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Fuzzy Rule Control-based Energy Management Strategy for Hybrid Energy Storage System of Electric Vehicle

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Abstract

To improve the energy control effect of electric vehicles, this paper investigates the energy management strategy (EMS) of the hybrid energy storage system (HESS) composed of lithium batteries and ultracapacitor, which proposes an energy management strategy based on a fuzzy rule algorithm. Firstly, the HESS is built on the MATLAB/Simulink platform by utilizing the electric vehicle driving power and the equivalent model of the HESS. Then, the fuzzy variables, fuzzy language and fuzzy membership functions of the control algorithm are set to construct the fuzzy rule-based control decision model. In order to verify the control performance of the proposed strategy, the control effectiveness of the algorithm is analyzed using the standard UDDS driving cycle conditions. Finally, the performance of the fuzzy rule-based EMS is compared with the rule-based EMS. The results show that the fuzzy rule-based EMS improves the economy by 8.81% and better suppresses the peak current of the lithium battery, which has demonstrated stronger adaptability.

Keywords

Hybrid Energy Storage System; Energy Management; Fuzzy Control.

1. Introduction

In recent years, the occurrence of extreme weather events resulting from high carbon emissions has been increasing. Therefore, in response to the country's "dual carbon" strategy, there has been rapid development in electric vehicle technology [1]. However, in the face of the complex and ever-changing external road environment, the single energy source primarily composed of lithium batteries often faces challenges of high-rate and frequent charge-discharge cycles. This can accelerate the aging of lithium batteries and impact their lifespan [2]. To compensate for the limitations of a single lithium battery energy source in this regard, some scholars have proposed the incorporation of ultracapacitor as an additional energy source in energy storage systems [3]. The ultracapacitors have been widely applied in sectors such as aerospace and energy storage with their advantages of long cycle life and high-power density [4]. Therefore, the hybrid energy storage system (HESS) is combined with the advantages of battery and ultracapacitor. Due to the presence of multiple energy sources in the HESS, the rational allocation of power output between different energy sources has become a crucial issue that engineers must consider [5]. For this reason, the efficient control algorithm plays a significant role in the energy management system (EMS) of HESS. Currently, the EMSs for HESS can be broadly classified into three categories: rule-based EMSs, optimization-based EMSs and artificial intelligence-based EMSs.

The rule-based EMSs have been widely used in the energy management of HESS due to their advantages such as low computational complexity, strong robustness and high reliability. Generally, these EMSs can be further divided into two categories: rule-based EMSs and fuzzy rule-based EMSs [6]. However, the rule-based EMSs have rarely been applied alone in the energy management of

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HESS in recent years, but rather as a comparison to optimization control strategies [7]. Yonggang Liu et al. [8] used the Markov chain to predict the driving patterns of electric vehicles and modified the deterministic rule-based strategy based on the prediction results. Simulation results showed that the proposed strategy effectively reduced fuel consumption. R. Rodriguez et al. [9] used fuzzy algorithms to predict vehicle speed and embedded it into the deterministic rule-based EMS. The validation results showed improved efficiency of the proposed HESS. In addition, compared to deterministic rule-based EMS, the main advantage of fuzzy rule-based EMS is that the output of the fuzzy controller is smoother and does not experience instantaneous changes. The performance of the fuzzy controller is entirely determined by the fuzzy rules and fuzzy membership functions [10]. However, the design of fuzzy controllers also relies on engineers' past experiences which is similar to rule-based EMS, making it difficult to directly design a fuzzy controller with excellent control performance. Therefore, fuzzy control is often combined with other methods to achieve better control effectiveness. In addressing the energy management issue of HESS, Zhe Wang et al. [11] improved the fuzzy control strategy by introducing the parameter of demand power change rate and conducted secondary development simulations. The improved strategy showed significant enhancements in both economy and durability. K. V. Singh et al. [12] incorporated Elman neural networks into fuzzy control and optimized it with the objectives of minimal fuel consumption and battery lifespan. The experimental results showed that the proposed strategy outperformed traditional strategies in terms of fuel economy and response speed. Q. Zhang et al. [13] proposed a real-time EMS composed of neural networks, wavelet transforms and fuzzy control. The wavelet transforms were used to decompose the demand power to form an offline dataset for training, neural networks were used for online prediction of the vehicle's demand power, and the fuzzy controller was used to control the voltage of the supercapacitor within a suitable range. Finally, the effectiveness of the proposed EMS was verified through a real-time simulation platform based on the developed HESS. In addressing the energy management issue of battery and supercapacitor in HESS, A. U. Rahman et al. [14] designed a nonlinear controller based on hyper-twisting sliding mode control. The simulation results showed that the proposed strategy effectively reduced fuel consumption by 29%. Additionally, the robustness test results verified the controller's disturbance rejection capability against external and internal parameter variations.

