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Article

Fuzzy Adaptive Filtering-Based Energy Management for Hybrid Energy Storage System

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Abstract: Regarding the problem of the short driving distance of pure electric vehicles, a battery, super-capacitor, and DC/DC converter are combined to form a hybrid energy storage system (HESS). A fuzzy adaptive filtering-based energy management strategy (FAFBEMS) is proposed to allocate the required power of the vehicle. Firstly, the state of charge (SOC) of the super-capacitor is limited according to the driving/braking mode of the vehicle to ensure that it is in a suitable working state, and fuzzy rules are designed to adaptively adjust the filtering time constant, to realize reasonable power allocation. Then, the positive and negative power are determined, and the average power of driving/braking is calculated so as to limit the power amplitude to protect the battery. To verify the proposed FAFBEMS strategy for HESS, simulations are performed under the UDDS (Urban Dynamometer Driving Schedule) driving cycle. The results show that the FAFBEMS strategy can effectively reduce the current amplitude of the battery, and the final SOC of the battery and super-capacitor is optimized to varying degrees. The energy consumption is 7.8% less than that of the rule-based energy management strategy, 10.9% less than that of the fuzzy control energy management strategy, and 13.1% less than that of the filtering-based energy management strategy, which verifies the effectiveness of the FAFBEMS strategy.

Keywords: Hybrid energy storage system; energy management; fuzzy adaptive filtering; electric vehicle

1 Introduction

With the depletion of petroleum resources and increasingly serious pollution problems, electric vehicles have become an important alternative in the development of the vehicle industry, with the advantages of energy conservation and environmental protection. However, the development of electric vehicles is limited by the low power density and short cycle life of the battery [1–3]. To solve these problems, a new energy storage component, the super-capacitor, with the advantages of high power density and a long cycle life, is used as an auxiliary power source [4,5]. The hybrid energy storage system composed of a battery, super-capacitor, and DC/DC converter can effectively improve the power performance and driving distance of electric vehicles [6,7].

Research on HESS presently addresses the aspects of energy storage type selection and parameter matching, converter topology control strategy, and energy management strategy for power allocation. In Jung et al. [8], an advanced topology of the vehicle-mounted hybrid energy storage system is proposed, which provides a new idea for the energy management of HESS. In Rui et al. [9], four structures of the hybrid energy storage system were analyzed, and a real-time energy management strategy based on a deep learning algorithm was proposed, to minimize energy loss. However, the required calculation was too extensive. In Zhang et al. [10], a neural network-based methodology for power demand prediction and a power distribution strategy was proposed to reduce the cost of HESS. However, the neural network model requires a large amount of raw data as samples. In Golchoubian et al. [11], a nonlinear model predictive control method was presented as an energy management strategy of HESS to optimizes its performance. However, this method requires high model accuracy. In Choi et al. [12], an optimal energy management strategy based on the multiplicative-increase additive-decrease principle was presented, and a feasible optimal solution was obtained. However, the calculation process of this method was too complex. In Chen et al. [13], particle swarm optimization (PSO) was used to determine the optimal power allocation and reduce energy loss during the driving process. However, the PSO algorithm easily fell into a local optimal solution and did not obtain the optimal allocation result. In addition, rule-based [14], filtering-based [15], and fuzzy control [16] energy management strategy, as well as Pontryagin's Minimum Principle method [17] have been used to manage the energy of HESS.

This paper proposes a fuzzy adaptive filtering-based energy management strategy (FAFBEMS) to allocate the required power of a vehicle. Firstly, the SOC of the super-capacitor is limited according to the driving/braking mode of the vehicle to ensure that it is in a suitable working state, and fuzzy rules are designed to adaptively adjust the filtering time constant so that the power allocation over driving is more reasonable. Then, the positive and negative power are determined, and the average power of driving/braking is calculated such that the power amplitude is limited to protect the battery. The vehicle model with the FAFBEMS strategy is built in the Advanced Vehicle Simulator (ADVISOR), and the performance is compared to that of several energy management strategies. The simulation results show that the total energy consumption of the pure battery is lowest over the actual driving cycle, but the required power of the vehicle is provided by the battery, and the high-amplitude current can cause irreversible damage to the battery. Compared with the rule-based, fuzzy control, and filtering-based energy management strategies, the FAFBEMS strategy has better performance in terms of protecting the battery and reducing energy consumption.

The remainder of this paper is organized as follows: In Section 2, the system model is introduced. The design of the FAFBEMS strategy is presented in Section 3. In Section 4, the FAFBEMS strategy is simulated over the UDDS driving cycle. In the end, the conclusions are presented in section 5.

