Enhancing energy management through driving style recognition in vehicular communication systems

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Abstract: Driving style, a critical indicator that affects vehicle fuel economy, its recognition has traditionally relied on onboard sensors and limited vehicle-to-vehicle communication. However, 6G technology facilitates the collection of vast amounts of data, including vital signs like vehicle speed, power sources performance, and real-time traffic conditions, which can be used for real-time driving style recognition. It enables vehicles to make informed decisions about power allocation and fuel consumption, thereby advancing the future of green and efficient transportation. For driving style recognition problem, the principal component analysis (PCA) method is adopted to select the speed and the absolute values of acceleration as driving style identification parameters and the fuzzy-logic controller optimized by genetic algorithm (GA) is designed to identify driving style. Afterwards, the driving style optimal control strategy is realized by matching the recognized driving style with the optimal equivalent factor in each driving condition and the matched equivalent factor is combined with the objective function of equivalent consumption minimum strategy (ECMS). The effectiveness of proposed driving style based on ECMS is validated by real vehicle test, which indicates that, compared with the strategy without considering driving styles, the proposed driving style recognition based ECMS reduces the hydrogen consumption of FCHEV by 3.7% in the combination of HWFET and UDDS.

Keywords: Fuel cell hybrid electric vehicle, energy management strategy, driving style recognition, equivalent consumption minimum strategy, genetic algorithm

1. INTRODUCTION

6G vehicular communication systems are at the forefront of next-generation wireless technologies, promising to revolutionize various aspects of automotive operations. One of the promising domains for their application is energy management strategy for fuel cell electric vehicle(FCHEV), particularly in the context of vehicle driving style recognition. The FCHEV equipped with fuel cell (FC), battery (BAT) and super capacitor (SC), among which fuel cell can provide the power demand continuously and steadily (Hmidi et al., 2020), battery can provide the power demand rapidly (Zhang et al., 2021), and super capacitor can provide the transient high power (Li et al., 2019), the three energy sources exert their respective advantages to provide the power demand for hybrid electric vehicle (Rahman et al., 2021). The key technology of FCHEV is to coordinate the output power of energy sources to achieve optimal economic performance and practical performance (Wang et al., 2019). Studies show that FCHEVs (Sun et al., 2020), like conventional vehicles (Fu et al., 2020), are profoundly influenced by the driver's driving style in terms of fuel economy and emissions (Tao et al., 2020). By integrating 6G vehicular communication into energy management systems, vehicles can continuously exchange data with the infrastructure and other connected vehicles, allowing for real-time assessment of the driver's driving style. This recognition enables dynamic adjustments to vehicle power allocation, optimizing fuel consumption and Increasing driving comfort. For instance, a driver with a more aggressive driving style might benefit from adaptive power allocation that encourages smoother accelerations and decelerations. Therefore, it is of great significance to develop an appropriate and effective energy management strategy (EMS) based on driving style to improve the fuel economy of FCHEV and expand the lifespan of energy sources.

For driving styles, there are many factors influencing driving style recognition (Feng et al., 2020). Such as personal driving habits (Xia et al., 2021), driving environment,

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driving conditions, etc. These factors are a great challenge for the identification of driving styles (Wu et al., 2020). In the existing researches, driving styles are usually divided into three categories: aggressive, normal and calm. In the aggressive driving style, the pedal range is larger and the speed of FCHEV is fast, so the fuel consumption of FCHEV is relatively high. However (Fernandes et al., 2021), in the normal or calm driving style (Fu et al., 2020), the pedal range is relatively reasonable and the speed of FCHEV is moderate (Li et al., 2019), so the fuel consumption is relatively reasonable (Quan et al., 2021). To achieve better fuel economy for FCHEV (Deng et al., 2017), it is necessary to understand and develop driving style recognition in advance (Zhang et al., 2020).

The first step of driving style recognition consists of determining the characteristic variables to describe driving styles and classify them. The driving styles of drivers can be reflected by the following driving characteristics: speed, acceleration, brake pedal position, throttle opening and fuel consumption, so these parameters are extensively used to identify driving style. For example, the longitudinal acceleration and lateral yaw rate are taken as the driving style identification parameters, and an artificial neural network method using a large amount of data is adopted to classify driving styles (Efremov et al., 2017). Although the classification accuracy is improved, it is time-consuming in the calculation process. To reduce the calculation time, the longitudinal acceleration and throttle pedal opening and closing are taken as the identification parameters of driving style which are classified into aggressive and normal by using a semi-supervised support vector machine method (Wang et al., 2017). In addition, to reduce the number of samples, with brake pedal position, vehicle acceleration and accelerator pedal position as identification parameters, the expectation maximization method and K-nearest Neighbor algorithm are used to classify driving style styles into conservative and aggressive types (Guo et al., 2020). In the research on driving style recognition methods, different algorithms, such as machine learning algorithms, fuzzy control and statistical algorithms, are frequently used. By analyzing the selected characteristic parameters, the optimum characteristic parameters are selected, so as to realize the recognition of different driving styles. Among them, fuzzy control is a better method to identify driving styles, because the relationship between driving styles and characteristic parameters can be described by a set of vague driving rules that have been developed through the conditions and the experiences of different drivers. The throttle pedal openness and the change rate of openness are used as driving style identification parameters to identify the newly added driving styles, and fuzzy logic rules are designed to divide driving styles into four categories: economical, comfortable, normal and aggressive (Guo et al., 2019).

To reduce the fuel consumption of the whole vehicle under different driving styles, many scholars have proposed an energy management strategy combining driving style recognition and equivalent consumption minimum strategy (ECMS). Driving styles are divided into six categories from moderate to radical by kernel density estimation and entropy theory, then the optimal equivalent factor adjustment rules in ECMS strategy are designed to improve the fuel economy of hybrid electric vehicles (Yang et al., 2018). Driving styles are divided into economic, comfort, common and aggressive by using fuzzy logic rules, and the relationship between driving styles and equivalent factors are optimized by using ECMS, particle swarm optimization (PSO) and GA, verifying the effectiveness of the driving style adaptive optimal control strategy (Guo et al., 2019). An EMS strategy based on driving style is proposed, which uses the K means clustering algorithm to divide driving style into three categories: aggressive, normal and calm. The ECMS is optimized by GA to adjust the battery SOC punishment function and charge-discharge coefficient, compared with the traditional ECMS, the proposed strategy has low fuel consumption (Gong et al., 2019). The K-nearest neighbor method is used to preprocess the driving style samples, and the driving style is divided into offensive and conservative types through the expectation maximization method. At the same time, the driving style is integrated into ECMS, and the simulation results show that the charging sustainability and the equivalent fuel consumption of the strategy are superior traditional ECMS (Tian et al., 2019).

