Parameters	Value	Unit
Vehicle	Unladen mass	1550	kg
	Frontal area	2.56	m^2
	Coefficient of rolling resistance	0.012	—
	Coefficient of air resistance	0.36	—
	Final ratio	13	—
Fuel cell system	Nominal power	38	kW
	Number of cells	200	—
	Max. current	375	A
	Hydrogen capacity	1.6	kg
Battery	Energy content	20	kWh
	Nominal voltage	365	V
	Technology	Li-Ion	—
	Number of cells	100	—

As is shown in Figure 1, the system includes a fuel cell system (FCS) 1, a lithium-ion battery 2, a unidirectional DC/DC converter 3, a bidirectional DC/DC converter 4, Power control unit (PCU) 5，Vehicle control unit (VCU) 6，Motor control unit (MCU) 7，Motor 8. When the vehicle is operating，the VCU 6 receives the power demand signal，and calculates the torque command, which is sent to the MCU 7. Then PCU 5 receives the current demand signal calculated by MCU 7 and sends it to each power source, including battery and FCS. In this way, the control of power distribution is completed. A part of parameters of the system is listed in Table 1.

2.1. Vehicle

The traction force is calculated according to the longitudinal dynamics of vehicle, as is shown in Equation (1):

$$F_t = mgC_r cos\theta + \frac{C_d A\rho V^2}{2} + mgsin\theta + \delta_m ma \tag{1}$$

Where: F_t is the traction force(N), g=9.81 is the gravity acceleration (m/s^2), C_r is the rolling resistance coefficient, θ the road slope (°), C_d is the air resistance coefficient, A is the windward area (m^2), δ_m is the rotary mass coefficient, ρ represents the air density (kg/m^3), V is the vehicle speed(m/s), a is the vehicle acceleration (m/s^2).

Then the vehicle obtains the power demand according to the current vehicle speed V and traction force F_t, as shown in Equation (2):

$$P_{req} = F_t \cdot V \tag{2}$$

Here, P_{req} is the power demand(W).

2.2. Fuel Cell System

The working efficiency of the FCS is related to the hydrogen consumption rate of FCs，and the hydrogen consumption rate is non-linearly proportional to the system output current. As a result, it is necessary to study the relationship between hydrogen consumption, output current and working efficiency of the FCs, as is shown in Equations (3), (4), (5):

$$I_{fc} = I_{cell} \cdot N \tag{3}$$

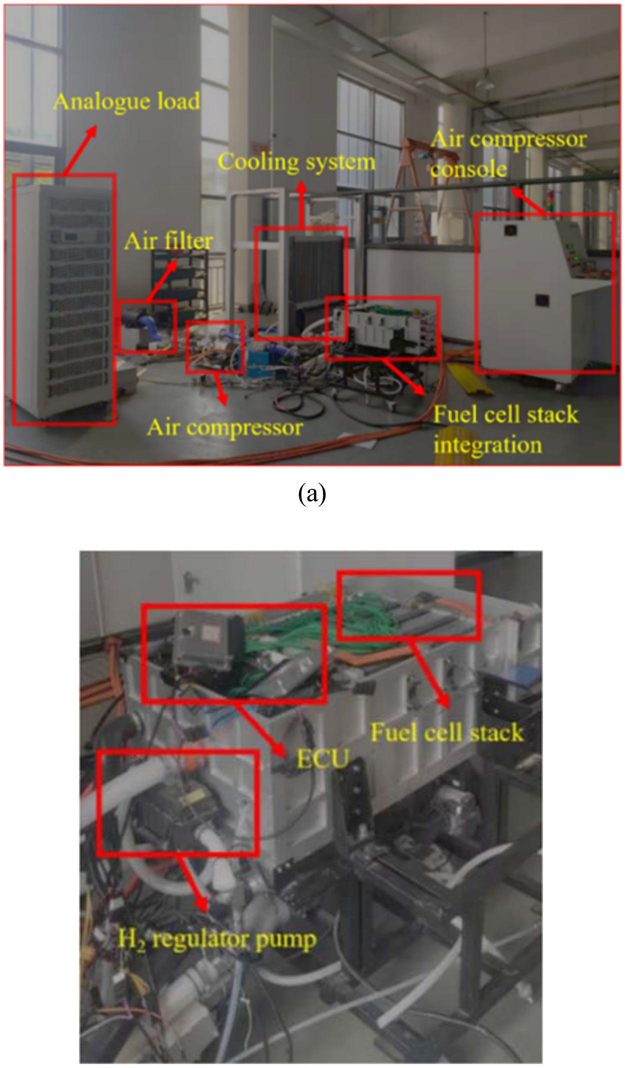
$$m_{fc} = \frac{NI_{fc}M_{H_2}}{2F} \tag{4}$$

$$\eta_{fc} = \frac{P_{fc}}{m_{fc}Q_{\mathrm{LHV}}} \tag{5}$$

Where, m_{fc} represents the system instantaneous hydrogen consumption rate (g/s), N is the number of single cell, I_{fc} is the output current of FCs (A), I_{cell} is the output current of single cell, M_{H_2} represents hydrogen molar mass (g/mol), F indicates the faraday constant, η_{fc} is the system working efficiency, Q_{LHV} is the hydrogen low heating value (kJ/kg).

