Research on Energy Management Strategy of Fuel Cell Buses In and Out of Bus Stop Based on Speed Optimization

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Abstract. As a typical scenario in bus driving, buses entering and leaving stations without speed planning will lead to high energy consumption problems such as frequent start and stop. This research suggests a predictive energy management strategy (EMS) for fuel cell (FC) hybrid electric buses based on speed optimization to lower energy consumption of speed variation while taking into account the features of the vehicle as it enters and leaves bus stops. In the distance of 100 m before and after the bus enters and leaves the bus stop, the speed optimization method based on dynamic programming considers the speed and travel time of the controlled vehicle based on the space step. The results of the simulation demonstrate that the proposed model predictive control (MPC) energy management method, which is based on speed optimization, can maintain the battery's operational status and follow the need for power. At the same time, the proposed strategy can greatly reduce the fluctuation of the FC working range. And compared with the MPC strategy without speed optimization, the energy consumption is reduced by 26.47%.

Keywords: Electric buses · Fuel cell hybrid power system · Speed optimization · Energy management

1 Introduction

The FC is a future development path for new energy vehicles with the advantages of zero emissions and zero pollution [1]. Furthermore, a fuel cell hybrid electric vehicle (FCHEV) has the characteristics of a fuel cell and battery [2]. Therefore, improving energy management is very important for FCHEVs [3].

Currently, Rule-based and optimization-based strategies are the two primary categories of EMSs [1]. The rule-based strategy is relatively simple and has a small amount of calculation [4]. However, the rule-based strategy has the disadvantage of poor adaptability and cannot get a good vehicle energy-saving effect under changeable working conditions [5, 6].

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The energy management strategy based on optimization has strong adaptability and can improve the energy-saving effect of vehicles [7, 8]. Based on double-loop dynamic programming, Hou suggested an approach for managing and optimising battery size. The results show that dynamic programming (DP) provides more accurate results [9]. Yangzhou has studied a new energy management strategy based on MPC, which can save more than 3.79% of hydrogen consumption [10]. Although the MPC-based control strategy cannot provide the ideal global solution, it can forecast future working conditions and requires less computation than the dynamic programming technique [11, 12].

In recent years, many scholars have combined the external traffic information of vehicles with energy management, carried out speed planning for different vehicle operating conditions, and put forward targeted energy management [13, 14]. Guo Jinquan suggested an intersection speed planning-based real-time energy management technique for fuel cell electric hybrid buses, which reduces hydrogen consumption by 3.04% when compared to the previous strategy [15]. The fuel cell electric hybrid bus (FCHEB), as a widely used type of fuel cell system, has its unique traffic mode. As a unique working condition of FCHEB, inbound and outbound stations account for a large proportion of the process of FCHEB operation, so the energy management of FCHEB in this situation is essential.

The fuel cell hybrid power system and the vehicle longitudinal dynamics model are established in this work using an FCHEB as the research object. The traffic network at the bus station is constructed using intelligent traffic simulation software to replicate the real-world traffic scenario. According to the simulation data provided by the traffic simulation software, the speed planning is carried out within the range of 100 m before and after the bus station. And then, to boost the economy, energy management based on MPC is implemented. The technical framework of this article is shown in Fig. 1.

2 Construction of Traffic Simulation Environment

This paper uses SUMO to construct a traffic simulation environment, which can quickly build a traffic network and design vehicles and traffic flow in the road network [16]. This study focuses on the energy management within 100 m before and after the bus station entry and exit. Still, the working condition of an entry and exit station is too simple. Therefore, this paper studies the scene conditions of 10 times bus entering and leaving the station and establishes a ring road network. By controlling the controlled vehicles to extend the cycle of the ring road network, the traffic information of the bus entering and leaving the station ten times is obtained, and only the traffic information within the range of 100 m before and after the bus stop is extracted. The vehicle information in the simulation environment is shown in Table 1.

3 FCHEB Model

This section details the modeling process of FCHEB. The configuration information of FCHEB is shown in Table 2.

