
Fengyan Yi, Dagang Lu, Xingmao Wang, Chaofeng Pan, Yuanxue Tao, Jiaming Zhou, and Changli Zhao

Abstract: The development of energy management strategy (EMS), which considers how power is distributed between the battery and ultracapacitor, can reduce the electric vehicle’s power consumption and slow down battery degradation. Therefore, the purpose of this paper is to develop an EMS for hybrid energy storage electric vehicles based on Pontryagin’s minimums principle (PMP) considering battery degradation. To verify the EMS, the hybrid energy storage electric vehicle model is first established. In the meantime, the battery cycle life trials are finished in order to develop a battery degradation model. Following that, a rule-based control approach and the PMP optimization algorithm are used to allocate power in a hybrid energy storage system (HESS) in a reasonable manner. Finally, a simulation experiment under urban dynamometer driving schedule (UDDS) settings verifies the established EMS, and the findings reveal that the suggested EMS has a lower energy consumption rate and battery deterioration rate than the rule-based method.

Keywords: electric vehicle; hybrid energy storage system; energy management strategy; Pontryagin’s minimums principle; battery degradation

1. Introduction

The development of hybrid energy storage systems that can improve the power and mileage of electric vehicles has been attracting more attention nowadays. In a hybrid energy storage system, batteries and ultracapacitors are crucial components. Ultracapacitors’ benefits of high power density, quick charge and discharge, and multiple cycles can compensate for lithium-ion battery shortages, resulting in longer battery life and improved power performance [1]. At the same time, the performance of the battery will be constantly attenuated due to the effect of electrochemical reactions and the condition of the battery, which will affect the battery lifetime, and these factors will have a direct impact on the power and economy performance of the vehicle [2]. Furthermore, in the hybrid electric vehicle, the energy management system is accountable for managing and distributing the output power of the power battery and ultracapacitor [3]. The energy management system must consider the battery degradation while meeting the demand power, thereby extending battery life and maximizing vehicle efficiency [4]. As a result, the fundamental challenge of an energy management strategy for hybrid energy storage electric vehicles is how to properly distribute the energy of the power battery and ultracapacitor. The design of energy management strategy, the establishment of the battery decay model, the matching of ultracapacitor, and DC/DC converters are hotspots in the research on...
energy management of hybrid energy storage electric vehicles. Domestic and international researchers have presented models to depict battery life/performance reduction and aging based on battery aging parameters. Based on these evaluation models, energy management strategies considering battery degradation are proposed [5].

At present, capacity degradation models for lithium-ion batteries are split into three categories: mechanism, equivalent model, and empirical model. The mechanism model is based on the physical and chemical characteristics of the battery, helping to explore the influencing factors of battery capacity decline. However, the mechanism model’s construction process is more complicated and obtaining the electrochemical parameters involved in the model is difficult, so it is generally used in battery research, rather than control problems [6]. Although the equivalent circuit model has a wide range of applications, the electrical components may suffer losses, and the model’s accuracy is influenced by a variety of external circumstances. However, the establishment and calculation of the empirical model [7] are relatively simple and can meet the model accuracy requirements of this study. For formula-fitting construct, a large amount of test data of battery life are used [8], taking into account the battery capacity decline and the physical interaction between various parameters. John Wang et al. [9] found that when the discharge ratio is high, it is the key factor affecting battery aging. At a low discharge ratio, temperature has the greatest impact on battery aging, whereas discharge depth has the least impact. Therefore, the established semiempirical battery aging model ignores battery states of charge (SOC) and only considers the effects of temperature and charge-discharge ratio. Suri et al. [10] used battery aging data retrieved during the battery maintenance stage to create a battery life loss model for hybrid energy storage electric vehicles in operation, taking into account the influence of battery SOC on battery aging.