In order to obtain the system characteristics, the testing bench of the FCs is built in the laboratory. The testing bench is shown in Figure 2. Table 2 lists the parameters of the air compressor. Generally speaking, the load changing capacity of the FCs is positively correlated with the output power change capacity of the air compressor (Hu *et al*., 2020).

As mentioned in the introduction, fuel cell durability is a key factor to be considered in the optimization process of EMS. Zhang *et al*. (2018) pointed out in Applied Energy that the factors affect the durability of fuel cells during operation mainly include variable load, start-stop, idling load, and high-power load, etc. According to the research in (Song *et al*., 2020; Song *et al*., 2018), The durability model of the fuel cell is built as follows:



(a)

(b)

Figure 2. (a) FCs testing bench. (b) Fuel cell stack integration.

Table 2. Air compressor parameters.

Parameter	Value	Unit
Flow rate	45	g/s
Pressure ratio	1.7	
Power consumption	≤4.6 kw	kW
Noise grade	<85	dB(A)

$$D_{fc} = \sum_{i=1}^{n}\left[d_{change}(i) + d_{on-off}(i) + d_{idling}(i) + d_{high}(i)\right] \tag{6}$$

$$d_{change}(i) = k_1 \cdot \frac{|I_{fc}(i) - I_{fc}(i-1)|}{I_{max} - I_{min}} \tag{7}$$

$$D_{fc}^{*} = \sum_{i=1}^{n} d_{change}(i) \tag{8}$$

Here, D_{fc} represents the whole degradation of fuel cell(%), d_{change} is the load change degradation, d_{on-off} is the on-off degradation, d_{idling} represents idling degradation, d_{high} is the high power degradation; n represents the number of simulaiton time steps; k_1 is 5.39×10^{-5}; $I_{fc}(i)$ and $I_{fc}(i-1)$ represent the output current of the fuel cell at the i-th and (i-1)-th time step respectively, I_{max}, I_{min} indicate the maximum and minimum current allowed by the fuel cell. D_{fc}^{*} represents the whole degradation of fuel cell in this paper (%), n is the simulation step size.

Based on the fuzzy logic, the energy management strategy is constructed. Fuzzy control is used to update the output current of the FCs in real time. When the fuel cell startup SOC value in the strategy is small (≤40 %), the fuel cell starts and stops frequently during the complete driving range cycle. So, the durability loss caused by start-stop and idleness can be ignored. In addition, the output current of FCs is limited in the high efficiency region by the fuzzy control, the output current is relatively small. As a result, the durability loss caused by the high power can also be ignored. Therefore, limiting the load changing rate is significant in the proposed strategy.

2.3. Power Battery

The battery adopts the equivalent internal resistance open circuit voltage model. The relationship between battery power, output current, internal resistance and SOC is shown in Equations (9) and (10):

$$P_{bat} = U_{oc}I_{bat} - I_{bat}^{2}R_{bat} \tag{9}$$

$$\Delta SOC = \eta_c \frac{\int_{t_0}^{t_1} I_{bat}dt}{C_{bat}} \tag{10}$$

Where, P_{bat} represents battery output power(W), U_{oc} represents open voltage(V), I_{bat} is output current(A), R_{bat} is internal resistance(Ω), η_c is coulombic efficiency, C_{bat} is battery capacity.

2.4. Motor

When the vehicle is operating, the motor receives the electrical power from EMS and converts it into mechanical power after a certain convert efficiency:

$$P_{mec} = \eta_{mat} \cdot P_{ele} \tag{11}$$

Where P_{ele} represents the electric power, P_{mec} is the mechanical power, η_{mat} is the motor efficiency.

The motor adopts a torque control method. The motor current demand is calculated according to the VCU torque command and the current motor speed. In this way, power distribution is actually transformed into a current demand distribution problem. The demand current calculation is shown in Equation (12):

$$I_{req} = \frac{N_{com} \cdot V_{mot} - P_{lost}}{U} \tag{12}$$

Here, I_{req} represents demand current(A), N_{com} is the command torque(N), V_{mot} is the motor rotary velocity (rev/min), P_{lost} is the lost power(W), U is the voltage of the motor (V).

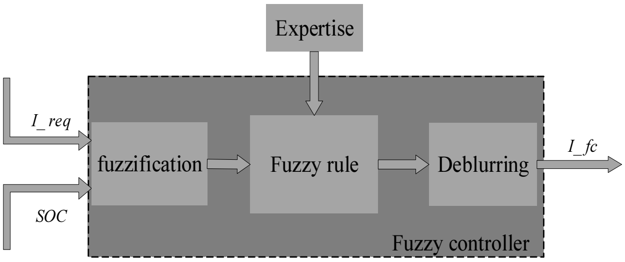


Figure 3. (a) FCs testing bench. (b) Fuel cell stack integration.