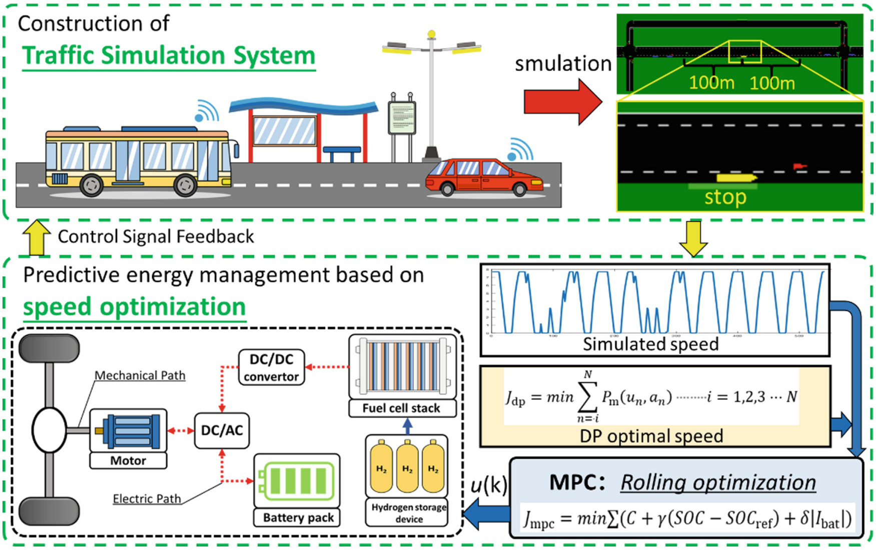

Fig. 1. Energy Management Strategy of fuel Cell buses in and out of station based on Speed Optimization.

Table 1. Vehicle types and their corresponding period and car-following models.

Vehicle type	Period	Following model
Bus	80	Krauss
Passenger	30 and 40	Krauss
Truck	50	Krauss

3.1 Drive Motor Model

According to the principle of vehicle dynamics, the drive model of motor is established as Eqs. (1)–(3), where the influence of slope resistance is ignored.

$$n_g = 60u/R/i/2\pi \tag{1}$$

$$T_m = R(mgf_d + AC_d u^2/21.15 + ma)/i \tag{2}$$

$$P_m = \begin{cases} T_m n_g 2\pi/60/\eta_m, T_m \geq 0 \\ \eta_m T_m n_g 2\pi/60, T_m < 0 \end{cases} \tag{3}$$

where, n_g is the drive motor speed, T_m is the motor torque, P_m is the motor power, u is the speed of FCHEB, a is the acceleration of FCHEB, η_m is the motor efficiency.

Table 2. Parameter of FCHEB power system.

Component	Parameter	Value
FCHEB mass/(m)	kg	13500
Rolling resistance coefficient/(f_d)	–	0.0085
Wheel rolling radius/(R)	m	0.4671
Equivalent windward area/(A)	m^2	8.16
Air drag coefficient/(C_d)	–	0.55
Total transmission ratio/(i)	–	6.2
FC engine rated output power	Kw	60
Battery capacity	Ah	176
Motor peak power	Kw	200

3.2 Fuel Cell Hybrid Power System Model

This paper uses the data-driven modelling method because the data-driven approach can reduce computational costs and model errors [17]. Using test data, create a look-up table model for the FC stack and DC/DC. The battery system is modelled using the Rint equivalent current model [18], and the battery power is expressed as Eqs. (4)–(9).

$$P_{\text{bat}} = P_{\text{m}} - P_{\text{fc}}\eta_{\text{DC/DC}} \tag{4}$$

$$I_{\text{bat}} = \left(V_{\text{oc}} - \text{sqrt}\left(V_{\text{OC}}^2 - 4R_{\text{int}}P_{\text{bat}}\right)\right)/2/R_{\text{int}} \tag{5}$$

$$U_{\text{bat}} = V_{\text{OC}} - P_{\text{bat\_req}}R_{\text{int}}/10 \tag{6}$$

$$P_{\text{bat}} = I_{\text{bat}} \times U_{\text{bat}} \tag{7}$$

$$\Delta SOC = \left(V_{\text{oc}} - \text{sqrt}\left(V_{\text{OC}}^2 - 4R_{\text{int}}P_{\text{bat}}\right)\right)/2/R_{\text{int}}/Q_{\text{bat}} \tag{8}$$

$$C_{\text{bat}} = \begin{cases} \alpha P_{\text{bat}}, P_{\text{bat}} \geq 0 \\ \beta P_{\text{bat}}, P_{\text{bat}} < 0 \end{cases} \tag{9}$$

where, I_{bat} is the circuit current, V_{oc} is the open circuit voltage, R_{int} is the internal resistance, P_{bat} is the battery output power, P_{fc} is the fuel cell stack output power, $\eta_{DC/DC}$ is the DC/DC efficiency, U_{bat} is the battery voltage, ΔSOC is the change of the SOC, Q_{bat} is the battery capacity, C_{bat} is the battery equivalent hydrogen consumption, α and β are the weight parameters after the test, respectively.