2 System Model

2.1 Structure of the HESS

There are four conventional structures of HESS as shown in Fig. 1. In Fig. 1a, the battery and the super-capacitor are directly connected to the DC bus in parallel, which has the advantages of a simple structure and low cost, but the current of the battery and super-capacitor cannot be controlled precisely. In Fig. 1b, the battery is connected in series with a DC/DC converter, and then connected to the DC bus in parallel with the super-capacitor. This structure can only control the current of the battery, and cannot effectively play the role of the super-capacitor. In Fig. 1c, the super-capacitor is connected in series with the DC/DC converter, and connected to the DC bus in parallel with the battery. This structure makes full use of the high energy density of the battery, which can maintain the stability of the bus voltage, and at the same time, the voltage range of the super-capacitor is increased by the series DC/DC converter. In Fig. 1d, the battery and the super-capacitor are connected in series with the DC/DC converter, and then connected to the DC bus in parallel. This structure requires separate control of the battery and the super-capacitor, which has a high cost, and the control strategy is complex. The structure in Fig. 1c is selected in this paper. The battery is used as the main power source to provide the average power to the load, and the super-capacitor is used as an auxiliary energy source to provide the peak power and recover the braking energy.

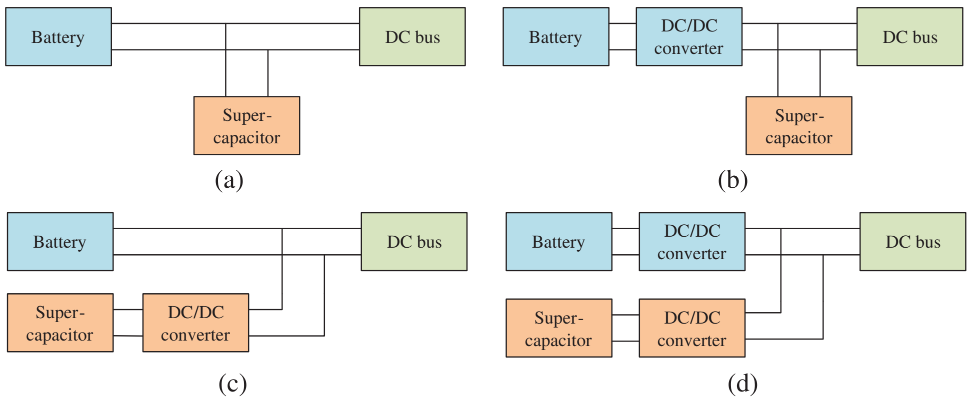

Figure 1: Four conventional structures of HESS

2.2 The Longitudinal Dynamic Model of the Vehicle

According to the principles of vehicle dynamics, the required power P_{req} at a certain speed can be calculated by the longitudinal dynamic model of the vehicle [18]:

$$P_{\mathrm{req}} = \frac{1}{3600\eta}\left(\delta m\frac{\mathrm{d}v}{\mathrm{d}t} + \frac{C_{\mathrm{a}}A}{21.15}v^2 + mgf\cos(\theta) + mg\sin(\theta)\right)v \tag{1}$$

where η represents the efficiency of the transmission system, v represents the speed of the vehicle, δ represents the conversion ratio of the vehicle rolling mass, m represents the curb weight, C_{a} represents the air drag coefficient, A represents the fronted area, g represents gravitational acceleration, f represents the rolling resistance coefficient, and θ represents the slope of the road.

In this paper, the parameters of the vehicle model used are shown in Tab. 1. For simplicity, the road slope is set to be zero. According to the parameters in Tab. 1 and Eq. (1), the required power of the UDDS driving cycle (see Fig. 2a) can be obtained as shown in Fig. 2b.

Table 1: Parameters of vehicle model

Parameters	Value
Air drag coefficient C_{a}	0.36
Transmission system efficiency η	0.9
Rolling resistance coefficient f	0.012
Frontal Area A (m^2)	2.12
Curb weight m (kg)	1500
Motor power (kW)	75

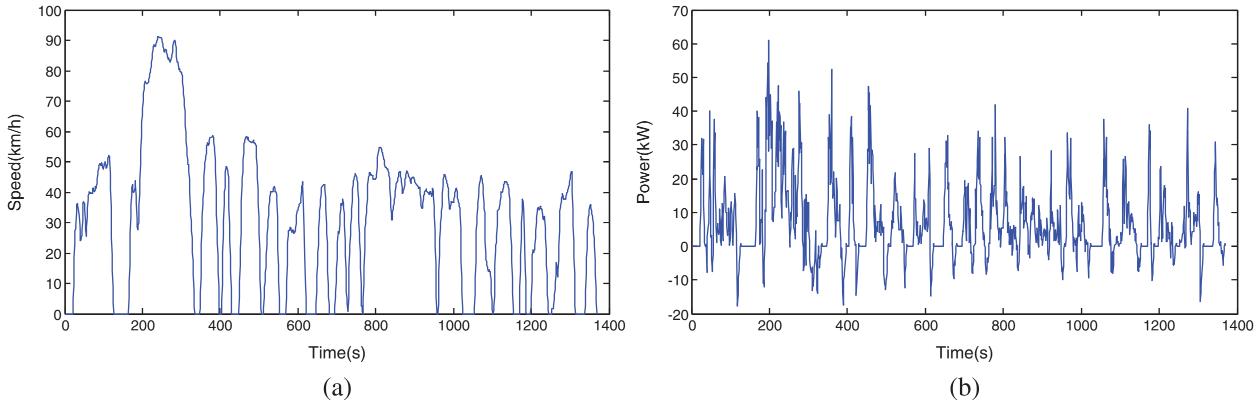

Figure 2: (a) The UDDS driving cycle. (b) The required power for UDDS driving cycle