3. ENERGY MANAGEMENT STRATEGY

3.1. Fuzzy Control Strategy

For complex controlled objects, some control variables are not easy to quantify, and it is difficult to accurately control them with conventional control methods. Therefore, the fuzzy control strategy using expertise provides a better solution for the complex and changeable control environment. In this paper, fuzzy logic is used to control the output current of FCs. The *I_ fc* is controlled in real time combining with SOC and demand current *I_ req* of motor. Among them, the *I_fc* is limited to the high efficiency area, as is shown in Figure 8 (III). The principle of fuzzy control is shown in Figures 3 and 4 demonstrates the control logic.

In Figures 3 and 4, *SOC_ switch* and *SOC_ low* represent the fuel cell turn-on threshold and SOC lower limit, respectively. *SOC_ int* Indicates the threshold for entering pure electric mode. *I_ fc* is the output current of fuel cell, *I_bat* is the output current of battery, *I_ req* the demand current, H_2 is the hydrogen consumption of FCS, *H_2_con* represents the total amount of hydrogen.

Under the control logic shown in Figure 4, the default initial SOC is 100 %，*SOC_ int* is 20 %, *SOC_ high* is 40 %, and *SOC_ low* is 10 %. At the beginning, the vehicle operates in electric mode, and the battery alone meets the current demand. Then, when the SOC drops to 40 %, the fuel cell

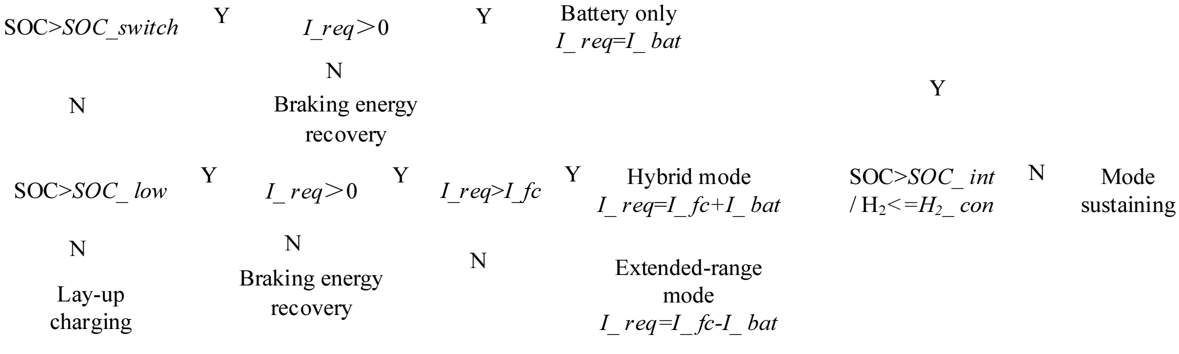


Figure 4. Fuzzy control strategy.

will get started. If $I\_{}_{req} > I\_fc$, the demand current is provided by battery and FCs together. If $I\_{}_{req} \leq I\_fc$, the demand current is only provided by fuel cell, and the surplus current ($I\_fc - I\_{}_{req}$) is used to discharge the battery. when the SOC rises to 40 %, the fuel cell is turned off and the vehicle returns to pure electric mode. This kind of cycle continues until the hydrogen is consumed completely. Finally, the vehicle enters the pure electric mode and stops until the SOC is lower than 10 %.

3.2. Series Fuzzy Control Strategy

As mentioned above, although fuzzy control strategy can reasonably control the output current of FCs, it does not consider the limitation of the load changing capacity of the FCs.

In order to realize the control of load changing amplitude and size, a series fuzzy control strategy is proposed. The first-level fuzzy controller is the original fuzzy control, which is used to determine the output of the FCs (I_fc). The input of the second-level fuzzy controller is the first-level fuzzy output (I_fc), the real-time SOC of the battery and the change of demand current (ΔI_req), and its output is the current change of FCs (ΔI_fc). The function of the second-level fuzzy controller is to control ΔI_fc within 5A/s, that is,$\Delta I_fc \leq 5$A/s. As shown in Figure 5:

Where, I_fc* represents the output current of the fuel cell system. I_fc represents the output current of first-level fuzzy control. ΔI_req is the change of demand current. ΔI_fc is the current change of FCs.

The control logic of series fuzzy control can be seen in Equqtion (13) :

$$\begin{cases} I\_fc^* = I\,fc + 5 & d_{I\_fc} > 5 \\ I\_fc^* = I\,fc + \Delta I\,fc & d_{I\_fc} \leq 5 \end{cases} \tag{13}$$

The control rules of fuzzy1 and fuzzy 2 are shown in Figure 6. Fuzzy rule diagram shows the relationship between fuzzy control input and output.