The research on energy management strategy design of hybrid energy storage electric vehicles can be classified into two categories: rule-based strategy [11] and optimization-based strategy [12]. Control strategies based on static logic thresholds and fuzzy logic are included in the former, while control strategies based on all-around optimization [13] and instantaneous optimization are included in the later. Many studies on the energy management strategy of hybrid energy storage electric vehicles have used a rule-based technique when just considering the vehicle’s energy consumption rate. Tavakol-Sisakht [14] proposed an energy management method based on fuzzy logic control, and simulation results demonstrate that the fuzzy logic energy management technique can reduce battery current variations. The following data types are often input to the fuzzy controller: ultracapacitor SOC, vehicle demand power, and battery SOC. The output term is the battery power distribution coefficient, which is used to calculate the battery discharging power and capacitor discharging power. Although the structure of this management method is basic and straightforward to apply, the control rules are entirely dependent on extensive manual experience. As a result, it is impossible to fully use the benefits of composite power supplies, and the optimal control cannot be realized. For the purpose of emphasizing consciousness of both thermal safety and degradation of the onboard lithium-ion battery system, the paper [15–17] proposed a universal algorithmic framework combining a model-based state observer and a deep reinforcement learning-based optimizer, which has validated its superiority in terms of charging rapidity, enforcement of lithium-ion battery thermal safety, and life extension, as well as computational tractability. To obtain the optimal strategy to solve the issue of battery decline, ref. [18] proposed an energy management strategy for rechargeable hybrid energy storage electric vehicles and a battery model that can be used for energy management optimization. In this model, the battery health damage under different states of charge (SOC) and battery pack temperatures can be estimated. Then, stochastic dynamic program (SDP) and particle swarm optimization (PSO) are used to solve the multi-objective optimal control problem numerically, and the balance between energy consumption and battery health is considered while meeting the vehicle power demand. The health of the battery was taken into consideration, as well as the energy consumption. The SDP-based energy management technique is frequently utilised to find the best global
solution for known operating conditions. Motivated by the problem of charging a number of electric vehicles via limited capacity infrastructure [19], borrowing from communication networks and distributed convex optimization [20] can maximize utilization. In order to minimize electricity generation costs [21] and achieve the optimal charging, obtained as the solution of a scheduling problem of a fleet of electric vehicles, ref. [22] proposed a novel distributed control strategy which relies on an iterative distributed algorithm based on duality, proximity, and consensus theory. According to a simulated case study, this approach allows achieving the global optimum. However, the obvious flaw in this energy management technique is that it requires a considerable amount of computing and takes a long time, making online control unfeasible and relying too heavily on the cyclic state of driving conditions. For the sake of prolonging the life of lithium batteries in hybrid electric vehicles, ref. [23] proposed an optimal control strategy for serial and parallel plug-in hybrid electric buses based on the degradation model of lithium batteries to minimize running costs throughout the life cycle. A method based on the two-dimensional Pontryagin’s minimums principle (PMP) is proposed to get the global optimal strategy. When compared to a plug-in hybrid bus with single energy storage, the battery deterioration was greatly reduced, and the total cost was lowered by 21.7% after using the optimization technique. The results further demonstrate the ultracapacitor of the PMP algorithm in battery degradation control.

There are only a few studies in the open literature that look at the impact of battery deterioration on the development of energy management techniques for hybrid electric vehicles. Most research employed a unified empirical model due to the complexity and duration of the experiments, which is difficult to connect with the practical application. The EMS used by hybrid power source vehicles composed of power batteries and an ultracapacitor is not considered the impact of battery degradation. The peak power output of power batteries is frequent during use, which damages the life of the power battery and reduces the efficiency of the power battery. The uncertainties in the battery model further degrade the accuracy and robustness of the SOC estimate, especially the unexpected sensing shown to cause the biased identification of model parameters [24,25]. In this study, the battery degradation model was obtained from the experiments according to different decay factors considered in practice. As a result of the limitations of current research on the energy management strategy of hybrid energy storage electric vehicles, and in order to reduce battery degradation, the goal of this study is to propose an energy management strategy based on PMP for hybrid energy storage electric vehicles considering battery degradation, which is incorporated into the design of the EMS according to the characteristics of hybrid energy storage systems and the impact of battery decline on performance [26]. The energy management strategy is then constructed utilizing a PMP strategy, which can be used to find the solution of the optimal control in the constrained problem of control variables, with a modest computation amount when compared to other optimization control strategies. Furthermore, the electric vehicle energy management problem is a typical optimal control problem for time-varying nonlinear systems with constraints. A vehicle model of a hybrid energy storage electric vehicle must be built as the basis for confirming the simulation experiment of the energy management strategy. The battery decay experiment is then designed and performed based on the battery performance degradation factor and the battery decay model is established, all according to the HESS’s features. A rule-based control EMS [27] and a PMP energy management strategy considering battery decay are proposed based on the model and the simulation was carried out in MATLAB/Simulink based on the vehicle model. The restricted energy of hybrid energy storage electric vehicles is fairly distributed and exploited to realize the optimization investigation of the energy management technique considering battery decrease.