2.3 The Model of the Battery and Super-Capacitor

The model of the battery is shown in Fig. 3a, which is composed of an open circuit voltage source E_{bat} and an equivalent series resistance R_{bat}. The model of the super-capacitor is shown in Fig. 3b, which is composed of an ideal capacitor C and an equivalent series resistance R_{sc}. The terminal voltage of the battery and the super-capacitor can be calculated as follows:

$$\begin{cases} \dot{V}_{bat} = E_{bat} - i_{bat} \cdot R_{bat} \\ \dot{V}_{sc} = E_{sc} - i_{sc} \cdot R_{sc} \end{cases} \tag{2}$$

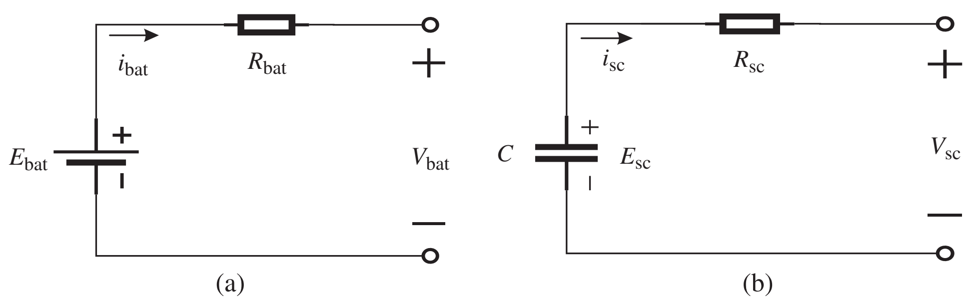

Figure 3: (a) Model of the battery. (b) Model of the super-capacitor

2.4 The Model of the DC/DC Converter

In the research on energy management strategies, the transfer efficiency of the DC/DC converter is mainly considered, which is related to the input voltage, output voltage, and input power. In the selected HESS structure, the DC/DC converter is connected in series with the super-capacitor and then connected in parallel with the battery. The input voltage of the DC/DC converter is the super-capacitor terminal voltage, the output voltage is the battery terminal voltage, and the input power is the power of the super-capacitor. Fig. 4 shows the transfer efficiency curves of the DC/DC converter under different voltage ratios. The transfer efficiency model of the DC/DC converter can be established by two-dimensional table interpolation.

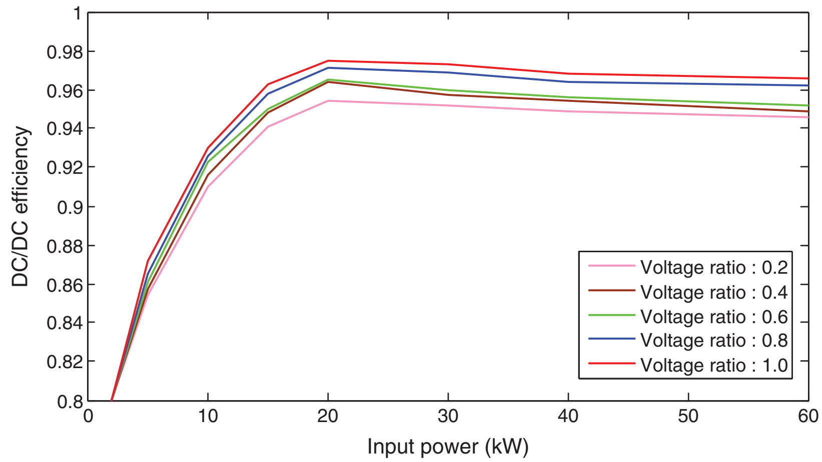

Figure 4: Efficiency curves of DC/DC converter

3 Energy Management Strategy

The role of an energy management strategy is to reasonably allocate the required power between the battery and the super-capacitor, to protect the battery, and reduce energy loss. This section introduces the proposed fuzzy adaptive filtering-based energy management strategy.

3.1 Filtering-Based Energy Management Strategy

The filtering-based energy management strategy is shown in Fig. 5 [19], which divides the required power into two parts: low-frequency power and high-frequency power. The low-frequency power is obtained by filtering the required power with a low-pass filter, which is mainly provided by the battery and the remaining high-frequency power is provided by the super-capacitor, which can give full play to the characteristics of the super-capacitor with high power density, and avoid the damage of high amplitude current to the battery. The low-pass filtering function is expressed by Eq. (3), where τ is the filtering time constant.

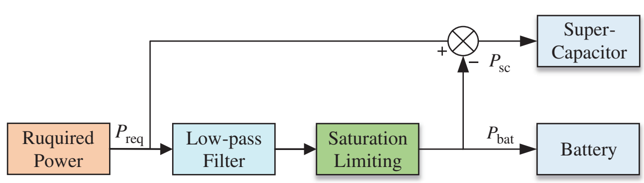

Figure 5: Structure of the filtering-based energy management strategy

$$f(s) = \frac{1}{1 + \tau s} \tag{3}$$

Thus, the power of the battery P_{bat} and the power of the super-capacitor P_{sc} can be obtained as follows:

$$P_{bat} = P_{req} \frac{1}{1 + \tau s} \tag{4}$$

$$P_{sc} = P_{req}(1 - \frac{1}{1 + \tau s}) \quad (5)$$

3.2 Fuzzy Adaptive Filtering-Based Energy Management Strategy

In the above-mentioned filtering-based energy management strategy, does not consider the charging and discharging states of the HESS, the filtering time constant τ is fixed, and cannot be adjusted according to the working state of the HESS, and its adaptability is poor. Therefore, a fuzzy adaptive filtering-based energy management strategy is proposed, which comprehensively considers the required power P_{req}, the state of charge SOC_{bat} of the battery, and the state of charge SOC_{sc} of the super-capacitor. The structure of the FAFBEMS is shown in Fig. 6.