According to the current research, most of the researches have classified the driving style into 2 to 4 categories. To make the driving style classify more accurately and reduce the fuel consumption of FCHEV, this paper proposes driving-style-aware EMS for FCHEV based on ECMS. The motivation and contributions of this paper can be summarized as follows.

(1) Considering the on-line use of recognition algorithm, a recognition algorithm based on fuzzy control is designed, in which fuzzy rules are optimized by GA.

(2) Considering the influence of different driving styles on fuel consumption of the FCHEV, driving styles are identified under the optimized fuzzy logic rules based on GA. Then the optimal equivalent factor of each driving style is solved by weighted average and the equivalent factor query table is made. The identified driving style is matched with the corresponding equivalent factor. The matched equivalent factor is embedded into the objective function of ECMS to ensure the minimum fuel consumption of the FCHEV.

(3)Considering the battery SOC balance and keeping the battery in the high efficiency range, the penalty factor function is designed to consider the battery and fuel cell lifespan.

The remainder of this paper is organized as follows. In Section 2, the power train of FCHEV is modeled and built in detail. In Section 3, the fuzzy-logic controller optimized by GA is designed to identify driving styles and the matched equivalent factor is combined with the objective function of ECMS. On this basis, in Section 4, the simulation test of the EMS is given in this section and analyzed to verify the effectiveness of the proposed driving style based on ECMS. Finally, the conclusions are drawn in Section 5.

2. SYSTEM DESCRIPTION AND MODELING

The model of FCHEV is shown in Fig. 1. FC is the primary energy source that delivers power to a motor via a unidirectional DC/DC converter. BAT and SC are equipped as energy storage system, where BAT is used to supply auxiliary power for FC. SC is connected to the bi-directional DC/DC to provide/absorb peak power. The above three energy sources provide power to satisfy the power demand of the vehicle.

2.1 Power model

To allocate the power requirements of the hybrid system, the total power of the hybrid system should be calculated firstly. FCHEV is supposed to overcome the climb resistance, acceleration resistance, rolling resistance and air resistance during the journey, which can be calculated by Equation 1. The relationship between power demand and above resistances shown as Equation 2.

$$\begin{cases} F_r = \varepsilon mg\cos\theta \\ F_b = 0.5\rho ACdv^2 \\ F_c = mg\sin\theta \\ F_r = ma \end{cases} \tag{1}$$

$$P_{req} = (F_r + F_b + F_c + F_r)v \tag{2}$$

where F_r,F_b,F_c and F_a represent the rolling resistance, air resistance, climb resistance and acceleration resistance, respectively, ξ is the rolling resistance coefficient, m is the vehicle mass, θ is the road angle, ρ is the air density, A is the front projection area of the vehicle, C_d is the air resistance coefficient of the vehicle, v and a represent the speed and acceleration, respectively, P_{req} is the power demand of vehicle. The power demand of the hybrid system comes from FC, BAT and SC, which can be calculated as follows:

$$P_{req} = P_{fc} + P_{bat} + P_{sc} \tag{3}$$

where P_{fc}, P_{bat} and P_{sc} are the power of FC, BAT and SC, respectively.

2.2 Fuel cell model

In this paper, fuel cell is the Proton Exchange Membrane Fuel Cell. Hydrogen and oxygen through chemical reaction convert the chemical energy into electric energy. The P_{fc} can be described as follows:

$$P_{fc} = \eta_{fc} \times \int_0^t \frac{m_{H_2}(t) \times 1.4 \times 10^8}{3600} dt \tag{4}$$

where m_{H_2} indicates the mass of H_2, η_{fc} indicates the efficiency of hydrogen combustion into power which can be described as follows:

$$\eta_{fc} = \frac{P_{fc}}{P_{H_2}} \tag{5}$$

where P_{H_2} indicates the power of hydrogen.

The hydrogen consumption of FC can be described by Equation (6).

$$C_{fc} = \int_0^t \frac{i_{fc}(t)}{2 \times NA \times \mathrm{e}} dt \tag{6}$$

where $i_{fc}(t)$ represents the current generated by the FC at time t, NA represents Avogadro constant, e means the electric quantity of electrons.

2.3 Battery model

Ignoring the internal resistance of the battery, the P_{bat} can be expressed as follows:

$$P_{\mathrm{bat}} = u \int_0^t i(t)dt \tag{7}$$

where u indicates the voltage of battery, $i(t)$ indicates the instantaneous current of battery at time t.

To prevent BAT from overworking to prolong its lifespan, the SOC of BAT should be changed within a reasonable range. The SOC of BAT can be calculated as follows:

$$SOC_{bat} = SOC_{bat\_\mathrm{int}} - \int_0^t \frac{i(t)}{Q_{\mathrm{bat}}} dt \tag{8}$$

where SOC_{bat} indicates the SOC of battery, SOC_{bat_int} indicates the initial SOC of battery, Q_{bat} indicates the maximum charge of battery, and $i(t)$ indicates the current of battery $i(t) < 0$ means the battery is charged, and $i(t) > 0$ means the battery is discharged.

2.4 Supercapacitor model

The SOC of SC can be expressed as follows:

$$SOC_{sc} = SOC_{sc\_\mathrm{int}} - \frac{Q_0 - \int_0^t \frac{u(t)}{R_i} dt}{Q_{sc\_\max}} \tag{9}$$

where SOC_{sc} indicates the SOC of SC, SOC_{sc_int} indicates the initial SOC of SC, indicates the initial charge of SC, $Q_{sc\_\max}$ indicates the maximum charge of SC, $u(t)$ indicates the instantaneous voltage of SC at time t, R_i indicates the internal resistance of SC.

3. EMS BASED ON DRIVING STYLE IDENTIFICATION OPTIMIZED BY GA

The EMS is proposed in this paper as shown in Fig. 2. In part I, the driving styles are identified by the fuzzy controller and GA is used to optimize membership functions of the fuzzy controller. In part II, firstly, off-line simulation processing using ECMS strategy is carried out to obtain the optimal equivalent factor under each driving condition. secondly, according to the proportion of a certain driving style in the whole working condition, the optimal equivalent factor for a certain driving style is obtained. Finally, based on driving style recognition results, the optimal equivalent factor of each driving style is matched with ECMS for energy allocation.

