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Enhanced Hybrid Energy Storage Management Using MPC with Real- Time Battery Aging

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Abstract--- In order to dynamically distribute power between the hybrid energy storage system's battery and ultracapacitor, the suggested energy management approach makes use of an Adaptive Model Predictive Control (MPC) architecture. In contrast to traditional MPC methods that use static parameters, adaptive MPC constantly adjusts its internal model and control goals in response to actual system conditions. Online data on battery aging, in particular the instantaneous, time-varying C-rate calculated from the observed battery current, drives the adaptive process. The controller may modify power-split decisions in reaction to anticipated high-stress operating situations by including this real-time degradation indicator into the MPC cost function and limitations. In particular, the adaptive MPC moves more high-frequency power demand to the ultracapacitor and increases the weighting associated with battery deterioration when aggressive load transients or increased C-rates are expected within the prediction horizon. On the other side, when things aren't too hectic, the controller lowers degradation penalties to make the system work better and use less energy. An adaptive trade-off between performance, efficiency, and battery lifespan is made possible by the suggested technique by adaptively changing the MPC weighting factors and control actions. When contrasted with fixed-parameter MPC techniques, this adaptive structure increases resilience against driving-cycle variability, decreases stress on the battery, and considerably lessens capacity fading.

Keywords: Hybrid energy storage system (HESS), Adaptive model predictive control (AMPC), Battery aging, Ultracapacitor, Electric vehicles (EVs), Real-time energy management, C- rate, Capacity fade, Power-split optimization

I. INTRODUCTION

Given the current state of affairs on Earth, many nations are putting a premium on sustainable development. The electrification of transportation has been gaining traction and attention as a means to reduce carbon emissions. Hybrid electric vehicles (HEVs), plug-in HEVs, and EVs are quickly becoming the de facto standard in the automotive industry. Electric vehicles' efficiency, dependability, and performance are largely dictated by the features of its onboard energy storage system. Due to their efficiency, extended cycle life, and high energy density, lithium-ion batteries (LIBs) are now the most popular choice for electric vehicle energy sources. Modern power systems rely on LIBs for transportation and the incorporation of renewable energy sources. Despite the many benefits of EVs, one major obstacle that reduces their long-term performance and economic feasibility is the aging of their batteries. Discharge

depth, operational temperature, charge-discharge rates, and the extremely dynamic load profiles experienced under real-world driving circumstances are some of the many elements that contribute to battery deterioration. High C-rate operation and frequent current transients are two of the variables that shorten the battery's lifespan since they speed up capacity fading and internal resistance increase. Hybrid energy storage systems (HESSs) combine batteries with ultracapacitors (UCs) to solve these problems. In contrast to the battery, which provides power on an average, UCs can manage power fluctuations with ease because to their high power density, rapid charge-discharge capabilities, and extended cycle life. For use in EVs, several HESS topologies have been suggested, including passive, semi-active, and active models. It takes a smart and efficient energy management system (EMS) to get the battery and the UC to share power appropriately. Offline and online methods are the two main categories into which existing EMSs fall. A few examples of offline EMSs are rule-based strategies and global optimization tools like dynamic programming, as well as deterministic and fuzzy logic approaches. Despite their near-optimal performance, offline EMSs aren't adaptable to real-time operating circumstances and need information of the driving cycle in advance. In contrast, online EMSs incorporate learning-based methodologies, predictive control tactics, and methods based on immediate optimization. Improving power distribution in HESS-based EVs has been the focus of recent research into prediction-based EMSs that use velocity forecasting, machine learning, and pattern recognition. Model Predictive Control (MPC) is a potential EMS among online techniques since it may optimize control operations over a constrained horizon, forecast behavior, and explicitly address system restrictions. To improve HESS performance in dc microgrids and electric vehicles, many research have used MPC or one of its derivatives. Optimal power sharing and energy utilization can also be achieved by hierarchical and game-theoretic predictive control systems. Unfortunately, when it comes to unpredictable and ever-changing real-world driving situations, the majority of current EMSs based on MPC use set weighting factors and oversimplified assumptions about battery aging, which severely restricts their usefulness. A lot of work has gone into integrating battery aging into EMS design as battery longevity is a deciding element in EVs' broad adoption. Degradation has been studied in the past with models that account for cycle-based aging, long-term capacity loss, or similar series resistance. But many of these methods assess aging using a set driving cycle or presume constant C-rate operating, which results in an inaccurate assessment of deterioration. Ignoring the continual change in battery current and C-rate during real-world EV operation leads to faulty aging evaluation and less-than-ideal management decisions. Despite the existence of dynamic capacity fade models derived from Arrhenius-type equations, their limited applicability in real-time control stems from their focus on long-term evaluation. In order to overcome these constraints, this study suggests an energy management approach for a battery/UC-based HESS that makes explicit use of real-time data on battery aging, which is based on adaptable Model Predictive Control (AMPC). The

