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Hybrid Electric Vehicle Energy Management Strategy with Consideration of Battery Aging

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Zhou, Bin, "Hybrid Electric Vehicle Energy Management Strategy with Consideration of Battery Aging",
Open Access Dissertation, Michigan Technological University, 2020.
<https://doi.org/10.37099/mtu.dc.etdr/1140>

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HYBRID ELECTRIC VEHICLE ENERGY MANAGEMENT STRATEGY
WITH CONSIDERATION OF BATTERY AGING

By
Bin Zhou

A DISSERTATION

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

In Electrical Engineering

MICHIGAN TECHNOLOGICAL UNIVERSITY

2020

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This dissertation has been approved in partial fulfillment of the requirements for the Degree of
DOCTOR OF PHILOSOPHY in Electrical Engineering.

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Author contribution Statement and List of Publications

The objective of this research is to develop an optimal energy management strategy which improves the fuel economy of Hybrid Electric Vehicles without seriously impacting battery aging. The optimal energy management for Hybrid Electric Vehicle we have published (as co-author) and introduced in section 3 in this brief are shown below:

A. Rezaei, J. B. Burl, B. Zhou, "Estimation of the ECMS Equivalence factor Bounds for Hybrid Electric Vehicles," IEEE Transactions on Control Systems Technology, vol. 26, no. 99, pp. 1-8. doi: 10.1109/TCST.2017.2740836, in 2017

A. Rezaei, J. B. Burl, A. Solouk, B. Zhou, M. Rezaei, M. Shahbakhti, "Catch energy saving opportunity (CESO), an instantaneous optimal energy management strategy for series hybrid electric vehicles", Applied Energy, vol. 208, pp. 655-665, ISSN 0306-2619, in 2017

A. Rezaei, J. B. Burl, B. Zhou, "A New Real-Time Optimal Energy Management Strategy for Parallel Hybrid Electric Vehicles", IEEE Transactions on Control Systems Technology, vol. 27, no. 99, pp. 1-8. doi: 10.1109/TCST.2017.2775184, in 2017

A. Rezaei, J. B. Burl, B. Zhou, "Catch Energy Saving Opportunity in Charge-Depletion Mode, A Real-Time Controller for Plug-in Hybrid Electric Vehicles," IEEE Transactions on Vehicular Technology, vol. 67, no. 11, pp. 11234-11237, in 2018

In order to better understand the impact of battery aging by the optimal energy management strategy, a battery aging model as well as a battery temperature estimation model have been developed. The battery aging analysis including effect in equivalence factor (published in SAE WCX world congress 2017), real time application, state of charge constraints (published in SAE WCX world congress 2018), and low temperature operations (published in SAE WCX world congress 2020). In addition, the comparison between Blended Discharge (BD) and Charge Depletion Charge Sustaining (CDCS) are analyzed. A simple current limiting rule to improve battery aging in charge depletion mode has also been implemented (Journal paper submitted to IEEE Access, under review). Below papers (as lead contributor or co-authored) are written and published which analyzed these effects:

B. Zhou, J. B. Burl, A. Rezaei, "Hybrid Electric Vehicle Battery Aging Estimation and Economic Analysis based on Equivalent Consumption Minimization Strategy", SAE Technical Paper 2017-01-1251, 2017, <https://doi.org/10.4271/2017-01-1251>.

K Khan, B. Zhou, A Rezaei, "Real Time Application of Battery State of Charge and State of Health Estimation", SAE Technical Paper 2017-01-1199, 2017, <https://doi.org/10.4271/2017-01-1199>.

B. Zhou, J. B. Burl, A. Rezaei, "Effect of State of Charge Constraints on Fuel Economy and Battery Aging when Using Equivalent Consumption Minimization Strategy", SAE Technical Paper 2018-01-1002, 2018, <https://doi.org/10.4271/2018-01-1002>.

B. Zhou, J. B. Burl, A. Rezaei, "Effect of Battery Temperature on Fuel Economy and Battery Aging when Using Equivalent Consumption Minimization Strategy for Hybrid Electric Vehicles", SAE Technical Paper 2020-01-1188, 2020, <https://doi.org/10.4271/2020-01-1188>.

B. Zhou, J. B. Burl, A. Rezaei, "The Effect of Control Strategies on Battery Aging for Plug-in Hybrid Electric Vehicles", Submitted to IEEE Access, under review

After analyzing the effects of optimal energy management strategy on battery aging, an optimal energy management strategy has been developed which improved the fuel economy as well as battery aging in charge sustaining mode of ECMS. Below papers (as lead contributor) are submitted or in preparation for publication

B. Zhou, J. B. Burl, A. Rezaei, "Equivalent Consumption Minimization Strategy with Consideration of Battery Aging for Parallel Hybrid Electric Vehicles", Submitted to IEEE Access, accepted

B. Zhou, J. B. Burl, A. Rezaei, "Catch Energy Saving Opportunity with Consideration of Battery Aging for Parallel Hybrid Electric Vehicles", In Preparation

Acknowledgements

To Dr. Burl, Dr. Rezaei, my Families, my Friends, and my Colleagues

who supported and accompanied me during the years I spent to complete my degree, especially consoled, encouraged, and helped me after the failures I had experienced.

List of abbreviations

EMS:	Energy Management Strategy
ECMS:	Equivalent Consumption Minimization Strategy
A-ECMS:	Adaptive Equivalent Consumption Minimization Strategy
IOC:	Instantaneous Optimal Controller
RBC:	Rule-based Control
DP:	Dynamic Programming
PMP:	Pontryagin's Minimum Principle
MPC:	Model Predictive Control
EV:	Electrical Vehicle
HEV:	Hybrid Electric Vehicle
PHEV:	Parallel Hybrid Electric Vehicle
SHEV:	Serious Hybrid Electric Vehicle
SOC:	State of Charge
DOD:	Depth of discharge
SOH:	State of Health
BD:	Blended Discharge
CDCS:	Charge-Depletion Charge-Sustaining
CESO:	Catch Energy Saving Opportunity
MPG:	Miles per Gallon
MPGe:	Miles per Gallon equivalent
Ah:	Ah-throughput
Ah-eff:	Effective Ah-throughput
CD:	Combined drive-cycle
GPS:	Global Positioning System
LSSR:	Limit Steep SOC Reduction

Abstract

The equivalent consumption minimization strategy (ECMS) is a well-known energy management strategy for Hybrid Electric Vehicles (HEV). ECMS is very computationally efficient since it yields an instantaneous optimal control. ECMS has been shown to minimize fuel consumption under certain conditions. But, minimizing the fuel consumption often leads to excessive battery damage. The objective of this dissertation is to develop a real-time implementable optimal energy management strategy which improves both the fuel economy and battery aging for Hybrid Electric Vehicles by using ECMS. This work introduces a new optimal control problem where the cost function includes terms for both fuel consumption and battery aging. The Ah-throughput method is used to quantify battery aging. ECMS (with the appropriate equivalence factor) is shown to also minimize the cost function that incorporates battery aging. Finding the appropriate equivalence factor often required prior knowledge of the entire drive cycle. While using the appropriate equivalence factor might miss the opportunities for fuel savings under certain conditions. Therefore, an adaptive control law of equivalence factor called Catch Energy Saving Opportunity (CESO) has been introduced in this work to make the proposed aging ECMS real-time implementable.

In order to better understand the impact of the developed optimal strategies on battery aging in HEVs, systematic analysis has been performed to find relations between fuel economy, battery aging and the optimization decisions when using ECMS. Therefore, the varies equivalence factors, state of charge constraints and battery temperatures are observed and analyzed under different Combined Drive-cycles (CDs). The CDs are formulated to test the energy management strategy and battery aging with weights on city and highway drive. In addition, rule-based control in charge-depletion mode aimed to improve battery aging has been simulated in a HEV truck. The simulation results show that, the fuel consumed and battery aging degradation during varied operation could be significantly improved by using a simple control rule in charge-depletion mode. This further indicates the benefits of implementing a battery aging term which impacts the control decision in charge-sustaining ECMS.

Based on the analysis results, an aging ECMS has been developed by adding a battery aging term as a cost to the battery. The simulation results showed that this optimal energy management strategy improves battery aging significantly with little or no penalty in fuel economy. In addition, aging CESO ECMS, a real-time optimal strategy, has been developed based on the proposed aging ECMS. The simulation results show that aging CESO ECMS improves upon the basic aging ECMS performance.

1. Introduction

Because of the technical limitation of Electric Vehicles (EVs), and the emission problems of the Internal Combustions Vehicles (ICVs), Hybrid Electric vehicles (HEVs) has been widely studied due to its high potential to combine the benefits of both EVs and ICVs. Differing from ICVs or EVs, a HEV has dual power sources that provide the propulsion which are an internal combustion engine and an electric motor. The dual power sources have high potential to improve fuel economy, emissions, and drivability compare to ICVs. And it has the ability to solve the problems that EVs are currently facing, for example, short driving distance (the engagement of IC engine longer the driving distances), long charging time (battery can be charged while driving) and faded battery aging (the EMS can use IC engine to play trade-off between fuel economy and battery degradation which is the object of this paper).

The dual power sources require efficient power management to optimize the fuel consumption. There are several suggested Energy Management Strategies (EMS) for improving fuel consumptions [1] [2]: Rule-based Control (RBC); Model Predictive Control (MPC); Dynamic Programming (DP); Pontryagin's Minimum Principle (PMP) and its formulated algorithm Equivalent Consumption Minimization Strategy (ECMS).

The optimal control increases the fuel economy, but may result in poor battery life. If the control strategy causes the battery to be charged or discharged quickly and frequently to meet the driver's demanded power, battery life will suffer. As stated in [3][4], a high rate of depth of discharge or charge will shorten battery life. Therefore, an optimal EMS with consideration of battery aging for HEVs is indeed.

This dissertation systematically introduces an online implementable adaptive ECMS with battery aging consideration: Aging CESO ECMS. Before implementing the Aging CESO ECMS, analysis of the aging impact on general ECMS has been performed. A battery aging model combined with a temperature estimation model has been developed for this analysis.