2. The Model of HESS

(1) The topology of HESS

The topology structure of a HESS directly influences the formulation of EMSs for electric vehicles. Therefore, considering the computational accuracy and control efficiency of the topology structure, this study selects the semi-active topology structure as shown in Figure 1. The characteristic of this structure is that the lithium battery pack is connected in series with the DC/DC converter and parallel to the supercapacitor pack. This topology structure allows the supercapacitor to operate within a wider voltage range which can prevent peak currents from damaging the lithium battery. The purpose of this design is to protect the lithium battery and extend the lifespan of the electric vehicle. Therefore, this topology structure provides an effective solution for the formulation of EMS for electric vehicles.

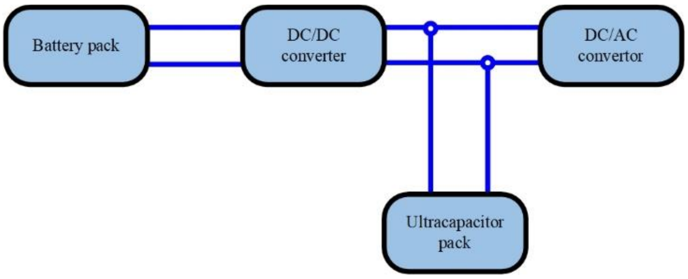

Figure 1. The topology of HESS

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The main parameters and performance indicators of an electric vehicle are shown in the table 1. Based on the dynamic model, the required power of the vehicle is determined by the equation:

$$P = \frac{1}{\eta} v \left[\frac{Mgfcos\alpha}{3600} + \frac{C_D A v^2}{76140} + \frac{Mgsin\alpha}{3600} + \frac{\delta M}{3600} \frac{dv}{dt} \right] \tag{1}$$

where P and v represent the required power and speed, respectively. Among them $\eta = \eta_1 * \eta_2 * \eta_3$.

Table 1. Main characteristic parameters of the electric vehicle

Parameters	Values
Effective mass of vehicle m	1845 kg
Roll resistance coefficient f	0.025
Air resistance coefficient C_D	0.36
Windward area A	2.53 m^2
The grade of the road α	0
Correction coefficient of the rotation mass δ	1.03
The efficiency of the transmission system n_1	0.91
The efficiency of the motor n_2	0.95
The efficiency of the DC/AC convertor n_3	0.95
Gravity acceleration g	9.8 m^2

