Research Article

Fuzzy energy management strategy for hybrid electric vehicles on battery state-of-charge estimation by particle filter

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Abstract
The battery/ultracapacitor hybrid power supply system can solve the problems of high cost and short life of a single power system, and the energy management of hybrid power system has become a vital issue in the field of electric vehicles. In this paper, a fuzzy energy management strategy on the state-of-charge (SOC) estimation of power battery is proposed. Particle filter (PF) algorithm is used to estimate SOC of power battery, then estimated result is regarded as the input variable of fuzzy energy management controller, and the energy distribution result is obtained after fuzzy logic operation. The simulation results show that the SOC estimation result of the PF algorithm is closer to the actual value of power battery SOC. When the SOC estimation result of PF is embedded into the fuzzy controller for joint simulation, it is found that the charge and discharge current, and SOC consumption of the power battery are reduced, which shows the algorithm's effectiveness. It also provides a specific reference value for the further study of the power supply control strategy of hybrid electric vehicles.

Keywords Hybrid electric vehicle (HEV) · SOC estimation · Energy management strategy · Fuzzy controller · Particle filter algorithm

1 Introduction

Electric vehicles rely on electric traction motors for propulsion, and the motors rely on energy storage power sources such as power batteries or ultracapacitors for power supply [1]. With the popularity of electric vehicles, single-power electric vehicles have some defects, such as weak endurance, insufficient acceleration power, and short battery life. The appearance of a battery/ ultracapacitor hybrid power supply provides a good idea to solve the above problems. Ultracapacitor can protect the battery well and extend the service life of the battery [2]. Then the performance of HEV is closely related to its energy management strategy. The primary function of the energy management strategy is to coordinate the distribution of load power demand of power battery and ultracapacitor, to meet the electrochemical characteristics of power battery and ultracapacitor, which is the key to system energy management [3].

The state estimation of power battery, especially the state-of-charge and remaining discharge time, is the core problem of battery management system [4], which directly affects the reliability, safety, and service life of the battery. However, due to the influence of charging and discharging current, temperature, cycle life, and other factors, the SOC of the battery cannot be measured directly. Still, it can only be estimated indirectly by specific algorithm [5]. Currently, the popular SOC estimation methods are discharging experiment, Ampere-Hour integral method, open-circuit voltage (OCV), Extended Kalman filter, and neural

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network algorithm [6, 7]. Among these methods, the discharge experiment is not suitable for online use. The accuracy of Ampere-Hour integration depends on SOC initial value calculation, measuring instrument error, current and temperature, and other factors [8, 9], the sensor error and the initial error will lead to greater error of SOC [10]. OCV takes a long time to stabilize the voltage state, which is not suitable for real-time dynamic estimation of SOC [11, 12]. Neural network requires a large amount of data for training, so that the calculation amount is large, and the error is affected by the training data and methods [13]. Extended Kalman filter is easy to realize because of the calculation amount is relatively small, but the white noise with known statistical characteristics is difficult to recognize for electric vehicles, which affects the SOC estimation accuracy [14]. Compared with these SOC estimation methods, the particle filter (PF) is suitable for all nonlinear and non-Gaussian distribution random systems represented by state space models. It has no restrictions on the measurement noise and process noise of the system, and its accuracy can be close to the optimal estimation. It has specific applicability for power battery SOC estimation [15].

Energy management strategies of hybrid power supply can be divided into rule-based and optimization-based [16]. The rule-based control strategy is based on the mathematical model and expert experience, and pre-set rules are applied to allocate various energy sources in the multi-energy scenario [17]. The rule control strategy has been developed from a simple deterministic logic threshold control to an intelligent control strategy based on fuzzy rules, which has high robustness and reliability. However, due to excessive reliance on human experience, the flexibility and adaptability to periodic changes are relatively poor [18]. Optimization-based energy management strategy uses optimal control theory and optimization principle to control the parameters or real-time operation data, such as the Equivalent Consumption Minimization Strategy (ECMS) [19], Dynamic programming (DP) [20], Pontryagin's minimum principle(PMP) [21, 22], et al. However, most of the real-time optimal control strategies cannot be implemented in real vehicles due to a large amount of calculation or the limitation of microprocessor chips, which needs further research.

A fuzzy control strategy does not rely on accurate mathematical models. It has the advantages of good adaptability, robustness, and practicability, which is very suitable for the hybrid power system with time-varying, nonlinear, delayed, and uncertain models [23]. To solve the problem that the determination of logic rules and membership functions in fuzzy control strategy relies too much on expert experience, intelligent algorithms are used to optimize it [24, 25]. Pei et al. [26] applied quantum chaotic pigeon-inspired optimization (QCPIO) algorithm to the optimization of membership function of the fuzzy logic controller, compared it with particle swarm optimization fuzzy algorithm and original fuzzy algorithm on the SOC of power supply and emissions under different working conditions. Chen et al. [27] used particle swarm to optimize the threshold of the rule-based strategy and took the minimum total energy cost of the vehicle as the optimization objective. Then the driving cycle was taken as an example to verify the online control performance of this method.