The research method of this article is divided into five steps in total, namely Section 2.2 vehicle modeling, Section 2.3 battery-degradation modeling, Section 3.2 energy management strategy based on fuzzy control, Section 3.3 energy management strategy based
on PMP global optimization, Section 4 simulation experiments and analyses of energy management strategies.

The remainder of this paper is organized as follows: The construction of the hybrid electric vehicle model is given in Section 2, and Section 3 analyzes and studies the energy management strategy based on battery decay. Section 4 conducts simulation experiments and analyses of energy management strategies. The main conclusion is shown in Section 5.

2. Hybrid Energy Storage Electric Vehicle Modeling
2.1. Vehicle Configuration

This paper investigates a parallel hybrid energy storage electric vehicle with controller, motor, and HESS, which includes ultracapacitor, battery, and DC/DC, as shown in Figure 1. The main parameters are listed in Table 1.

![Figure 1](image.png)

**Figure 1.** The configuration and detailed structure of a parallel hybrid electric vehicle.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vehicle mass</td>
<td>775 kg</td>
<td></td>
</tr>
<tr>
<td>Windward area</td>
<td>2.04 m²</td>
<td></td>
</tr>
<tr>
<td>Rolling resistance coeff</td>
<td>0.0112</td>
<td></td>
</tr>
<tr>
<td>Air resistance coeff</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>Wheel radius</td>
<td>0.252 m</td>
<td></td>
</tr>
<tr>
<td>Transmission ratio</td>
<td>6.515</td>
<td></td>
</tr>
<tr>
<td>Transmission efficiency</td>
<td>95</td>
<td></td>
</tr>
</tbody>
</table>

2.2. Vehicle Modeling

The goal of analyzing the simulation experiment of energy management is to build a hybrid electric vehicle model. As a result, this study builds a vehicle model that includes a driver model, a vehicle longitudinal dynamic model, a motor model, and a HESS model. The motor model is developed using the experimental method, whereas the others are built using mathematical modeling.

The motor model specifies the HESS's power requirements, thus the maps of the motor's driving and recovered states are measured in trials for modeling. The motor efficiency map is shown in Figure 2a,b.
The UC semi-active hybrid topology is used in this study, with the UC module connected to the DC bus through a bidirectional DC/DC converter and the battery module connected directly to the DC bus. At the same time, the DC/DC converter can control the output power of the UC to provide the maximum power for the vehicle, thereby reducing the power requirements of the battery and prolonging battery lifetime [28]. The HESS model is established according to the characteristics and related parameters of batteries, UC, and DC/DC. The battery model selects the Rint equivalent circuit model. The open circuit voltage and internal resistance of the power battery in the model are related to SOC and temperature, and their values can be obtained through testing. Maxwell’s automotive ultracapacitor BCAP0650 is adopted, and the classic model of UC is modeled. The buck-boost bidirectional DC/DC converter is used as the executive part of the power distribution of the HESS, and the bidirectional DC/DC converter model is established based on its working principle and parameters. In order to better describe the structure of the HESS, a model is provided as shown in Figure 3, and the main parameters of the HESS are shown in Table 2.
Figure 3. HESS model.

Table 2. Main parameters of HESS.

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Value</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery module rated capacity</td>
<td>120</td>
<td>Ah</td>
</tr>
<tr>
<td>Battery module rated voltage</td>
<td>144</td>
<td>V</td>
</tr>
<tr>
<td>Series number of battery cells</td>
<td>40</td>
<td>/</td>
</tr>
<tr>
<td>Parallel number of battery cells</td>
<td>32</td>
<td>/</td>
</tr>
<tr>
<td>UC module rated capacitance</td>
<td>33</td>
<td>F</td>
</tr>
<tr>
<td>UC module rated voltage</td>
<td>94.5</td>
<td>V</td>
</tr>
<tr>
<td>Internal resistance of UC module</td>
<td>13.825</td>
<td>mΩ</td>
</tr>
<tr>
<td>Series number of UC cells</td>
<td>35</td>
<td>/</td>
</tr>
<tr>
<td>Parallel number of UC cells</td>
<td>2</td>
<td>/</td>
</tr>
<tr>
<td>Energy efficiency of DC/DC</td>
<td>0.95</td>
<td>/</td>
</tr>
</tbody>
</table>

