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Design of an Intelligent Controller-Driven Energy Management Strategy for Hybrid Energy Storage Electric Vehicles

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Abstract
Developing an effective Energy Management Strategy (EMS) that optimally allocates power between the battery and ultracapacitor is essential for reducing overall energy consumption in electric vehicles (EVs) and extending battery lifespan. Accordingly, this study aims to design a Fuzzy Logic Controller (FLC)-based EMS for Hybrid Electric Vehicles (HEVs), with explicit consideration of battery degradation mechanisms. To evaluate the proposed EMS, a comprehensive hybrid energy storage electric vehicle model is first developed. In parallel, detailed battery degradation modeling experiments are conducted. Subsequently, a rule-based control approach is employed to achieve intelligent and balanced power distribution within the Hybrid Energy Storage System (HESS). Comparative analysis between the proposed EMS and existing strategies demonstrates that the proposed approach achieves lower energy consumption and significantly mitigates battery degradation.

Keywords: Electric Vehicle; Hybrid Energy Storage System; Energy Management Strategy; Fuzzy Logic Controller; Battery Degradation

1. Introduction

The rapid advancement of electric vehicle (EV) technologies has intensified interest in Hybrid Energy Storage Systems (HESSs) due to their ability to enhance vehicle performance, power density, and operational reliability. Conventional lithium-ion batteries remain central to EV energy storage; however, they alone often struggle to meet the demanding power transients and long service life required for modern driving conditions. Ultracapacitors have therefore emerged as promising complementary devices in HESS configurations owing to their high power density, rapid charge–discharge capability, and exceptional cycle life. Their integration helps relieve stress on batteries during high-power events, mitigate thermal and electrochemical load, and reduce overall battery degradation, thereby improving system efficiency and longevity [1].

Despite these advantages, lithium-ion batteries inherently suffer from gradual performance deterioration induced by complex electrochemical aging mechanisms and varying operational conditions such as temperature, load cycles, and depth of discharge [2]. Managing this degradation is particularly important in hybrid electric vehicles (HEVs), where the Energy Management System (EMS) supervises the allocation of power between the battery and ultracapacitor to meet real-time driving demands [3]. An effective EMS must therefore not only handle immediate power distribution but also account for long-term degradation effects to optimize energy utilization, safeguard battery health, and extend system lifespan. This dual requirement places significant emphasis on the development of degradation-aware EMS strategies for HESS-based EVs.

Research on HESS energy management encompasses several critical domains, including optimal power-sharing strategies, accurate battery aging modeling, and effective design of ultracapacitor–DC/DC converter configurations. Numerous degradation models have been proposed to quantify battery aging behavior and integrate it into EMS decision-making [5]. Broadly, these models fall into mechanistic, equivalent circuit, and empirical categories. Mechanistic models describe aging at the electrochemical level, offering detailed insights into degradation pathways but at the cost of high computational complexity and extensive parameter identification [6]. Equivalent circuit models simplify the representation but are sensitive to environmental and operational variations, which limits reliability. Empirical models, conversely, offer practical advantages for EMS applications by using statistically derived relationships based on extensive experimental data, enabling accurate yet computationally feasible estimation of capacity fade [7, 8].

Prior studies highlight discharge rate, temperature, and state of charge (SOC) as key influencers of battery aging. H. A. Gabbar et al. [9] demonstrated that temperature strongly affects battery deterioration at low discharge rates, whereas depth of discharge has comparatively less impact under these conditions. Although traditional semi-empirical approaches primarily consider temperature and charge/discharge ratios, newer works have emphasized SOC as a crucial factor in capturing realistic aging dynamics X. Yue et al. [10] proposed a model that incorporates SOC-dependent degradation patterns specifically for HESS-powered electric vehicles, demonstrating improved representation of real-world aging behavior.