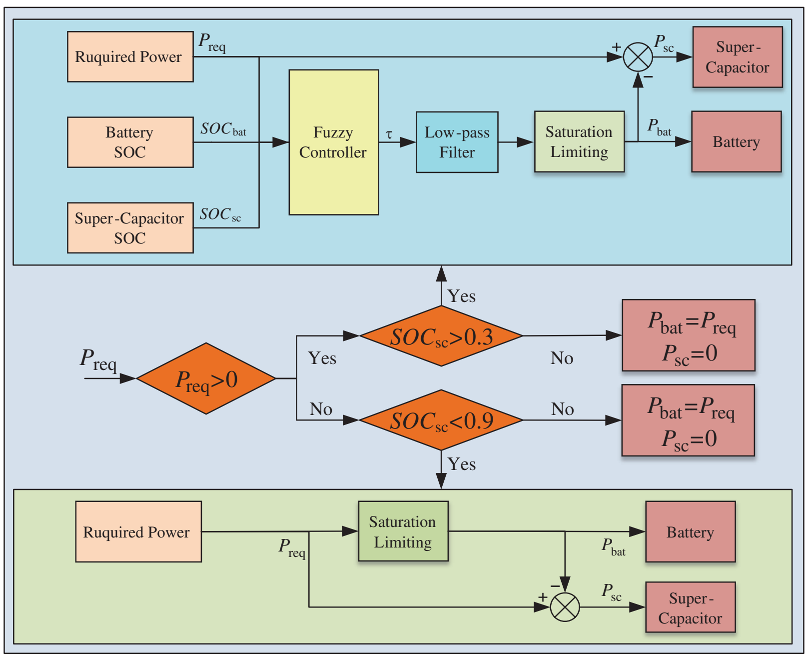

Figure 6: Structure of FAFBEMS

Firstly, the SOC of the super-capacitor is limited according to the driving/braking mode of the vehicle to ensure that it is in a suitable working state, and the fuzzy rules are designed to adaptively adjust the filter time constant according to the change of P_{req}, SOC_{bat}, and SOC_{sc}, to make the power allocation more reasonable. Then, the positive and negative power are determined, and the average power of driving/braking is calculated such that the power amplitude is limited to protect the battery. The design is as follows.

***Situation* 1:** $P_{req} > 0$ (driving)

1. If $SOC_{sc} > 0.3$, then the required power P_{req} is allocated by the fuzzy adaptive filtering strategy;
2. If $SOC_{sc} < 0.3$, then the required power P_{req} is borne by the battery to avoid excessive discharge of the super-capacitor.

***Situation* 2:** $P_{req} < 0$ (braking)

1. If $SOC_{sc} > 0.9$, then the required power P_{req} is absorbed by the battery to avoid overcharging of the super-capacitor;

2. If $SOC_{sc} < 0.9$, then the required power P_{req} is limited. The battery absorbs the threshold power and the remaining power is absorbed by the super-capacitor.

3.2.1 Design of Fuzzy Rules

In this paper, the P_{req}, SOC_{bat}, and SOC_{sc} are selected as inputs of the fuzzy controller, and the filtering time constant τ is selected as the output of the fuzzy controller. According to the characteristics of the battery and the super-capacitor, the fuzzy domain of SOC_{bat} is set to [0.2,0.9], the fuzzy domain of SOC_{sc} is set to [0.3,0.9], and the fuzzy domain of P_{req} is set to [0,1]. It should be noted that the actual domain of P_{req} is [0, P_{max}], and the quantitative factor $K_p = 1/P_{max}$ is needed to change it from the actual domain to the fuzzy domain, where P_{max} is the maximum required power under the driving cycle. Fig. 7 shows the change of battery SOC with different values of the filter time constant τ over the UDDS driving cycle. It can be seen that the battery SOC decreases with the increase of τ, which means that the power of the battery increases with the increase of τ. Therefore, the fuzzy domain of τ is set to [0,10] to avoid excessive discharge power of the battery.