3.1 Driving style identification based on GA-based fuzzy logic control

Considering that there is no clear boundary for driving style classification (Wang et al., 2019), fuzzy logic control strategy is very suitable for driving style classification as a method that relies on personal subjectivity (Wang et al., 2019). Before driving style identification, driving style identification parameters need to be constructed (Wu et al., 2020), such as speed, acceleration, impact, pedal position, etc. In this paper, the parameters of speed and acceleration are used to identify the driving style, and the fuzzy logic control strategy is adopted to identify the driving style, The main advantage of this method is that

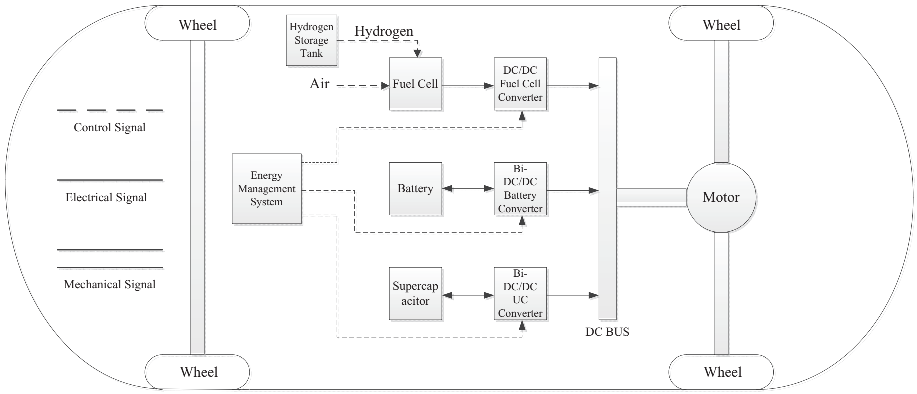

Fig. 1. The power structure of FCHEV.

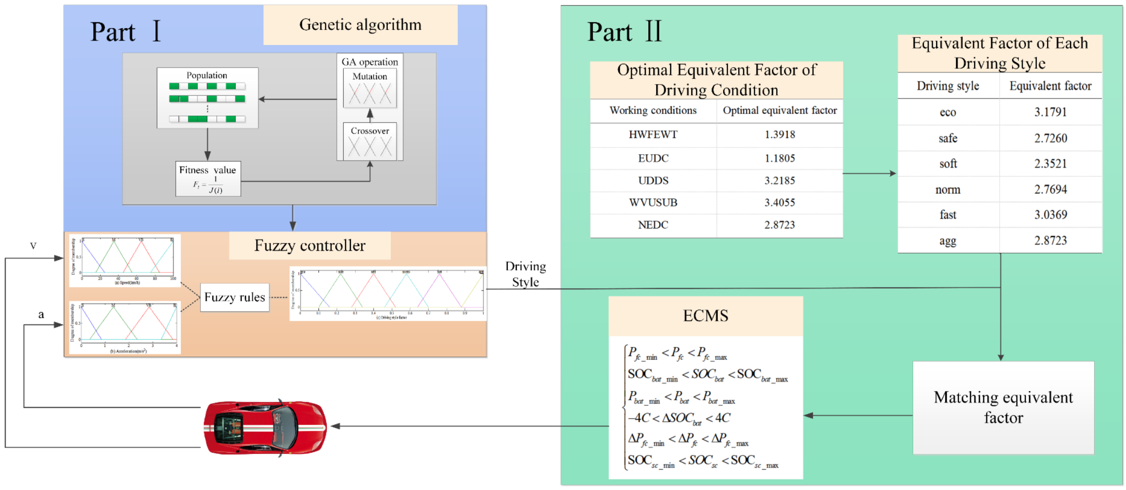

Fig. 2. The flow diagram of A-ECMS based on driving style.

fuzzy logic control classification is simple, the calculation is small, and the accuracy of classification is guaranteed by optimizing the member function of the genetic algorithm.

The proposed fuzzy logic control strategy consists of two inputs and one output. The two input parameters are the velocity and the acceleration, which mainly reflect the power demand of the automobile and its changing trend. The output parameter is the driving style factor, reflecting the driving style of driver. The driving style factor is divided into six categories: economical, safe, soft, normal, fast, and aggressive. Based on the experience and practical application, the range of input and output, membership functions, fuzzy logic rule can be designed as follows:

(1) The range of input and output

According to the practical application and expert experience, the membership degree range of speed, acceleration and driving style parameters of involved are listed in Table 1,2,3.

(2) Membership functions

Considering triangular membership functions can adequately cover the universe of discourse without unnecessary complexity, which is beneficial for online control application of actual vehicle. Meanwhile, to unify the membership function of input and output parameters, therefore, this article will choose for the triangular membership function parameters of membership functions. The absolute value of speed and acceleration and the member function of driving style factor are shown in Fig. 3.

(3) Fuzzy logic rule

To our best knowledge, at the same speed, if the acceleration is larger, the driving style is more aggressive. Meanwhile, at the same acceleration, if the speed is faster, the driving style is more aggressive. After fuzzy logic

Table 1. The membership degree range setting for speed.

	S(trimf)	M(trimf)	VB(trimf)	B(trimf)
Speed	0-20	20-50	50-80	80-100

trimf: triangular membership function

Table 2. The membership degree range setting for acceleration.

	S(trimf)	M(trimf)	VB(trimf)	B(trimf)
Acceleration	0-1	1-2	2-3	3-4

Table 3. The membership degree range setting for driving style factor.

	eco	safe	soft	norm	fast	agg
Driving style factor	0-0.1	0.1-0.3	0.3-0.5	0.5-0.7	0.7-0.9	0.9-1

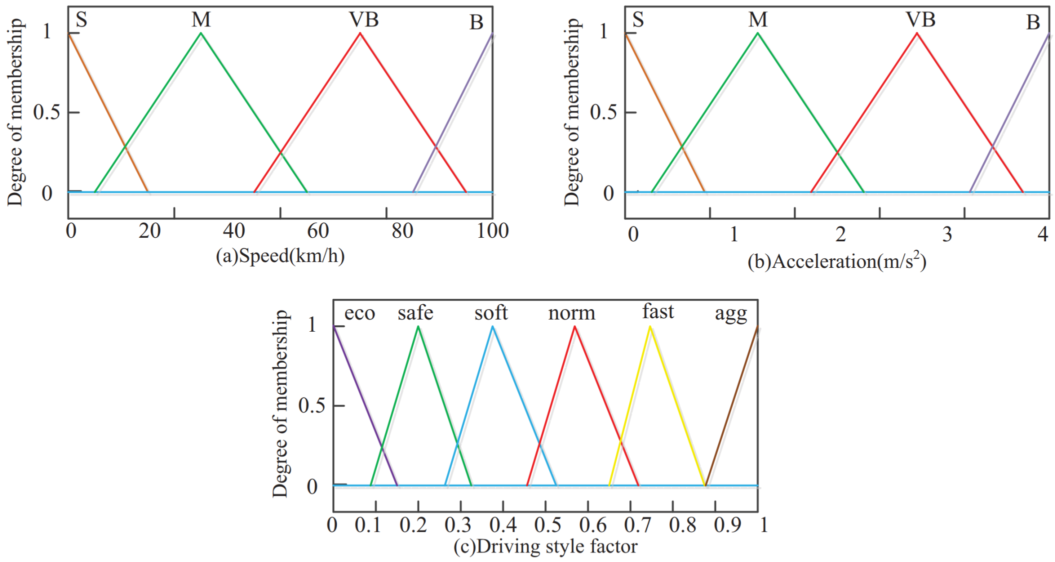

Fig. 3. The fuzzy membership functions.