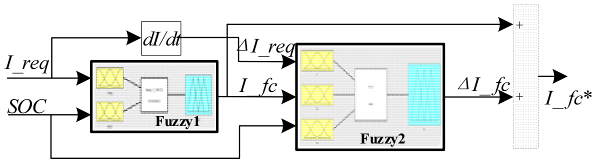
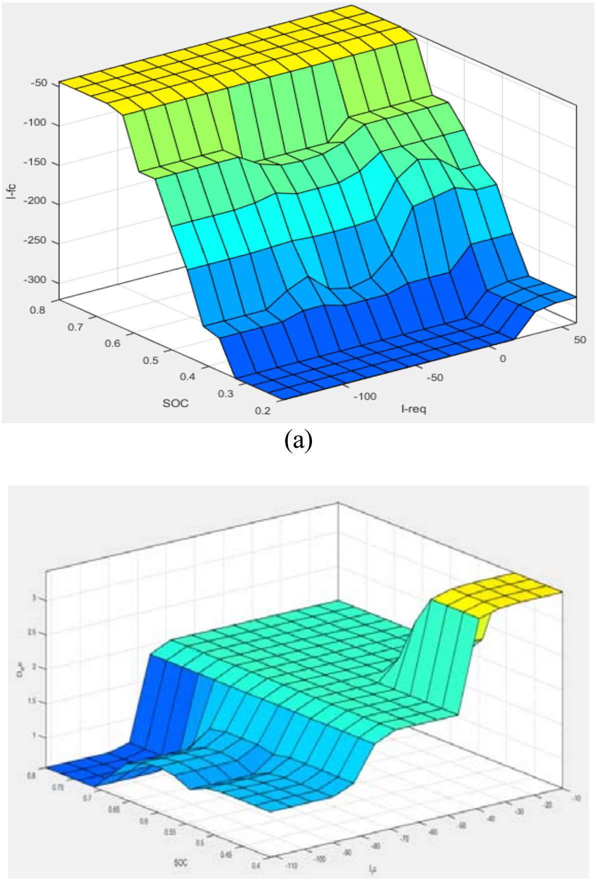


Figure 5. (a) FCs testing bench. (b) Fuel cell stack integration.

3.3. Series Fuzzy Control Strategy

As is mentioned above, not only the optimization of durability, but also fuel economy are need to be considered in the process of fuzzy control optimization. For hybrid electric vehicles (HEV), the fuel consumption is one of the indicators to measure the economy of the vehicle. In addition, the proposed fuzzy control has not been optimized, especially for the membership function and the weight of fuzzy rules. In this way, it is necessary to use optimization algorithms to optimize various parameters of fuzzy control with the goal that both consider economy and durability. Particle Swarm optimization (PSO) is a random search algorithm that can converge to the global optimal solution with a high probability (Darwich *et al*., 2019). Compared with traditional optimization algorithms, PSO has a faster calculation speed and better global search capability. Figure 7 shows the process of PSO.

As shown in Figure 8 (a), the endpoints and vertices of each membership function are taken as the vectors of the PSO in turn, which are ordered to be X1, X2, X3 *et al.* In addition, the weight of each fuzzy rule weight is also used as the algorithm vector. The evaluation function result (g_{best}) calculated by PSO continuously updates the particles (position and velocity) until the evaluation function value is found. The Optimization searching process is shown in



(a)

(b)

Figure 6. The control rules of (a)fuzzy1 and (b)fuzzy2.

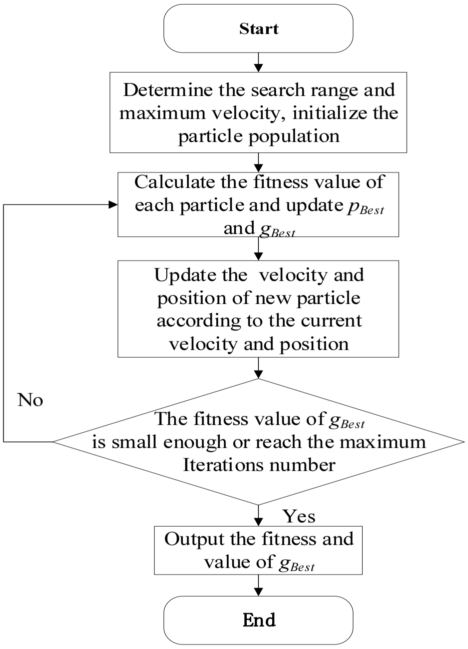
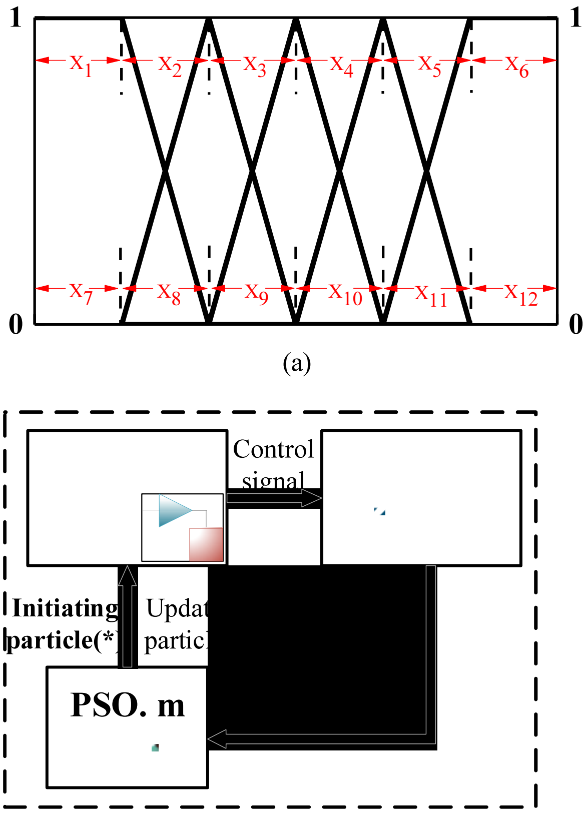