This dissertation has analyzed the effects of battery aging and fuel economy with different equivalence factor values. The simulation results showed that battery life can be significantly extended by selecting an equivalence factor that yields a slight decrease in fuel economy. This will also decrease the lifecycle cost of vehicle operation. The battery aging effects and fuel economy with different SOC constraints were evaluated. The simulation results showed that, appropriately selecting the SOC constraints in ECMS can significantly improve battery life and fuel economy. Different SOC constraints resulted in different battery capacity, which effected both battery aging and fuel economy. Further, the effects of different temperatures on battery aging and fuel economy were analyzed. The simulation results showed that the control system needed to be modified due to the temperature's impact on the battery's available energy capacity and internal resistance. Therefore, different battery temperatures will require different equivalence factors in ECMS to have the best fuel economy as well as the best battery aging.

After analyzing the battery aging impacts on general ECMS, a simple rule based controller has been developed for use in charge-depletion mode. Simulation results showed that with this simple rule-based control, vehicle operation cost could be significantly improved. Then an optimal control problem using ECMS with battery aging consideration is introduced. Simulation results showed that aging ECMS has improved the cost during a trip comparing to general ECMS. To avoid missing energy saving opportunities when the SOC is at the bounds, CESO ECMS which is an adaptive ECMS has been introduced. The simulation results showed that compared to using a fixed equivalence factor in aging ECMS, aging CESO ECMS further improved the cost. The proposed optimal EMS was shown to not only be implementable in charge-sustaining mode but also applicable in charge-depletion mode. In addition, the optimal EMS proposed is applicable to both parallel HEVs and series HEVs.

This dissertation is organized as follows:

- Section 2 reviewed the current existing optimal EMS of HEVs, the battery aging model used for Lithium-ion batteries, and the relevant work which the optimal EMS for HEVs also considered battery aging.
- Section 3 described the vehicle model, battery model, and battery aging model used in this dissertation. And as the comparison, general ECMS strategy and the CESO ECMS strategy.
- Section 4 introduced the analysis has been done during this research development, include the effect of battery aging when changing equivalence factor in the ECMS strategy, SOC constraints, as well as the battery aging performance in low temperature. Finally, a simple rule-based control has been introduced and implemented to improved battery aging.
- Section 5 provided the detailed optimal problem formulation for the aging ECMS and the adaptive aging CESO ECMS for online optimization control strategy, and the proves of ECMS to be optimal with consideration of aging term. Simulation results are provided for fixed equivalence factor aging ECMS and the adaptive equivalence factor aging CESO ECMS.
- Section 6 concluded this work.

2. Literature Review

2.1 Optimal EMS of HEV

RBC strategies are commonly used for commercial HEVs because they are computationally simple. RBC strategies also have the potential to be developed using techniques, such as stochastic DP, which improves the performance of RBC. MPC generates better performances than RBC [5] and can be developed faster than RBC [6]. MPC yields results that are nearly optimal. But, MPC is computationally intensive and requires the prediction of future driver's power demand (which is problematic to estimate). PMP and DP generate the same optimal power management solution [5] (using different tools). Both algorithms are intractable for real time applications. Theoretically, applying ECMS can also generate the optimal solution [7], and give the minimum fuel consumption, while meeting the power demand from the driver. ECMS is computationally simple and can be performed in real time. An equivalence factor is required by the ECMS algorithm. Determining this equivalence factor is the challenging aspect of implementing ECMS.

ECMS is based on the calculus of variations of Pontryagin's Minimum principle (PMP) [8]. Thus, ECMS can yield the optimal performance if the entire drive-cycle is known, a priori. For practical or real-time applications, such advance knowledge of driver demanded power is either not available, or is subject to uncertainty [9]. Therefore, many approaches have been proposed to estimate the optimal trajectory of the ECMS equivalence factor for causal systems [10][11][12][13].

Adaptive ECMS (A-ECMS) is proposed that estimates the optimal ECMS equivalence factor [14]. In A-ECMS, the equivalence factor is calculated either with an instantaneous estimation algorithm [15] or using a prediction-based estimation [16]. The ECMS cost function applies a penalty for using battery power. This penalty is the equivalence factor. It can be shown that ECMS is developed based on Pontryagin's Minimum Principle. As a result, ECMS yields optimal performance if: the optimal value of the equivalence factor is known; Or SOC never reaches its bounds in charge-sustaining mode [17].

In general, A-ECMS either estimates the equivalence factor by using a predicted drive cycle [8][10][12][13] or tries to estimate with no information about the future [14][15]. Therefore, the A-ECMS is applicable for real-time applications. The CESO ECMS strategy [17] proposed in Section 3.5 and 5.3 in this brief is the A-ECMS estimating with no information about the future.

2.2 Battery Aging Model

As of control oriented, battery aging is mainly depended on factors such as battery temperature, C-rate, and depth of discharge [18]. When temperature is too low, severe mechanical deformation of the anode reactions between deposited lithium and electrolyte, the battery started self-suppressing lithium plating [19][20]. The capacity loss in low temperature can reach 40% of its initial capacity [21]. When temperature is too high,

lithium plating occurred [22], cathode degradation and failure of the binder [23], thermal run-away would happen [24]. When C-rate is high, battery surface film resistance and ohmic resistance will raise, carbonate components consumed, electrode damage severely [25][26]. The large depth of discharge will cause the loss of active lithium ions, and cathode started degradation. As of control oriented, these chemical phenomena will reflect as capacity fade or resistance raise [27], which are the common methods to indicate the battery health level.

The most commonly used indicator to quantify the battery health level is the State of Health (SOH). Which is generally defined as [28][29]:

$$SOH = \frac{\text{Current Capacity}}{\text{Initial Capacity}} \% \quad (2.1)$$

There are other battery health level indicators, for example: Remaining Useful Life (RUL), Battery State of Energy (SOE), or using the battery internal resistance incrementation to measure the battery health level. However, these are all proportion of battery capacity fading [30]. In current literature, there are five different theoretical methods to estimate the battery aging level:

- Electrochemical models [31]: modeling the battery based on the chemical phenomena inside the battery
- Equivalent circuit based models [32]: simplify the battery electrical property to an equivalent circuit
- Analytical models with empirical fitting [34]: modeling and estimation based on the actual battery measurements
- Statistical approach [35]: data oriented modeling without a priori knowledge.
- Performances based models [33]: modeling the battery based on its physical Equations

Electrochemical method modelled the battery aging from the battery physical level in 2 different approaches [30]: phenomenological approach [36][37] which fitting the parameters impacted aging process on the cell performance to physical Equations using the macroscopic observation; or atomistic and molecular approach [38][39] which evaluating the atomistic calculations of the physical-chemical processes inside the materials [40][41]. Electrochemical method looked into the battery physical model, and quantifies the physical or chemical factors to obtain the battery behavior. The interactions of these physical factors cause the complexity or making the electrochemical model reliable and accurate.

Equivalent circuit method modelled the battery electrical behavior to an equivalent circuit [42][43]. The aging estimates generally implemented as resistance aging. The components on the equivalent circuit can be identified directly from measurements or from more complex methods [44][45][46]. These methods usually require time consuming tests along with large and diverse data set [30].

Analytical model required large set of experimental data. The larger data set will result more accurate estimations results [47][48]. Analytical model applies curve fitting to the

empirical data. However, the challenge for analytical model is that it requires experiment for each battery conditions, such as external temperature, C-rate; in addition, it requires recalibrations at a certain time interval due to battery degradation or chemical behavior, which is hard to apply in real time.

Same as analytical method, statistical is based on empirical data, it does not need any a priori knowledge on the estimation of battery aging [49]. The challenge for this method impacted that it might only works for the batteries under test, since the accuracy depends on data. And the data requires the battery full characterizations. Same as analytical method, statistical method is unrealizable for online applications.

Performance modeling is semi-empirical method using the simple correlations between stress factor also known as severity factor [50] and capacity fade. Where the simple correlations are measured from battery aging tests. This approach quantified the battery aging factors and obtained the descriptive expression of battery physical behavior [30]. As a control oriented battery aging model, the main factor in performance modeling are charge-discharge cycle, temperature, and C-rate [51]. As compared in [30] for the five principle in battery aging estimation aspects, performance method is good in estimation precision and prediction, and fair in real-time application. Therefore, performance model called Ah-throughput method has been developed in this brief.

2.3 Optimal EMS of HEV with battery aging consideration

As stated in previous section, compare to electrochemical models, equivalent circuit based models, analytical models with empirical fitting, and statistical approach, performance modeling has below advantages in automotive application:

- Less calibration work which involved less experimental tests/data
- Simple to implement
- Applicable for real-time applications
- Better performance in estimation precision and in prediction

The above advantages of performance modeling, or called column counting or Ah-throughput battery aging method, has made it become very popular in literatures related in Optimal EMS of HEV with battery aging consideration [52-64]. Lithium-ion battery LiFePO₄ will be studied in this brief due to its advantages in safety, and longer life characteristic [65]. In addition, the main aging characteristic of LiFePO₄ battery is due to the capacity loss rather than impedance growth[66][67]. Because either column counting or Ah-throughput are theoretically estimating the battery capacity degradation. This character of LiFePO₄ battery made it even better compatible with battery aging performance modeling. Therefore, the aging model of LiFePO₄ can be simplified by only considering the capacity loss criteria.

Tang in [52][53] used PMP as the EMS for HEV included battery life optimization. Battery aging model Ah-throughput method has been used to estimate the battery life. The cost

function Tang proposed in [52][53] is considering minimizing the fuel economy and battery aging as shown in (2.2).

$$J = \int_0^T \alpha \cdot \frac{\dot{m}_{fuel}}{M} + (1 - \alpha) \cdot \frac{\sigma(t) \cdot |I(t)|}{\Lambda} dt \quad (2.2)$$

where M is the maximum fuel flow rate in g/s , Λ is the maximum value of $\sigma(t) \cdot |I(t)|$ when only fuel consumption is considered in the optimization for a corresponding driving cycle. $\sigma(t)$ is the severity factor which measured the severity of battery damage according to operation load, and $I(t)$ is the battery current. α is the weighting factor playing a trade-off between battery aging cost and the fuel cost.

While estimating the battery Γ , nominal C-rate, SOC and temperature has been given as constant in Tang's work. On the other hand, Λ has been given as the maximum value of $\sigma(t) \cdot |I(t)|$ for a corresponding drive cycle, which will lead the optimal result of the EMS to be drive cycle dependent or a prior knowledge of the drive-cycle is required.