In this paper, the results of PF estimation of power battery SOC are applied to the fuzzy logic controller as the energy management strategy of HEV hybrid power supply, and the effectiveness of the strategy is verified by joint simulation. The rest of this paper are arranged as follows: Sect. 2 describes the structure and working mode of the vehicle hybrid power supply, which is the basis of the design of the energy management strategy of the hybrid power supply. Section 3 introduces the design of the battery SOC estimation algorithm, first is the establishment of the battery SOC estimation model, then introduces the PF algorithm and the algorithm flow of the filter algorithm to estimate the power battery SOC. Section 4 is the design of the fuzzy controller of the hybrid power supply energy management, including the discharge and charge fuzzy controller. In Sect. 5, according to the relevant parameters of electric vehicle and power supply, the simulation results under different working conditions are obtained and analyzed in ADVISOR environment. Finally, the conclusion is given in Sect. 6.

2 Structure and working modes of hybrid power supply

2.1 Hybrid power supply structure of the electric vehicle

The topology design of vehicle hybrid power supply plays an essential role in the power distribution and dynamic performance of the whole hybrid power supply system [28]. According to the number of bidirectional DC/DC power converters and their connection positions, the topology of a hybrid power supply can be divided into passive, semi-active, and active structures. In the passive structure, the battery and the ultracapacitor are connected in parallel directly. The voltage of the ultracapacitor is limited by the battery voltage, the usage of ultracapacitor decreases. In the active structure, the ultracapacitor and battery are connected in series with DC/DC converters and then connected in parallel, which has a high cost and complex control strategy. The semi-active structure has only one DC/DC converter, which is connected in series with the ultracapacitor and then connected in parallel with the battery to protect the battery from the impact of peak current. The voltage fluctuation of the DC bus is slight, and the energy utilization efficiency is improved. In this paper, we use the ultracapacitor semi-active structure as the research object, and the topological structure is shown in Fig. 1.

The ultracapacitor is connected to the bidirectional DC/DC power converter, then connected to the DC bus in parallel with the power battery to supply power to the load. Among them, the power battery provides the main power to meet the basic requirements of the whole vehicle for driving range. The ultracapacitor is used as the auxiliary power supply to meet the demand of short-term high power such as frequent starting, acceleration or climbing, and realize the energy recovery when the vehicle is braking. The bidirectional DC/DC power converter realizes the voltage balance between the power and load and undertakes the energy distribution and management of the power system.

2.2 Hybrid power supply working modes of electric vehicle

During the driving process of electric vehicles, the hybrid power supply presents different working modes, the analysis of its power flow can be summarized into four working modes:

(1) Power battery alone working mode. In this case, the vehicle is working at a constant speed or under acceleration driving conditions with small power demand, so the power demand of the vehicle is not high, provided by the power battery alone. And the vehicle driving for a long time in this condition, the energy demand is enormous, the battery can give full play to the advantages of the energy density.
(2) Ultracapacitor single working mode. When the vehicle starts, the power supply is required to provide a significant power output in a short time and does not require much energy. At this time, the power is supplied by the ultracapacitor alone, which can give full play to the advantage of the high-power density of the ultracapacitor.
(3) Power battery and ultracapacitor working mode. When the vehicle is driving under rapid acceleration, climbing, or at high speed, the maximum power threshold of the power battery may not meet the power demand of the vehicle, while the ultracapacitor alone is not enough to drive the vehicle. At this time, the power battery and ultracapacitor should work together to meet the power demand of the vehicle, and the output power ratio of the two should be reasonably distributed.
(4) Regenerative braking mode. When the vehicle works in the deceleration or downhill driving state, the motor is regeneratively braked, and working in the power generation state. The generated electric energy is returned to the hybrid power supply. At this time, the recovered power is distributed according to the SOC state of the power battery and the ultracapacitor. Still, to avoid the impact of high current on the power battery, the ultracapacitor is charged preferentially.

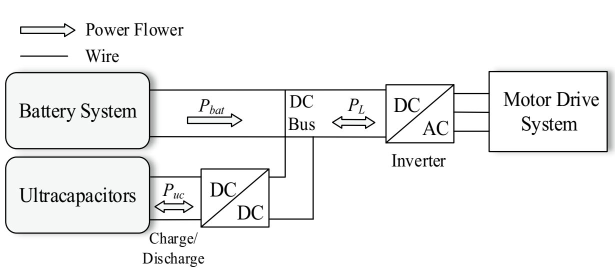

Fig. 1 Topological structure of hybrid power supply system

3 Battery SOC estimation algorithm design

PF algorithm can solve the nonlinear filtering problem, and the estimation accuracy is close to the optimal estimation. Therefore, this paper uses the PF algorithm to estimate power battery SOC and applies the estimation results to the design of a fuzzy controller.

3.1 Battery SOC estimation model

The battery SOC is the state variable of the model, and the state equation is derived from Eq. 1:

$$SOC(t) = SOC_0 - \int_0^t \frac{i(\tau)}{C_n} d\tau \tag{1}$$

where $SOC(t)$ is the SOC value of the battery at t. SOC_0 is the initial SOC value of the battery. C_n is the rated capacity of the battery pack. $i(t)$ is the instantaneous charging and discharging current of the battery, which is positive when discharging and negative when charging. Equation 1 is discretized as:

$$SOC_k = SOC_{k-1} - \frac{\Delta t}{C_n} i_{k-1} \tag{2}$$

where SOC_k is the SOC value of the battery at k. i_{k-1} is the battery's current at k-1. Δt is the time interval.