Since vehicle vibration and operating stability are not studied in this paper, it is only necessary to build a vehicle longitudinal dynamic model. The driving force generated by the power system must overcome rolling resistance, air resistance, ramp resistance, and acceleration resistance during driving. The dynamic equation can be described as:

\[
F_t = F_f + F_w + F_i + F_j = m g f \cos \alpha + \frac{C_D A v^2}{21.15} + mg \sin \alpha + \delta m \frac{dv}{3.6 dt}
\]

(1)

where \(F_t, F_f, F_w, F_i, F_j\) are driving force, rolling resistance, aerodynamic resistance, climbing resistance, and acceleration resistance, respectively. \(m(\text{kg})\) is the gross vehicle mass, \(f\) is rolling resistance coefficient, \(C_D\) is air resistance coefficient, \(A(\text{m}^2)\) is windward area, \(v(\text{km/h})\) is relative the speed of vehicle, \(\alpha\) is the road gradient, \(\delta\) is the rotational inertia of rotating parts equivalent to the quality factor of translational mass, and \(dv/dt(\text{m/s}^2)\) is driving acceleration.

The driver model in this study uses a real-time tracking target speed control method, with the PID algorithm comparing the target speed to the actual speed output by the longitudinal dynamic model, and then determining the opening degree of accelerator pedal and brake pedal to track the target speed. The control algorithm is as follows:
where, $u_p(t)$, $u_i(t)$, and $u_d(t)$ represent the proportional, integral, and differential parts of the PID controller, respectively; $K_p$, $K_i$, and $K_d$ are scaling factor, integrating factor, and differential factor; and $v_{act}(t)$ and $v_{tag}(t)$ are the actual speed and target speed (km/h).

2.3. Battery-Degradation Modeling

Battery deterioration has a significant impact on the cost and performance of electric vehicles across their entire life cycle. A credible battery degradation model is required to estimate the impact of degradation and the associated economic cost. The properties of the battery decline process, as well as the associated experimental data, must be extracted for the building of this model. The battery-degradation model is established using a semi-empirical data model based on the exterior features of the battery in this study.

The degradation factors of battery can be divided into internal and external factors. The internal factors include electrode plate performance degradation, electrolyte decomposition, separator aging, material structure destruction, etc. [29,30] and external factors include battery charge-discharge rate, depth of discharge (DOD), environment temperature, cut-off voltage, etc. Because the research focuses on the influence of energy management system strategies on battery performance degradation, the impact of internal factors is excluded. The discharge ratio (DR) and DOD are chosen as the main factors affecting performance decline, and the NCR18650GA (Panasonic, Osaka, Japan) monomer ternary lithium battery frequently used in electric vehicles is selected as the test object. The equipment adopts the NBT30V100AC4-T battery test system, and the degradation experiments of different DR and DOD in the CD-CS mode were conducted, respectively. A total of nine sets of battery charge and discharge tests were carried out, with 300 charge and discharge cycles in each group. Table 3 shows the nine sets of battery decay experimental schemes with different charge and discharge ratios and different discharge depths.

<table>
<thead>
<tr>
<th>DR/C</th>
<th>DOD/%</th>
<th>Cycles/N</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5</td>
<td>60</td>
<td>300</td>
</tr>
<tr>
<td>0.5</td>
<td>80</td>
<td>300</td>
</tr>
<tr>
<td>0.5</td>
<td>100</td>
<td>300</td>
</tr>
<tr>
<td>1</td>
<td>60</td>
<td>300</td>
</tr>
<tr>
<td>1</td>
<td>80</td>
<td>300</td>
</tr>
<tr>
<td>1</td>
<td>100</td>
<td>300</td>
</tr>
<tr>
<td>2</td>
<td>60</td>
<td>300</td>
</tr>
<tr>
<td>2</td>
<td>80</td>
<td>300</td>
</tr>
<tr>
<td>2</td>
<td>100</td>
<td>300</td>
</tr>
</tbody>
</table>


This section may be divided by subheadings. It should provide a concise and precise description of the experimental results and their interpretation, as well as the experimental conclusions that can be drawn.