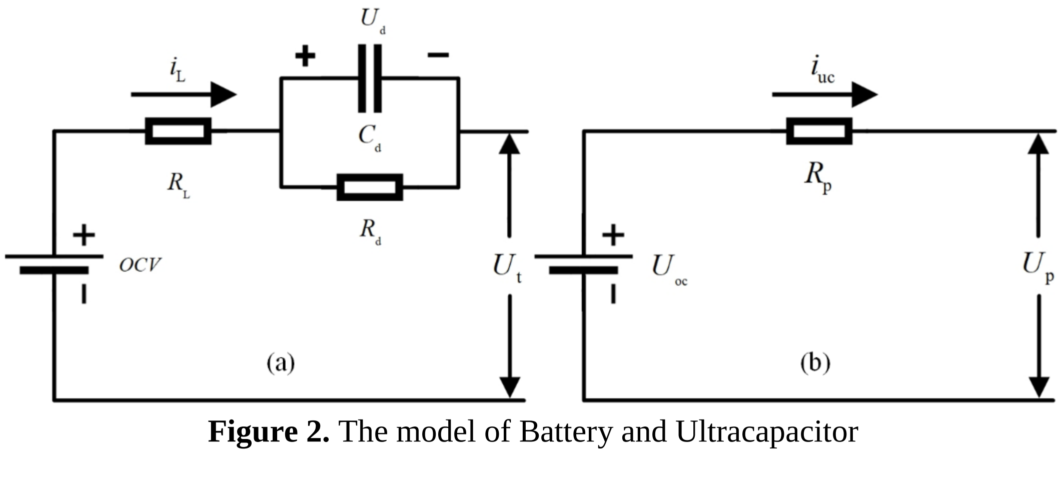

Figure 2. The model of Battery and Ultracapacitor

(2) The model of battery and ultracapacitor

In order to simplify the system computation, this study chose the Thevenin model and Rint model to describe the overall battery and supercapacitor system. The Thevenin model consists of a circuit element with an RC parallel connection, which is shown in Figure 2. In this model, Uoc represents the open-circuit voltage, RL represents the DC internal resistance of the lithium battery, Rd and Cd represent the polarization resistance and polarization capacitance, respectively. The iL represents the current, Ud represents the voltage across the RC module, and Ut represents the voltage at the lithium

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battery terminal. In Figure 2, iuc represents the current, Rp represents the ohmic resistance of the supercapacitor, and Up represents the terminal voltage of the supercapacitor. By Kirchhoff's voltage law, the discrete state-space equations of this model can be derived.

$$\begin{cases} U_{d}(k)=U_{d}(k-1)exp^{-\Delta t/\tau}+\left(1-exp^{-\Delta t/\tau}\right)i_{L,k-1}R_{d} \\ U_{t}(k)=OCV(k)-U_{d}(k)-i_{L,k}R_{L} \end{cases} \tag{2}$$

$$U_{p}(k)=U_{oc}(k)-i_{uc,k}R_{p} \tag{3}$$

(3) The model of DC/DC convertor

Due to the complexity of the DC/DC model, it would result in a significant increase in computational burden when applied it to energy management problems. In order to improve computational efficiency, this study ultimately adopted an efficiency interpolation method to model the DC/DC converter. The efficiency data of the selected DC/DC converter is shown in Table 2.

Table 2. The efficiency table of DC/DC convertor

	0	5kW	10kW	20kW	30kW	40kW	50kW	≥120kW
0A	50%	50%	50%	50%	50%	50%	50%	50%
5A	63%	67%	71%	73%	74%	73%	72%	72%
10A	75%	84%	92%	95%	97%	95%	94%	94%
50A	73%	82%	91%	93%	96%	93%	92%	92%
100A	72%	80%	88%	91%	95%	92%	91%	91%
150A	70%	76%	82%	89%	92%	91%	90%	90%
≥300A	70%	76%	82%	89%	92%	91%	90%	90%

3. Fuzzy Rule-based Energy Management Strategy

The fuzzy logic control exhibits characteristics similar to the human brain. It is an accurate mathematical model-based on engineering experience, reasoning techniques and control system status conditions which can be without relying on physical processes. A fuzzy control system is composed of four main components, including input-output linguistic variables, fuzzy linguistic values, membership functions and a fuzzy rule base. In this study, the overall scheme of the fuzzy control strategy for the hybrid power system, adopting the Mamdani inference structure is illustrated in Figure 3. The designed fuzzy controller for the HESS consists of three input variables and one output variable. The input variables include the required power Preq, the state of charge (SOC) in battery SOCbat and supercapacitor SOCuc, while the output variable is the battery power allocation factor Kbat. The required power Preq is a crucial parameter for the propulsion system, which is determining the output power of the hybrid power system. The battery SOCbat reflects the electric vehicle's driving range, while the supercapacitor SOCuc reflects the vehicle's instantaneous acceleration and climbing ability. Therefore, these three parameters are selected as the input and output variables for the fuzzy control system due to they play a vital role in formulating EMS of HESS.

