A Control Strategy for Capacity Allocation of Hybrid Energy Storage System Based on Hierarchical Processing of Demand Power

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Abstract: Pursuing optimal power distribution in hybrid energy storage systems has always been the goal of researchers. Here, HESS is a combination of lithium battery and supercapacitor; this combination has been proven to effectively compensate for some of the deficiencies of lithium batteries as an energy system for electric vehicles. For example, the energy storage system with only lithium batteries cannot provide high power in a short time to meet the high acceleration performance of electric vehicles, and the excessive discharge current will cause the temperature of the battery pack to be too high, which will cause safety problems for the car. This paper proposes an intelligent energy management strategy combining fuzzy controller and improved Savitzky-Golay filter for real-time control. The simulation results show that compared with only using the fuzzy controller, the maximum current of the battery proposed by the strategy is reduced by 2.43%, and the usable cycle life of the battery is increased by 5.01% during the test driving cycle. By simply comparing the latest supercapacitors on the market with the existing supercapacitors in the laboratory, it is possible to roughly predict the performance improvement that the future capacitors may bring in hybrid energy storage systems.

Keywords: Hybrid energy storage system; Fuzzy logic control.

1. Introduction

In recent years, the development of electric vehicles (EV) and battery technology [1] [2] has attracted widespread attention. In the development of electric vehicles, the development of battery packs is incredibly essential. Although the performance indicators of lithium batteries have been greatly improved than before, the existing battery performance still has certain limitations. For example, the high initial cost and the reliability of the energy storage system [3] [4]. Lithium batteries provide the required power through chemical reactions, but when the required power changes too much, it is difficult to ensure that the battery pack can provide the required power, and providing high power for a long time may cause safety problems and reduce the lithium battery Life expectancy [5, 6]. Now, a more widely and
effectively used method to solve these problems is to couple lithium batteries and backup supercapacitors together, which can effectively improve the safety of hybrid energy storage systems through reasonable power distribution. Supercapacitors are usually used to cut peak power, which can significantly slow down the impact of high current on the life and temperature of lithium batteries [7, 8]. In view of the nonlinear characteristics of electric vehicle power demand, this paper chooses fuzzy logic control for control, and then adds an improved Savitzky-Golay filter is added for real-time control of intelligent energy management strategies. Through the analysis of the power demand of the passenger car, the proposed control strategy can effectively reduce the loss of the hybrid energy storage system and improve the economy of the energy storage system.

In order to fully improve the performance of HESS, researchers have proposed various power control strategies. These control strategies can be roughly divided into rule-based strategies [9, 10] and optimisation-based strategies. The fuzzy-based control strategy is developed based on the engineer’s development experience. Baisden et al. [11]. A simple table lookup method is introduced. The method is divided into three modes, each used to provide power in the form of different power requirements. Bowman et al. [12] and Lee and Sul [13] proposed a torque control strategy for parallel electric vehicles based on fuzzy rules as early as 1998. Zhang et al.[14] proposed a filtering method to provide the high-frequency part of the required power to the supercapacitor and the low-frequency part to the lithium battery. Compared with the traditional control strategy, it effectively increases the life of the energy storage system and reduces the power loss of the energy storage system.

Based on the optimisation strategy, the degradation cost of the lithium battery and the battery system loss cost is usually regarded as the evaluation function of offline optimisation, and the subfunction founds the optimal power distribution point. They are using global optimisation techniques such as the non-dominated sorting genetic algorithm-II (NSGA-II) [15], dynamic programming (DP) [16, 17], offline solution of the optimal power allocation problem of the hybrid power system based on the a priori knowledge of the entire drive cycle. Because they relied on initial drive cycles and high computational burdens, these technologies are usually not real-time solutions, but merely serve as benchmarks for achieving optimal system performance. Some other global optimisation methods, such as genetic algorithm[18, 19], particle swarm optimisation [20], simulated annealing [6][21], and so on, are usually used for the development of optimal controllers.