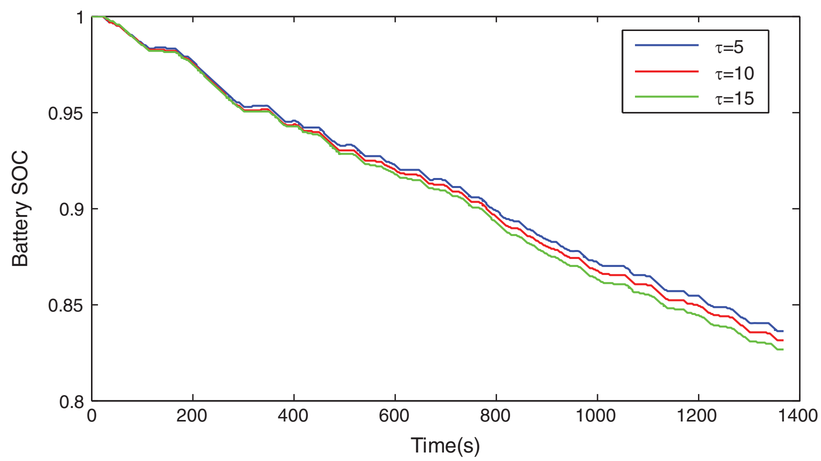

Figure 7: Curve of battery SOC under different time constants τ

Tab. 2 shows the fuzzy domain of fuzzy variables and their language values, where TS is too small, S is small, M is medium, B is large, and TB is too large. The membership function of the fuzzy variables is shown in Fig. 8. The Mamdani structure with three inputs and one output is adopted in the fuzzy controller. The designed fuzzy rules are listed in Tab. 3, and the relation of the inputs and output of the fuzzy controller is shown in Fig. 9.

Table 2: Language value of fuzzy variables

Variables	Fuzzy domain	Language values
P_{req}	[0,1]	TS, S, M, B, TB
SOC_{bat}	[0.2,0.9]	S, M, B
SOC_{sc}	[0.3,0.9]	TS, S, M, B
τ	[0,10]	TS, S, M, B, TB

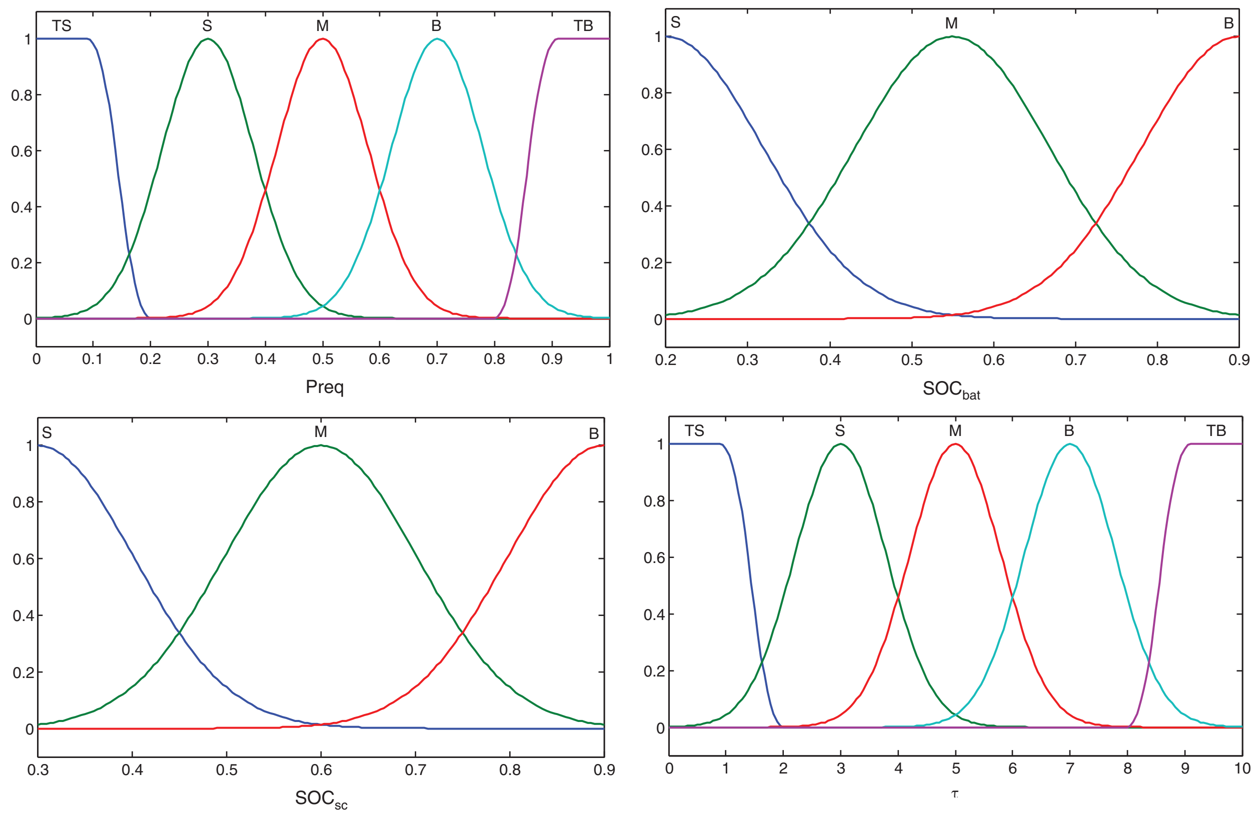

Figure 8: Membership function of fuzzy variables

Table 3: Fuzzy rules

τ		P_{req}				
		TS	S	M	B	TB
SOC_{bat} (SOC_{sc} = S)	S	TB	B	B	B	B
	M	TB	TB	TB	B	B
	B	TB	TB	TB	TB	B
SOC_{bat} (SOC_{sc} = M)	S	M	M	S	S	TS
	M	B	B	M	M	S
	B	B	B	M	M	M
SOC_{bat} (SOC_{sc} = B)	S	S	S	S	S	TS
	M	M	M	M	S	S
	B	B	B	M	M	S