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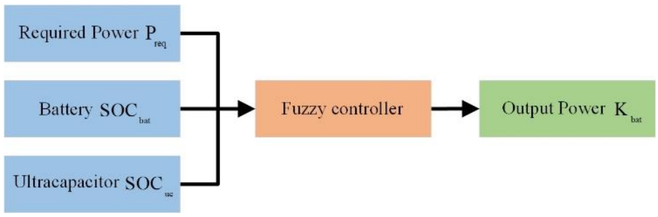

Figure 3. The framework of fuzzy rule control-based EMS

The primary task of fuzzification is to transform the domain of variables. A common approach is to normalize the domain to achieve comparability of incomparable data while preserving relative relationships. The fuzzy domains in battery SOCbat, supercapacitor SOCuc and battery power allocation factor Kbat are set to [0, 1] in this study, while the domain of required power is set to [-1, 1]. Currently, the fuzzy partitioning mainly relies on expert experience. Consequently, the fuzzy linguistic values and fuzzy domains of the input and output variables are shown in Table 3. The establishment accurate of fuzzy rules has a crucial impact on the effectiveness of the fuzzy controller. The ultracapacitor play a role in peak shaving and valley filling, which is braking energy recovery and surged current suppression in the formulation of the EMS for HESS. Therefore, the final fuzzy rule is based on the experience and knowledge of experts, as shown in Table 4.

Table 3. Fuzzy language value and Fuzzy domain

Variable	Fuzzy language value	Fuzzy domain
P_{req}	NB, NM, NS, ZE, PS, PM, PB	[−1, 1]
SOC_{bat}	L, M, H	[0, 1]
SOC_{uc}	L, M, H	[0, 1]
K_{bat}	LE, ML, ME, MB, GE	[0, 1]

Table 4. Fuzzy logic control rules

$P_{req}(t)$	$SOC_{bat}(t)$&SOC_{uc}(L)			$SOC_{bat}(t)$&SOC_{uc}(M)			$SOC_{bat}(t)$&SOC_{uc}(H)		
	L	M	H	L	M	H	L	M	H
NB	ML	LE	LE	ME	NB	LE	GE	GE	ME
NM	ME	LE	LE	ME	ML	LE	ME	GE	GE
NS	ML	LE	LE	LE	ME	LE	GE	ML	ME
ZE	LE	LE	LE	LE	LE	LE	LE	LE	LE
PS	LE	GE	GE	LE	ML	ME	LE	LE	ML
PM	ML	GE	GE	LE	ML	ME	LE	ML	ME
PB	ME	GE	GE	LE	ME	MB	LE	ML	ME

The design of fuzzy membership functions is crucial for a fuzzy controller to achieve outstanding control performance, as they indicate the transition states between different fuzzy subsets. Due to the influence of subjective factors from the designer, there are various expressions for fuzzy membership functions. The common fuzzy membership functions include triangular membership functions, Gaussian membership functions, sigmoidal membership functions and trapezoidal membership functions. In this study, triangular membership functions were selected for constructing the input and output variables of the fuzzy controller due to their simplicity and fast response algorithm, as shown in Figure 4.