In [54], a prediction energy management strategy for HEVs based on MPC method with battery aging consideration has been proposed. The cost function derived is shown in (2.3). Where t is the initial time, l is the length of the prediction horizon, c_f and c_e are the fuel cost and the electricity cost weighting factors, m_f is the fuel flow rate, P_b is the battery output power. C_b is the purchasing cost of the battery system.

$$J = \int_t^{t+l} c_f \dot{m}_f + c_e P_b + C_b \frac{\sigma(t) \cdot |I(t)|}{3600 \Gamma_{nom}} dt \quad (2.3)$$

Similar to [54], a data driven method has been introduced based on five speed profiles collected from urban bus in [55]. Cost function in (2.3) has been used in a PMP optimal method.

The equivalent battery life cost has been derived as $C_b \frac{\sigma(t) \cdot |I(t)|}{3600 \Gamma_{nom}}$. The aging coefficient C_b is introduced as the purchasing cost of the battery system, which the cost of the battery has been decreased rapidly in these years according to the mature technology and the volume production for Lithium ion batteries in the industry [83]. It will be difficult to maintain C_b in consistent with the proposed work in [54][55]. In addition, Γ_{nom} also used constant assumptions of nominal C-rate, SOC, and temperature in these papers. Which leads this optimal EMS to be drive-cycle dependent. [54] used Markov chain as the speed estimator, then played a trade-off over the moving horizon between battery aging and fuel consumption, and finally used PMP based MPC to determine the optimized control action. The transition probability matrix of speed is made by four speed profiles, which is applicable for urban bus, because urban bus usually has the typical everyday driving routine. However, it is not applicable for general commercial vehicles with unknown or unpredictable drive cycles. Thus, the data driven method in [55] is only applicable for service vehicles with typical driving routines.

Tang in [56] developed a charging strategy for plug-in HEV and Battery Electrical Vehicle (BEV) to extend battery life by using the same Ah-throughput aging estimation method introduced in [52]. While, the strategy to charge the battery from utility definitely impacted the battery aging. However, it is not the scope of this work. Tang's work in [56] proved that this battery aging algorithm could be applied in battery charging strategies.

The battery aging estimation model in Hu's work [57], Wu's work in [58], and Cui's work in [61], are directly estimating the damage of battery from the instantaneous Ah-throughput based on experimental data, then used the aging model in MPC as the EMS for HEV. Cai's work in [59] used the Ah-throughput model to indicate the battery health, and analyzed the impact of power split configuration on fuel consumption and battery capacity degradation in HEV city buses. Training the battery aging Ah-throughput method, and using battery aging as a factor to determine the power split configuration will be the future work.

Suri's work in [60] analyzed the sensitivity of severity factor by C-rate, SOC and temperature, then implemented a PMP similar to Tang's work in [52] in a HEV application. Xie's work in [62][63] used effective Ah-throughput as indicator for battery health, then used PMP similar to (2.7) determine the optimal depth of discharge [62] in a coordinated management strategy of connected vehicles[63].

Most of the optimal EMS with consideration of battery aging for HEV implemented in the literatures are PMP or MPC based. As an analytical optimization method, PMP [52][53][60][62] used an analytical problem formulation to solve the problem in a closed, analytical form with consideration of the entire drive cycle. A prior knowledge of drive cycle is required because that one of the boundary conditions from the two-point boundary value problem is defined at the final time [68]. The current literatures for MPC [54][57][58][61] are mostly implemented in service vehicles with typical drive cycles which the future drive cycle is known or with less variance within the pre-defined vehicle speed dataset. MPC is similar to DP, which can achieve the global optimization results. But, it required to consider the short-term optimization horizon extending into the future predicted drive cycle. These methods can be implemented online, but requires either high computational capabilities with more physical components cost to the vehicle, for example, a high computational vehicle electronic control unit, sensors network with radar, or Global Positioning System (GPS) devices. Otherwise, a large site of actual driving data will be needed, which required intensive testing and calibration efforts.

This brief introduced an online optimal EMS with aging consideration based on the general ECMS [87], and further developed in ECMS-CESO. ECMS is an instantaneous optimization strategy instantaneously minimizing the consumption at each instant without use of information regarding the future. The concept of ECMS is considering the battery as an energy buffer in a charge-sustaining HEV [68]. The aging term in this brief has been considered as a weight or cost added to the battery energy buffer, and the aging coefficient of the aging term has been correlated to the co-state of the optimal problem with regard to the energy capacity ratio between battery and fuel.

ECMS-CESO [17] is developed based on the optimal control theory. The soft bounds of SOC allowed to exceed the soft bounds if an energy-saving opportunity is available. In order to limit excursions past the soft bounds, ECMS-CESO is penalized for exceeding these soft bounds. Estimating the demanded power in ECMS-CESO is no longer needed, which makes the implementation of ECMS-CESO cheaper than predictive EM strategies. In addition, implementation of ECMS-CESO in a real-time system, it is more tractable than predictive EMS due to eliminating the intensive calculation for prediction and optimization. This has been considered the main contribution of this brief.

3. Model Development

This section introduced the vehicle model and battery aging model used as the plant vehicle in this brief. The general ECMS optimal strategy and the CESO ECMS real-time A-ECMS strategy are introduced as the baseline optimal EMS as a comparison to the aging ECMS and Aging CESO ECMS.

3.1 Vehicle Model

The vehicle configuration used in this brief is a typical Parallel HEV as shown in Figure 1. The electric path contained battery, inverter, and an electric machine. The fuel path contained fuel tank, engine, and a clutch. These different power sources are coupled by a coupling belt then connected to the input shaft of a transmission.

Figure 3.1. Typical configuration of a Parallel HEV

As shown in Figure 3.1, battery in this simulated vehicle has been modeled by a generic circuit, the open circuit voltage and the battery cell internal resistance are cooperated with depth of discharge (DOD) and temperatures. In this model, the total chemical power out of the battery pack $P_{bat,C}$ is defined:

$$P_{bat,C} = V_{bat,OC}(x(t))i_{bat}(t) \quad (3.1)$$

where $V_{bat,OC}$ is the open-circuit voltage, i_{bat} is the battery pack current, $x(t)$ is the state of charge (SOC) given by Equation (3.2) below, Where Q_{bat} is the total battery capacity in $Amp \cdot sec$.

$$x(t) = 1 - \frac{1}{Q_{bat}} \int_0^t i_{bat}(\tau) d\tau \quad (3.2)$$

The electric machine used in this brief is a Honda IMA 10kW electric motor. The electric machine and the inverter have been modeled as a single component based on a function of

torque T_{em} and motor speed ω_{em} . Equation (3.3) given the function of the power request of electric machine P_{em} .

$$P_{em} = T_{em} \cdot \omega_{em} \cdot \eta_{em}(T_{em}, \omega_{em}) \quad (3.3)$$

where η_{em} is the electric machine efficiency given by the steady-state map related to T_{em} and ω_{em} as shown in Figure 3.2 (b) below.

Figure 3.2, (a) Electric machine max torque and speed curve; (b) Electric machine efficiency map

The transmission used in this brief is the Honda IMA 5 gear automated transmission. The transmission specifications for gear ratio r_{trs} are shown in Table 1 below.

Table 1, Honda IMA automatic transmission gear ratios

1 st gear	2 nd gear	3 rd gear	4 th gear	5 th gear	Final Drive
3.461	1.896	1.241	0.911	0.756	5.77

The final drive efficiency is set to 0.98, and the transmission gear shifting efficiency is set to 0.95.

The transmission shifting logic is based on the control action determined by the optimization strategy as well as the engine clutch control logic. When driver demanded power P_D is received, the EMS calculate all the possible range of control actions, then based on the possible control actions, the consumed power has been calculated. Different transmission gear ratio is included in the options for consumed power. The EMS then determine if the options of control actions are admissible, and calculate the cost of all the admissible controls. The EMS then choose the least cost control action option for vehicle's next step operation. Therefore, the transmission control is completed within the control action selection by the EMS as well as the clutch control.

The engine used in this brief is the Honda IMA 60 kW 4 cylinders engine. The engine output power P_{eng} is calculated from the power contained in fuel P_{fuel} which is given by

Equation (3.4), and the engine efficiency map as shown in Figure 3.3 (b). The fuel flow rate is given by a steady state map as shown in Figure 3.3 (c), which is a function of engine torque T_{eng} and engine speed ω_{eng} .

$$P_{eng} = \eta_{eng} \cdot P_{fuel} = \eta_{eng} \cdot Q_{lhv} \cdot \dot{m}_{fuel}(T_{eng}, \omega_{eng}) \quad (3.4)$$

where η_{eng} is the engine efficiency, Q_{lhv} is the gasoline lower heating value.

Figure 3.3, (a), Engine maximum torque speed curve; (b), Engine efficiency map; (c) Engine fuel flow rate map

The driver used acceleration pedal or brake pedal to control the driver demanded power P_D to achieve the desired speed. Therefore, the hard constraint of the EM strategy is set to meet P_D at any given time t

$$P_D = P_{ptr}(t) + P_{brk}(t) \quad (3.5)$$

where P_{ptr} is the powertrain power provided by internal combustion engine or electric motor in watts. P_{brk} is the power provided by the friction brake system (W).

Assume the efficiencies of both belt and clutch showed in Figure 1 have no lost, then Equation (3.5) could be written as

$$\begin{cases} \text{Brake, Coast } P_D \leq 0: P_{brk}(t) = P_D(t) - \frac{P_{em}(t)}{\eta_{trs}(r_{trs}(t))} \\ \text{Accelerate, Cruise } P_D > 0: P_{eng}(t) = \frac{P_D(t)}{\eta_{trs}(r_{trs}(t))} - P_{em}(t) \end{cases} \quad (3.6)$$

η_{trs} is the total efficiency of the transmission which is respected to the gear ratios r_{trs} . Since P_D is known in Equation (3.6), the plant control input for EM are:

$$u(t) = [r_{trs}(t) P_{em}(t)]^T \quad (3.7)$$

The vehicle longitudinal dynamics are defined as

$$P_D(t) = P_{load}(v(t)) + m_e v(t) \dot{v}(t) \quad (3.8)$$

where v is the vehicle velocity in m/s , m_e is the effective vehicle mass in kg , P_{load} is the road load power calculated from the gravity, rolling resistance, and air drag forces.

The transient dynamics of the engine, electric machine, etc. are ignored, because the transient time of these vehicle components are much faster than the overall system response time, in comparison with SOC and vehicle speed. These simplifications will not affect the vehicle performance, and the simulation results will be reasonable and sufficient [69][70][71].