Considering the accuracy of the battery model, a comprehensive model combining Shepherd model, Unnewehr universal model, and Nernst model is used as the observation equation [28, 29], as shown in Eq. 3:

$$U_k = U_0 - Ri_k - \frac{k_1}{SOC_k} - k_2 SOC_k + k_3 \ln\left(SOC_k\right) + k_4 \ln\left(1 - SOC_k\right) \tag{3}$$

where U_k is the output voltage of the battery at k; R is the internal resistance of the battery; k_1 is the polarization resistance; k_2, k_3 and k_4 are unknown models matching parameters that are determined by the battery.

In conclusion, the battery model is as follows:

State equation:

$$SOC_k = SOC_{k-1} - \frac{\Delta t}{C_n} i_{k-1} + w_k \tag{4}$$

Observation equation:

$$U_k = U_0 - Ri_k - \frac{k_1}{SOC_k} - k_2 SOC_k + k_3 \ln\left(SOC_k\right) + k_4 \ln\left(1 - SOC_k\right) + v_k \tag{5}$$

where w_k is the state noise of corresponding SOC, and v_k is the observation noise of corresponding SOC. They are independent random noises.

3.2 Estimation of battery SOC by PF

Particle filter is a statistical method based on recursive Bayesian estimation and Monte Carlo method. It uses random samples in the state space to approximate the posterior probability density function and estimates the state value according to Monte Carlo method [30].

Particle filter algorithm is applied to estimate the SOC of battery, and a group of random samples with relevant weights are used to approximate the posterior probability density function:

$$P\left(\vec{X}_k \middle| U_k\right) \approx \sum_{i=1}^{N_s} \omega_k^i \cdot \delta\left(\vec{X}_k - \vec{X}_k^i\right) \tag{6}$$

where $\vec{X}_k = \left[SOC_k, U_k\right]^T$ is a column vector composed of the SOC and the output voltage of the battery at any k time, which represents the state set. $\vec{X}_k^i = \left[SOC_k^i, U_k^i\right]^T$ is the $i(i = 1\text{-}N_s)$ random particle set generated by the corresponding weight of ω_k^i at k time. $\delta(\cdot)$ is Dirac delta function.

The weight at k is updated by Gaussian distribution probability density function based on the weight of k-1. Gaussian distribution is used to approximate the importance density function to generate the importance distribution of particle filter, the formula of renewal law as:

$$\omega_k^i = \omega_{k-1}^i P\left(U_k \middle| \vec{X}_k^i\right) = \omega_{k-1}^i \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{1}{2}\frac{\left(U_k - \hat{U}_k\right)^2}{\sigma^2}\right) \tag{7}$$

where U_k and $\hat{U}_k$ are the measured value of the battery output voltage and the average value of the model output voltage at k, σ is their standard deviations.

Normalize the weights of particles:

$$\overline{\omega}_k^i = \omega_k^i \Big/ \sum_{j=1}^{N_s} \omega_k^j \tag{8}$$

After considering the total weight of all particles, the prediction result can be expressed:

$$\vec{X}_k = \sum_{i=1}^{N_s} \vec{X}_k^i \cdot \overline{\omega}_k^i \tag{9}$$

The steps of using the PF algorithm to predict battery SOC are as follows:

Step 1 Initialization: the particle set $\left\{x_0^i\right\}_{i=1}^{N_s}$ is generated from the initial probability distribution $p(x_0)$, and the particle weights are initialized to $\omega_0^i = 1/N_s$;

Step 2 Calculation of state value: calculate the state value and corresponding observation value of particles at k according to space states Eqs. 4 and 5;

Step 3 Calculation of weight: calculate the particle weight according to Eq. 7, and normalize the weight according to Eq. 8;

Step 4 Resampling: calculate the number of effective particles according to Eq. 10:

$$N_{eff} = \frac{1}{\sum_{i=1}^{N_s} \left(\omega_k^i\right)^2} \tag{10}$$

Set a valid number of samples N_{thres} as the threshold, if $N_{eff} \le N_{thres}$, then resample can be done.

Step 5 Update SOC value: calculate state estimation value according to Eq. 9 and update SOC value:

$$SOC_k = \overline{X}_k \tag{11}$$

Step 6 Judgment and loop: if the number of iterations is reached, the algorithm ends, otherwise, $k = k + 1$, and return to Step 2.

The SOC value estimated by the PF algorithm is used as the input variable of the fuzzy controller to verify the estimation accuracy of SOC.

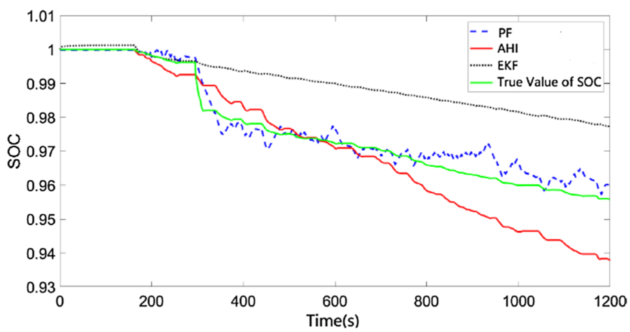

Fig. 2 Comparison of estimated values with initial SOC value of 1

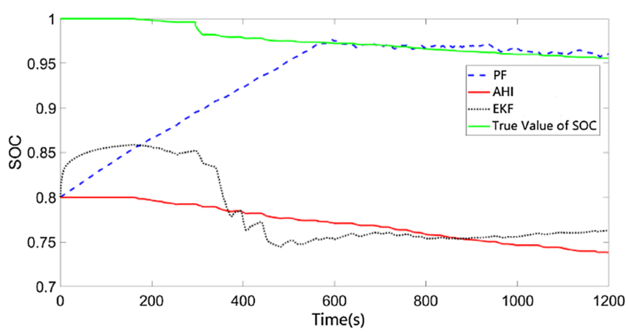

Fig. 3 Comparison of estimated values with initial SOC value of 0.8

3.3 Battery SOC estimation results

To more objectively reflect the advantages of particle filter algorithm in SOC estimation, the initial SOC values of power battery are set to 1 and 0.8, respectively. The estimated values of PF algorithm, Ampere-Hour integral method (AHI), and Extended Kalman filter (EKF) method are compared with the actual values, and the results shown in Figs. 2 and 3 are obtained.