Fuel cell hydrogen consumption and battery equivalent hydrogen consumption are used to calculate the overall hydrogen consumption, such as Eq. (10).

$$C_{\text{all}} = C_{\text{fc}} + C_{\text{bat}} \tag{10}$$

4 Energy Management of FCHEB with Optimized Speed

4.1 Speed Optimization Based on DP

Speed planning is carried out for the distance range of 100 m before and after the bus stop, and an optimal speed sequence is planned by using DP. It is worth noting that, different from the previous speed planning, the space-based method is used to design the speed. The disturbance of the speed planning system is the distance, that is, the spread of the cycle composed of ten "one hundred meters before and after the bus stop", and the total length is 2000 m. The vehicle's acceleration serves as the control quantity, while the speed and time serve as the state quantity. The speed planning algorithm aims to reduce energy consumption as much as possible when ensuring a distance of 100 m before and after a certain speed passes through the bus station. It is clear from the energy consumption calculation formula in Sect. 3 that the overall energy consumption is influenced by the power of the power system. Here, the energy consumption is substituted by a reduction in total power consumption, preventing the calculation error brought on by the model's complexity. The objective function is shown in Eq. (11).

$$J_{\mathrm{dp}} = min\sum_{n=i}^{N} P_{\mathrm{m}}(u_n, a_n) i = 1, 2, 3 \cdots N \tag{11}$$

where, n is the simulation step, N is the whole simulation duration.

The physical constraints of the DP speed optimization system are shown in Eq. (12).

$$\begin{cases} u_{\min} \le u \le u_{\max} \\ a_{\min} \le a \le a_{\max} \\ u(n+1) = \sqrt{2na(k) + u^2(k)} \end{cases} \tag{12}$$

4.2 Energy Management Based on MPC

This section will implement the energy management of the FCHEB power system. A proposed predictive energy management system based on MPC takes the speed sequence that DP planned as the reference trajectory. The energy consumption is optimised by using the battery SOC and FC power as state variables, the fuel cell change rate as the control quantity, the disturbance as the speed and acceleration, and the power distribution. In addition, to prevent the power battery from being charged all the time, the SOC of the battery has been maintained at a higher position which is not conducive to energy efficiency. And to prevent the battery current from being too large, SOC and current are added to the cost function, which is shown in Eq. (13).

$$J_{\mathrm{mpc}} = min\sum (C_{\mathrm{all}} + \gamma(SOC - SOC_{\mathrm{ref}}) + \delta|I_{\mathrm{bat}}|) \tag{13}$$

where, SOC_{ref} is the reference SOC, γ and δ are weight coefficients, respectively.

The physical constraints of power system energy management are shown in Eq. (14).

$$\text{Motor}\begin{cases} P_{\mathrm{m\_min}} \le P_{\mathrm{m}} \le P_{\mathrm{m\_max}} \\ T_{\mathrm{m\_min}} \le T_{\mathrm{m}} \le T_{\mathrm{m\_max}} \end{cases}$$

$$\text{Fuel Cell}\begin{cases} P_{fc}(k+1) = P_{fc}(k) + \Delta P_{fc}(k) \\ 0 < P_{fc.min} \le P_{fc} \le P_{fc.max} \end{cases} \tag{14}$$

$$\text{Battery}\begin{cases} P_{bat.min} \le P_{bat} \le P_{bat.max} \\ SOC_{min} \le SOC \le SOC_{max} \end{cases}$$

5 Simulation Results and Discussions

The proposed EMS is simulated and verified in this section based on the Matlab & SUMO co-simulation platform. The space-based velocity trajectory planned by DP is transformed into a time-step-based velocity trajectory, as shown in Fig. 2. Since the maximum power consumption is limited, and the designed working condition is that the distance between two bus stops is only 200m, so the speed is not high. The bottom of the curve is the average speed of the simulated bus when it stops at the bus stop.