instantaneous, time-varying C-rate, which is generated from observed battery current, is used as an online deterioration indicator in the proposed AMPC architecture. The controller is able to adapt power-split choices on the fly to anticipated high-stress operating situations since this data is included in the MPC cost function and limitations through adaptive weighting factors. In order to safeguard the batteries, the AMPC moves high-frequency power needs to the UC when high C-rates or strong load transients are expected. In contrast, when the system is not under heavy strain, the degradation penalty is loosened to increase system utilization and energy efficiency.

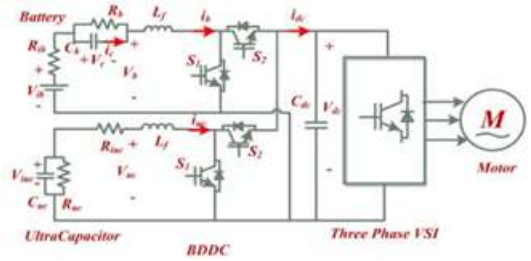


Fig. 1. System configuration for the battery- and UC-based HESS.

II. SYSTEM DESCRIPTION

Hybrid energy storage systems (HESSs) have been implemented in various topologies, including battery semi-active, UC semi-active, parallel, and cascaded configurations. In this study, an active HESS topology is adopted, as shown in Fig. 1, comprising a battery and an ultracapacitor (UC) connected via two bidirectional DC–DC converters (BDDCs) to a common DC link that feeds an EV motor through a DC– AC inverter. The voltage from two sources is

elevated to the dc link, and the dc link power is used to feed the motor through an inverter. The power balance equation for the system is as follows:

$$P_d = \eta_{\text{bat}} P_{\text{bat}} + \eta_{\text{uc}} P_{\text{uc}}$$

A. Battery and UC Modeling

To evaluate the HESS, the battery and the UC are modeled as a first-order RC circuit, as shown in Fig. 1. The battery model consists of polarization components (RC) in a parallel configuration and a voltage source in series with the internal resistance of the battery.

The cell voltage of the battery is given by

$$V_b = V_{ib} - R_{ib} i_b - V_c$$

$$i_c = C_b \frac{dVc}{dt}$$

B. Battery and UC Sizing

The traction battery used in study contains five modules of 72 V and 110 Ah. The total voltage of the battery pack in the HESS is 360 V. The UC pack usually utilizes about 75% of energy stored in the bank by discharging from its rated voltage (Vuc max) to half of its rated voltage (Vuc min) [28]. The energy extracted from the UC pack is

$$E = k\left[\frac{1}{2} C_{\text{eq}}\ V_{\text{uc max}}^2 - \frac{1}{2} C_{\text{eq}}\ V_{\text{uc min}}^2\right]$$

C. Battery Aging Model

The dynamic capacity fade model based on the original Arrhenius degradation equation estimates the capacity loss of the LFP battery, which mainly depends upon the C-rate and the DoD.