The comparison results show that the particle filter algorithm is closer to the actual value in SOC estimation. To measure the accuracy of SOC estimation, the maximum error, average error, and root mean square error (RMSE) are selected for statistical analysis. The estimation errors of the three methods when the initial SOC values are 1 and 0.8 are shown in Tables 1 and 2.

According to the error statistical results in Tables 1 and 2, the estimation result of power battery SOC by PF algorithm is closer to the actual value. This lays a foundation for applying the result of PF estimating of power battery SOC to the fuzzy controller in the next step.

Table1 Estimation error of SOC with initial value of 1

Algorithm	Maximum error (%)	Average error (%)	RMSE
PF	1	0.24	0.0032
AHI	1.8	0.61	0.0082
EKF	2.21	1.41	0.0162

Table2 Estimation error of SOC with initial value of 0.8

Algorithm	Maximum error (%)	Average error (%)	RMSE
PF	20.00	4.89	0.0797
AHI	21.80	20.45	0.2046
EKF	23.04	19.09	0.1932

4 Fuzzy control management strategy of hybrid power system

According to the different working states of hybrid power supply in driving mode and braking mode of the electric vehicle, two parallel fuzzy controllers of discharging and charging are designed. The structure is shown in Fig. 4.

Under different operating conditions of the vehicle, the required power P_{req}, the state-of-charge of the power battery SOC_{bat} and the state-of-charge of the ultracapacitor SOC_{uc} are taken as the input variables of the fuzzy controller. The distribution parameter $K_{uc.1}$ and $K_{uc.2}$ of ultracapacitor are taken as the output variables of the two fuzzy controllers. The internal logic structure of a fuzzy controller includes fuzzification, fuzzy inference, and defuzzification. The process of fuzzy inferences depends on the knowledge base, as shown in Fig. 5.

The input and output variables of the fuzzy controller need to be fuzzed before logic operation and optimization. Firstly, set the domain of membership function. For the convenience of analysis, the domain of membership function of motor demand power P_{req} and power distribution

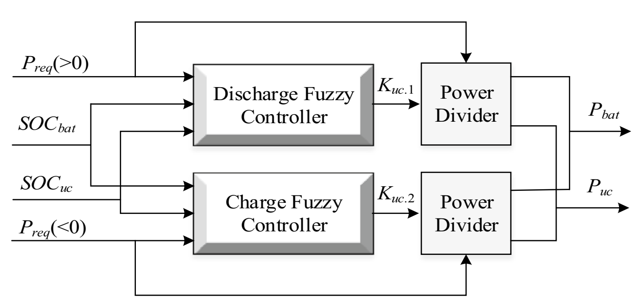

Fig. 4 Structure of fuzzy controller for vehicle hybrid power supply

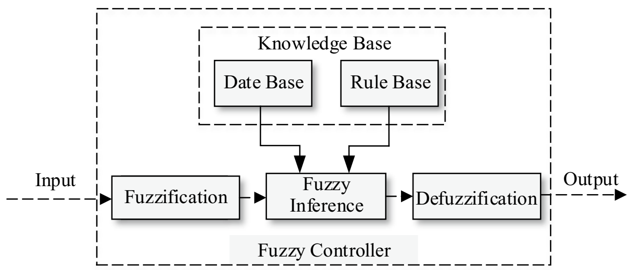

Fig. 5 Structure diagram of fuzzy controller

Table 3 Fuzzy domain and fuzzy subset of variables

Input/Output variables	Working mode	Domain interval	Fuzzy subset
Demand power	Discharge	0.0–1.0	(TS,S,M,B,TB)
P_{req}	Charge	0.0–1.0	(TS,S,M,B,TB)
Battery SOC_{bat}	Discharge	0.2–0.9	(L,M,H)
	Charge	0.2–0.9	(L,M,H)
Ultracapacitor	Discharge	0.2–1.0	(L,M,H)
SOC_{uc}	Charge	0.2–1.0	(VL,L,M,H)
Parameter K_{uc}	Discharge	0.0–1.0	(TS,S,M,B,TB)
	Charge	0.0–1.0	(TS,S,M,B)

parameter K_{uc} of the ultracapacitor is converted to continuous interval [0,1]. The domain of membership function of power battery state-of-charge SOC_{bat} and ultracapacitor state-of-charge SOC_{uc} are set to [0.2,0.9] and [0.2,1] respectively according to the working conditions. The corresponding fuzzy subsets are shown in Table 3, where TS is a little small, S is small, M is middle, B is big, TB is a little big, L is low, and H is high.

It is essential to set the membership function and control rules of the fuzzy logic controller. The smoother the membership function curve is, the smoother the output curve follows the input, the better the system stability is. Whereas the sharper the curve shape is, the higher the resolution is. In this paper, the membership function is designed by the combination of Gaussian (gaussmf) and triangle (trimf). Figures 6 and 7 show the setting result of membership function curves of input and output variables.