Figure 7. The process of particle swarm optimization.



(a)

(b)

Figure 8. (a) Vectors in subject function. (b) Optimization searching process of PSO.

Figure 8 (b), the convergence result is obtained after 200 iterations. At this time, the corresponding membership function distribution and fuzzy rule weight are the final optimization results. In this way, the original expert experience in fuzzy control is replaced by fuel economy and durability optimization, eliminating the uncertainty of manual experience. The optimization results are shown in Section 4.

The evaluation function of PSO is established as follow:

$$S_{inl} = \frac{con_{H_2}}{mile} \cdot C_{H_2} + \frac{Q_{bat}}{mile} \cdot C_{ele} + \frac{D_{fc}^*}{mile \cdot 20} \cdot C_{fc} \cdot P_{fc} \qquad (14)$$

In the above, S_{inl} represents the evaluation index, which indicates the operating cost per unit of driving mileage. con_{H_2} represents the total hydrogen capacity (kg). Q_{bat} indicates the battery capacity (kW·h). P_{fc} is the power of FCs. $mile$ is the driving mileage (km). 20(%) represents the allowed performance degradation percentages of FCs used in this paper. C_{H_2}, C_{fc} and C_{ele} are the price of the hydrogen, electricity and fuel cell system respectively. According to the data of U.S.DOE (Marcinkoski *et al.*, 2015), the price of hydrogen is 28.72 (¥/kg), the cost of electricity is about 0.572 (¥/kW·h) and the cost of FCs is 1000(¥/kW).

4. RESULTS AND DISCUSSION

In this section, the optimization results of each strategy listed in section 3 will be compared and analyzed. First, compared with fuzzy control strategy (FCS), the control effect of Series fuzzy control strategy (SFCS) is going to be illustrated. Second, the differences in the driving mileage of the vehicle before and after the optimization of PSO(SFCS and PSFCS). At the same time, the optimization result of PSFCS will be listed. In this paper, the characteristics of FCs are obtained through bench tests, as shown in Figure 9.

The load changing capacity of FCs is also caught through the testing bench. The impact of load changing on the durability of FCs accounts for the largest proportion of all influencing factors. The capacity is limited by the power of the air compressor. Through the testing bench, the actual load changing capacity of the FCs used in this paper is 5 A/s.

The WLTC and UDDS cycle are used as the simulation cycle. Both of these two conditions have relatively frequent speed changes, and they are more able to reflect the effectiveness of the proposed control strategy. In this paper, the vehicle energy flow model and EMS model are established respectively in AMESIM (SIEMENS®) and MATLAB/Simulink (MATHWORKS®), and the model in the loop (MIL) is realized. In addition, the PSO program is compiled in MATLAB, which is transferred to calculate the evaluation function results. Figure 10 demonstrate the vehicle energy flow model in AMESIM.

The simulation results of the series fuzzy control strategy (SFCS) under the cycle of WLTC and UDDS are shown in

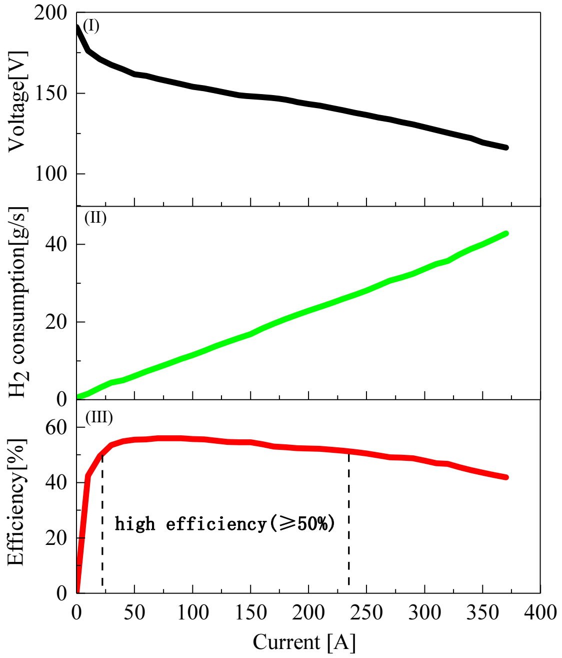


Figure 9. (I) Volt-ampere characteristics. (II) Hydrogen consumption. (III) FCs efficiency.