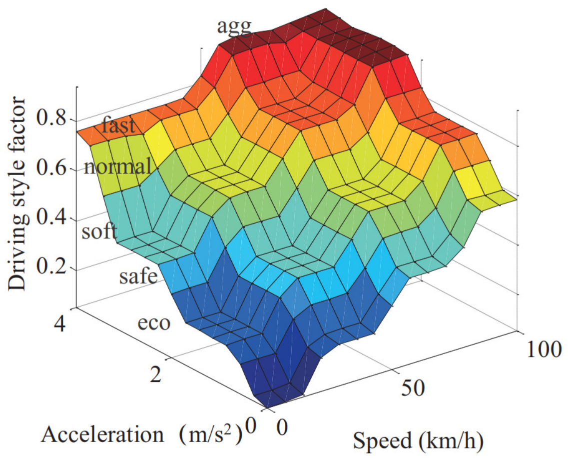

Fig. 4. Fuzzy logic surfaces of driving style.

rule calculation, the driving style can be divided into six categories as shown in Fig. 4.

3.2 GA-based Optimization of the membership function

Considering the fuzzy control is highly dependent on expert experience and actual theory, so the optimization algorithm is needed to optimize the fuzzy controller to achieve the optimal driving style classification effect. GA has strong global search ability and can carry out distributed computing, which is more efficient than simulation degradation algorithm. The optimization process based GA can be designed as follows:

(1) Select population

The essence of optimizing the membership functions of fuzzy controller is to optimize the coordinate values of the vertices of the membership functions. Thus, it is necessary to partition the input/output membership functions. As shown in Fig. 5, x1∼x10, x11∼x20, x21∼x36 represent membership functions partition points of speed, acceleration and driving style factor, respectively. Then, a 36 one-dimensional decimal matrices x1∼x36 is chosen as the chromosomes of the initial population.

(2) Select the individual

The selection of individuals is based on the fitness assessment of individuals in the population. The more adaptable an individual is, the better it can be passed on to the next generation. The fitness function of population can be shown as follows:

$$\begin{aligned} f(i) &= \frac{1}{J(i)}(i = 1, \cdots, N) \\ J(i) &= C_{fc} + C_{bat} + C_{sc} \end{aligned} \tag{10}$$

where $f(i)$ represents the fitness function of individual, $J(i)$ represents the total energy consumption of FCHEV, C_{fc}, C_{bat} and C_{sc} represent hydrogen consumption of FC, BAT, and SC, respectively.

According to the principles of evolution, the greater the individual fitness, the more likely it is to be selected, and vice versa. A uniform random number between [0,1] is generated in each round, which is used as a selection pointer to determine the selected individual.

$$P(i) = \frac{f(i)}{\sum_{i=1}^{36} f(i)} \tag{11}$$

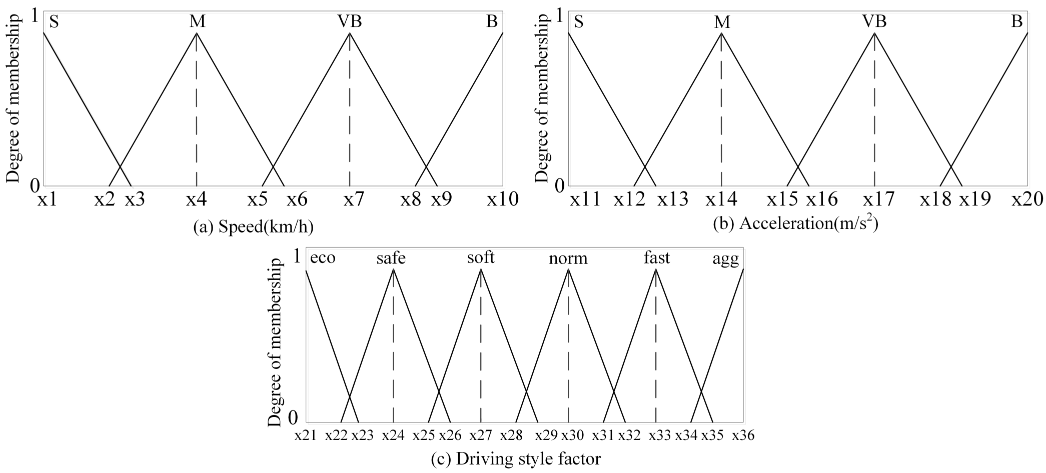

Fig. 5. The results of driving style classification.

where $P(i)$ represents the probability that the th individual is selected.

(3) Crossover and mutation

The point of GA is the crossover operator of genetic operation. The crossover is the operation of replacing and recombining the partial structure of two parent individuals to generate a new individual. By crossing, parts of two individuals are swapped to produce a new combination. The crossover can be calculated as follows:

$$\left\{\begin{array}{l} {I_i}' = (1-\alpha)I_i + \alpha I_{i+1} \\ {I_{i+1}}' = \alpha I_i + (1-\alpha)I_{i+1} \end{array}\right. \tag{12}$$

where the I_i and I_{i+1} represent the i th and $i+1$ th individuals, respectively, the ${I_i}'$ and ${I_{i+1}}'$ represent the i th and $i+1$ th offspring individuals, α is a random number between 0 and 1. New individuals formed after crossover operation have a certain probability of genetic variation. Like selection operation, this operation is based on probability, which is called mutation probability. Generally, mutation probability is less than or equal to 0.05. For the mutation probability, the membership function of fuzzy logic controller is designed as:

$$\left\{\begin{array}{l} a' = a_{\min} + \alpha(a_{\max} - a_{\min}) \\ b' = b_{\min} + \alpha(b_{\max} - b_{\min}) \\ c' = c_{\min} + \alpha(c_{\max} - c_{\min}) \end{array}\right. \tag{13}$$

where the a' , b' and c' are respectively the values of the three vertices of the triangle membership function in the mutated fuzzy rule, the $a_{\max}$, $b_{\max}$ and $c_{\max}$ are respectively the maximum values of the three vertices of the triangle membership function, and $a_{\min}$, $b_{\min}$ and $c_{\min}$ are its respectively the minimum values.