There are four topological ways to couple the lithium battery and supercapacitor in Hess: A passive topology structure, two semi-active topologies and fully active topologies. Semi-active HESS only uses one DC / DC converter. However, it can provide the right balance between costs. Therefore, this study uses a typical semi-active HESS, as shown in Fig.1.
Supercapacitor controlled semi-active topological hybrid system.

Fig.1. Supercapacitor controlled semi-active topological hybrid system.

II. HESS MODELING

A. Dynamic Model of the Battery

The battery model used in this paper is the PNGV equivalent circuit model proposed by the United States’ new-generation automotive cooperation plan in 2001. The PNGV model adds a capacitor $C_p$ based on the Thévenin model to describe the open-circuit voltage change generated by the cumulative load current time. As shown in Fig.2. Where $U_{oc}$ represents an ideal voltage source, and is used to describe the battery open-voltage; $R_p$ is the ohm resistance; Polarisation $R_s$ and capacitance $C_s$ describe the battery over-voltage $U_p$; $U_L$ and $I_{bat}$ are the load voltage and current of the battery, respectively. The basic parameters of the tested battery pack are listed in Table I.

![PNGV equivalent circuit model of the battery.](image)

**Fig.2.** PNGV equivalent circuit model of the battery.

| Parameters                | Value   | Unit |
|---------------------------|---------|------|
| Battery Type              | Lithium-ion battery |      |
| Nominal pack voltage      | 348     | V    |
| Nominal pack capacity     | 40      | Ah   |
| Parallel number           | 2       |      |
| Normal cell capacity      | 20      | Ah   |

Based on the equivalent circuit, the following voltage state equation can be established:

$$U_{oc} = U_L - R_sI_S - \frac{1}{C_p} \left( \int I_{bat} dt \right) - I_{bat}R_p \quad (1)$$

$$\frac{dl_s}{dt} = I_L - I_S \quad (2)$$

$$\tau = R_sC_s \quad (3)$$
In formula (3), \( \tau \) denotes the time constant.

Where the remaining charge \( \text{SOC}(t) \) of a battery at a specific time \( t \) is usually calculated based on the initial time \( \text{SOC}_0 \). By calculating the integral of current to time in time \( t \), thus calculating the percentage of remaining power, which is defined by

\[
\text{SOC}(t) = \text{SOC}_0 \frac{1}{Q_N} \int_0^t \eta I(t) \, dt \quad (4)
\]

Among them, \( Q_N \) is the battery rated capacity, \( I(t) \) is the battery current in time \( t \), and \( \eta \) is the charge and discharge efficiency.

The calculation method of the total actual power loss of the battery pack during time \( \lambda \) is as follows:

\[
Q_{\text{loss}} = \sum_{t=0}^\lambda (I(t)^2R/m - U(t)I(t)(1 - Q_c)) \quad (5)
\]

Where \( I(t) \) is the output current of the battery pack at time \( t \), \( R \) is the resistance of the battery pack, \( U(t) \) and \( Q_c \) are the terminal voltage and Coulomb efficiency of the battery pack at time \( t \), respectively. \( M \) is the number of parallel branches of the battery pack.

B. Dynamic Model of the Supercapacitor

In order to describe the dynamic characteristics of the supercapacitor, the RC equivalent circuit model is used to model the supercapacitor, as shown in Fig. 3. The model includes a large capacitor \( C_b \) and a characteristic small capacitor \( C_s \). The large capacitor \( C_b \) is usually used to simulate the static state of the supercapacitor, and the capacitor \( C_s \) is used to describe the dynamic state of the supercapacitor. The resistance \( R_t \) is used to simulate the resistance of the supercapacitor. The resistance \( R_e \) and the surface resistance \( R_s \) are used to reflect the storage capacity and dynamic characteristics of the supercapacitor, respectively.

Fig.3. RC equivalent circuit model of the supercapacitor.