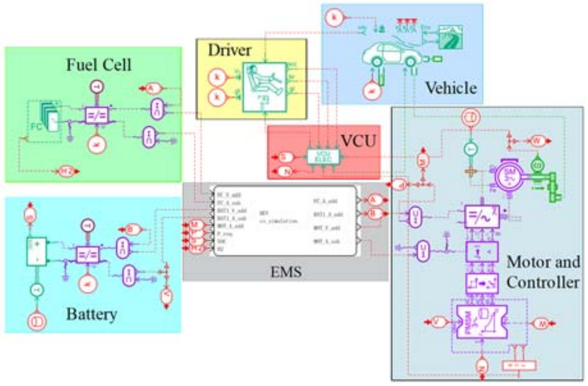
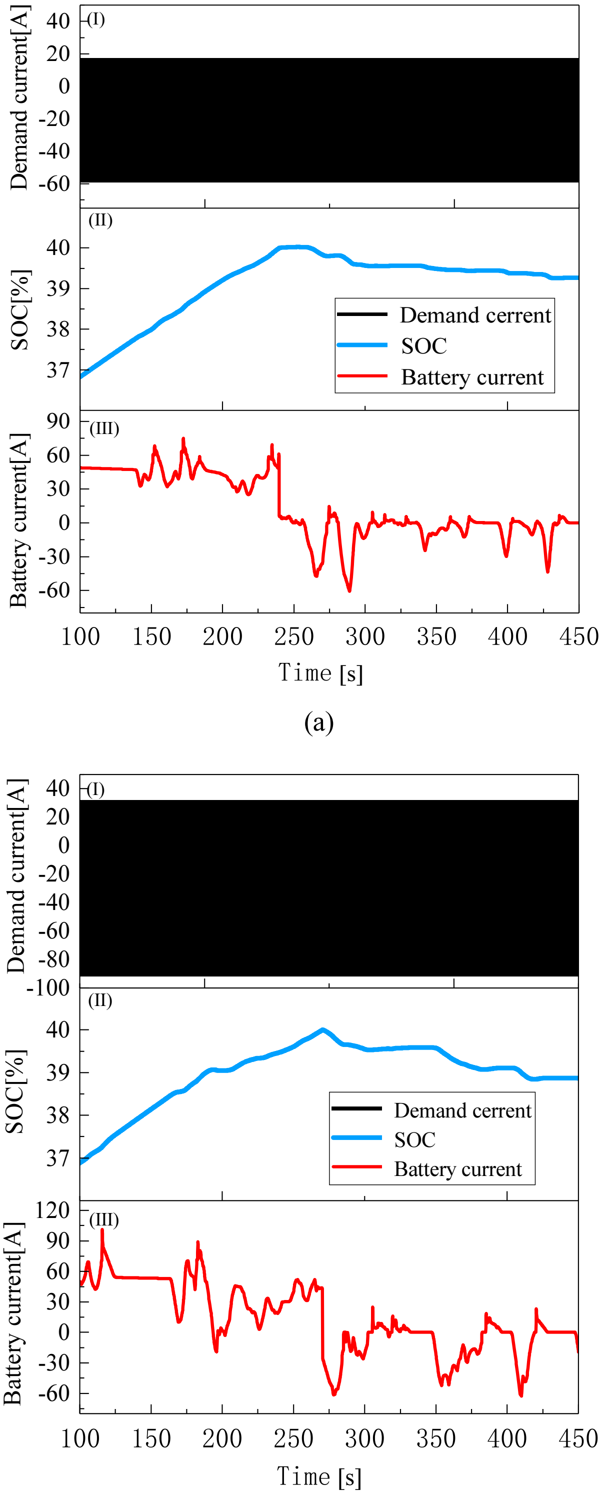


Figure 10. Vehicle energy flow model.

Figure 11. The total working time of WLTC and UDDS is 1800 s and 1369 s respectively. In order to show the trend of each result with the demand current and the effect of series fuzzy control strategy, the simulation results in this paper only intercept part of the results.It is necessary to notice that, the vehicle is braking and coasting when the demand current is positive or zero. Otherwise, the vehicle is driving. For the battery, positive current means charging and a negative current means discharging. According to Figure 4, when the vehicle is braking or coasting, the fuel cell remains on to charge the battery under the premise that the battery needs to be charged. As a result, the charging current of the lithium battery is not complete equal to the demand current in the braking state.