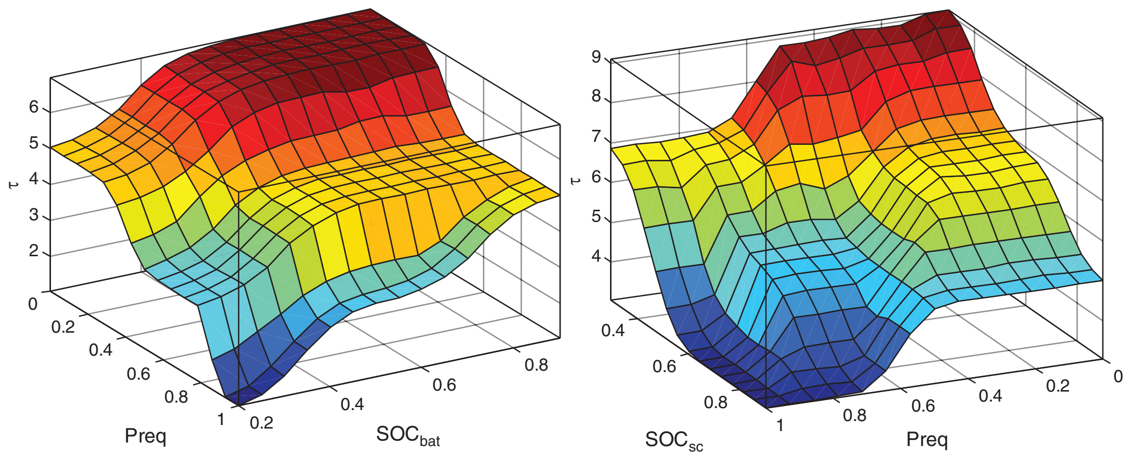

Figure 9: Relation of the inputs and output of the fuzzy controller

3.2.2 Design of Saturation Limiting

In this paper, the UDDS driving cycle is selected to simulate the proposed FAFBEMS strategy. According to the positive and negative statistics of the required power under the UDDS driving cycle in Fig. 2b, the corresponding total required power under driving and braking can be obtained. Then the average required power under driving and braking can be obtained by dividing the time of driving and braking. The results are shown in Tab. 4. The positive and negative average power obtained is the saturation limit threshold.

Table 4: Average power of UDDS

Mode	Time (s)	Total power (kW)	Average power (kW)
Driving	901	9341.67	10.37
Braking	227	–1211.06	–5.34

4 Simulation Results and Analysis

A vehicle model with the FAFBEMS strategy was built in ADVISOR, and simulated in the UDDS driving cycle shown in Fig. 2a. The parameters of the vehicle model are shown in Tab. 1, and the parameters of the HESS model are shown in Tab. 5. From Fig. 4, the interpolation table of the DC/DC converter efficiency is shown in Tab. 6.

4.1 Results

Fig. 10 shows the vehicle speed tracking curve over the FAFBEMS strategy. It can be seen that the actual vehicle speed tracks the expected vehicle speed very well, and there is almost no deviation, indicating that the FAFBEMS strategy can meet the vehicle's driving demand. Fig. 11 shows the power distribution results under the FAFBEMS strategy. It can be seen that the peak power is fully borne by the super-capacitor, which achieves the purpose of battery protection. Fig. 12 shows the battery and super-capacitor SOC change curves under the FAFBEMS strategy. It can be seen that the battery SOC changes relatively slowly and the super-capacitor SOC fluctuates greatly, indicating that most of the regenerative braking energy is recovered by the super-capacitor, which improves the energy utilization rate.

Table 5: Parameters of the HESS model

Component	Parameters	Value
Battery	Monomer Nominal voltage (V)	2.7
	Monomer Nominal capacity (A·h)	10
	Number of series monomer	80
	Number of parallel monomer	6
	Initial SOC	1
Super-capacitor	Monomer Nominal voltage (V)	2.7
	Monomer Nominal capacity (F)	9500
	Number of series monomer	100
	Number of parallel monomer	2
	Initial SOC	1

Table 6: Efficiency interpolation table of DC-DC converter

DC/DC converter efficiency		Power of super-capacitor (W)							
		2000	5000	10000	15000	20000	30000	40000	60000
Voltage Ratio $\frac{V_{bat}}{V_{sc}}$	0.2	0.8	0.854	0.910	0.941	0.954	0.952	0.949	0.946
	0.4	0.8	0.857	0.916	0.948	0.964	0.957	0.954	0.949
	0.6	0.8	0.861	0.923	0.950	0.965	0.960	0.956	0.952
	0.8	0.8	0.865	0.926	0.958	0.971	0.969	0.964	0.962
	1	0.8	0.872	0.930	0.963	0.975	0.973	0.968	0.966