Energy management strategies for HESS can be broadly classified into rule-based and optimization-based approaches. Rule-based methods—including threshold logic and fuzzy logic—are widely used due to their simplicity and ease of implementation. For instance, X. Lin et al. [13] introduced a fuzzy logic EMS that regulates current fluctuations using battery and ultracapacitor SOC as key inputs. While intuitive, such strategies depend heavily on expert knowledge and often lack the ability to ensure globally optimal performance across diverse driving profiles. In contrast, optimization-based EMS approaches, including global optimization techniques [13], near real-time control, and reinforcement learning, aim to systematically balance power efficiency, battery health preservation, and computational feasibility. Recent works have explored advanced frameworks combining model-based observers with deep reinforcement learning to enhance thermal safety, charging performance, and battery lifespan in HEV applications [15–17]. Another study [18] developed a multi-objective EMS using stochastic dynamic programming and particle swarm optimization, incorporating a detailed degradation model to jointly optimize energy consumption and battery life.

While substantial progress has been made, challenges remain in developing EMS strategies that efficiently balance transient power demand, battery stress reduction, and long-term degradation management in real-world HEV driving scenarios. Many existing studies either simplify degradation models or neglect the synergistic dynamics between the battery and ultracapacitor under varying loads. Moreover, computational complexity limits the real-time applicability of advanced optimization frameworks.

In this context, the present research aims to develop a Fuzzy Logic Controller (FLC)-based degradation-aware EMS for hybrid energy storage electric vehicles**.** The proposed system integrates a realistic battery aging model and an intelligent rule-based controller to achieve efficient and balanced power distribution within the HESS. A comprehensive vehicle model is developed to evaluate the EMS, and a comparative assessment with conventional strategies demonstrates the superiority of the proposed method in reducing energy consumption and mitigating battery degradation.

Hybrid Energy Storage Systems (HESSs), consisting primarily of lithium-ion batteries and ultracapacitors, have emerged as an effective solution to improve the efficiency, reliability, and power-handling capability of electric vehicles (EVs). Ultracapacitors provide high power density, rapid charge–discharge capability, and exceptional cycle life, enabling them to compensate for the limitations of batteries during peak-power events and reducing battery stress and degradation [1]. However, lithium-ion batteries inherently experience electrochemical aging, influenced by operational parameters such as temperature, discharge rate, and state of charge (SOC), ultimately compromising performance and lifetime [2]. Therefore, the development of Energy Management Systems (EMSs) that can intelligently allocate power between storage units while explicitly considering battery degradation has become a central area of research in HESS-equipped electric vehicles [3].

Several studies have focused on developing battery degradation models to support degradation-aware EMS design. Mechanistic models offer high accuracy but are computationally intensive and impractical for real-time control, whereas equivalent circuit models are sensitive to environmental variations. Empirical models, built from extensive experimental data, have gained widespread use due to their balance of simplicity and accuracy [5–8]. Research has demonstrated that discharge rate, temperature, and SOC significantly influence aging, with SOC-dependent degradation effects being especially relevant for HESS applications [9, 10].

Energy management strategies for HESSs generally fall under rule-based or optimization-based categories. Rule-based methods—including threshold logic and fuzzy logic—are simple and easy to implement but may lack global optimality under diverse driving conditions [14]. Optimization-based approaches, such as global optimization, stochastic dynamic programming (SDP), and deep reinforcement learning, can achieve superior performance but often demand extensive computational resources and rely heavily on driving-cycle information [13, 15–17]. For instance, SDP has been applied to derive globally optimal energy consumption profiles under fixed conditions, while distributed convex optimization methods have been explored for intelligent charging coordination in regions with inadequate charging infrastructure [19, 20]. Although these approaches achieve promising results, their execution is time-consuming and not suitable for real-time vehicle control.

Pontryagin's Minimum Principle (PMP) has gained attention as a promising alternative due to its ability to provide near-optimal solutions with significantly reduced computational effort. PMP-based strategies have been applied to plug-in hybrid electric buses, incorporating battery degradation considerations to minimize lifetime operational costs. Results indicate that ultracapacitor-assisted PMP control can slow battery degradation and reduce cost by over 20%, demonstrating the potential of PMP in degradation-aware EMS design.