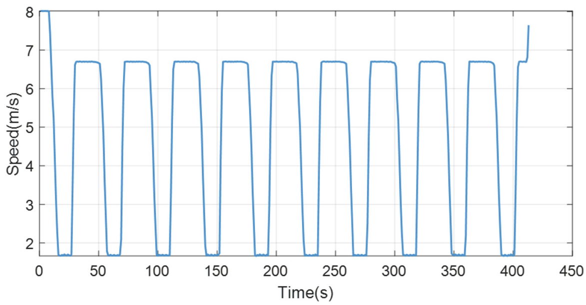

Fig. 2. DP-based speed planning curve.

According to Fig. 3, which shows that the suggested MPC strategy based on speed optimization almost matches the SOC trajectory based on the DP approach, battery power is consumed, which is consistent with the functional characteristics of FCHEB. Additionally, the proposed strategy's SOC trajectory fluctuates more, which is more in keeping with the actual working circumstances. Contrarily, the simulation duration is longer and the SOC curve decreases slowly for the MPC method without speed planning, showing the suggested strategy's quick reaction to changes in operating conditions.

Table 3 compares the energy consumption of the proposed speed-optimized MPC strategy, the MPC strategy without speed optimization, and the strategy based on DP. The energy consumption of MPC strategy based on speed optimization is close to that of DP and slightly higher than that of DP. In contrast, the energy consumption of MPC without speed optimization is higher due to the influence of SUMO simulation software and 26.47% higher energy consumption than the proposed strategy.

The power following situation of the proposed EMS is shown in Fig. 4. P_m is satisfied by both P_{fc} and P_{bat}. Due to the control of the FC change rate by the MPC strategy, the FC constantly fluctuates in a minimal range, which is in line with the fact that the FC

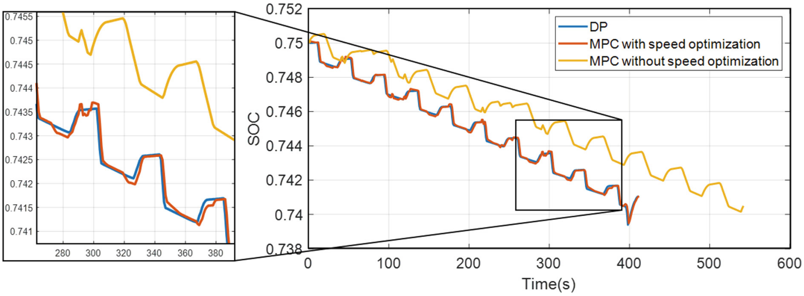

Fig. 3. The FCHEB SOC change curve.

cannot change back and forth in the extensive power range. Furthermore, since the SOC is high and the demand power is not high, the FC always works around a small value and charges the battery, which is in line with the characteristic that FCHEB does not need to charge the battery.

Table 3. Consumption of hydrogen under different strategies

EMSs	Hydrogen consumption	Compared with DP
DP	6.67311 (kg/100 km)	–
MPC with optimized speed	6.8213 (kg/100 km)	+2.22%
MPC without optimized speed	8.6272 (kg/100 km)	+29.28%

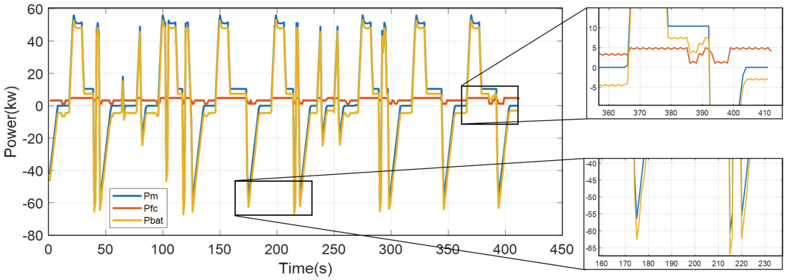

Fig. 4. The power following the situation of the proposed EMS.

6 Conclusion

This study addresses the bus in and out of the station through energy management optimization, and a hierarchical predictive EMS based on speed optimization is proposed. Based on time and speed, an optimal speed sequence is planned on the spatial step based on the DP planning algorithm as the reference trajectory of the following energy management, and MPC method is utilised for energy management in the lower level. Simulation is utilised to confirm the viability of the suggested control strategy, and it results in a 26.47% reduction in energy consumption when compared to the EMS without speed optimization.

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