The fuzzy rules are the core of fuzzy controllers. After determining the fuzzy subsets and membership functions of input and output variables, the fuzzy rules are selected as follows:

R^i: If x_1 is X_1^i and x_2 is X_2^i,…, and x_i is X_n^i, Then y is Y^i, $i=1$, 2, …, n

where R^i is the rule i, x_i is the input, and y is the output.

Fuzzy rules map language input variables (P_{req}, SOC_{uc}, SOC_{bat}) to output variables (K_{uc}) through IF–THEN statements. Under charging and discharging mode, 57 rules are formulated in fuzzy controller FIS, and each rule is based on expert experience or knowledge base, as shown in Tables 4 and 5.

Furthermore, the fuzzy regular 3D surface is shown in Fig. 8, which reflects the mapping relationship between input and output variables.

Based on the fuzzy rules, the inference method of the Mamdani model is used for fuzzy inference. The results are defuzzified by the barycenter method, and finally transformed into the actual control quantity.

5 Simulation and result analysis

To verify the effectiveness of the designed fuzzy energy management strategy based on SOC estimation, a simulation model of the hybrid electric vehicle is built in the ADVISOR, and the basic simulation parameters are shown in Table 6.

The PF algorithm is compiled to.m file in MATLAB environment, encapsulated and embedded into the power battery model of the hybrid power supply to achieve the estimation of power battery SOC. In ADVISOR, the vehicle operating conditions of the New European Driving Cycle (NEDC) and Urban Dynamometer Driving Schedule (UDDS) are selected for simulation test. The SOC results of power battery are obtained by the single power electric vehicle (EV), hybrid electric vehicle (HEV) of battery SOC estimation by the original and PF algorithm. The comparison graphs are shown in Figs. 9 and 10.

Figures 9 and 10 show the change of electric vehicle power battery SOC under NEDC and UDDS by using single-power battery power supply, hybrid power with SOC original estimation and PF estimation. From the figures, we observed that the initial SOC value of the battery is 1. After one cycle of NEDC, the SOC becomes 0.932 under the action of single-power supply, and then the SOC under the fuzzy control strategy of the hybrid power supply becomes 0.95 (SOC original estimation) and 0.965(SOC PF estimation); after one cycle of UDDS, the SOC values of the three strategies are 0.929, 0.945 and 0.96 respectively.

Therefore, compared with single-supply electric vehicles, the SOC consumption value of the power battery of the hybrid electric vehicle is reduced under any cycle conditions. While, compared with the original fuzzy control strategy based on the Ampere-Hour integral method to get the SOC, the fuzzy control strategy based on PF algorithm to estimate the SOC of the power battery gets consistent overall trend of the SOC consumption curve of the

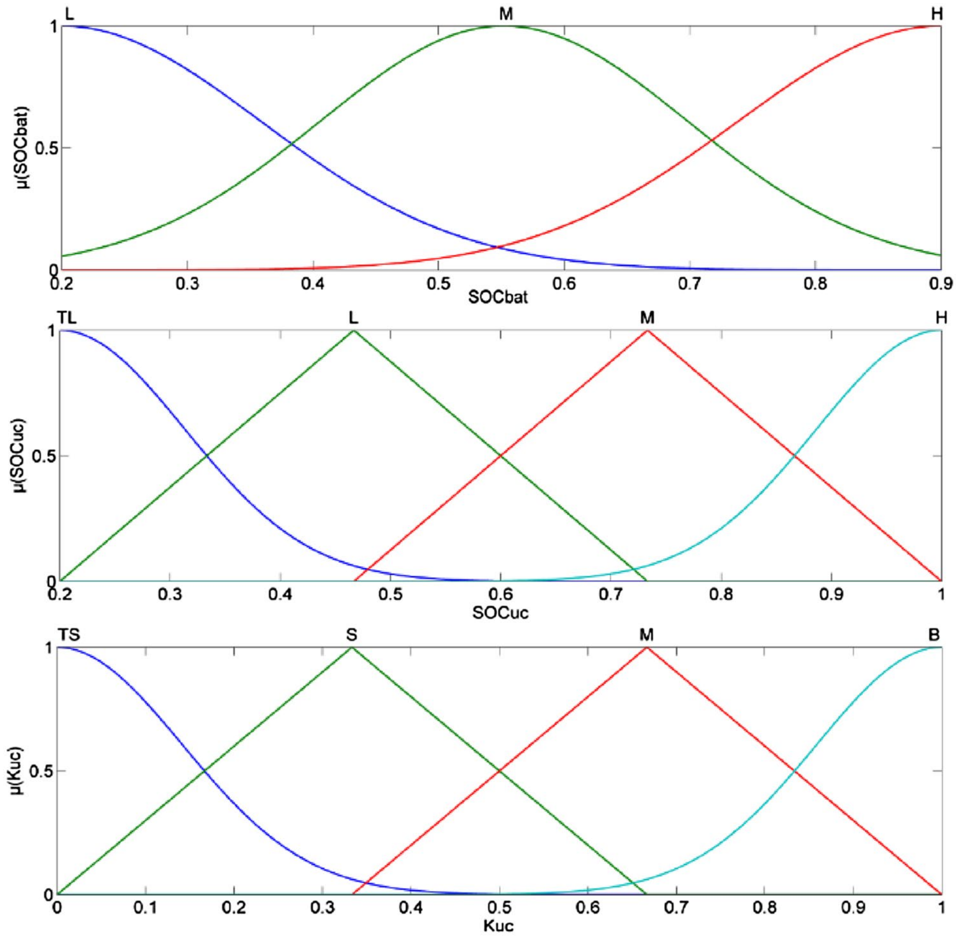

Fig. 6 Input and output membership function of charging fuzzy controller

power battery, and the error is small. The results show that for SOC of the power battery, the fuzzy control strategy of the hybrid power supply can reduce the SOC consumption of the power battery, and it is feasible to use the PF algorithm to estimate the battery SOC in the fuzzy control strategy of the hybrid power supply.