The decline rate of battery capacity is shown as follows:

$$Q_{loss} = \frac{Q_i - Q}{Q} \times 100$$  \hspace{1cm} (3) \hspace{1cm}

where $Q_i$ is the available capacity of the battery after $i$ cycles, $i = 300$; and $Q$ is the actual capacity of the battery calibrated before use. Therefore, the function of capacity decline
model is to measure the degree of battery degradation after 300 cycles. The relationship is as follows:

\[ Q_{\text{loss}}(\text{DR, DOD}) = 2.714 + 3.13\text{DR} - 2.34\text{DR}^2 - 0.573\text{DOD} + 0.004\text{DOD}^2 + 0.069\text{DR} \cdot \text{DOD} \]  

(4)

where \( Q_{\text{loss}} \) refers to the decline rate of the battery, DR is the discharge rate, and DOD is the discharge depth. In Figure 4a,b, it can be seen that the relationship between capacity decline rate and discharge ratio and discharge depth is respectively based on the experiment data and fitted by the fitting tool in MATLAB. The fitting surface diagram of capacity decline rate, discharge ratio, and discharge depth is shown in Figure 5.

![Figure 4](image-url)

Figure 4. Factors affecting battery degradation. (a) The relationship between capacity decline and DR. (b) The relationship between capacity decline and DOD.
It is known from Figure 4a that in the state where the ambient temperature is 25 °C and the DOD is 100%, that is, full discharge, the larger the DR is, the greater the capacity decay rate is. In addition, under the condition of high discharge ratio, the decline rate is significantly accelerated with the increase of the number of cycles. As can be seen from Figure 4b, when the ambient temperature is 25 °C and the discharge rate is 1C, the decline rate of battery capacity increases with the increase of discharge depth in the whole charge-discharge cycle. Figure 5 shows that after 300 cycles, the decline rate of the battery is about 8–19% under different discharge depths and discharge ratios. The decline rate of the battery has a great correlation with the discharge rate, while the correlation with the battery DOD is small. At the same time, as the discharge rate changes within the range of 0.5–2C, the decline rate of the battery increases significantly, which conforms to the general law of battery work consumption.


We used Pontryagin’s minimum value principle to design the energy management strategy because it can be used in the problem of constrained control variables to solve the optimal control problem, and the energy management problem of hybrid electric vehicles (HEV) based on battery decay is a typical optimal control problem with constrained variables [31]. That is, the energy management strategy is designed to minimize battery recession and energy consumption in the case of meeting the power demand. At the same time, most of the research on the energy management strategy of HESS is based on a simple rule control strategy, but it cannot get the optimal solution in considering battery degradation and energy consumption. Therefore, for the sake of verifying the validity of PMP energy management strategy, we compared the optimized energy management strategy with the rule-based energy management strategy, namely the fuzzy control strategy and the PMP strategy discussed in this study. Under the condition of satisfying the vehicle power demand, the optimization goal of reducing battery decline can be achieved by designing an appropriate control strategy to reasonably allocate the power between the battery and ultracapacitor.

3.2. Energy Management Strategy Based on Fuzzy Control

For hybrid electric vehicles, the energy management strategy mainly controls power distribution. The fuzzy control strategy, as a rule-based control strategy, has strong adaptability and robustness [32]. How to keep the battery in the best discharge condition is a key issue of energy management strategy design. From the establishment of the battery decay model, it can be seen that there is a convex function between the discharge current and the
capacity decay rate. Therefore, the optimization goal of the energy management strategy of the hybrid energy storage system is to reduce the larger rate during the entire driving process. This goal can be achieved by distributing the output power of the battery and the ultracapacitor, which is equivalent to distributing the discharge current of the battery and the ultracapacitor. The distributed current multiplier is input into the battery decay model, and the battery decay rate is calculated to check the validity of the strategy. This paper introduces the concept of power distribution coefficient \( K \) to represent the weight assigned to battery power, and selects the vehicle demand power, ultracapacitor \( \text{SOC}_{u} \), and battery \( \text{SOC}_{b} \) to obtain the optimal power distribution ratio. Based on this, the fuzzy controller with the power distribution coefficient is analyzed:

\[
K = \frac{P_{b}}{P_{req}} \quad (5)
\]

\[
P_{c} = P_{req}(1 - k) \quad (6)
\]

where \( P_{b} \) is the power allocated to the battery, \( P_{c} \) is the UC power, and \( P_{req} \) is the power demand of the vehicle.