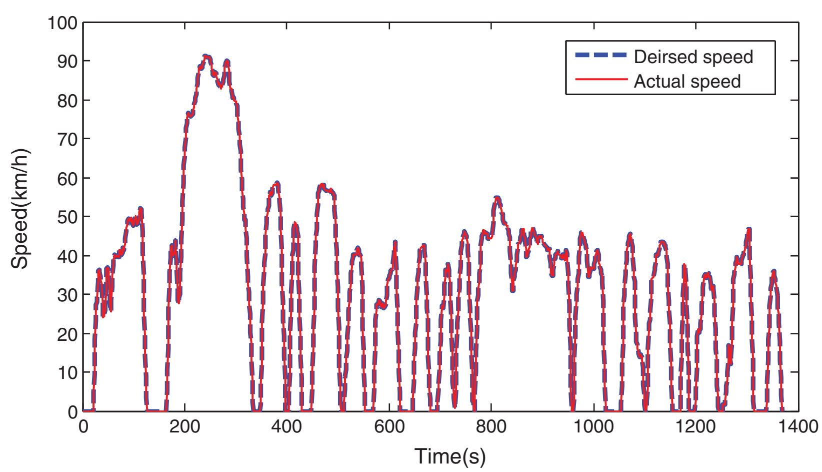

Figure 10: Vehicle speed tracking curve

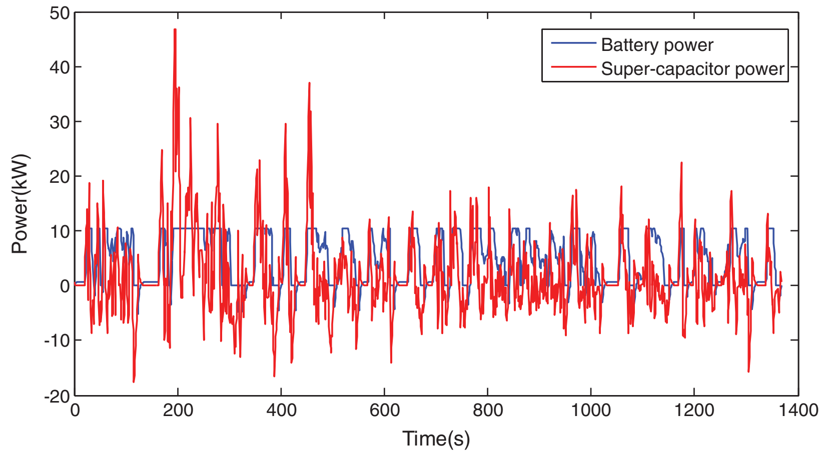

Figure 11: Power allocation results

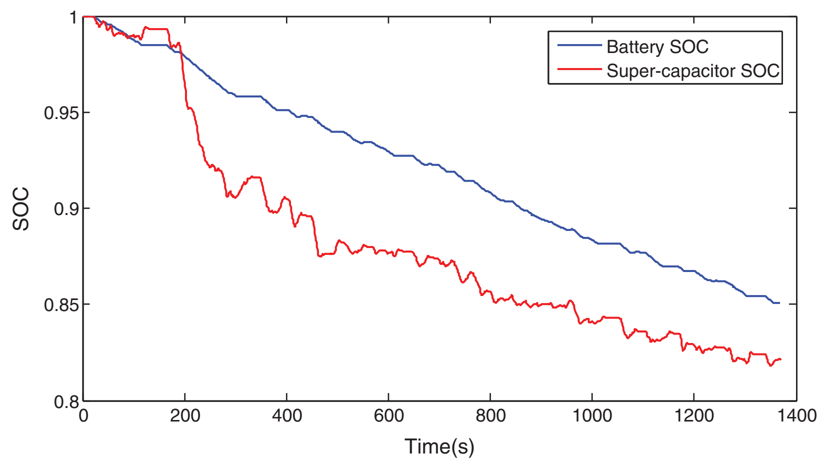

Figure 12: Battery and super-capacitor SOC change curves

4.2 Performance Comparison

To demonstrate the effectiveness of the FAFBEMS strategy, it is compared with the pure battery, as well as the rule-based, fuzzy control, and filtering-based energy management strategies over the UDDS driving cycle. Fig. 13 shows the change curve of the battery SOC, Fig. 14 shows the change curve of the super-capacitor SOC, and Fig. 15 shows the change curve of energy consumption. The remaining results are presented in Tab. 7.

It can be seen that although the energy consumption of the pure battery is the lowest, the SOC of the battery decreases the fastest, and the required power is provided by the battery, which causes irreversible damage to the battery due to the high-amplitude current. The final value of the battery SOC of the FAFBEMS strategy increases by 1.6% compared with the rule-based energy management strategy, decreases by 0.98% compared with the fuzzy control energy management strategy, and increases by 1.48% compared with the filtering-based energy management strategy. The final value of the super-capacitor SOC of the FAFBEMS strategy decreases by 3.66% compared with the rule-based energy management strategy, increases by 3.93% compared with the fuzzy control energy management strategy, and decreases by 3.29% compared with the filtering-based energy management strategy. The energy consumption of the FAFBEMS strategy decreases by 7.8% compared with the rule-based strategy, decreases by 10.9% compared with the fuzzy control strategy, and decreases by 13.1% compared with the filtering-based energy management strategy. The results show that the FAFBEMS strategy can distribute power between the battery and super-capacitor reasonably well, and reduces energy consumption. In addition, the maximum battery current of the FAFBEMS strategy is the smallest, which shows that it can reduce the damage to the battery caused by the high-amplitude current. The effectiveness of the FAFBEMS strategy has been verified.