The PF estimation algorithm is applied to the hybrid power fuzzy supply controller of hybrid power supply for joint algorithm simulation, the discharge current of power battery under different conditions is simulated, and the comparison results as shown in Figs. 11 and 12.

Figure 11 is obtained under the NEDC cycle condition. From the trend of three curves, we can see that compared with hybrid electric vehicles, the current of the power battery of single-supply electric vehicles is significantly higher, with a maximum discharge current of 105.2A. With the assistance of the ultracapacitor, the power battery current of the electric vehicle is reduced, and the maximum discharge current of the fuzzy algorithm is 73.81A. After adding PF SOC estimation, the result of joint algorithm is 73.39A.

In the simulation results Fig. 12 of the UDDS cycle, we can see that the power battery current is 92.47A for single-supply EV. The power battery currents of the fuzzy algorithm and joint algorithm for HEV are 62.66A and 61.8A, respectively. It shows that the hybrid power supply composed of power battery and ultracapacitor can effectively reduce the charging and discharging current of the power battery and protect the power battery. Joint algorithm of HEV can reduce the charging and discharging current. It can verify the feasibility of estimating the battery SOC by PF algorithm to be applied to the fuzzy control strategy of hybrid power supply, which has specific reference value.

6 Conclusion

In this paper, the energy management strategy of power battery and ultracapacitor in HEV is studied, and a fuzzy logic control strategy on power battery SOC estimation by PF algorithm is designed. Power battery SOC estimation uses the PF algorithm to realize the accurate estimation of the power battery state-of-charge. The estimation results are applied to the fuzzy controller, which takes the power

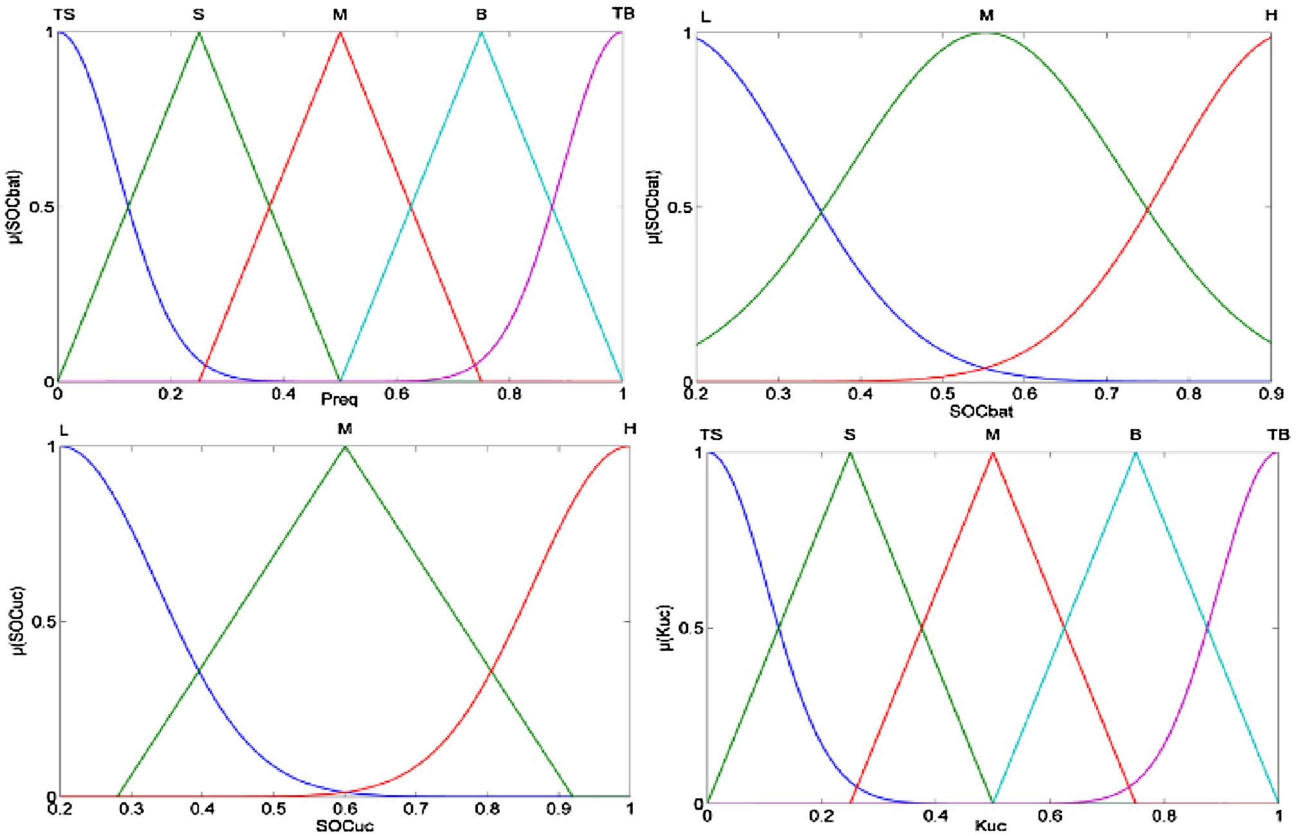

Fig. 7 Input and output membership function of discharge fuzzy controller

Table 4 Fuzzy rule table in charging mode($P_{req}<0$)