Despite these advancements, only a limited number of studies explicitly incorporate battery degradation into EMS design for hybrid energy storage electric vehicles. Many existing works rely on simplified empirical models due to the complexity of experimental degradation characterization. Moreover, inaccuracies arising from parameter uncertainties and sensor noise can compromise the robustness of SOC estimation and limit the effectiveness of degradation-aware control. This highlights the need for EMS strategies that consider realistic battery aging behavior, balance power flow effectively, and remain computationally feasible for real-time implementation.

To address these challenges, the present study develops a PMP-based degradation-aware EMS for HESS-equipped electric vehicles. A comprehensive battery degradation model is constructed using experimental datasets collected under varying aging conditions. A detailed hybrid EV model incorporating HESS dynamics, battery degradation, and ultracapacitor characteristics is developed in MATLAB/Simulink. Both a rule-based EMS and a PMP-based EMS are designed and evaluated to assess the impact of degradation-aware control on power distribution, battery stress reduction, and overall energy efficiency.

In conclusion, this study contributes a computationally efficient, degradation-oriented energy management strategy tailored to hybrid energy storage electric vehicles. By integrating a realistic battery degradation model with PMP-based optimal control, the proposed method ensures equitable power sharing, reduces battery stress, and improves long-term energy utilization, thereby advancing the state of energy management for next-generation electric vehicles.

2. Modeling of Hybrid Energy Storage Electric Vehicles

In this paper, a detailed analysis is conducted on the parallel Hybrid Energy Storage System (HESS) illustrated in Figure 1, which comprises a battery, ultracapacitor, DC/DC converter, electric motor, and a supervisory controller.