The following control ideas can be obtained based on the working characteristics of the hybrid energy storage electric vehicle: when the required power is positive, the hybrid energy storage system outputs power, and on the one hand, the ultracapacitor is used to protect the battery from discharging smoothly, and on the other hand, it provides instantaneous power to the drive motor. When the demand power is negative, the hybrid energy storage system recovers energy. The ultracapacitor recovers brake feedback energy and protects the battery from acceleration loss due to large current impacts [33]. The two operating states have different power sizes and amplitudes, as well as various control emphasis. Therefore, distinct control strategies for the two operating modes of the composite power supply should be developed. According to the above control ideas, the control strategy is divided into two states: driving and braking. The power in discharge state is distributed reasonably by fuzzy controller 1, and the distributed power in charge state is obtained by fuzzy controller 2. When the demand power is positive, the demand power \( P_{req} \), ultracapacitor \( \text{SOC}_{u} \), and battery \( \text{SOC}_{b} \) are used as the input parameters of fuzzy controller 1, and the power distribution coefficient \( K_{1} \) is used as the output parameter. When the demand power is negative, the ultracapacitor \( \text{SOC}_{u} \) and the battery \( \text{SOC}_{b} \) are regarded as the input parameters of fuzzy controller 2, and the power distribution coefficient \( K_{2} \) is regarded as the output parameter.

In the established vehicle model, the distributed demand power is transferred to the battery and the ultracapacitor, and the DR and DOD can be obtained after the fuzzy control management strategy, which is input into the battery degradation model to solve the battery decay amount after 300 cycles under this energy management strategy. Figure 6 shows the specific energy management strategy.
Figure 6. Fuzzy control energy management strategy.

3.3. Energy Management Strategy Based on PMP Global Optimization

PMP is used to design energy management strategies in this research. PMP is also an off-line global optimal control method and its computational efficiency is higher than that of dynamic programming. It is used to obtain the minimum energy consumption in the whole journey. The main principle of the PMP algorithm is to seek the optimal control quantity $u(t)$, so that the Hamiltonian function gets the minimum value. Therefore, the optimal control for battery/supercapacitor hybrid energy storage systems can be described as searching for the optimal battery output power to minimize the battery decay $Q_{\text{loss}}$. Since battery decline is related to the DR and DOD, the discharge ratio can be obtained through the simple relationship with battery power. So, battery decay rate can be regarded as related to battery power and SOC. Hence, the energy management strategy based on PMP is designed by combining the characteristics of hybrid energy storage systems and PMP practical applications.

The performance of rule-based strategies depends on engineering experience and cannot achieve optimal energy management strategies for HEV. The PMP-based optimization algorithm proposed in this paper is used to allocate power in the HESS in a reasonable way to achieve the optimal energy management strategy of HEV.

A certain cycle condition was randomly selected to establish the objective function $J$ with the battery output power $P_b(t)$ as the control variable $u(t)$, and the battery charged state $SOC_b(t)$ as the state variable. The power of the battery and the ultracapacitor was allocated under the condition of satisfying the power demand of $P_{\text{req}}$ to obtain the control strategy with the minimum battery decay. The target function $J$ of the energy management control strategy is expressed as follows:

$$J(u(t), SOC_b(t), t) = \int_{t_0}^{t_1} L(u(t), SOC_b(t), t) dt$$  \hspace{1cm} (7)

where $L(u(t), SOC_b(t), t)$ represents the decay rate related to $SOC_b$ and $P_b$, and $t$ is the simulation duration. According to Equation (7), the Hamiltonian function can be defined as follows:

$$(u(t), SOC_b(t), \lambda(t)) = L(u(t), SOC_b(t), t) + \lambda(t) \frac{dSOC_b(t)}{dt}$$  \hspace{1cm} (8)

where $\lambda(t)$ is a covariate variable, and the covariance equation is expressed as:

$$\lambda(t) = -\frac{\partial H(u(t), SOC_b(t), \lambda(t))}{\partial SOC}$$  \hspace{1cm} (9)
where \( Q_b \) is the battery capacity and \( I_b \) is the battery current. The state equation can be obtained by derivation of the above formula:

\[
SOC_b = -\frac{I_b(t)}{Q_b}
\]  