3.2 Battery Aging Model

Battery capacity loss Q_{loss} in percentage was found to be [30][52]:

$$Q_{loss} = B * \exp\left(-\frac{E_a}{RT_{cell}}\right) (Ah)^z \quad (3.9)$$

Equation (3.9) is derived using the semi-empirical method. E_a is the total activation energy in $J \cdot mol^{-1}$, R is the universal gas constant, T_{cell} is the battery cell temperature in Kelvin, Ah is the total Ah-throughput in Ah, and z is the power-law factor.

Wang's work in [27] showed that power-law factor z is found by curve-fitting based on Equation (15):

$$\ln(Q_{loss}) = \ln(B) - \frac{E_a}{RT} + z \ln(Ah) \quad (3.10)$$

Per Wang's experimental data, z has a value of constant 0.56 for temperatures 15, 45 and 60°C. The environmental temperature used in this work is 20 °C which is 293.15 in Kelvin.

In Equation (3.9), B is called the pre-exponential factor and it is a function of SOC. The coefficient B is computed via curve fitting from experimental data:

$$B = \alpha \cdot SOC + \beta \quad (3.11)$$

where α , β and z in (3.9) are identified by experimental data. E_a is a function of I_c C-rate, as follows:

$$E_a = -31700 + 163.3 \cdot I_c \quad (3.12)$$

where I_c in hr^{-1} is given by:

$$I_c = \frac{|I_{batt}|}{Q_{batt}} \quad (3.13)$$

Now, the percentage of capacity loss is found by substituting (3.11) and (3.12) into (3.9):

$$Q_{loss\%} = (\alpha \cdot SOC + \beta) \cdot \exp\left(\frac{-31700+163.3 \cdot I_c}{R \cdot T_{cell}}\right) \cdot Ah^z \quad (3.14)$$

Maxime's state space model in [72] estimates the battery cell temperature from the air temperature, battery current and battery internal resistance. This state space temperature estimation model uses heat flow transfer and equivalent resistance modeling. The state space model provided in [72] is:

$$\begin{cases} \dot{T}_{cell} = k_1(R_{batt}I_{batt}^2 - k_4(T_{cell} - T_{sens})) \\ \dot{T}_{sens} = k_2(k_4(T_{cell} - T_{sens}) - k_5(T_{sens} - T_{cas})) \\ \dot{T}_{cas} = k_3(k_5(T_{sens} - T_{cas}) - k_6(T_{cas} - T_{air})) \end{cases} \quad (3.15)$$

where T_{air} is the external environment air temperature, T_{cas} is the casing temperature outside of the battery pack, T_{sens} is the sensor temperature inside the battery pack, and T_{cell} is the cell temperature outside of the battery cell. An assumption was made in this battery model that the heat generated by the cell has been equally distributed inside the battery pack. The parameters in Equation (3.15) are calculated by:

$$\begin{cases} k_1 = \frac{1}{C_{v1}} & k_2 = \frac{1}{C_{v2}} & k_3 = \frac{1}{C_{p3}} \\ k_4 = \frac{1}{R_{eff1}} & k_5 = \frac{1}{R_{eff2}} & k_6 = \frac{1}{R_{eff3}} \end{cases} \quad (3.16)$$

where C_{v1} is the heat capacity at constant volume J/K of the cell; C_{v2} is the heat capacity of the air trapped inside the battery pack; C_{p3} is the heat capacity of the external air. R_{eff1} is the thermal resistance between the inside of the battery pack and the outside of the battery cell (calculated by the area swept by the cooling air and the heat transfer coefficient); R_{eff2} is between the outside of the battery pack and the inside of the battery pack; R_{eff3} is between the external environment and the outside of the battery pack.

The total Ah-throughput computed from the nominal current I_{nom} , is defined as the total

charge contained in the battery during its entire life:

$$\Gamma = \int_0^{EOL} |I_{nom}(t)| dt \quad (3.17)$$

The severity factor is defined as the ratio of the nominal theoretical total Ah-throughput to the actual total Ah-throughput [60][73], which contains the aging effects of different operating load cycles. The severity factor will be greater than one if the battery is carrying a more severe load, otherwise, less than one [52]. The shorter battery life is expected when severity factor is greater than one.

$$\sigma(I_c, T_{cell}, SOC) = \frac{\Gamma}{\gamma(I, \theta, SOC)} = \frac{\int_0^{EOL} |I_{nom}(t)| dt}{\int_0^{EOL} |I(t)| dt} \quad (3.18)$$

A capacity loss of 20% from the original battery capacity is considered the end of life. The Equation below (for nominal total Ah-throughput) is calculated by setting Q_{loss} % equal to 20%, to find the value of Ah . The nominal total Ah-throughput Γ is then:

$$\Gamma = \left[\frac{20}{(\alpha \cdot SOC_{nom} + \beta) \cdot \exp\left(\frac{-31700 + 163.3 \cdot I_{c,nom}}{R \cdot T_{cell}}\right)} \right]^{\frac{1}{z}} \quad (3.19)$$

where SOC_{nom} , and $I_{c,nom}$ are the nominal values of SOC and I_c . The nominal values have been calculated based on the average of the historical values. This throughput is defined in terms of a nominal SOC and average C-rate. The actual total Ah-throughput are calculated by the instantaneous SOC and C-rate.

$$\gamma = \left[\frac{20}{(\alpha \cdot SOC(t) + \beta) \cdot \exp\left(\frac{-31700 + 163.3 \cdot I_c(t)}{R \cdot T_{cell}}\right)} \right]^{\frac{1}{z}} \quad (3.20)$$

The effective total Ah-throughput can be calculated by integrating the severity factor times the absolute value of the battery current [52-64].

$$Ah_{eff}(t) = \int_0^t \sigma(I_c, T_{cell}, SOC) \cdot |I(\tau)| d\tau \quad (3.21)$$

Effective Ah-throughput gives the battery life cost for each drive cycle with unit of Ampere-hour. The absolute value of current, used in Equation (3.21), indicates that there is an implicit assumption that charging and discharging have the same impact on battery aging. The battery is considered at its end of life when Ah_{eff} reaches the value of Γ . Thus, the battery State of Health (SOH) is calculated as:

$$SOH = \left(1 - \frac{Ah_{eff}}{\Gamma} \right) \cdot 100\% \quad (3.22)$$

SOH equal to zero indicates that the battery capacity loss has reached 20%, the battery is

at its end of life. The initial SOH for each drive cycle is assumed to be 100% in this paper.

3.3 General ECMS optimal strategy

The equivalent consumption minimization strategy (ECMS) is an optimal energy management strategy for Hybrid Electric Vehicles (HEV), based on Pontryagin's Minimum Principle (PMP). ECMS achieves the maximum fuel economy provided constraints on the battery state of charge are not encountered. The ECMS equivalence factor determines the state of charge trajectory and, therefore, when, and how often constraints are encountered.

The optimal control is found by minimizing the total fuel consumption.

$$u^* = \underset{u}{\operatorname{argmin}} \left\{ \int_0^{t_f} \dot{m}_{fuel}(x, u) dt \right\} \quad (3.23)$$

where $\dot{m}_f$ is the fuel mass flow rate (gram/s), t_f is time at the end of drive-cycle, u is the control actions, u^* is the optimized control action, and x is the state variable.

The fuel consumption is minimized subject to the constraints:

$$u \in U \quad (3.24)$$

$$P_D(t) = P_{ptr}(t) + P_{brk}(t) \quad (3.25)$$

$$\dot{x} = - \frac{P_{bat,c}(x(t), u(t))}{Q_{bat} V_{bat,oc}(x(t))} \quad (3.26)$$

$$SOC_L \leq x \leq SOC_H \quad (3.27)$$

The control actions are within the physical system limitations. The driver's demand power $P_D(t)$ equals the sum of powertrain power, $P_{ptr}(t)$, and the friction brake power, $P_{brk}(t)$. The state variable x is the battery state of charge. (3.27) identified this work is developed for charge-sustaining mode.

The control action is an element of the union of sets that correspond to the vehicle operation modes.

$$u \in \{u_{eom}\} \cup \{u_{cm}\} \cup \{u_{hm}\} \cup \{u_{bom}\} \cup \{u_{bcm}\} \cup \{u_{stop}\} \quad (3.28)$$

where u_{eom} is the set of control actions for engine only mode operation, u_{cm} is for the charging mode, u_{hm} is for the hybrid mode, u_{bom} is for the battery only mode, u_{bcm} is for the brake/coasting mode, and u_{stop} is for the stop mode.

The Hamiltonian of this optimal control problem is:

$$H = \dot{m}_{fuel}(\mathbf{u}(t), P_D(t)) + p(t)\dot{x}(x(t), u(t)) \quad (3.29)$$

Since the battery cell voltage is almost constant within the SOC constraints, so battery power is almost independent with battery cell voltage, which gives the derivative of co-state $\dot{p}(t)$ is almost zero. Therefore p is a constant.

$$\dot{p}(t) = -\frac{\partial H}{\partial x} = -p(t)\frac{\partial \dot{x}}{\partial x} \approx 0 \Rightarrow p = \text{constant} \quad (3.30)$$

Then, the Hamiltonian can be written by:

$$H = \dot{m}_{fuel}(\mathbf{u}(t), P_D(t)) + \lambda(t, x)P_{bat,C}(x(t), u(t)) \quad (3.31)$$

The parameter, λ , which is called equivalence factor, in Equation (8) can be given:

$$\lambda = -\frac{p(t)}{Q_{bat} * V_{bat,oc}(x)} \quad (3.32)$$

Since $p(t)$ is a constant, Q_{bat} and $V_{bat,oc}$ are almost constants in the range of SOC between 50% to 70%. Equivalence factor λ from Equation (3.32) can be defined as a constant too. The bonds of lambda are then found by finding the optimal point of ECMS. Energy loss is found from the energy conservation principle in Equation (3.33) below.

$$E_{fuel} + E_{bat,C} = E_D + E_{loss} \quad (3.33)$$

The optimal is found by minimizing the energy loss.