The capacity loss is estimated as follows:

$$Q_{\text{loss}} = B.\exp\left(\frac{-Ea + \alpha \times C_{\text{rate}}}{R \times T}\right)(Ah)^{0.55}$$

This model estimates the battery capacity loss for a long duration of time, but it is not suitable when dynamic changes occur.

III. ADAPTIVE MPC-BASED

ENERGY MANAGEMENT STRATEGY

To evaluate the performance of the system, MPC is used as the EMS. MPC works on the principle of predicting the future output of the system over prediction horizon by using a linearized model of the system. The control minimizes the objective function subjected to constraints and predicts system response with accuracy. In this work, MPC has been used to predict the SoC of the UC. The EMS optimizes the objective function to maintain the SoC at desired level and minimizes fluctuations in battery current. The objective function works in a way such that the UC must supply a sudden large current demand and deliver more power to the load to reduce the stress on the battery. The constraints outlining the objective function are between the maximum and minimum allowable limits of the battery current and the SoC of the UC. In the MATLAB/Simulink environment, MPC is implemented using the MPC toolbox. The information related to the system, such as manipulated variable, measured and unmeasured outputs, and the objective function, and related constraints are provided in the toolbox. The simplified battery and UC models are considered, and a continuous state-space model of the HESS is developed, which is linearized using the MPC toolbox.

The discretized objective function at time k is given by

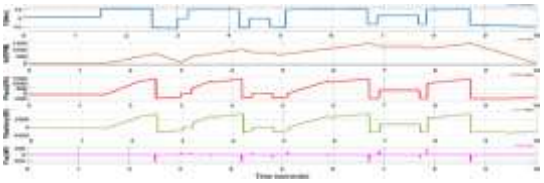
$$J = \sum_{j=1}^{P_H} w_1 [\mathrm{SoC}^*_{\mathrm{uc}}(k+j/k) - \mathrm{SoC}_{\mathrm{uc}}(k+j/k)]^2 + \sum_{j=1}^{C_H} w_2 [i^*_b(k+j/k) - i_b(k+j/k)]^2$$

The MPC controller produces reference currents such that the UC provides sudden and large amount of power and the battery operates to provide constant power. In the objective function, weight w2 is given high priority such that battery current fluctuation is minimized; therefore, the C-rate corresponding to the current is limited for a given drive cycle. Since the battery current during the drive cycle changes as power requirement changes, the corresponding C-rate varies over a range. In evaluating the battery capacity loss for a drive cycle, considering a single C-rate for the entire drive cycle provides inaccurate results. Therefore, the C-rate corresponding to the actual battery current is obtained by sampling the battery current for a given drive cycle by using numerical methods. Here, the IDC is used to evaluate the system. The duration of drive cycle is 108 s; hence, current is sampled at every 1 s, and the corresponding C-rate is computed. For estimating the capacity loss, the actual C-rate is used to calculate the pre-exponential factor B, given by

$$B = \exp\left[1.226^{-0.297 \times C_{\mathrm{rate}}} + 9.263\right]$$

IV. SIMULATION RESULTS

The performance of the proposed battery/UC-based HESS is evaluated in MATLAB/Simulink using the Indian Drive Cycle (IDC). From the longitudinal vehicle model, the velocity profile, wheel torque, and total power demand are computed. The HESS supplies the load power, which is shared between the battery and the UC, as shown in Figure.



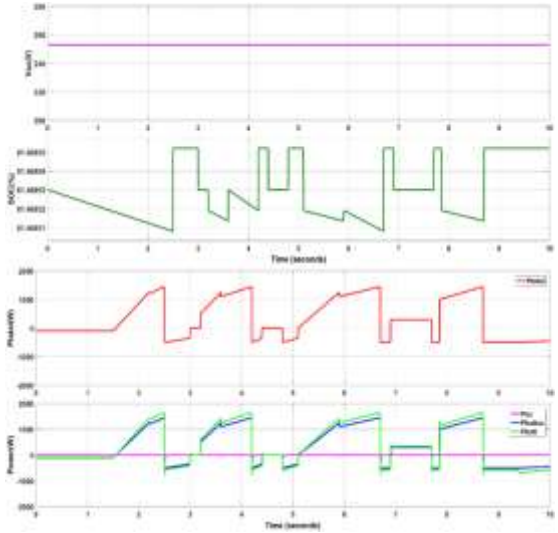


Fig. 2. Results for the complete drive cycle showing: (a) torque, speed, load power, battery power, and UC power; (b) voltage of UC and SoC; and (c) load power and battery power with and without UC