K_{uc}	SOC_{uc}			
	VL	L	M	H
SOC_{bat}				
L	B	M	S	TS
M	B	B	M	TS
H	B	B	B	M

battery SOC, ultracapacitor SOC, and the required power under the vehicle operating conditions as input variables, and the distribution parameter of the ultracapacitor is obtained by fuzzy reasoning. Then the output power of the ultracapacitor and the power battery is obtained, to realize the effective power distribution of the HEV hybrid power supply.

Set the initial value of the power battery as 1 and 0.8. Comparing the results of SOC estimation algorithms such

Table 5 Fuzzy rule table in discharging mode($P_{req}>0$)

K_{uc}		$P_{req}>0$				
		TS	S	M	B	TB
SOC_{bat} ($SOC_{uc=}$L)	L	TS	TS	TS	S	S
	M	TS	TS	TS	TS	S
	H	TS	TS	TS	TS	TS
SOC_{bat} ($SOC_{uc=}$M)	L	TS	S	M	B	B
	M	TS	TS	S	M	B
	H	TS	TS	TS	S	M
SOC_{bat} ($SOC_{uc=}$H)	L	S	M	B	TB	TB
	M	TS	S	M	B	TB
	H	TS	TS	S	M	B

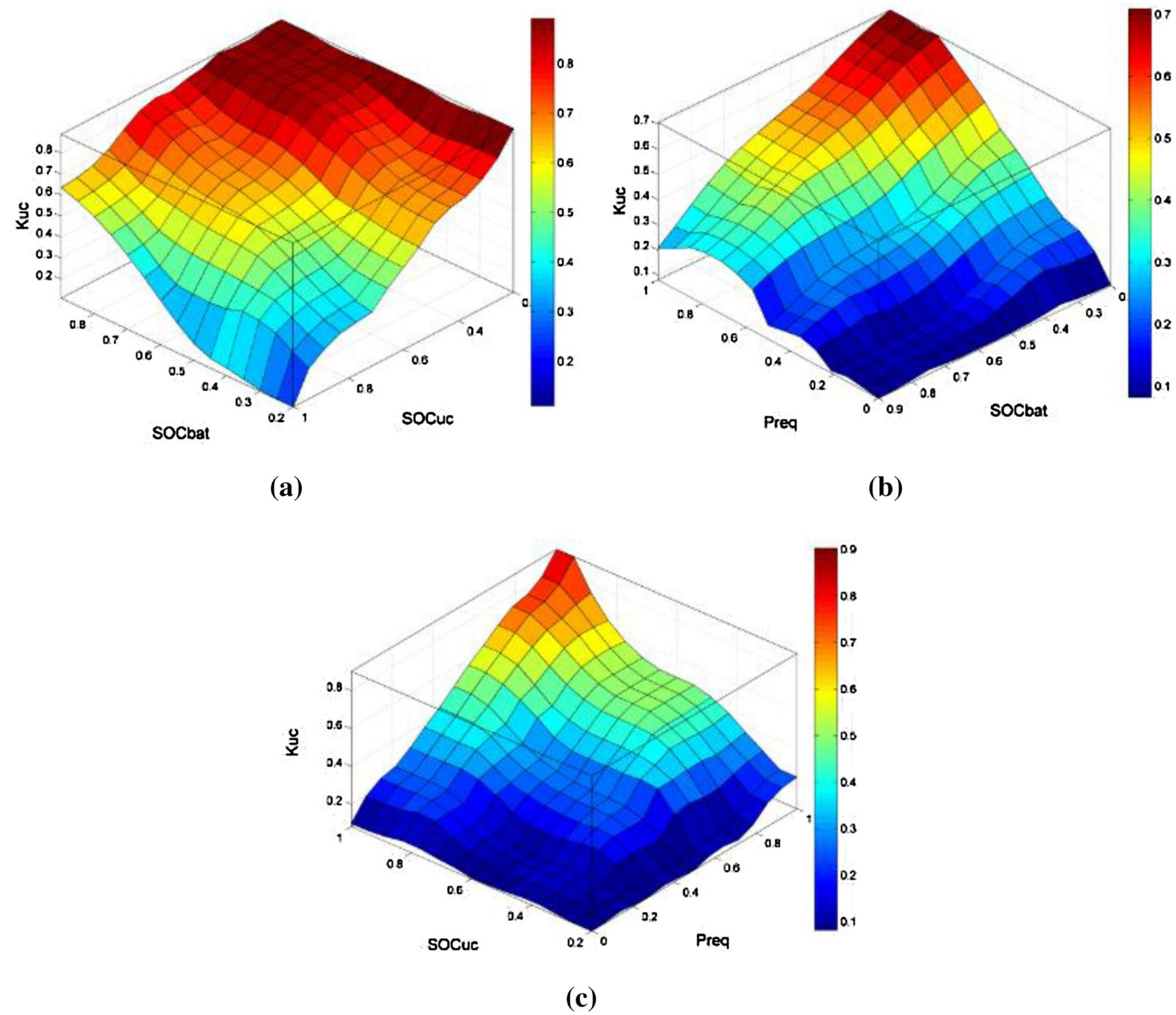

Fig. 8 Regular surface graph of fuzzy controller: (a)Input and output mapping surfaces in charging mode; (b)Input (P_{req} and SOC_{bat}) and output mapping surfaces in discharging mode;(c)Input (P_{req} and SOC_{uc}) and output mapping surfaces in discharging mode