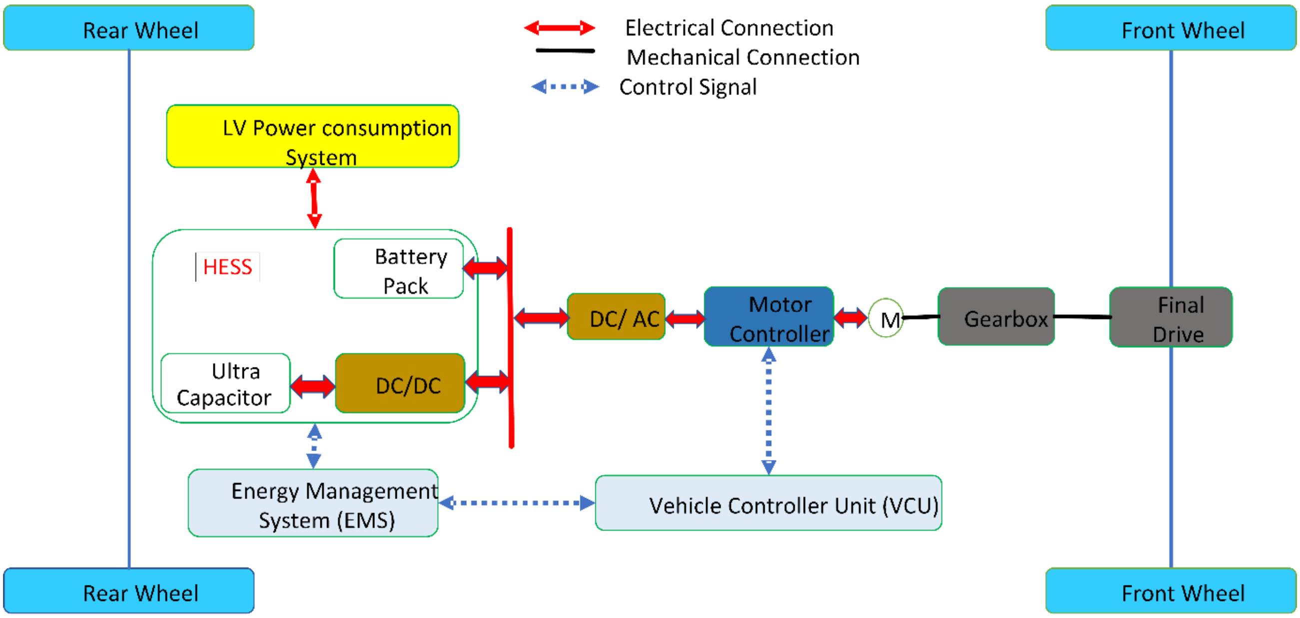

Figure 1. The configuration and detailed structure of a parallel hybrid electric vehicle

2.1. Vehicle Modelling

To effectively simulate a hybrid electric vehicle, this study develops a comprehensive model that supports energy management analysis. The simulation platform includes a driver model, a longitudinal vehicle dynamics model, a motor model, and a Hybrid Energy Storage System (HESS) model. While most components are created through mathematical modeling, the motor model is derived from experimental data to ensure realistic behavior. In the proposed semi-active HESS topology, the battery is directly connected to the DC bus, whereas the ultracapacitor (UC) is linked through a bidirectional DC/DC converter, enabling controlled UC power flow. This configuration allows the UC to handle peak power demands efficiently while reducing overall system energy consumption and forms the basis for evaluating energy management strategies.