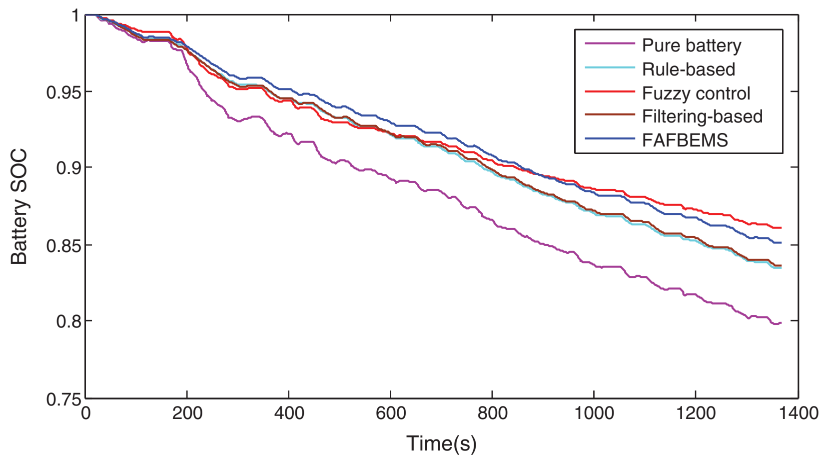

Figure 13: Change curve of battery SOC

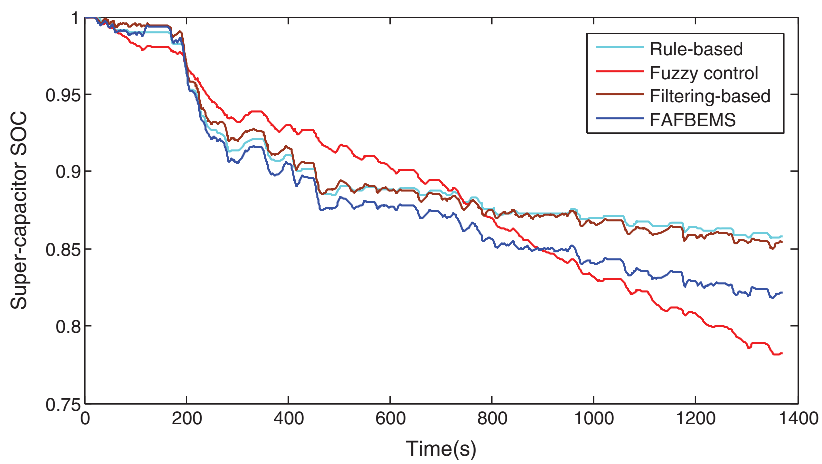

Figure 14: Change curve of super-capacitor SOC

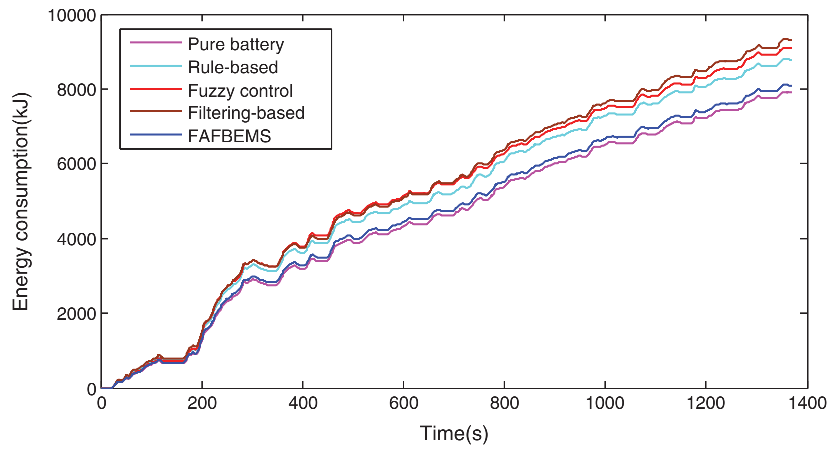

Figure 15: Change curve of energy consumption

Table 7: Simulation results

	Final battery SOC	Final super-capacitor SOC	Energy consumption (kJ)	Max battery current (A)
Pure battery	0.7986	N/A	7904.2	252.8
Rule-based	0.8349	0.8580	8773.8	61.4
Fuzzy control	0.8607	0.7821	9081.4	192.2
Filtering-based	0.8361	0.8543	9305.6	54.3
FAFBEMS	0.8509	0.8214	8089.1	49.3

5 Conclusion

In this paper, a super-capacitor was connected in series with a DC/DC converter and connected to a DC bus in parallel with a battery to form a hybrid energy storage system, and a fuzzy adaptive filter-based energy management strategy (FAFBEMS) was proposed to allocate the required power of the vehicle. A vehicle model with the FAFBEMS strategy was built in ADVISOR. The simulation results show that the proposed FAFBEMS strategy performs well in an actual driving cycle, which can protect the battery and reduce energy consumption.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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