(10)

where the expression of \( I_b \) is as follows:

\[
I_b = \frac{U_b - \sqrt{U_b^2 - 4R_b \cdot 4P_b / \eta}}{2R_b}
\]  

(11)

according to the power balance relationship:

\[
P_b(t) = P_{req}(t) - P_u(t)
\]  

(12)

To ensure the safety of the HESS, its output power and SOC must meet the following constraints:

\[
P_{\text{bmin}} \leq P_b \leq P_{\text{bmax}}
\]  

(13)

\[
SOC_{\text{bmin}} \leq SOC_b \leq SOC_{\text{bmax}}
\]  

(14)

\[
SOC_{\text{umin}} \leq SOC_u \leq SOC_{\text{umax}}
\]  

(15)

The PMP-based energy management strategy flow chart is shown in Figure 7.
4. Results and Discussion

It is required to conduct simulation experiments under dynamic load cycles in order to test the effectiveness of the suggested energy management approach based on PMP global optimization. Simulation experiments are carried out under UDDS conditions and the initial is set at 0.9 and DOD is set at 80% in this research. A certain cycle condition is selected to analyze the test results in detail, and its effectiveness is verified by simulation comparison with the fuzzy control energy management strategy. The simulation results of UDDS working conditions are shown in Figure 8.

Figure 8. (a) Result curve of speed and power distribution for the fuzzy control strategy. (b) Result curve of speed and power distribution for PMP strategy.

The optimal power distribution of the HESS with different energy management strategies under UDDS working conditions is shown in Figure 8a,b, indicating both strategies can effectively distribute the power of batteries and the ultracapacitor. However, in the PMP strategy, the energy storage system equipped with an ultracapacitor can share the peak power for the battery, resulting in less power allocated to the battery, which results in less load of the battery. Figure 9a,b is the battery current and the voltage flow curve. It shows that the PMP strategy has better performance. Compared with the fuzzy strategy, the battery current spike is markedly decreased to effectively reduce the damage of the large current for power battery to extend battery life, showing the PMP has better performance in battery protection. Moreover, the voltage drops amplitude of the battery based on the PMP control strategy is the smallest, which indicates that the voltage stability is better under this strategy. Figure 9c expresses the curve of the battery charging state. When the vehicle is running, the charging state of the battery decreases with time, and the SOC
decline rate based on the PMP strategy is slower than that of the fuzzy rule control strategy. This indicates that, under the same conditions, the control effect based on the PMP strategy is better than that based on the fuzzy rule strategy.

Figure 9. (a) Comparison of battery currents of different strategies. (b) Comparison diagram of the battery voltage of different strategies. (c) SOC voltage comparison diagram of different strategies.
Under the condition of UDDS, the comprehensive control effects of the two control strategies are compared, and Table 4 shows the results. From the table, we know that, compared with the strategy based on fuzzy control, the maximum battery current of the PMP strategy decreased by 13.87%, the battery decay rate is reduced by 2.33%, and the driving range increased by 27.72 km. Battery energy consumption decreased by 17.06%. It is verified that the control effect of the PMP-based energy management strategy is better, which can significantly reduce battery energy loss and slow down the battery decline in the case of meeting the driving demand, and protect the battery and save energy.

Table 4. Comprehensive control effects of different strategies.

<table>
<thead>
<tr>
<th>Strategies</th>
<th>Energy Management Strategy Based on Fuzzy Control</th>
<th>Energy Management Strategy Based on Pmp</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum battery current (A)</td>
<td>212.6553</td>
<td>183.1516</td>
</tr>
<tr>
<td>Battery decay rate (%)</td>
<td>11.8677</td>
<td>10.2354</td>
</tr>
<tr>
<td>Driven distance (km)</td>
<td>118.4334</td>
<td>143.1504</td>
</tr>
<tr>
<td>Battery energy consumption rate (kWh/100 km)</td>
<td>14.13</td>
<td>11.72</td>
</tr>
</tbody>
</table>