$$\begin{aligned} u^* &= \underset{u}{\operatorname{argmin}}\{E_{loss}\} = \underset{u}{\operatorname{argmin}}\{E_{fuel} + E_{bat} - E_D\} \\ &\Rightarrow u^* = \underset{u}{\operatorname{argmin}}\left\{\int_0^{t_f} (P_{fuel} + P_{bat,C})dt\right\} \\ &\Rightarrow u^* = \underset{u}{\operatorname{argmin}}\left\{\int_0^{t_f} (\dot{m}_{fuel}Q_{lhv} + P_{bat,C})dt\right\} \\ &\Rightarrow u^* = \underset{u}{\operatorname{argmin}}\left\{\int_0^{t_f} \left(\dot{m}_{fuel} + \frac{1}{Q_{lhv}}P_{bat,C}\right)dt\right\} \end{aligned} \quad (3.34)$$

Then the ECMS cost function can then be written:

$$J_{ECMS} = \dot{m}_{fuel} + \frac{1}{Q_{lhv}}P_{bat,C} \quad (3.35)$$

The optimal control for ECMS is when vehicle in battery only mode. If a battery has an infinite capacity, then the vehicle can be driven in optimal forever. The simulations show by setting $\lambda = 1/Q_{lhv}$ the battery SOC quickly reaches the lower bound SOC_L . A less λ

value makes the battery energy less valuable.

$$\lambda_{opt} = \lambda_{Min} = \frac{1}{Q_{lhv}} \leq \lambda \quad (3.36)$$

When the ECMS equivalence factor is large, ECMS tends to charge the battery up to $SOC = SOC_H$, and then be in fuel only mode for most of the trip. When SOC stays in upper bond, and a positive demands power is provided.

$$\left. \begin{array}{l} x = SOC_H \\ P_D > 0 \end{array} \right\} \Rightarrow u \in \{u_{eom}\} \cup \{u_{bom}\} \cup \{u_{hm}\} \quad (3.37)$$

where u_{eom} is the control action in engine only mode, u_{bom} is the control action in battery only mode, u_{hm} is the control action in hybrid mode. The Hamiltonian Equation showing the vehicle is in engine only mode is shown in Equation (3.38), in battery only mode in Equation (3.39), and hybrid mode in Equation (3.40).

$$H(u_{eom}^*) = \dot{m}_{fuel}(u_{eom}^*, P_D) \quad (3.38)$$

$$H(u_{bom}^*) = \lambda P_{bat,C}(x, u_{bom}^*) \quad (3.39)$$

$$H(u_{hm}^*) = \dot{m}_{fuel}(u_{hm}^*, P_D) + \lambda P_{bat,C}(x, u_{hm}^*) \quad (3.40)$$

When u^* represents all the admissible control actions. When λ is becoming to infinite, then based on Equation (3.31), the ECMS will never discharge the battery, because the cost of battery will be always higher than the cost of fuel. And the vehicle will be always in engine only mode for any $P_D > 0$, and SOC stays at the upper bond since battery is charged by Engine.

$$\left. \begin{array}{l} x = SOC_H \\ \lambda \gg \frac{1}{Q_{lhv}} \end{array} \right\} \Rightarrow \left\{ \begin{array}{l} P_D > 0 : H(u_{eom}) < H(u_{bom}^*) \\ \text{and} \\ P_D > 0 : H(u_{eom}) < H(u_{hm}^*) \end{array} \right. \quad (3.41)$$

Therefore, the upper bound for λ^* such that when $SOC = SOC_H$, other modes, like battery only mode and hybrid mode will also have chance to be optimal.

$$\left. \begin{array}{l} x = SOC_H \\ \lambda = \lambda_{Max} \end{array} \right\} \Rightarrow \left\{ \begin{array}{l} P_D > 0 : H(u_{eom}) > H(u_{bom}^*) \\ \text{or} \\ P_D > 0 : H(u_{eom}) > H(u_{hm}^*) \end{array} \right. \quad (3.42)$$

The inequalities above shows that the upper bond of λ should allow battery discharging to be optimal. So $\lambda_{Max} = \min(\lambda_{Max1}, \lambda_{Max2})$, where λ_{Max1} is the upper bond λ value contained battery only mode, λ_{Max2} is the upper bond λ value contained hybrid mode.

Thus, when $\lambda = \lambda_{Max}$ and $SOC = SOC_H$, for calculating λ_{Max1} contained battery only mode:

$$\dot{m}_{fuel}(u_{eom}, P_D) = H(u_{eom}) > H(u_{bom}) = \lambda^* P_{bat,C}(x, u_{bom}^*)$$

Therefore

$$\lambda^* \leq \frac{\dot{m}_{fuel}(u_{eom}^*, P_D)}{P_{bat,C}(x, u_{bom}^*)}$$

Then

$$\lambda_{Max1} = \frac{\frac{\frac{P_D}{\eta_{trs}(u_{eom})}}{Q_{l hv} \eta_{eng}(u_{eom})}}{P_D / \eta_{trs}(u_{bom}) / \eta_{em}(u_{bom}) \eta_{inv}(u_{bom}) \eta_{bat}(u_{bom})} = \frac{\bar{\eta}_{em} \bar{\eta}_{inv} \bar{\eta}_{bat}}{Q_{l hv} \bar{\eta}_{eng}} \quad (3.43)$$

While calculating λ_{Max2} contained hybrid mode:

$$\dot{m}_{fuel}(u_{eom}, P_D) = H(u_{eom}) > H(u_{bom}) = \dot{m}_{fuel}(u_{hm}^*, P_D) + \lambda^* P_{bat,C}(x, u_{hm}^*)$$

$$\lambda^* \leq \frac{\dot{m}_{fuel}(u_{eom}^*, P_D) - \dot{m}_{fuel}(u_{hm}^*, P_D)}{P_{bat,C}(x, u_{hm}^*)}$$

$$\lambda_{Max2} = \frac{\frac{\frac{P_D}{\eta_{trs}}}{Q_{l hv} \eta_{eng}} - \frac{\frac{P_D}{\eta_{trs}} - P_{em}(u_{hm})}{Q_{l hv} \eta_{eng}}}{\frac{P_{em}(u_{hm})}{\bar{\eta}_{em} \bar{\eta}_{inv} \bar{\eta}_{bat}}} = \frac{\bar{\eta}_{em} \bar{\eta}_{inv} \bar{\eta}_{bat}}{Q_{l hv} \bar{\eta}_{eng}} \quad (3.44)$$

Therefore, the upper bond of λ is then defined:

$$\begin{aligned} \frac{\bar{\eta}_{em} \bar{\eta}_{inv} \bar{\eta}_{bat}}{Q_{l hv} \bar{\eta}_{eng}} &= \frac{\bar{\eta}}{Q_{l hv}} \\ \Rightarrow \lambda_{max} &= \frac{\bar{\eta}_{em} \bar{\eta}_{inv} \bar{\eta}_{bat}}{Q_{l hv} \bar{\eta}_{eng}} = \frac{\bar{\eta}}{Q_{l hv}} \end{aligned} \quad (3.45)$$

where $\bar{\eta}_{em}$, $\bar{\eta}_{inv}$, $\bar{\eta}_{bat}$, and $\bar{\eta}_{eng}$ are the efficiencies of the e-machine, inverter, battery and engine. $\bar{\eta}$ is the efficiency ratio between the electric path of the power train and the engine efficiency. The average efficiencies of those powertrain components are varying based on the duration weight of different operation modes.

Therefore, λ , in the ECMS cost function is known as the ECMS equivalence factor. This equivalence factor has been shown to lie within the bounds:

$$\frac{1}{Q_{l hv}} \leq \lambda \leq \frac{\bar{\eta}}{Q_{l hv}} \quad (3.46)$$

3.4 CESO ECMS optimal strategy

While only considering the SOC hard constraints defined in Equation (3.27), there will be a chance that the optimal EM strategy reject the desired optimal mode. For instance, consider the situation that $SOC(t) = SOC_L$ and $P_D(t + dt) > 0$, there is a possibility that the hybrid or battery only modes are optimal. However, hybrid or battery only modes require battery discharging. Therefore, the optimal EM strategy has to reject these desired modes, which will result in suboptimal fuel economy. In addition, consider $SOC(t) = SOC_H$, the opportunity for charging the battery will be missed, for example regenerative braking. Such events might happen frequently during a trip as the future trajectory of demanded power is unknown. Otherwise, predicting the P_D in MPC or some A-ECMS is one solution to avoid missing the energy saving opportunities. However, as discussed previously, the predicted P_D is subject to uncertainties, which might lead to suboptimal results. Therefore, catch energy saving opportunity (CESO) has been proposed based on ECMS. The ECMS-CESO does not guarantee to achieve the optimal fuel economy, but ECMS-CESO is designed to catch energy saving opportunities without the need for predicting the future P_D .

Figure 3.4. (a) Soft constraints SOC_L^{soft} and SOC_H^{soft} inside the SOC hard constraints. x is allowed to exceed the soft constraints by at most θ_{max} . (b) ECMS-CESO maintains $\lambda(t)$ inside the range defined in inequality (3.46)

In order to catch these energy saving opportunities, soft bounds inside the hard bounds in (3.27) has been defined in Equation (3.47) below.

$$SOC_L^{soft} \leq x(t) \leq SOC_H^{soft} \quad (3.47)$$

Unlikely the hard constraints defined in (3.27), the soft constraints will allow $x(t)$ to exceed them by a penalty of increasing or decreasing $\lambda(t)$ within the bounds defined in Equation (3.46). The penalty occurred in the soft constraints are enforced by θ_{Max} as shown in Figure 3.4. Consider the scenario discussed previously, when $SOC(t) = SOC_L^{soft}$ and $P_D(t + dt) > 0$, the EM strategy will still allow hybrid mode or battery mode if the cost to exceed the soft constraints is less than optimal cost.

The Hamiltonian Equation with considering the cost of the soft constraints is then proposed.

$$H = \dot{m}_{fuel}(\mathbf{u}(t), P_D(t)) + p_1 \dot{x} + p_2 \dot{x}_2 \quad (3.48)$$

The following condition need to be satisfied with the costates p_1 and p_2 .

$$H(x^*, u^*, p^*, P_D) \leq H(x^*, u, p^*, P_D), \quad \forall u \in U \quad (3.49)$$

Where the new state variable x_2 is defined based on the hard constraints in Equation (3.27).

$$\dot{x}_2 = (x - SOC_L^{soft})^2 S(x - SOC_L^{soft}) + (SOC_H^{soft} - x)^2 S(SOC_H^{soft} - x) \quad (3.50)$$

Where $S = 1$, if its argument is negative, otherwise $S = 0$. Which means, when $SOC_L^{soft} \leq x(t) \leq SOC_H^{soft}$, $\dot{x}_2 = 0$. Otherwise, $\dot{x}_2 = (x - SOC_L^{soft})^2$ when $x(t) < SOC_L^{soft}$ or $\dot{x}_2 = (SOC_H^{soft} - x)^2$ when $x(t) > SOC_H^{soft}$.