The population size will affect the optimality of the offspring. When the population size is large, the optimization time will be longer, while when the population size is small, the offspring may not be optimal. The 36 membership function points of the fuzzy controller were optimized. Under the premise of guaranteeing both the optimization rate and individual optimality, 30 population, 0.9 crossover probability and 0.09 mutation probability were selected. On the premise of ensuring the optimal solution, it is necessary to set a reasonable genetic algebra to reduce the optimization time. According to the actual needs, the number of optimization iterations is set as 200.

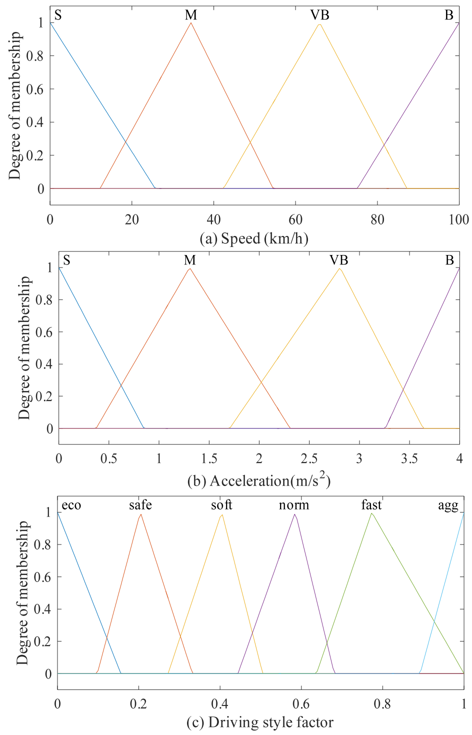

Fig. 6. The fuzzy membership functions after GA optimizing

The optimization operation of membership function based on the above GA. The membership of speed, acceleration and driving style factors is reclassified as shown in Table 4. After the optimization of fuzzy logic by GA, the new fuzzy membership functions and fuzzy logic surfaces are shown in Fig. 6 and Fig. 7. From Fig. 6, it can be seen that the overlapping of membership functions is very reasonable, which satisfies the requirements for coverage of discourse.

By comparing with Fig. 4, it can be found that the optimized driving style classification is more accurate when the speed is 50-80 km/h and the acceleration is 3-4 m/s^2. However,when the speed is 30-40 km/h and the acceleration is

Table 4. The Reclassification of the membership of speed, acceleration and driving style factors.

parameter	Value									
$x_{01}\cdots x_{10}$	0	12.238	25.678	34.427	42.400	54.509	65.870	75.079	87.212	100
$x_{11}\cdots x_{20}$	0	0.373	0.848	1.305	1.705	2.308	2.806	3.258	3.636	4
$x_{21}\cdots x_{36}$	0	0.098	0.156	0.204	0.272	0.332	0.404	0.444	0.505	0.585
			0.637	0.681	0.773	0.837	0.892	1		

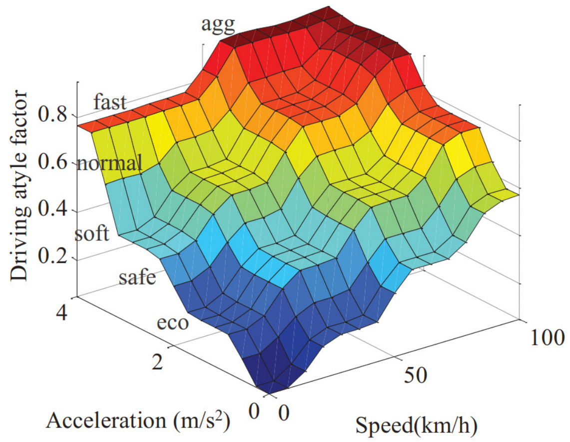

Fig. 7. Fuzzy logic surfaces of driving style optimized by GA.

3-4 m/s^2, the driving style recognition after optimization is quite different from that before optimization. Therefore, the classification of fuzzy logic rules optimized by genetic algorithm is more accurate.

4. A-ECMS BASED ON DRIVING STYLE IDENTIFICATION

The essence of minimum equivalent consumption is to convert the battery power into equivalent fuel consumption and optimize the total hydrogen consumption to minimize the fuel consumption of FCHEV. The hydrogen consumption of hybrid electric vehicles consists of the equivalent hydrogen consumption of BAT, FC, and SC, and the total hydrogen consumption can be expressed as follows:

$$C_m = C_{fc} + C_{bat} + C_{sc} = P_{fc} + \lambda_{bat} P_{bat} + \lambda_{sc} P_{sc} \qquad (14)$$

where the C_m represents the minimum hydrogen consumption, λ_{bat} and λ_{sc} are the equivalent factor of BAT and SC, respectively.

To keep the SOC of BAT and SC changing in a reasonable area. The relevant penalty coefficients are added into equation (12), and the objective function is defined as follows:

$$C_m = C_{fc} + C_{bat} + C_{sc} = P_{fc} + \mathrm{k}_{bat}\lambda_{bat} P_{bat} + \mathrm{k}_{sc}\lambda_{sc} P_{sc} \qquad (15)$$

where the k_{bat} and k_{sc} is the penalty function of SOC of BAT and SC, respectively.

To reduce the optimization complexity of the ECMS, the high-frequency power provided by the SC has been separated previously, so only the battery and fuel cell are optimized during the ECMS optimization process, equation (15) can be reconstructed as follows:

$$C_m = C_{fc} + C_{bat} = P_{fc} + \mathrm{k}_{bat}\lambda_{bat} P_{bat} \qquad (16)$$

The hydrogen consumption of FC can be expressed by equation (17).

$$C_{fc} = \int_0^t \frac{i_{fc}(t)}{2 \times NA \times \mathrm{e}} dt \qquad (17)$$

where $i_{fc}(t)$ represents the current generated by the FC at time t, NA represents Avogadro constant, e means the electric quantity of electrons.