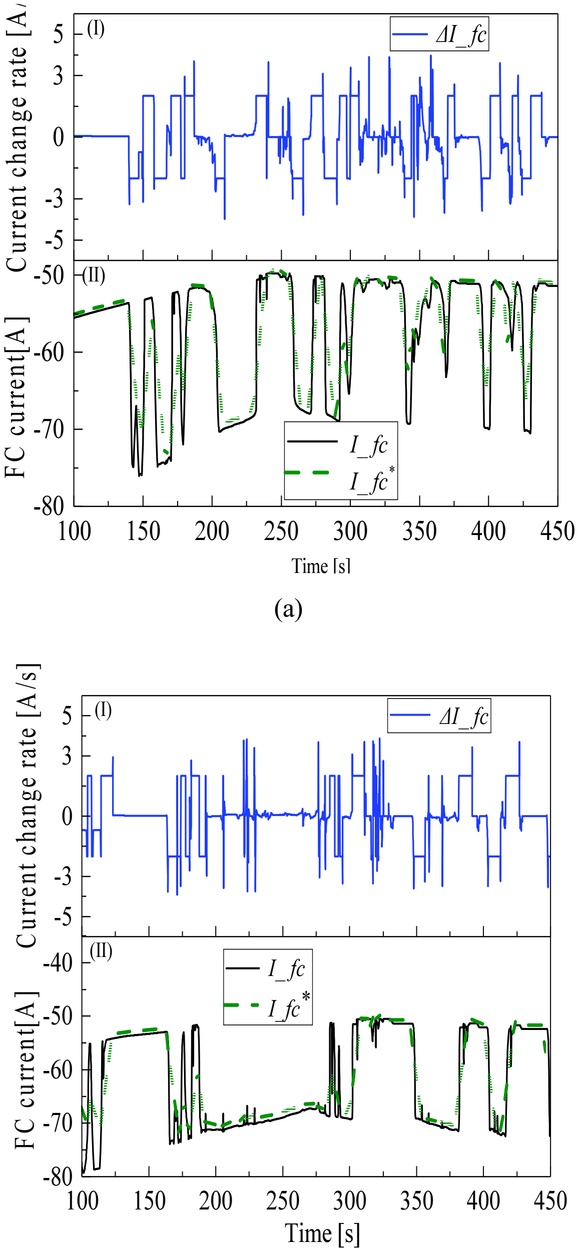


(a)

(b)

Figure 11. The demand current, SOC and battery current of SFCS in (a) WLTC. (b) UDDS cycle.

Figure 12 illustrates the optimization results of SFCS. Figure 12 (I) represents the current fluctuation of FCs (*ΔI_fc*). Figure 12 (II) indicates the actual output current of the fuel cell before and after SFCS optimization (*I_fc, I_fc**). It can be seen that when *ΔI_fc* is large, SFCS starts to take effect, limiting the fluctuation rate of fuel cell output current. *ΔI_fc* is limited to the range of 5A/s. The current fluctuation rate of FCs decreases significantly under the premise of satisfying the load changing capacity.



(a)

(b)

Figure 12. The demand current, SOC and battery current of SFCS in (a) WLTC. (b) UDDS cycle.

In order to improve the operating cost of the vehicle, the series fuzzy control strategy should be optimized. The main optimization objects are subjection functions and fuzzy rule weights. PSO can find the optimal subjection function