According to the above RC battery equivalent circuit, the mathematical Model is compiled as follows.

\[
\frac{dU_b}{dt} = \frac{-1}{C_b(R_e + R_s)} \cdot \left( \frac{U_b}{U_s} \right) \cdot \left( \frac{-R_s}{C_e(R_e + R_s)} \right) \cdot \left( U_s \right) + \left( \frac{-R_s}{C_e(R_e + R_s)} \right) \cdot \left( U_c \right) \quad (6)
\]

\[
U_s = \frac{R_s - R_t}{R_e + R_s} U_b + \frac{R_s + R_t}{R_e + R_s} U_s + \frac{R_t R_s - R_s R_e}{R_e + R_s} I_{sc} \quad (7)
\]

The basic parameters of the supercapacitor are listed in Table II.

| BASIC PARAMETERS OF THE SUPERCAPACITOR |
| Parameters                    | Value   | Unit |
|------------------------------|---------|------|
| Battery Type                 | Supercapacitor |      |
| Nominal pack voltage         | 356     | V    |
| Nominal pack capacity        | 26      | F    |
| Parallel number              | 1       |      |
| Normal cell capacity         | 3400    | F    |

The SOC of the supercapacitor at the current moment can be expressed as

\[
SOC = \frac{Q_{\text{remaining}}}{Q_{\text{total}}} = \frac{C \cdot (U_{sc} - U_{\text{min}})}{C \cdot (U_{\text{max}} - U_{\text{min}})} = \frac{U_{sc} - U_{\text{min}}}{U_{\text{max}} - U_{\text{min}}}
\]  

(8)

Where \(Q_{\text{remaining}}\) is the amount of charge remaining in the current supercapacitor, \(Q_{\text{total}}\) is the total charge when the supercapacitor bank is full. \(U_{\text{min}}\) and \(U_{\text{max}}\) represent the minimum voltage and maximum voltage across the capacitor, respectively.

### III. Energy management strategy

The fuzzy controller has strong robustness and is suitable for solving the problems of non-linearity, strong coupling, time-varying, and hysteresis in process control. It is widespread in solving real-time control problems. This paper proposes a control strategy that combines a fuzzy controller with an improved least square method. The overall flow chart and a specific block diagram of the energy management system of this control strategy are shown in Figure 4.

![Flowchart for an energy management system.](image)
(b). Diagram of the proposed energy management system.

Figure 4. Flow chart of energy management of hybrid energy storage system.

A. Design of Fuzzy Controller

The proposed fuzzy controller has three inputs and one output. The first input is the required power $P_{req}$, the second input is the SOC of battery, and the last input is the SOC of the supercapacitor. The output is $K_{bat}$, which is the ratio of the power provided by the lithium battery to the total power. In the developed fuzzy logic controller, the relationship between the input and output of the fuzzy controller is shown in Figure 5 (a) and (b).

(a) The relationship between the input and output of the fuzzy controller $$(SOC_{bat}, P_{req} \text{ and } K_{bat})$$.
(a) The relationship between the input and output of the fuzzy controller

\[(SOC_{sec}, P_{req} \text{ and } K_{bat})\].

**Figure 5.** The relationship between the input and output of the fuzzy controller.

B. Improved Savitzky-Golay filter

Savitzky-Golay filter was proposed by Savitzky and Golay in 1964; it has been widely used in data stream smoothing and noise removal since then[22]. Its most prominent feature is that it can ensure the shape and width of the signal unchanged while filtering the noise. The steps to smooth the output power of renewable energy using the Savitzky-Golay filter are as follows.

Suppose the width of the filter window is \(n=2m+1\), and each measurement point is \(x=(-m,-m+1,\ldots,0,1,\ldots,m)\), and using \((k-1)\) order polynomial to fit the data points in the window

\[
y(x) = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + \cdots + a_{k-1} x^{k-1} = \sum_{i=1}^{k} a_{i-1} x^{i-1} \quad (9)
\]