The equivalent hydrogen consumption of BAT can be expressed as follows:

$$\begin{aligned} C_{bat} &= \int_0^t \frac{i_{fc}(t) \times P_{bat}}{2 \times NA \times \mathrm{e} \times P_{fc} \times \eta_{dis} \times \eta_{chg}} dt \\ &= \frac{C_{fc} \times P_{bat}}{P_{fc} \times \eta_{dis} \times \eta_{chg}} \end{aligned} \qquad (18)$$

where η_{chg} and η_{dis} indicate the charging and discharging efficiency of battery, respectively, which can be expressed as follows:

$$\begin{cases} \eta_{dis} = \left(1 + \sqrt{1 - 4R_{dis}P_{bat}/U^2}\right) \Big/ 2 \\ \eta_{chg} = 2 \Big/ \left(1 + \sqrt{1 - 4R_{dis}P_{bat}/U^2}\right) \end{cases} \qquad (19)$$

The equivalent factor of the equivalent hydrogen consumption of the BAT is related to the SOC of BAT. Considering the output performance of battery can be changed with the value of SOC in different variation range, the K_{bat} can be expressed as follows:

$$\mathrm{K}_{bat} = \begin{cases} \left(1 - \frac{2*(SOC - SOC_{bat\_int})}{SOC_{bat\_\max} - SOC_{bat\_\min}}\right)^4 \\ SOC_{bat\_\min} < SOC < SOC_{bat\_\max} \\ \left(1 - \frac{2*(SOC - SOC_{bat\_int})}{SOC_{bat\_\max} - SOC_{bat\_\min}}\right)^{20} \\ SOC < SOC_{bat\_\min} SOC > SOC_{bat\_\max} \end{cases} \qquad (20)$$

where the constant $SOC_{bat\_\max}$ and $SOC_{bat\_\min}$ represent the maximum and minimum SOC of battery, respectively. SOC_{bat_int} represents the initial SOC of the battery.

To extend lifespan of fuel cell and battery, the charging and discharging state of the BAT and the working range of the FC are taken as constraints, as shown in equation (20). Equation (21) represents the main constraints considered in EMS.

$$\begin{cases} P_{fc\_\min} < P_{fc} < P_{fc\_\max} \\ \mathrm{SOC}_{bat\_\min} < SOC_{bat} < \mathrm{SOC}_{bat\_\max} \\ P_{bat\_\min} < P_{bat} < P_{bat\_\max} \\ S\dot{O}C_{bat\_chg} < 2C \\ S\dot{O}C_{bat\_dis} < 4C \\ \mathrm{SOC}_{sc\_\min} < SOC_{sc} < \mathrm{SOC}_{sc\_\max} \end{cases} \qquad (21)$$

where $P_{fc\_\min}$ and $P_{fc\_\max}$ represent the minimum and maximum output power of FC, respectively, $P_{bat\_\min}$ and $P_{bat\_\max}$ represent the minimum and maximum output power of BAT, respectively, $S\dot{O}C_{bat\_chg}$ and $S\dot{O}C_{bat\_dis}$ mean the variation gradient in charging and discharging

Table 5. The optimal equivalent factor of six working conditions.

Working conditions	The optimal equivalent factor
HWFEWT	1.3918
EUDC	1.1805
UDDS	3.2185
WVUSUB	3.4055
NEDC	2.8723

status, respectively, $\mathrm{SOC}_{sc\_\max}$ and $\mathrm{SOC}_{sc\_\min}$ represent the maximum and minimum SOC of SC,respectively.

4.1 Optimization of equivalence factor based on driving style

The equivalent factor of ECMS is the main factor affecting the power distribution between energy sources, so most of the current studies combine driving style with equivalent factor. This section constructs an approach based on equivalent factor query tables that is easy to manipulate and query.

Five typical working conditions are used in this paper. According to the offline optimization objective function, the equivalent factor of each working condition is obtained by offline simulation for each typical working condition. The optimal equivalent factor is obtained by weighted average of the equivalent factor at each moment, which can be calculated by Equation (20), and the optimal equivalent factor of each typical working condition is shown in Table 5.

The optimization objective function of offline simulation can be expressed as:

$$\begin{cases} P_{fc\_\min} < P_{fc} < P_{fc\_\max} \\ \mathrm{SOC}_{bat\_\min} < SOC_{bat} < \mathrm{SOC}_{bat\_\max} \\ P_{bat\_\min} < P_{bat} < P_{bat\_\max} \\ S\dot{O}C_{bat\_chg} < 2C \\ S\dot{O}C_{bat\_dis} < 4C \\ \mathrm{SOC}_{sc\_\min} < SOC_{sc} < \mathrm{SOC}_{sc\_\max} \end{cases} \tag{22}$$

The $s(t) = \lambda(t) \cdot \frac{Q_{lhv}}{Q_{bat}(t)}$,then formula (22) can be expressed as:

$$H(x(t), u_1(t), u_2(t), \lambda(t), t) = m_f(P_{fc}(t), t) + s(t) \cdot \frac{Q_{bat}(t)}{Q_{lhv}} \cdot f(x(t), P_{bat}(t), t) \tag{23}$$

where, $\lambda(t)$ is the costate, $s(t)$ is the equivalent factor at each moment, Q_{bat} is the current capacity of the battery, Q_{lhv} is the calorific value of the fuel, and $x(t)$ is the SOC of lithium battery. According to equation (23), the equivalent factor at each moment of each driving condition can be calculated. Then, the optimal equivalent factor at each driving condition can be expressed as:

$$s(j) = \frac{1}{m} \sum_{a=1}^{m} s(a) \tag{24}$$

where $s(j)$ is the optimal equivalent factor of the j driving conditions, $s(a)$ is the equivalent factor at each moment of the j working conditions, m is the length of a single working condition.

Considering the different driving styles in a certain working condition, it is necessary to calculate the weight of a certain driving style in the working condition. Based on the fuzzy logic control strategy mentioned above, the length of each driving style in the certain working condition can be obtained, and the proportion of a certain driving style in the whole working condition can be calculated as follows:

$$P_j(r) = \frac{T_r(k)}{T(j)} (r = 1, 2, \cdots, n) \tag{25}$$

where $P_j(r)$ is the weight of rth driving style in the j working condition, $T_r(k)$ is the length of r th driving style, $T(j)$ is the length of jth working condition.

Considering that the optimal equivalent factor is obtained for a certain working condition.the driving style length is used to determine the specific gravity. The six typical working conditions are combined into a new working condition, the proportion of the typical working condition to the new working condition can be calculated as follows:

$$P_c(j) = \frac{T(j)}{\sum\limits_{j=1}^{c} T(j)} \tag{26}$$

The optimal equivalent factor for a certain driving style can be calculated as follows:

$$s(r) = \frac{\sum\limits_{j=1}^{c} s(j) P_j(i) P_c(j)}{\sum\limits_{j=1}^{n} P_j(i) P_c(j)} \tag{27}$$

where the $s(r)$ is the optimal equivalent factor for each driving style.