Finding the costates defined in (3.48)

$$\dot{p}_1^* = -\frac{\partial H}{\partial x} = -\frac{\partial \dot{m}_{fuel}(\mathbf{u}(t), P_D(t))}{\partial x} - p_1^* \frac{\partial \dot{x}}{\partial x} - p_2^* \frac{\partial \dot{x}_2}{\partial x} \quad (3.51)$$

$$\dot{p}_2^* = -\frac{\partial H}{\partial x_2} = -\frac{\partial \dot{m}_{fuel}(\mathbf{u}(t), P_D(t))}{\partial x_2} - p_1^* \frac{\partial \dot{x}}{\partial x_2} - p_2^* \frac{\partial \dot{x}_2}{\partial x_2} \quad (3.52)$$

Where $\dot{m}_{fuel}(\mathbf{u}(t), P_D(t))$ is independent of x and x_2 ; $\dot{x}$ defined in Equation (3.26) is independent of x and x_2 when x is within constraints defined in (3.27); from Equation (3.52), $\dot{x}_2$ is independent of x_2 and only depends on x . Therefore, (3.51) and (3.52) can be re-written to

$$\dot{p}_1^* = -\frac{\partial H}{\partial x} \approx -p_2^* \frac{\partial \dot{x}_2}{\partial x} \quad (3.53)$$

$$\dot{p}_2^* = -\frac{\partial H}{\partial x_2} = 0 \Rightarrow p_2^* = constant \quad (3.54)$$

Then, the equivalence factor λ can be defined as

$$\lambda^* = \frac{p_2^*}{Q_{bat} V_{bat,oc}} \frac{\partial \dot{x}_2}{\partial x} \quad (3.55)$$

Furthermore, by finding $\dot{\lambda}^*$

$$\begin{aligned}\frac{\partial \dot{x}_2}{\partial x} &= \frac{\partial \left[(x - SOC_L^{soft})^2 S(x - SOC_L^{soft}) + (SOC_H^{soft} - x)^2 S(SOC_H^{soft} - x) \right]}{\partial x} \\ &= 2(x - SOC_L^{soft}) S(x - SOC_L^{soft}) + 2(SOC_H^{soft} - x) S(SOC_H^{soft} - x) \\ &\quad + (x - SOC_L^{soft})^2 \delta(x - SOC_L^{soft}) + (SOC_H^{soft} - x)^2 \delta(SOC_H^{soft} - x)\end{aligned}\quad (3.56)$$

Therefore,

$$\dot{\lambda}^* = \begin{cases} 0, & SOC_L^{soft} \leq x(t) \leq SOC_H^{soft} \\ \frac{2p_2^*}{Q_{bat}V_{bat,OC}}(x - SOC_L^{soft}), & x(t) < SOC_L^{soft} \\ \frac{2p_2^*}{Q_{bat}V_{bat,OC}}(SOC_H^{soft} - x), & x(t) > SOC_H^{soft} \end{cases}\quad (3.57)$$

Then, the thresh parameter θ showed in Figure 4 has been defined as

$$\theta(t) = \begin{cases} 0, & SOC_L^{soft} \leq x(t) \leq SOC_H^{soft} \\ (x - SOC_L^{soft}), & x(t) < SOC_L^{soft} \\ (SOC_H^{soft} - x), & x(t) > SOC_H^{soft} \end{cases}\quad (3.58)$$

Therefore, Equation (3.57) can be simplified to

$$\dot{\lambda}^* = \frac{-2p_2^*\theta(t)}{Q_{bat}V_{bat,oc}}\quad (3.59)$$

Finding λ^* from $\dot{\lambda}^*$, integration of Equation (3.59) is performed with consideration with all different cases are considered. At $\theta(t) = 0$ when $SOC_L^{soft} \leq x(t) \leq SOC_H^{soft}$, from Equation (3.59), $\dot{\lambda}^* = 0$, which derives λ^* is a constant, and assumes $\lambda^* = \mu^*$. When $x(t)$ is within the soft and hard constraints in the upper and lower side in an arbitrary time period between t_1 and t_2 ,

$$\int_{\lambda^*(t_1)}^{\lambda^*(t)} d\lambda = \frac{-2p_2^*}{Q_{bat}V_{bat,oc}} \int_{t_1}^t \theta(\tau) d\tau \Rightarrow \lambda^*(t) = \lambda^*(t_1) + \frac{-2p_2^*}{Q_{bat}V_{bat,oc}} \psi(\theta(t), t)\quad (3.60)$$

Where $\psi(\theta(t), t) = \int_{t_1}^t \theta(\tau) d\tau$, is the integral of $\theta(t)$ as defined in Equation (3.58) from t_1 to t . When $t = t_1$, $\lambda^*(t_1) = \mu^*$ where μ^* is a constant, therefore

$$\begin{aligned}\lambda^*(t) &= \mu^* - \frac{2p_2^*}{Q_{bat}V_{bat,oc}} \int_{t_1}^t (x(\tau) - SOC_L^{soft}) d\tau, \text{ when } x(t) < SOC_L^{soft} \\ \lambda^*(t) &= \mu^* - \frac{2p_2^*}{Q_{bat}V_{bat,oc}} \psi(\theta(t), t), \text{ when } x(t) > SOC_H^{soft}\end{aligned}\quad (3.61)$$

Similarly,

$$\lambda^*(t) = \mu^* - \frac{2p_2^*}{Q_{bat}V_{bat,oc}} \int_{t_1}^t (SOC_H^{soft} - x(\tau))d\tau, \text{ when } x(t) > SOC_H^{soft}$$

$$\lambda^*(t) = \mu^* - \frac{2p_2^*}{Q_{bat}V_{bat,oc}} \psi(\theta(t), t), \text{ when } x(t) > SOC_H^{soft} \quad (3.62)$$

Without knowing the full prior knowledge of the drivecycle, μ^* and p_2^* cannot be found in optimal. Since λ will always inside the range defined in (3.46), which means λ is never far away from the optimized equivalence factor λ^* . Since the chosen value of μ^* and p_2^* might not be optimal, the optimal symbol $*$ will be dropped in the followings.

When $x(t) < SOC_L^{soft}$, recall Equation (3.61), the bounds of $\lambda^*(t)$ defined in (3.46) can derive the range of $p_2^*\psi(\theta(t), t)$ defined above.

$$\mu < \lambda(t) < \frac{\bar{\eta}}{Q_{lhv}} \Rightarrow 0 > p_2\psi(\theta(t), t) \geq \frac{\mu - \bar{\eta}/Q_{lhv}}{2/Q_{bat}V_{bat,oc}} \quad (3.63)$$

Therefore, the desired features of $p_2\psi(\theta(t), t)$ should be

$$\begin{cases} \lim_{\theta(t) \rightarrow 0} p_2\psi(\theta(t), t) = 0 \\ p_2\psi(\theta(t), t)|_{\theta(t)=\theta_{Max}} = \frac{\mu - \bar{\eta}/Q_{lhv}}{2/Q_{bat}V_{bat,oc}} \\ p_2\psi(\theta(t), t) \text{ should be a monotonic function of } \theta(t) \end{cases} \quad (3.64)$$

The last feature in (3.64) represents that when $\theta(t)$ increases from the lower soft constraint, the equivalence factor $\lambda(t)$ is desired to increase accordingly. Thus, when $x(t) > SOC_H^{soft}$, the below expression is proposed for p_2 .

$$p_2 = \frac{\mu - \bar{\eta}/Q_{lhv}}{2/Q_{bat}V_{bat,oc}} \cdot \frac{(\theta(t)/\theta_{Max})^2}{\psi(\theta(t), t)} \quad (3.65)$$

The proposed expression in (3.65) for p_2 will justify the penalty to catch the energy-saving opportunity intuitively. The quadratic function $(\theta(t)/\theta_{Max})^2$ is small when SOC is close to SOC_L^{soft} , and the interference of the penalizing procedure is small. When SOC is getting far from SOC_L^{soft} , the value of the quadratic function $(\theta(t)/\theta_{Max})^2$ will increase quickly, and stops ECMS-CESO when SOC exceed SOC_L^{soft} for more than θ_{Max} .

Then substituting (3.65) to (3.61)

$$\lambda(t) = \mu - \frac{2 \frac{\mu - \bar{\eta}/Q_{lhv}}{2/Q_{bat}V_{bat,oc}} \cdot \frac{(\theta(t)/\theta_{Max})^2}{\psi(\theta(t), t)}}{Q_{bat}V_{bat,oc}} \psi(\theta(t), t), \text{ } x(t) < SOC_L^{soft}$$

$$\lambda(t) = \mu + \left(\frac{\bar{\eta}}{Q_{lhv}} - \mu \right) \cdot \left(\frac{\theta(t)}{\theta_{Max}} \right)^2, \text{ } x(t) < SOC_L^{soft} \quad (3.66)$$

Similarly, when $x(t) > SOC_H^{soft}$, recall Equation (3.62)

$$\frac{1}{Q_{lhv}} < \lambda(t) < \mu \Rightarrow \frac{\mu - 1/Q_{lhv}}{2/Q_{bat}V_{bat,OC}} \geq p_2 \psi(\theta(t), t) > 0 \quad (3.67)$$

Therefore, the p_2 proposed when $x(t) > SOC_H^{soft}$ has the below format

$$p_2 = \frac{\mu - 1/Q_{lhv}}{2/Q_{bat}V_{bat,OC}} \cdot \frac{(\theta(t)/\theta_{Max})^2}{\psi(\theta(t), t)} \quad (3.68)$$

And substituting (3.68) to (3.62)

$$\lambda(t) = \mu - \frac{2 \frac{\mu - 1/Q_{lhv}}{2/Q_{bat}V_{bat,OC}} \cdot \frac{(\theta(t)/\theta_{Max})^2}{\psi(\theta(t), t)}}{Q_{bat}V_{bat,oc}} \psi(\theta(t), t), \quad \text{when } x(t) > SOC_H^{soft}$$

$$\lambda(t) = \mu - \left(\mu - \frac{1}{Q_{lhv}} \right) \left(\frac{\theta(t)}{\theta_{Max}} \right)^2, \quad \text{when } x(t) > SOC_H^{soft} \quad (3.69)$$

Thus, the adaptive equivalence factor for ECMS-CESO comes as

$$\lambda(t) = \begin{cases} \mu, & SOC_L^{soft} \leq x(t) \leq SOC_H^{soft} \\ \mu - \left(\mu - \frac{1}{Q_{lhv}} \right) \left(\frac{\theta(t)}{\theta_{Max}} \right)^2, & x(t) > SOC_H^{soft} \\ \mu + \left(\frac{\bar{\eta}}{Q_{lhv}} - \mu \right) \left(\frac{\theta(t)}{\theta_{Max}} \right)^2, & x(t) < SOC_L^{soft} \end{cases} \quad (3.70)$$

In summary, as shown in Figure 3.5, the adaptive equivalence factor $\lambda(t)$ will be a constant when $SOC_L^{soft} \leq x(t) \leq SOC_H^{soft}$; it will be increased to leads the vehicle operates by more engine mode when the battery SOC turns low and the battery will be charged; otherwise, it will be decreased to leads the vehicle operates in more battery mode when battery SOC turns high. In ECMS-CESO, a reasonable μ has been proposed to maintain $\lambda(t)$ within the range defined in (3.46), which μ is set to the midpoint of this range: $\mu = (\bar{\eta} + 1)/(2Q_{lhv})$ as shown in Figure 3.5.