Table 6 Basic parameters of the hybrid electric vehicle

Component	Parameter	Value
Vehicle	Mass(m) kg	1080
	Frontal Area(A) m^2	2.15
	Tire rolling radius (r) m	0.245
Motor	Type	AC
	Maximum power (P_{max}) kW	75
Power battery	Type	Ni–MH battery
	Capacity (C) Ah	90
	Voltage (U) V	312
Ultracapacitor	Cell capacity (C_0) F	1000
	Cell voltage (U_0) V	2.5
	Serial number(N_{uc})	124

as AHI, EKF and PF, it is found that the SOC estimation result of the PF algorithm is closer to the actual value of power battery SOC. And the SOC estimation result of PF is embedded into the fuzzy controller for joint simulation. In ADVISOR environment, the two cycle conditions of NEDC and UDDS are simulated and verified. It is found that the charge and discharge current, and SOC consumption of the power battery are reduced, which shows the effectiveness of the algorithm. It also provides a specific reference value for the further study of the power supply control strategy of HEV.

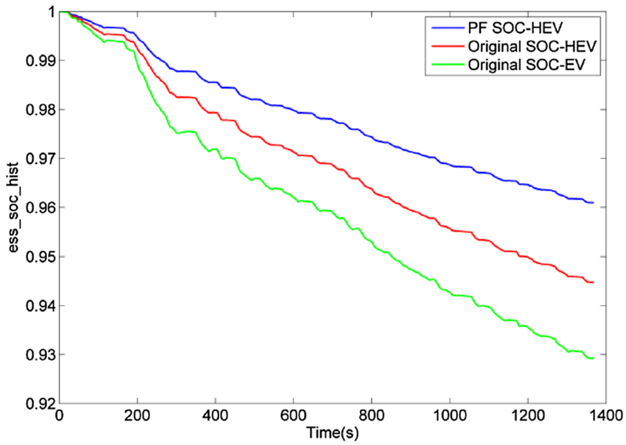

Fig. 9 SOC consumption of power battery under NEDC

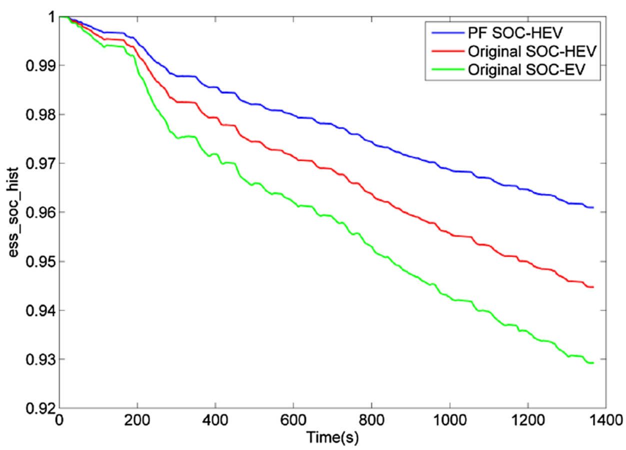

Fig. 10 SOC consumption of power battery under UDDS

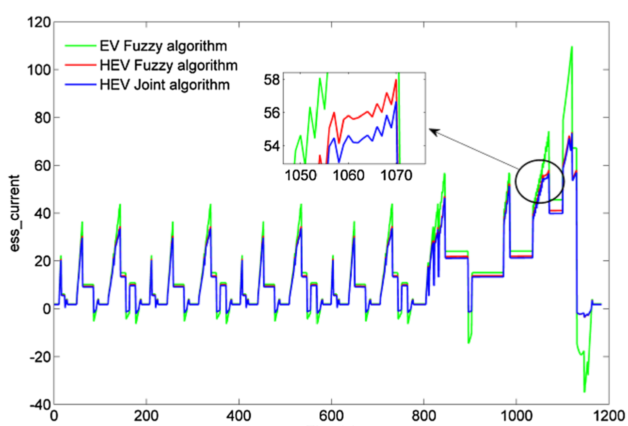

Fig. 11 Current curves of power battery under NEDC

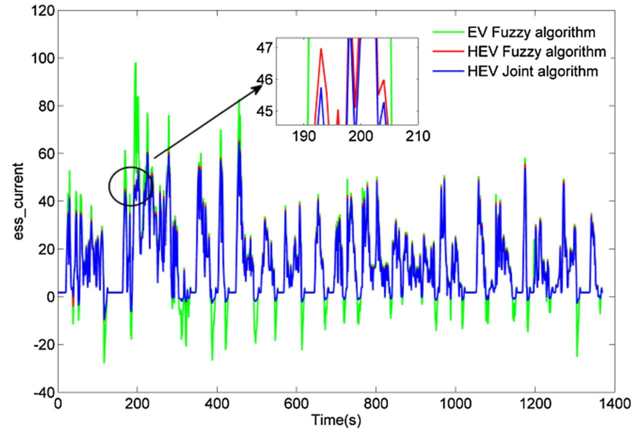

Fig. 12 Current curves of power battery under UDDS

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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