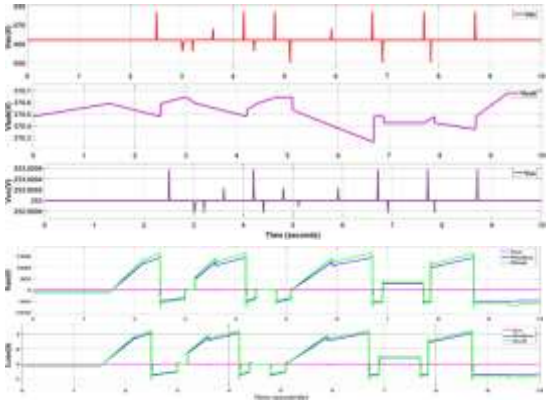


Fig. 3. Results showing (a) zoomed view of battery and UC power and current (b) dc bus voltage, battery voltage, and UC voltage for the complete drive cycle

The ultracapacitor, with its high-power density and fast dynamic response, primarily supplies high-frequency power fluctuations and absorbs regenerative energy efficiently. This is evident from the UC power spikes during acceleration and deceleration events. The UC voltage and SoC are maintained within prescribed limits throughout the drive cycle, as illustrated in Figure, indicating stable operation and effective energy management. Figure compares the load power contributions of the battery and the UC. The UC delivers transient power support during load transitions, while the battery provides the average power demand. This cooperative operation reduces battery stress and improves overall system efficiency. The results demonstrate that the HESS output is effectively the sum of battery and UC contributions, with the UC handling short- duration power peaks. Figure presents a detailed view of the HESS dynamics during acceleration, cruising, and deceleration phases. Battery and UC power, along with current profiles, are plotted to highlight their respective contributions. In the battery-only scenario, the battery alone meets all load requirements, resulting in larger current fluctuations and faster capacity fade. In contrast, during battery-with-UC operation, the UC absorbs the high-frequency component of power, mitigating battery stress. Specifically, the simulation shows that the UC supplies a peak positive power of 1190 W at 78 s and absorbs a peak negative power of 710 W at 76 s during regenerative braking. These results illustrate the UC's role in smoothing power demands on the battery and reducing battery degradation. The HESS parameters used in the simulations are summarized in Table II. Overall, the results validate the effectiveness of the AMPC-based EMS in maintaining UC SoC, minimizing battery current fluctuations, and prolonging battery life under realistic driving conditions.

CONCLUSION

This paper presents an Adaptive Model Predictive Control (AMPC) strategy for a battery/ultracapacitor-based hybrid energy

storage system (HESS) in electric vehicles. The proposed method incorporates real-time battery aging information, using the instantaneous C-rate and dynamic capacity loss model, to adjust MPC weighting factors adaptively. This enables the controller to shift high-frequency power demands to the ultracapacitor during high-stress conditions, while maintaining battery current near constant under normal operation. Reduces battery current fluctuations and mitigates capacity fade. Utilizes the ultracapacitor to supply transient power peaks, smoothing load on the battery. Maintains ultracapacitor SoC and voltage within prescribed limits throughout the drive cycle. Enhances robustness against dynamic and uncertain driving conditions compared to fixed-parameter MPC strategies. The proposed AMPC strategy provides a self-adjusting trade-off between battery lifetime, system efficiency, and performance, highlighting its potential for practical EV applications. Future work will focus on hardware-in-the-loop validation and extension to multi-battery and multi-ultracapacitor HESS configurations under stochastic driving patterns.

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