So there are \(n\) such equations, forming a \(k\) elements linear equation system. To make the equations have a solution, \(n\) should be greater than or equal to \(k\). Generally, \(n>k\) is selected, and the fitting parameter \(A\) is determined by the least-squares method. Can be obtained

\[
\begin{pmatrix}
y(-m) \\ y(-m+1) \\ \vdots \\ y(m)
\end{pmatrix} =
\begin{pmatrix}
1 & -m & \cdots & (-m)^{k-1} \\
1 & -m+1 & \cdots & (-m+1)^{k-1} \\
\vdots & \vdots & \ddots & \vdots \\
1 & m & \cdots & (m)^{k-1}
\end{pmatrix}
\begin{pmatrix}
a_0 \\ a_1 \\ \vdots \\ a_{k-1}
\end{pmatrix} \quad (10)
\]

The matrix can be represented as follows

\[
Y_{(2m+1)\times 1} = X_{(2m+1)\times k} A_{k\times 1} \quad (11)
\]

Suppose the \(E\) matrix is
Set up another auxiliary matrix $B$

$$B = E^T \cdot E \quad (13)$$

Then the least square solution $A$ of $A_{k \times 1}$ is

$$A = (E^T \cdot E)^{-1} \cdot E^T \cdot Y \quad (14)$$

Then the predicted value $\bar{Y}$ of $Y$ is

$$\bar{Y} = E \cdot A \quad (15)$$

The goodness of fit (denoted as $R^2$) as an output evaluation can be expressed as

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (16)$$

Assuming a data set includes $n$ recorded values of $k_0, k_1, \ldots, k_n$, and the corresponding model prediction values are $h_0, h_1, \ldots, h_{n-1}$ and $h_n$ respectively.

$$y = \frac{1}{n+1} \sum_{i=0}^{i=n} k_i \quad (17)$$

Then the total sum of squares can be obtained as

$$SS_{tot} = \sum_{i=0}^{i=n} (k_i - \bar{y})^2 \quad (18)$$

The regression sum of squares is

$$SS_{res} = \sum_{i=0}^{i=n} (k_i - h_i)^2 \quad (19)$$

Therefore, the goodness of fit can be defined as

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (20)$$

In the case of Mode I, the window is fixed (the collected data is constant) and the order of the polynomial (9) changes. If there are $c$ windows, the order of the polynomial varies within $[1, t-1]$. As shown in Figure 6.
In mode II, the window is changing (the number of collected data is different), and the order of polynomial (9) remains unchanged. As shown in Figure 7.

Rule-based selection is to prevent Model I and model II from overfitting through simple rules. When the output value of $P_{bat}$ is larger than the required power, which output may cause excessive power loss of the lithium battery, so at this time, the value of the fuzzy controller is output by the design of relevant rules.

IV. Simulation Results and Analysis

The simulation study to present the proposed control strategy is implemented in Matlab/Simulink environment for verifying the effectiveness of the strategy. The urban dynamometer driving schedule (CYC_NYCC+CYC_UDDS) is selected as the test driving cycle; the specific characteristics are shown in Fig.8. Moreover, the main parameters of the vehicle are listed in Table III.
The energy loss ($Q_{\text{loss}}$) of HESS is an essential indicator of the coordinated working efficiency of the battery and supercapacitor. When the battery and supercapacitor are charged and discharged within the allowable capacity, the energy loss of the energy storage system is small (under agreed cycling conditions), indicating that the strategies can effectively allocate the power. As shown in table IV, the energy loss of HESS with the proposed strategy was reduced by 4.73% in comparing with the fuzzy strategy.

**TABLE IV**

ENERGY LOSS OF ENERGY STORAGE SYSTEM

| Strategies        | $Q_{\text{bat-loss}} (KJ)$ | $Q_{\text{sc-loss}} (KJ)$ | $Q_{\text{loss}} (KJ)$ |
|-------------------|-----------------------------|---------------------------|-------------------------|
| Fuzzy strategy    | 296.57                      | 10.62                     | 307.20                  |
| Proposed strategy | 280.40                      | 12.25                     | 292.65                  |