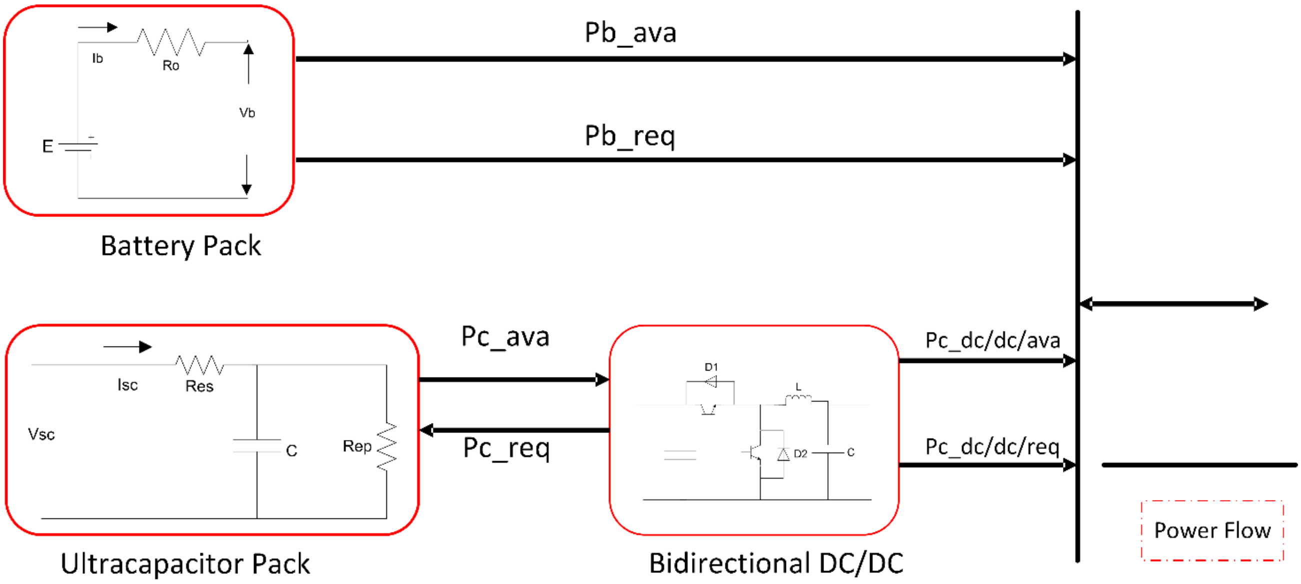

Figure.2 HESS Model

This paper develops a complete vehicle model consisting of a driver model, a longitudinal dynamics model, a motor model, and a HESS model. Most components are built using mathematical modeling, while the motor model is derived from experimental data. In the proposed UC semi-active hybrid topology, the battery is directly connected to the DC bus, and the ultracapacitor (UC) is linked through a bidirectional buck–boost DC/DC converter, which regulates UC power flow to meet peak demand, reduce overall energy consumption, and extend battery life. The HESS model is calibrated using the characteristics of the battery, UC, and DC/DC converter. The battery model adopts the R_{int} equivalent circuit, where open-circuit voltage and internal resistance vary with SOC and temperature based on experimental measurements. A conventional UC model is used, with the Maxwell BCAP0650 automotive ultracapacitor selected. The DC/DC converter model is developed according to its operating principles and specifications. Figure 2 illustrates the structure of the HESS.

2.2. Energy Management Strategy Based on Fuzzy Control

The primary role of an energy management strategy (EMS) in hybrid and fully electric vehicles is to regulate power distribution between energy sources. Among rule-based methods, fuzzy control is widely adopted due to its flexibility, robustness, and ease of implementation. A key challenge in EMS design is ensuring that the battery operates within its optimal discharge region to minimize degradation. Once a battery degradation model is established, the convex relationship between discharge current and capacity fade rate becomes evident. Therefore, an effective EMS must reduce high battery discharge currents throughout the drive cycle, which can be achieved by appropriately sharing the load between the battery and the ultracapacitor.

To evaluate this concept, the distributed current multiplier is incorporated into the degradation model to observe its impact on battery aging. In this study, a power distribution coefficient, K, is introduced to represent the weighting assigned to battery power. The vehicle power demand, ultracapacitor state of charge $(SOC)_{uc}$, and battery state of charge $(SOC)_b$ are selected as input variables to determine the optimal value of K. This framework enables the fuzzy controller to dynamically calculate the appropriate power distribution coefficient for the hybrid energy storage system.

$$K = \frac{P_b}{P_{req}} \quad (1)$$

$$P_b = P_{req}(1 - k) \quad (2)$$

where battery power (P_b), UC power (P_c), and vehicle power demand (P_{req}) are all inputs to the equation.

The operational characteristics of a hybrid energy storage electric vehicle enable the development of a structured energy management approach in which the control logic differs between driving and braking modes. When the required power is positive, the hybrid system supplies energy to the drivetrain, with the ultracapacitor mitigating battery stress by smoothing discharge currents while simultaneously delivering instantaneous power to the motor. When the required power is negative, the system transitions into energy recovery mode, where the ultracapacitor absorbs regenerative braking energy and protects the battery from high-current charging shocks. Because the power amplitude, dynamic response, and control priorities differ between these two operating states, separate fuzzy control strategies are required. Accordingly, the methodology employs two fuzzy controllers: fuzzy controller 1 governs power allocation during discharge, using demand power P_{req}, ultracapacitor SOC_u, and battery SOC_b as inputs to generate the power distribution coefficient K_1; fuzzy controller 2 manages charging by taking SOC_u and SOC_b as inputs and producing coefficient $K_2$when the vehicle is in regenerative mode. By applying the resulting depth-of-discharge (DOD) and discharge-rate (DR) profiles to the battery degradation model, the overall battery decay after 300 cycles can be quantitatively evaluated, and enabling assessment of the proposed fuzzy energy-management strategy.

3. Control Method

Fuzzy Logic Control (FLC) interprets input data using linguistic variables represented by continuous membership values between zero and one. The controller operates on a set of fuzzy rules derived from fuzzy set theory, enabling effective handling of nonlinearities and uncertainties. To address the PQ issue, an FLC is employed, consisting of three main stages: fuzzification, decision-making, and defuzzification. In the fuzzification stage, crisp numerical inputs are converted into fuzzy values, which are then processed through the rule base during the decision-making step. The final control signal is obtained through defuzzification, which transforms the fuzzy output back into a crisp value. Figure 3 illustrates the block diagram of the

FLC, which includes the fuzzification unit, defuzzification unit, input variables, and output variables. Seven membership functions are defined for the input variables error (E) and change in error (CE) as well as for the output variable (P_{loss}), as shown in Figures 5 and 6, with the overall output characteristics presented in Figure 4.