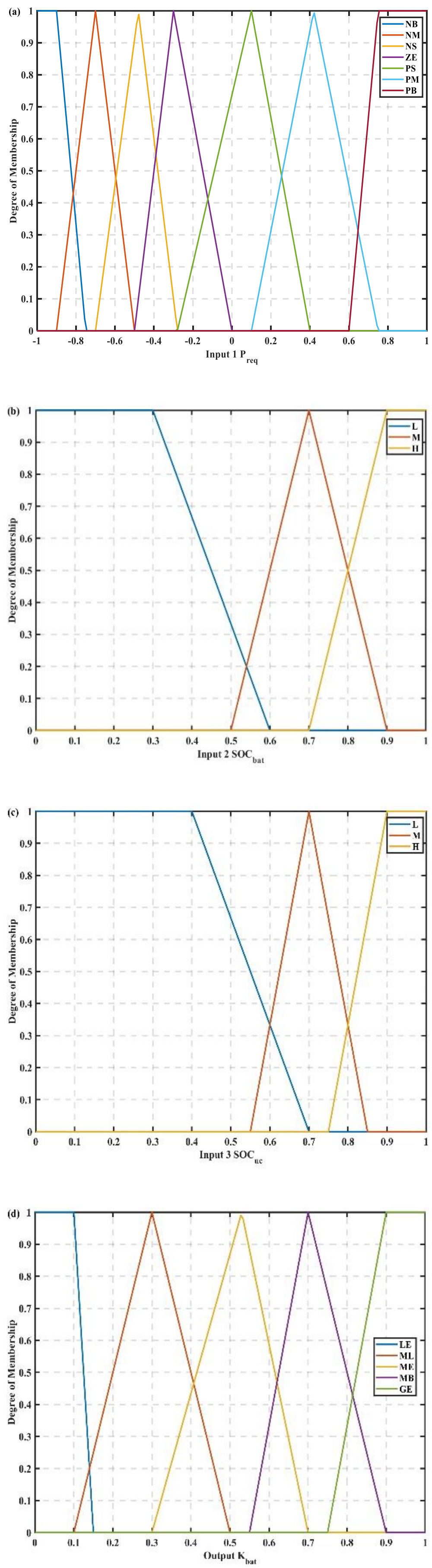

Figure 4. The membership functions of Fuzzy rule

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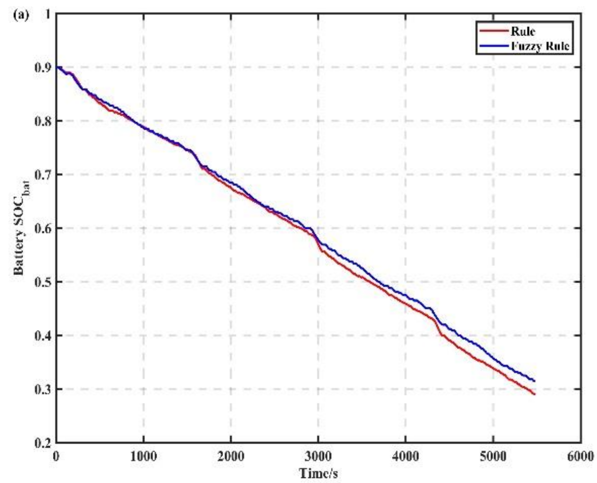
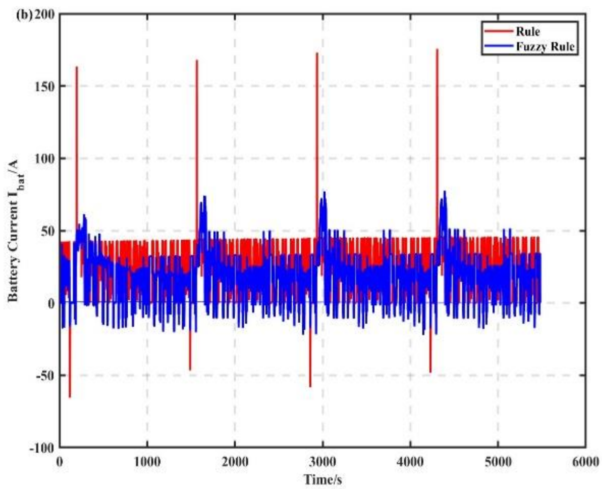
4. Simulation Results and Discussion