Table 6. The query table of optimal equivalent factors for each driving style.

Driving style	The optimal equivalent factor
eco	3.1791
safe	2.7260
soft	2.3521
norm	2.7694
fast	3.0329
agg	2.8723

The equivalent factor query table corresponding to each driving style obtained after weighted average is shown in Table 6. Once the driving style is determined, the equivalent factor can be matched by looking up the table. Meanwhile, to ensure that the SOC of the battery can maintain stability, the penalty function of designing Equation (20) is designed to modify the equivalent factor after matching, so obtain the optimal energy distribution under the driving style.

5. SIMULATION AND ANALYSIS

To verify the effectiveness of the proposed EMS, the proposed EMS is compared with the ECMS without considering the impact of driving style by the MATLAB/Simulink. The vehicle simulation model is established in Simulink, as shown in Fig. 8.

The verification is based on a compound driving condition involving Highway Fuel Economy Test (HWFET) driving cycle and Urban Dynamometer Driving Schedule (UDDS) driving cycle given in Fig. 9.

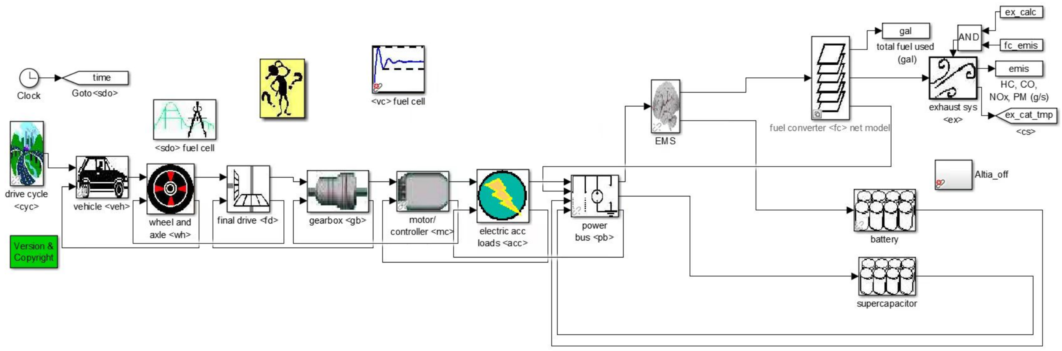

Fig. 8. The simulation model of FCHEV.

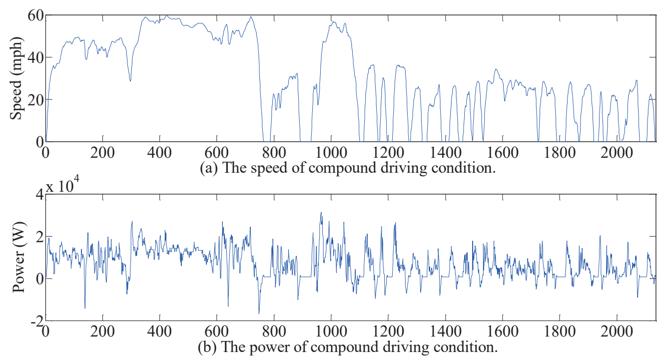

Fig. 9. The data of the driving condition.

The recognition results of the driving styles are shown in Fig. 10. In Fig. 10(1)-(5) respectively indicate eco, safe, soft, norm and fast driving styles. In this driving condition, most of the driving styles belong to safe and soft driving styles.

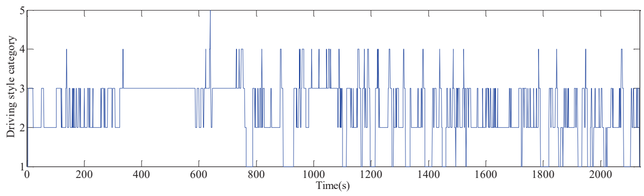

Fig. 10. Driving style recognition results of the compound driving cycle.

Fig. 11 shows the power distribution of FC, BA and SC in EMS based on driving style identification under compound driving conditions. For Fig. 11(a), as the main energy source among the three energy sources, the output power of the FC is always maintained in the range of 4.5-20 kW, providing a continuous and stable output power for the vehicle. From Fig. 11(b), the output power of the BAT is mostly kept in the range of (-10)-12 kW, which not only reflects the stability of the battery to the power output, but also helps to prolong the service life of the battery. Furthermore, as shown in Fig. 11(c), the output power of the SC is mainly in the range of (-5)-10kW, which reflects its advantages of providing transient high power.

Fig. 12 shows the sum of the output power of the three energy sources is almost the same as the required power

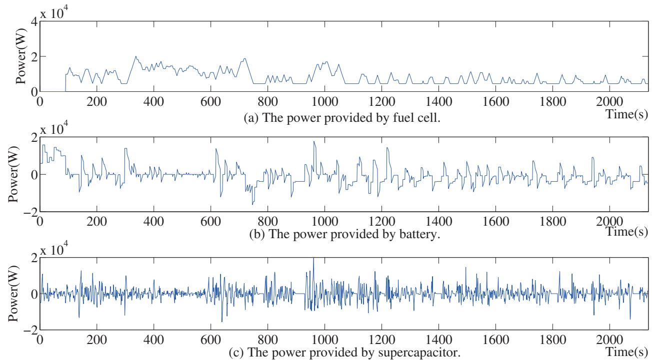

Fig. 11. The power provided by three sources.

of the vehicle, indicating that the power provided by the three energy sources can satisfy the required power of the vehicle. From Fig. 13, it is evident that the error between original power and real-time power maintain power fluctuations around 2200 samples between -20 and 0. It is nothing that the power provided by the three energy sources is greater than the power required by the vehicle due to energy loss by DC/DC converter.

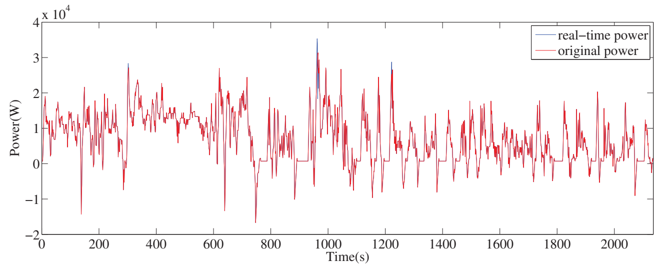

Fig. 12. Comparison diagram of three energy sources output power and vehicle demand power.