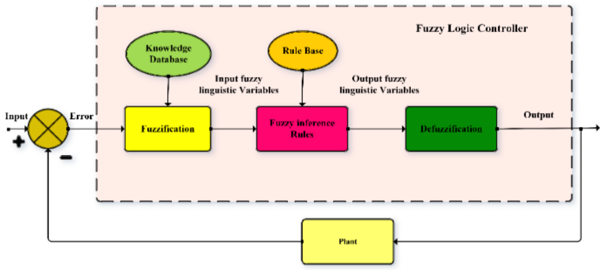

Figure 3. Block diagram of Fuzzy logic controller

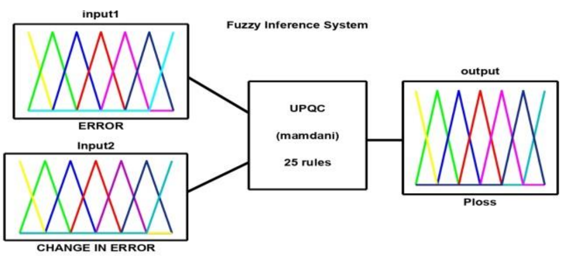

Figure 4. Fuzzy inference System

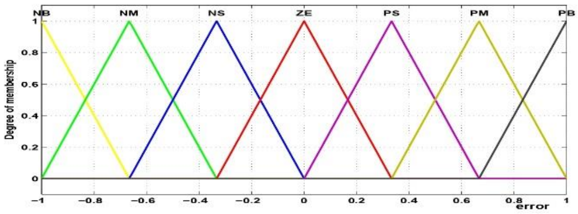

Figure 5. Membership functions for error

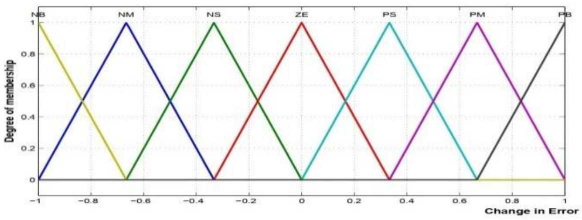

Figure 6. Membership functions for Change in Error

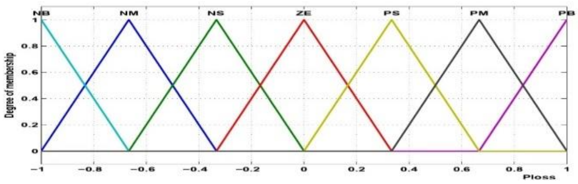

Figure 7. Membership functions for output

A Fuzzy Logic Controller (FLC) is an algorithm based on fuzzy logic or fuzzy inference principles. Fuzzy logic control is a nonlinear, adaptive control method that delivers robust and reliable performance for both linear and nonlinear systems, even in the presence of parameter variations. The membership functions for all fuzzy variables are defined as Negative Big (NB), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM), and Positive Big (PB).

4. Simulation Results

Figure 8 illustrates the power distribution of the HESS under UDDS driving conditions using two different energy management strategies, showing that both methods effectively allocate power between the battery and ultracapacitor. The results indicate that the PMP-based energy optimization strategy outperforms the fuzzy logic approach in mitigating battery degradation. Specifically, the PMP method reduces the battery's peak current by 29.5 A, decreases cell deterioration over 300 cycles by 2.33%, and lowers energy consumption by 11.72 kWh per 100 km. In summary, hybrid electric vehicles employing a PMP-based, degradation-aware energy management system can significantly extend battery life, improve energy efficiency, and protect the battery. To validate and ensure the reliability of these simulation results, future work should incorporate bench-scale experimental testing.