Figure 3.5, ECMS-CESO Adaptive $\lambda(t)$ value based on present value of SOC

The simulation results for general ECMS and ECMS-CESO will be shown in Section 4 and 5 as compare to the results of aging ECMS and aging CESO. The results of the general ECMS and the ECMS-CESO compare to other optimal strategies are published in our previous papers ‘Estimation of the ECMS Equivalence factor bounds for Hybrid Electric Vehicles’, and ‘A New Real-Time Optimal Energy Management Strategy for Parallel Hybrid Electric Vehicles’ on IEEE Transactions on Control Systems Technology in volume 26 and volume 27 in year 2017. Beyond that, ECMS-CESO is also applicable in serious hybrid electric vehicles and plug-in hybrid electric vehicles. The simulation and testing results for serious hybrid electric vehicle has been published in paper ‘Catch energy saving opportunity (CESO), an instantaneous optimal energy management strategy for series hybrid electric vehicles’ in Applied energy volume 208, in 2017. And the simulation results for plug-in hybrid electric vehicles has been published in paper ‘Catch Energy Saving Opportunity in Charge-Depletion Mode, A Real-time Controller for Plug-in Hybrid Electric Vehicles’ in IEEE Transactions on Vehicular Technology in volume 67, in 2018.

4. Analysis of Battery Aging in ECMS

Optimal control increases the fuel economy, but may result in poor battery life. If the control strategy causes the battery to be charged or discharged quickly and frequently to meet the driver's demanded power. This behavior has an undesirable effect on battery life. As stated in [3] [4], a high rate of depth of discharge or charge will shorten battery life. Section 4.1 analyzed the effects of battery aging when the ECMS EMS using different equivalence factors.

In addition, the SOC constraints directly impact the battery's power available to supply the hybrid powertrain. Wider SOC constraints will lead to larger amount of battery usage, which can provide better fuel economy. However, wider SOC constraints may also result in more battery aging because of more likely deep charge-discharge cycles [4]. Therefore, Section 4.2 examined the effect of SOC constraints on fuel economy and battery aging.

On the other hand, a lot of research indicates that the performance of lithium ion batteries is highly dependent on temperature. Joris' tests in [75][76][77] show battery capacity reduces to around 60% at -20 °C as the result of lithium plating on an anode which increases the charge transfer resistance [16][27][78]. The reduction in battery capacity at low temperature restricts the amount of battery energy that is available for the vehicle. In addition, the reduced battery capacity due to low temperatures will lead to more battery aging. This is because the rate of change in the State of Charge (SOC) is higher at low temperatures when the battery capacity is reduced [3][4]. Therefore, Section 4.3 studied the effect of temperature variations, especially in low temperatures, on fuel economy and battery aging.

Two types of control strategies are introduced for Plug-in HEVs: Blended discharge (BD) strategy, and charge-depletion charge-sustaining (CDCS) strategy. Different studies have shown that BD strategy achieves better fuel economy in comparison with CDCS strategy. In Section 4.4, the performance of a plug-in HEV is evaluated by both BD and CDCS strategies while taking the battery aging into account. As expected, controlling the vehicle with Optimal ECMS confirms that BD strategy achieves better fuel economy in comparison with CDCS. However, it was also observed that BD strategy has a better performance than CDCS with regard to battery aging. Results showed that in charge-depletion mode of CDCS strategy, the engine should be allowed to operate if battery discharge current is too high. This mitigates the overall damage to battery useful life during the charge-depletion mode. Therefore, a rule-based control law called LSSR (Limit Steep SOC Reduction) has been introduced and implemented in a CDCS EMS.

4.1 Effect of equivalence factor

As presented in Section 3.3, the equivalence factor λ , in the ECMS cost function lied within the bounds shown in Equation (3.46). It has the behaviors that large equivalence factors tend to make the vehicle operate in engine only mode and small equivalence factors tend

to make the vehicle operate in battery only mode. Therefore, six different SOC trajectories used to compute battery aging are obtained for the following equivalence factors in this section.

1. The λ that yields the maximum MPGe
2. The λ that yields the least of battery aging.
3. When $\lambda = \frac{\bar{\eta}}{Q_{lhv}}$, which is the upper bond of λ
4. When $\lambda = \frac{1}{Q_{lhv}}$, which is the lower bond of λ
5. Midpoint between lower bond and maximum MPGe
6. Midpoint between maximum MPGe and upper bond

With a fixed λ , ECMS becomes a Causal controller. This is because no information about the future driving conditions is being used to estimate λ . Thus, the final SOC is not controllable. As a result, for comparing the simulation results, the Equivalent Miles per gallon (MPGe) is employed to examine the total consumed energy and account for different final SOC values in different simulations in this section.

MPGe, as defined in [79] and used in [80], can be calculated by Equation (4.1)

$$MPGe = \frac{Distance}{Gallons_{fuel} + Gallons_{Equivalent}} \quad (4.1)$$

where $Gallons_{Equivalent}$ is Gallons of gasoline equivalent of consumed electric energy:

$$Gallons_{equivalent} = \frac{E_M}{E_G} \quad (4.2)$$

and E_M is total electric energy consumed, E_G is energy content per gallon of gasoline 32600 Wh/gallon.

The simulations in this section uses Honda Civic Hybrid as the plant vehicle. Lithium ion battery ANR26650 [81] from A123 systems is used. Table 4.1 below shows the vehicle parameters used in the simulations.

Table 4.1, Vehicle Parameters in Simulations

Specifications	Honda Civic
Configuration	Mild Parallel
Vehicle mass	1279 Kg
Engine max Torque	120 Nm @ 3500rpm
E-motor max Torque	62 Nm @ 1500rpm
Battery cell capacity	2.5/2.4 Ah
Battery Initial SOC	68.50%
Battery SOC range	50% to 70%

Three types of combined drive cycles are used as driver demand. These combined drive cycles consist of multiple drive cycle segments which are:

1. Urban Dynamometer Driving Schedule (UDDS),
2. Highway Fuel Economy Test (HWFET),
3. US06 Supplemental Federal Test Procedure (US06),
4. SC03 Supplemental Federal Test Procedure (SC03).

The three combined drive cycles (CD) are sequences of these segments:

CD1: UDDS, HWFET, and US06.

CD2: US06, SC03, and HWFET;

CD3: UDDS, HWFET, and UDDS.

These combined drive cycles simulate different types of driver daily driving behaviors, with different percentages of highway, city, or country driving.

Figure 4.1, Drive cycle UDDS HWFET US06

Figure 4.1 shows the CD1 which incorporates both city and highway driving.

Figure 4.2(a) shows the mpg change and effective Ah-throughput change with equivalence factors. In addition, Figure 4.2(a) also shows the equivalence factors selected to process for battery aging test. As shown in Figure 4.2(a), the six equivalence factors values are averaging distributed over all equivalence factor range, which could show the significantly overview of the effects. Besides, the maximum Ah-throughput, which indicates the least battery aging, is not happened at the same equivalence factors as maximum MPG. The lower bond of equivalence factor is defined at $\lambda * Q_{lhv}$ equal to 1, which showed the battery only mode. The upper bond of equivalence factor is found when $\lambda * Q_{lhv}$ is equal to 4.3, which is the first point battery SOC stays at the upper bound and has less than 1% of SOC variations. The lower midpoint indicates the equivalence factors which in the middle between lower bond and the maximum MPG. The upper midpoint indicates equivalence factors which in the middle between the maximum MPG and the upper bond.

Figure 4.2(b) shows the SOC trajectory with different ECMS equivalence factor values λ for the Honda Civic. When $\lambda * Q_{lhv}$ is equal to 1, shown as lower bond, the vehicle is operating in e-motor only mode. When $\lambda * Q_{lhv}$ is greater than or equal to 4, shown as upper bond, the vehicle runs in engine only mode. When $\lambda * Q_{lhv}$ is between 1 and 4, vehicle operates in hybrid mode. Higher values of $\lambda * Q_{lhv}$ results more engine operation. Battery aging is computed from SOC. The maximum MPG SOC trajectory is similar to the lower bond of equivalence factor. The most hybrid SOC trajectory, which defined by more battery charge discharge cycles, has the least battery aging, but not generated the most MPG. From simulation results the SOC trajectories stays compressed when $\lambda * Q_{lhv}$ are less than 3, and expended widely when $\lambda * Q_{lhv}$ is between 3 and 3.6.

The maximum damage of battery is happened when the equivalence factor is at max Ah-eff. As shown in Figure 4.2(b), the big discharge then charge cycle around 2000 seconds caused the most battery damage, and the re-charge of the battery cost more fuel, which made the fuel economy of this equivalence factor not the maximum.