In order to provide a more comprehensive evaluation of EMSs based on rules and fuzzy rules, the SOC and current of the battery and supercapacitor are compared under different EMSs, which the detailed comparison results are presented in Figure 5. Additionally, Table 4 provides a more detailed comparison of the battery SOC_{bat} and supercapacitor SOC_{uc}. It can be observed that the fuzzy rule-optimized EMS exhibits a more reliable range of SOC_{uc} compared to the deterministic rule-based EMS from Figure 5(a) and 5(c), with the SOC of the supercapacitor being well constrained between [0.4, 0.9]. Moreover, it can be known that the maximum current of the battery under the deterministic rule-based strategy and fuzzy control strategy are 175.6661A and 75.5221A from the figure 5(b), respectively. Obviously, the maximum current variation under the rule-based EMS is much higher than that under the fuzzy rule control EMS. The Table 5 described that the final SOC_{bat} under different strategies are 0.2894 and 0.3149, respectively. Compared to the rule-based EMS, the fuzzy rule-based EMS indicating an improvement of 8.81% in the economic performance, which can effectively reduce energy losses of HESS in electric vehicle. Meanwhile, the SOC_{uc} under the rule-based EMS and the fuzzy rule-based EMS are 0.8856 and 0.8320 respectively, which the difference is only 6.05% with them. Therefore, the fuzzy rules-based EMS not only leverages the advantages of ultracapacitors better and reduces the damage caused by high currents to the battery, but also effectively protects lithium batteries and extends their lifespan.





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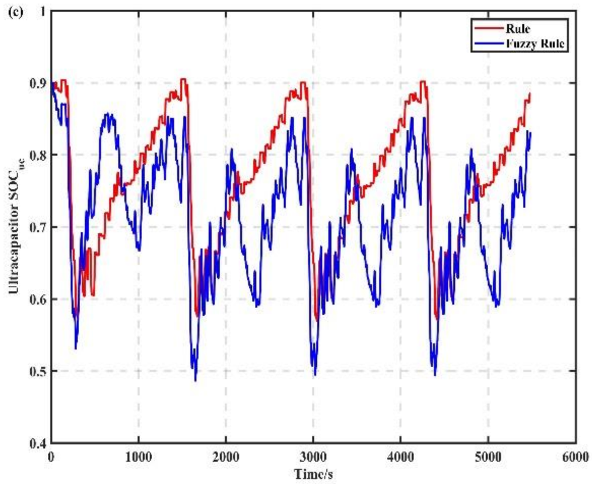

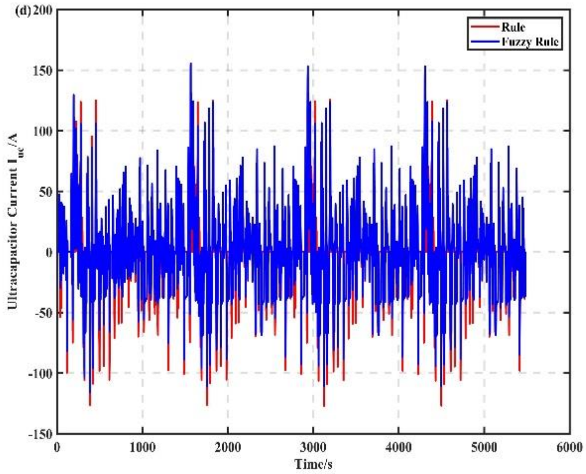

Figure 5. The results of Battery and Ultracapacitor

Table 5. Characteristic parameters in different control strategies

	Rule-based	Fuzzy rule-based
Battery SOC_{bat}	0.2894	0.3149
Ultracapacitor SOC_{uc}	0.8856	0.8320
Max Battery I_{bat}	175.6661	77.5221
Max Ultracapacitor I_{uc}	125.4566	155.5350

5. Conclusion

This study compares and analyzes the EMSs of HESS between rule-based and fuzzy rule-based. The whole-vehicle control is employed of the on-board HESS in the rule-based EMS and implemented a fuzzy-based EMS by leveraging the membership function characteristics of the fuzzy control algorithm. This fuzzy rule-based EMS exhibits better energy economy and robustness, which can enable faster response to variations in actual operating conditions.

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