From Figs. 14-15, it is reasonably seen that there are some apparent differences between EMS-considering driving style and EMS-without considering driving style. And as shown in Fig. 14, the battery SOC curves under the two strategies are consistent in the first 90 seconds. This is because fuel cells has not started, with only the battery and ultracapacitors providing power for the first 90 seconds. After 90 seconds, the battery SOC curves under both strategies began to change. In the former strategy, it is obvious that the values of battery SOC is only varying in the range from 0.66 to 0.72, which play an important

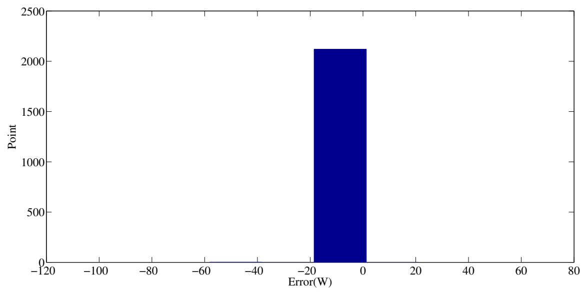

Fig. 13. The error between the three energy sources output power and the vehicle power demand.

role in improving battery economy and prolonging battery lifespan for FCHEV. In the latter strategy, battery SOC mainly varies from 0.6 to 0.66, with a large difference from the initial value of 0.7, which verify the stability of battery SOC of EMS-considering driving style. The battery SOC range of the two strategies is shown in Fig. 15. It is very evident that the SOC range of EMS-considering driving style is mainly between 0.64 and 0.72, while the SOC range of the EMS-without considering driving style is mostly between 0.6 and 0.66.

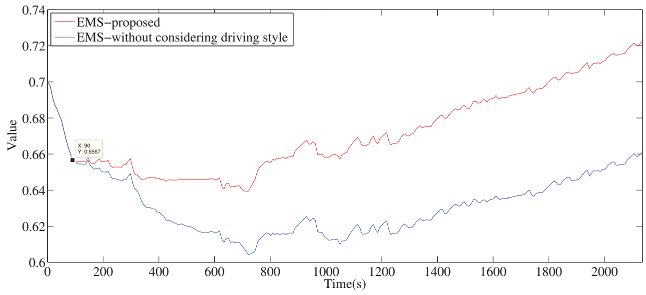

Fig. 14. The comparison of battery SOC via two EMSs.

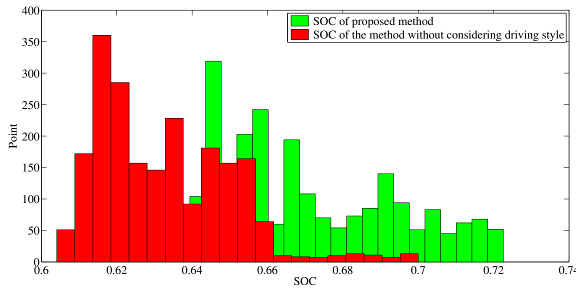

Fig. 15. The SOC range of the two strategies.

The power fluctuation of two energy sources of different optimization methods is listed and compared in Fig. 16 to show that EMS-considering driving style maintain power fluctuations around 1500 samples at 0 points, which have lower overall power fluctuations and verify the superiority of proposed strategy. From Fig. 16(a), under the constraint of battery charge-discharge gradient in Equations (5-11), most of the power fluctuation of the battery is near 100W/s, which effectively reduces the battery fluctuation and prolongs the service life of the battery. From Fig. 16(b), the fluctuation of fuel cell also decreases correspondingly, which not only benefits from the constraints of Equations (5-11), but also is assisted by BAT and SC.

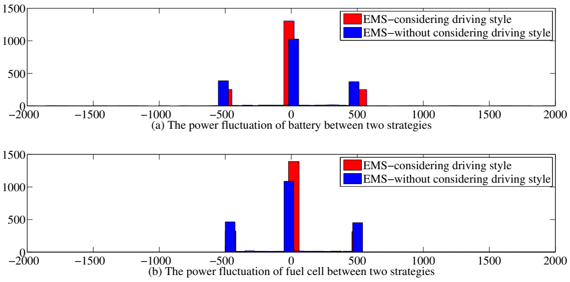

Fig. 16. The power fluctuation of energy sources between two strategies.

The ultimate goal of EMS based on driving style is to design corresponding energy management strategy according to driver's driving style to achieve the purpose of minimizing fuel consumption. To verify the effectiveness of EMS considering driving style in reducing hydrogen consumption, the EMS based on ECMS, fuzzy logic control (Tao et al., 2020) and model predictive control (Fu et al., 2020) are selected as the baseline strategy, where all three strategies don?t consider the driving style. Then the hydrogen consumption under four methods are list in Table 7. As can be seen from Table 7, under the HWFET and UDDS combined compound driving conditions, the hydrogen consumption of the proposed strategy reduced by about 3.7%, 4.92%, 3.85% compared with the EMS based on ECMS, fuzzy logic control and model predictive control, respectively.

6. CONCLUSION

In this paper, an EMS for FCHEV based on driving style recognition is proposed. Firstly, the speed and the absolute values of acceleration are selected as driving style identification parameters by principal component analysis method and fuzzy logic controller is designed to classify and recognize driving style. Considering the accuracy of recognition, the membership function of fuzzy logic controller is optimized by GA, and the optimized results is used to update fuzzy logic rules, so as to use the new fuzzy logic controller to reclassify and recognize the driving style. In the above-mentioned driving style recognition, the optimal equivalent factors under each driving style are obtained by weighted average, according to the relationship of driving style factors and the equivalent factor establish the query table of equivalent factor. The accuracy of classification results was verified by the combination of HWFET and UDDS. Simulation results confirm that, compared with the strategy without considering driving style, the proposed driving-style-aware EMS using ECMS can reduces the hydrogen consumption of FCHEV by about 3.7%.

Although the optimization result of membership function of fuzzy logic controller by using GA is outstanding, the searching ability of GA for optimal solution in new space is limited and cannot be optimized in real time. Therefore, in the future work, the optimization method based on intelligent algorithm (such as DDPG) is proposed to real-time optimize the parameters of fuzzy logic controller.

Table 7. The hydrogen consumption under two strategies.

Strategy	Hydrogen consumption(gal)	improvement
The proposed strategy	3.0618	-
The ECMS based EMS	3.1795	3.7%
The fuzzy logic control based EMS	3.2204	4.92%
The model predictive control based EMS	3.1845	3.85%

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