The following figures show the changes in various performance indicators of batteries and supercapacitors under the two strategies.
As can be seen in FIG. 9 (a), under the proposed strategy, the SOC of the battery in the hybrid energy storage system is higher than that under the fuzzy controller, their values are 0.7370 and 0.7495 respectively, and the proposed strategy improves 1.70% compared with the fuzzy controller. The output power of the strategy proposed in Figure (b) is smaller than that of the fuzzy controller, especially at peak power. Figure (c) shows the temperature change curve of the battery. The maximum temperature of the battery under the proposed strategy and fuzzy controller is 26.30°C and 25.99°C, respectively. Compared with the fuzzy controller, the proposed control strategy reduces 2.43%; the final temperature after the test cycle is 25.78°C and 25.49°C, respectively, the temperature drops by 1.12%. In Figure (d), the highest currents of the proposed strategy and fuzzy strategy are 87.17A and 91.53A, respectively, which is reduced by 4.76% by comparison. Figure (e) shows the SOC change of the supercapacitor under test conditions. The SOC of the proposed strategy and the fuzzy controller of the supercapacitor are 0.5151 and 0.8690, respectively.

As the primary power source of electric vehicles, LIB batteries have received much attention in their cycle life. Excessive charging and discharging will accelerate the decline of the cycle life. The combination of the supercapacitor of HESS is very beneficial for enhancing the battery cycle life. In the present study, the weighted Ah-throughput models were used to predict battery life, and it is based on the simulation of battery performance values (such as capacity, voltage, current, temperature, and so on.) to predict changes[23]. The Model is
based on the concept of cumulative Ah-throughput concerning t implemented by the following formula[24][25]:

$$Ah_{eff} = \int_{0}^{T} \sigma |I_{batt}(t)|dt$$  \hspace{1cm} (21)

Where $\sigma$ is called the severity factor, it is related to the battery's DOD, temperature, and the C-rate ($I_{c}$). In order to evaluate the strategy proposed in this article, a simple severity factor is selected [26], as follows:

$$\sigma = \frac{1.6}{625} (I_{c})^{2} + 1 = \frac{1.6}{625} \left( \frac{I(A)}{Q_{batt}(Ah)} \right)^{2} + 1$$ \hspace{1cm} (22)

The parameters required to define the nominal battery life are mentioned in [23]. The nominal battery life $\Gamma$ is defined as the total Ah throughput of the nominal duty cycle[23]:

$$\Gamma = \int_{0}^{EOL} |I_{nom}(t)|dt$$ \hspace{1cm} (23)

According to the literature [23], $A$ indicates that the battery Ah life (nominal cycle) is under the battery energy capacity of 1kWh. $Q_{batt}$ represents the battery capacity, $U_{nominal}$ refers to the nominal voltage of the battery. Where $I_{nom}(t)$ is the nominal current, $EOL$ represents the battery end of life. According to the literature [23], the predicted battery life is:

$$L = \frac{\Gamma}{2.3 \times Ah_{eff}} = \frac{20000 \times 348 \times 40}{2.3 \times Ah_{eff}}$$ \hspace{1cm} (24)

Therefore, from the above formula (17), it can be concluded that under the fuzzy controller and the proposed strategy, based on the formula (11), it can be concluded that the expected number of cycles available in HESS is 33008 and 34661 respectively. Compared with the fuzzy controller, the usable cycle life of the proposed strategy is increased by 5.01%.

Conclusion

This paper proposes an intelligent energy management strategy based on fuzzy logic control-improved Savitzky-Golay filter to control the demand power distribution of electric vehicles in real-time, aiming to improve the usable cycle life of the battery by optimising power distribution. By using model I and model II for selective fitting, the peak power of the battery can be effectively reduced, and the current fluctuation of the battery can be reduced. The improvement of these performance indicators helps to slow down the degradation of the battery and improve its service life.

In order to evaluate the performance of the proposed control strategy, MATLAB / Simulink was simulated based on the test drive cycle. The simulation results show that the method can effectively improve various performance indicators of the battery. For example, in terms of the maximum temperature of the battery, the proposed control strategy is better than The fuzzy control strategy dropped by 2.43%. Besides, the control strategy proposed in HESS increases the service life of the battery by 5.01% compared to the fuzzy controller, which helps to reduce the operating cost of electric vehicles. Under the proposed strategy, it can be roughly seen that supercapacitors can bring better performance in the future.

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