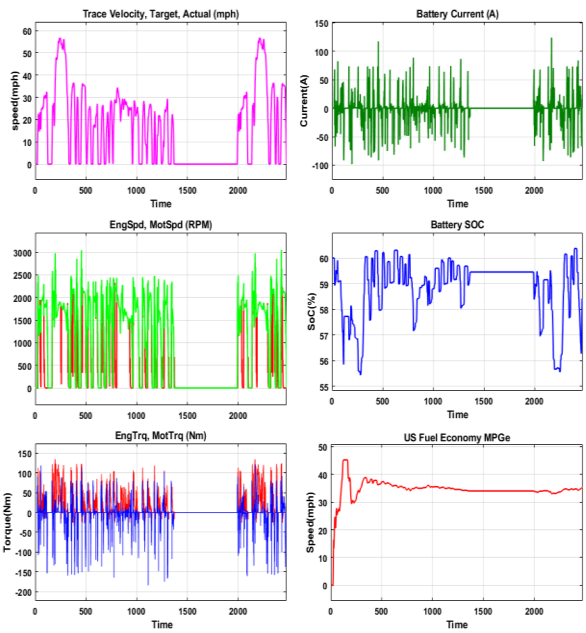

Figure 8. Result curve of speed and power distribution for the fuzzy control strategy.

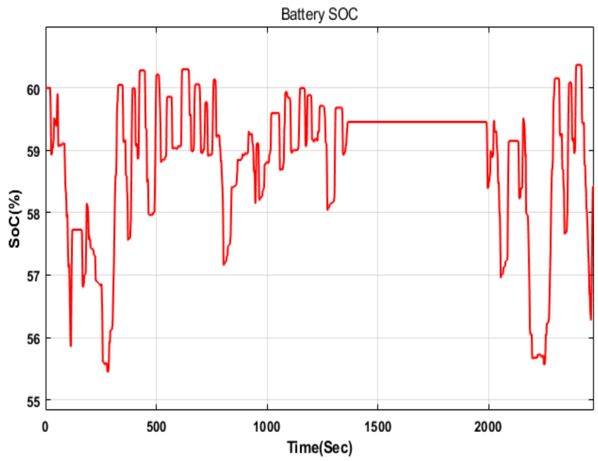

Figure 9. Simulation Result SOC

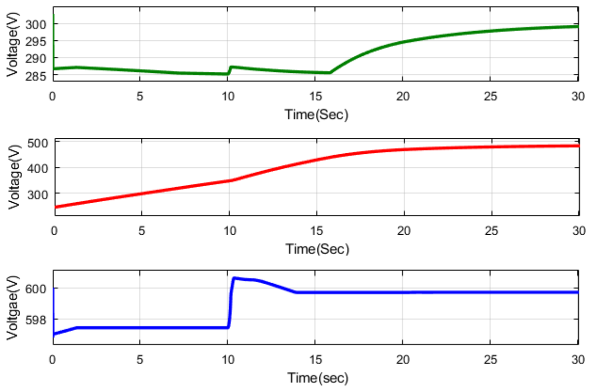

Figure 10. SOC voltage comparison diagram of different strategies

5. Conclusions

In conclusion, this paper presents a fuzzy logic controller (FLC)-based energy management strategy for hybrid electric vehicles that explicitly accounts for battery degradation. A hybrid vehicle model is established to validate the strategy, and nine experimental battery-aging schemes with varying charge–discharge ratios and depths of discharge provide a theoretical basis by incorporating the two primary factors influencing battery degradation: discharge rate (DR) and depth of discharge (DOD). The proposed fuzzy control approach effectively allocates power between the battery and ultracapacitor, reducing the battery's peak current by 29.5 A, decreasing cell deterioration over 300 cycles by 2.33%, and lowering energy consumption by 11.72 kWh per 100 km, while maintaining stable vehicle performance. Simulation results demonstrate that the strategy successfully balances energy efficiency, vehicle power demands, and battery longevity, highlighting its practical potential for hybrid electric vehicle applications.

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