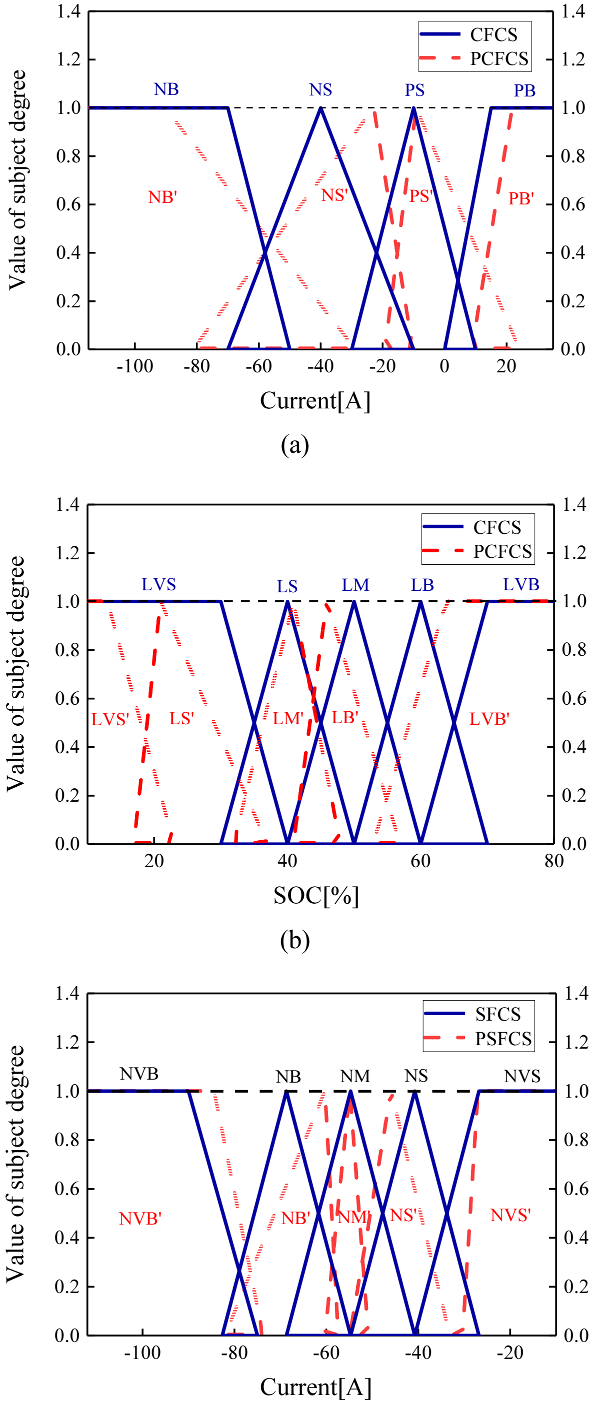


Figure 13. The subject function of (a) *I_ r* Equation (b) SOC. (c) *I_fc*.

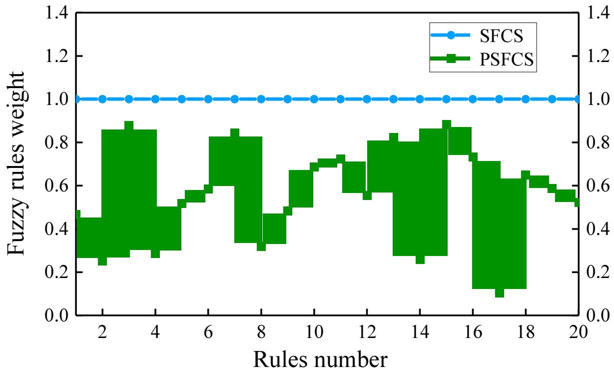


Figure 14. The optimization of fuzzy rules weight based on PSO.

distribution and fuzzy rule weight combination to maximize the evaluation function through iterative optimization. After 200 iterations of calculation, the subjection function distribution and the fuzzy rules weights of Fuzzy1 are shown in Figures 13 and 14. After 200 iterations, the algorithm has converged, that is to say, the optimal solution has been found.The optimization situation of Fuzzy2 is the same as Fuzzy1.

Figure 15 shows the simulation results of the driving mileage of each strategy under WLTC and UDDS. In WLTC, the driving mileage of FCS, SFCS, and PSFCS are respectively 238.07 km, 238.12 km, and 264.79 km. In UDDS, the mileage are 287.54 km, 287.72 km, and 313.08 km. It can be seen that SFCS can ensure the operating cost of the vehicle while optimizing the fuel cell load changing rate. Meanwhile, the effectiveness of PSFCS in optimizing the driving mileage has also been verified. The driving mileage increases by 11.2 % and 8.79 % respectively under WLTC and UDDS. The results also indirectly show that fuzzy control based on vehicle operating cost optimization is superior to fuzzy control based on manual experience.

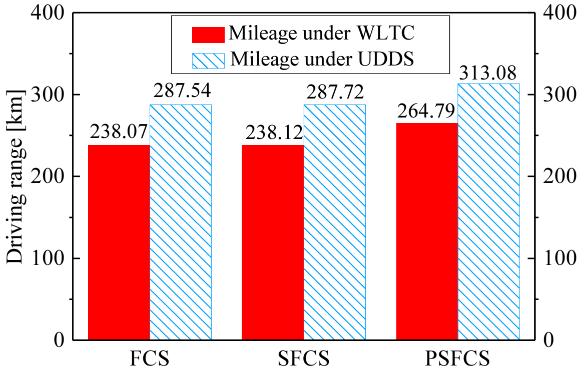


Figure 15. The driving range of the vehicle using three strategies.

5. CONCLUSION

In this paper, a series fuzzy control strategy (SFCS) is proposed, which can decrease the current fluctuation rate of fuel cell system (FCs) and improve the fuel cell durability. In order to increase the driving mileage, the optimal subjection function distribution and fuzzy rule weight combination is found with particle swarm optimization (PSO). Firstly, the volte-ampere characteristics and efficiency curve of FCs were constructed through bench test, and the actual load changing capacity of FCs was measured. Secondly, the fuzzy control strategy (FCS) is proposed. According to the change of SOC and demand current (I_req), the output current of FCs is dynamically adjusted and limited to the high efficiency area. Thirdly, the SFCS is presented. SFCS can limit the load changing rate of FCs below the capacity, reducing the durability loss of the system. Finally, PSO is used to optimize the SFCS, and the driving mileage has also been improved. By this way, the influence of manual experience can be eliminated. A combination of theoretical modeling and the way of simulation calculation is used to verify the feasibility of the proposed strategy. The simulation results show that SFCS can limit the load changing rate of FCs under the premise of ensuring vehicle operating cost, and reduce the degradation of fuel cell. PSFCS has a significant effect in the optimization of driving mileage. The mileage increases 11.2 % and 8.79 % respectively under WLTC and UDDS.

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