5. Conclusions

An energy management strategy based on PMP for hybrid electric vehicles considering battery degradation is proposed, with the goal of determining the impact of battery decrease on the power and economic benefits of electric vehicles. Firstly, to verify the effectiveness of the strategy, the model of hybrid electric vehicle is established. The battery loss model is established, which provides a theoretical basis for formulating the energy management strategy by combining the two major factors that affect battery decline, DR and DOD, through nine sets of battery decay experimental schemes with different charge and discharge ratios and different discharge depths. The fuzzy control method and PMP optimization strategy are then used to intelligently allocate the power of the ultracapacitor and battery, ensuring that battery deterioration is kept to a minimum, while maintaining vehicle power performance. Finally, simulation is used to validate the proposed control approach. The results reveal that, as compared to the fuzzy control approach, the PMP energy optimization management technique has a stronger control effect when considering battery degrading characteristics. The peak current of the battery is decreased by 29.5 A using the optimization technique, the cell degradation rate after 300 cycles is reduced by 2.33%, and the energy consumption rate is reduced by 11.72 (kWh/100 km). To summarize, a PMP-based energy management strategy for hybrid electric vehicles that considers battery degradation can dramatically delay battery decline and energy consumption, as well as save energy and protect batteries. In future research, we also need to conduct bench experiments to verify the accuracy and rationality of the simulation results.

Author Contributions: F.Y.: conceptualization, methodology, software, and supervision; D.L.: data curation and writing—original draft preparation; X.W.: writing—reviewing and editing; C.P.: software and supervision; Y.T.: writing—reviewing and editing and supervision; C.Z.: visualization and investigation. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the National Natural Science Foundation of China, key projects supported by the National Natural Science Foundation of China Automotive Industry Innovation and Development Joint Fund grant number [U1864202], and funded by the Natural Science Foundation of Shandong Province, grant number [ZR2019MEE029], and supported by Graduate Interdisciplinary Innovation Project of Yangtze Delta Region Academy of Beijing Institute of Technology (jiaxing) No. GIRP2021-017.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.
Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

- $F_d$: driving force, N·m
- $F_f$: rolling resistance, N·m
- $F_w$: aerodynamic resistance, N·m
- $F_i$: climbing resistance, N·m
- $F_a$: acceleration resistance, N·m
- $m$: gross vehicle mass, kg
- $f$: rolling resistance coefficient, N·m
- $C_D$: air resistance coefficient
- $A$: windward area, $m^2$
- $v$: relative the speed of vehicle, km/h
- $\alpha$: road gradient
- $\delta$: rotational inertia of rotating parts is equivalent to the quality factor of translational mass
- $Q_i$: available capacity of the battery after i cycles
- $Q$: actual capacity of the battery calibrated before use
- $Q_{loss}$: decline rate of the battery
- DR: discharge rate
- DOD: discharge depth
- $L(u(t), SOC_b(t), t)$: decay rate related to SOCb and Pb
- $dv/dt$: driving acceleration, m/s²
- $u_p(t)$: proportional parts of the PID controller, respectively
- $u_i(t)$: integral parts of the PID controller, respectively
- $u_d(t)$: differential parts of the PID controller, respectively
- $K_p$: scaling factor
- $K_i$: integrating factor
- $K_d$: differential factor
- $v_{act}(t)$: actual speed, km/h
- $v_{tag}(t)$: target speed, km/h
- $P_b$: power allocated to the battery
- $P_c$: UC power
- $P_{req}$: power demand of the vehicle
- $K$: power distribution coefficient
- $P_b(t)$: battery output power
- $u(t)$: control variable
- $SOC_b(t)$: battery charged state
- $\lambda(t)$: covariate variable
- $Q_b$: battery capacity
- $I_b$: battery current

References

Sustainability 2022, 14, 1214


10. Suri, G.; Onori, S. A control-oriented cycle-life model for hybrid electric vehicle lithium-ion batteries. Energy 2016, 96, 644–653. [CrossRef]


18. Wang, Y.; Jiao, X.; Sun, Z.; Li, P. Energy Management Strategy in Consideration of Battery Health for PHEV via Stochastic Control and Particle Swarm Optimization Algorithm. Energies 2017, 10, 1894. [CrossRef]


29. Han, X.; Lu, L.; Zheng, Y.; Feng, X.; Li, Z.; Li, J.; Ouyang, M. A review on the key issues of the lithium ion battery degradation among the whole life cycle. eTransportation 2019, 1, 100005. [CrossRef]