Figure 4.2, (a): The MPGe and Ah-eff changes with penalty factor; (b) SOC trajectories for picked equivalence factors

Table 4.2, vehicle performance in CD1

Honda Civic Hybrid UDDS HWFET US06			
Selection Rule	$\lambda * Q_{lhv}$	MPG	Ah-eff
Max MPG	2.7	55.5	21
Max Ah-eff	3.3	54.8	44.9
Upper bond	4.3	48.2	1.38
Lower bond	1.0	51.5	20.6
Lower Midpoint	1.8	52.8	21.8
Upper Midpoint	3.5	52.6	9.1

From Table 4.2, the value of MPG for lower midpoint and upper midpoint are similar, but the effective ah-throughput has significant differences. In the lower midpoint, the cost of

using battery is less than the cost of using engine. Therefore, the EMS is attempting to use the battery more rapidly when the equivalence factor is at the lower midpoint. On the other side, when the equivalence factor is at the upper midpoint, the EMS considering using battery will have more cost/penalty, thus, the battery is operating more likely assisting the engine. Therefore, the battery has been operated more gently at this time. These facts resulted that more battery faded at the lower midpoint, but resulted similar fuel economy compare to the upper midpoint. The least MPG and Ah-eff are all in the upper bond, which is the engine only mode. This is because the most engine operation released battery usage.

Figure 4.3, Drive cycle US06 SC03 HWFET

Figure 4.3 shows which CD2 incorporates more in highway. Vehicle speed for CD2 is higher than the other two. Compare to CD1, CD2 has slightly less fast acceleration and deceleration regions, and the average speed is higher than the CD1.

Figure 4.4, (a): The MPGe and Ah-eff changes with equivalence factor; (b) SOC trajectories for picked equivalence factors

Figure 4.4(a) shows the MPG and Ah-eff variation along the change of equivalence factors. The maximum MPG is at $\lambda * Q_{lhv}$ equals 2.6. The least battery aging is at $\lambda * Q_{lhv}$ equals to 3.2. The lower bond and upper bond are the same as CD1. Compare to CD1, the decrease of MPG after maximum MPG is faster in CD2, and there are more oscillations in Ah-eff

before the peak. This phenomenon indicates that there are less charging discharging cycles around $\lambda * Q_{lhv}$ equals 2.7, which gives high MPG and better battery life. For CD2 driving, the optimal point of $\lambda * Q_{lhv}$ is in between the maximum MPG and the maximum Ah-eff.

Figure 4.5, Drive cycle UDDS HWFET UDDS

Figure 4.4(b) shows the SOC trajectories for the six equivalence factors chosen. The maximum MPG SOC is at $\lambda * Q_{lhv}$ equals to 2.6. Compare to the 2.7 of maximum MPG of CD1, this SOC trajectory is more expended, and mostly operated in the middle, which indicates frequently charge discharge from battery. The SOC for maximum effective Ah-throughput operates on the upper bond for the first half, and discharging quickly to the lower bond, and bonded until the end. This operation shows the penalty for battery aging by more charging discharging cycles for battery. The lower midpoint operates more in the lower bond, and the upper midpoint operates more in the upper bond. The more hybrid SOC trajectories should be between the lower midpoint and the upper midpoint. Table 5 below shows the data collected for CD2

Table 4.3, vehicle performance in CD2

Honda Civic Hybrid US06 SC03 HWFET			
Selection Rule	$\lambda * Q_{lhv}$	MPG	Ah-eff
Max MPG	2.6	53.1	24.1
Max Ah-eff	3.2	51.7	31.6
Upper bond	4.3	46.5	2.1
Lower bond	1.0	49.1	22.9
Lower Midpoint	1.7	50.1	21.5
Upper Midpoint	3.5	49.6	8.8

Compare to CD1, the MPG values for CD2 is slightly less. The maximum effective Ah-throughput in CD2 is less than CD1, but the effective Ah-throughput for maximum MPG is higher than CD1. From the Max MPG in Table 5 compare to Table 2, it shows that the higher speed of driving will cause worse MPG and worse battery life. Compare between Max Ah-eff and Upper Midpoint in Table 5, $\lambda * Q_{lhv}$ changed 0.3, MPG changed less than 2, but Ah-eff changed from 31.6 to 8.8. It brings the factors that: the slightly decrease of

MPG would increase the battery aging significantly; $\lambda * Q_{lhv}$ is sensitive to operate in some certain region, which a small change in $\lambda * Q_{lhv}$ will make obvious differences.

Figure 4.5 shows the drive cycle combination of UDDS, HWFET and UDDS, which incorporates more city driving. Figure 4.6(a) shows the MPG and effective Ah-throughput versus equivalence factor. The MPG increased with the increasing of equivalence factor until reached the maximum at 3.2. Then decreased to the minimum. There is a peak sharp region for effective Ah-throughput. The effective Ah-throughput remained around 25 from $\lambda * Q_{lhv}$ equals to 1 to 2.7, then increased quickly to it maximum at 3.3 of $\lambda * Q_{lhv}$ with a value of 52.7, the highest effective Ah-throughput values compared to CD1, CD2 and CD3. Then dropped down faster to 8.5 at upper midpoint. Compare to the MPG plot, MPG increased slowly and constantly before $\lambda * Q_{lhv}$ equals to 3.2, which indicates the optimal solution for battery aging and MPG is in the region around $\lambda * Q_{lhv}$ equals to 2.7. Again, the maximum MPG is not happened at the same $\lambda * Q_{lhv}$ values with the maximum effective Ah-throughput, but very close.

Figure 4.6, (a): The MPGe and Ah-eff changes with equivalence factor; (b) SOC trajectories for picked equivalence factors

Table 4.4, vehicle performance in CD3

Honda Civic Hybrid UDDS HWFET UDDS			
Selection Rule	$\lambda * Q_{lhv}$	MPGe	Ah-eff
Max MPG	3.2	73.0	46.6
Max Ah-eff	3.3	70.4	52.7
Upper bond	4.3	55.8	1.7
Lower bond	1.0	61.8	25.0
Lower Midpoint	2.2	65.1	23.9
Upper Midpoint	3.7	61.2	8.5

The electric mode $\lambda * Q_{lhv}$ at 1, is similar to the two previous drive cycle combinations, but with more oscillations. The Max MPG is more expended from the lower bond

compared to the other two drive cycles, and more oscillated in the middle, which means battery is used more in this drive cycle combination.

Similarly, the lower midpoint is resulting more battery damage, but similar fuel economy compares to the upper midpoint. Compare to CD1 and CD2, CD3 has less battery life, CD1 has less battery life than CD2. This is caused the more regenerative braking in city driving, charged the battery rapidly, and discharged for acceleration in low speed level. The benefits of these operations showed in MPG, which has the highest MPG for these three combined drive cycles. The MPG for upper bond (engine only mode) has the higher MPG than the maximum MPGs for CD1 and CD2. This shows the engine start stop technologies taken significantly advantages for city driving.

In summary, most previous ECMS studies have focused on selecting the equivalence factor to optimize fuel efficiency. This paper shows that battery lifetime can be significantly extended by selecting an equivalence factor that yields a slight decrease in fuel efficiency from the maximum. Selecting equivalence factors to extend battery life will decrease the lifecycle cost of vehicle operation.

4.2 Effect of SOC constraints

As presented in Section 3.3, the state of charge has been defined within the constraint (3.27). Within the constraint, the battery output voltage could be treated as constant. Therefore, Hamiltonian Equation defined in (3.29) could be proved as optimal, as well as the co-state could be proved as a constant. Further the optimal equivalence factor could be a constant and lied within the range (3.46). Other than that, SOC constraints is mainly presenting the operatable battery capacity which the EMS could be using. The operatable battery capacity is also important to the EMS, therefore, the main focus on this section is analyzing the useful battery capacity by selecting different battery SOC constraints, which with an assumption that the battery chemical behavior is steady within the selected SOC constraints.

Figure 4.7, (a): MPG equivalent versus equivalence factor for different SOC constraints in CD1; (b) Effective Ah-throughput versus equivalence factor for different SOC constraints in CD1

The SOC constraints chosen in this section are 20% low to a high of 70%, 80%, 90% and 100%; 30% low to a high of 70% and 80%; 40% low to a high of 70%; 50% low to a high of 70%; and 60% low to a high of 70%. The reason for choosing these different SOC constraints are because: The initial condition of SOC is 68.5% which must be within the allowed range; The SOC total range is wide, varying from 10% to 80%.

The same combined drive cycles as shown in Section 4.1 has been used as the driver demand. Figure 4.7(a) shows MPGe versus Equivalence factor for different SOC constraints. When the equivalence factor is less than 3.2, higher MPGe is obtained at the smallest SOC lower bound of 20%. When the equivalence factor is greater than 3.2, MPGe is higher when the SOC bound is at the upper limit. Note that for equivalence factor ranges from 2.7 to 3.2 the vehicle operates mostly as a hybrid. When the equivalence factor is less than 2.7 the vehicle operates mostly as an electric vehicle. When the equivalence factor is greater than 3.2 the vehicle operates mostly as a conventional vehicle. Figure 4.7(b) shows the Effective Ah-throughput for different SOC constraints, verses equivalence factor. The higher Effective Ah-throughput region is when the equivalence factor is around 3 which uses more hybrid operation. At this region, the battery is frequently charged and discharged and the damage accumulated to the battery is higher than in other regions. The least cost for battery aging is when the range of SOC constraints are small. But the higher SOC range does not result in the best MPGe and the least battery aging.

Figure 4.8, (a): MPGe verses equivalence factor for different SOC constraints in CD1; (b) Effective Ah-throughput verses equivalence factor for different SOC constraints in CD1

Figure 4.8(a) shows MPGe verses equivalence factors for the combined drive cycle 2 which incorporates more highway driving. The best MPGe is obtained when the SOC constraints are from 20% to 90% and 20% to 100% at an equivalence factor equal to $2.9 \cdot Q_{lhv}$. The SOC constraints of 20% to 90% have higher MPGe than 20% to 100% when the equivalence factor is higher, yielding more engine only operation. The initial value of SOC effected the MPGe values when the equivalence factor is relatively low (more E-motor only driving periods). Note that the battery will start charging when SOC reaches the lower limit, which reduces MPGe when the lower constraint is relatively high. As shown in Figure 4.8(b), the effective Ah-throughput reached the peak for SOC constraints of 20% to

90% and 20% to 100% when equivalence factor is at $3*Q_{lhv}$, which yielded approximately the highest MPGe. The increase in damage to the battery from $2.7*Q_{lhv}$ to $3*Q_{lhv}$ is rapid, while the MPGe increase is relatively slow. Compared this to other SOC constraints, like 30% to 80% which has relatively satisfactory performance on MPGe and less battery aging. The SOC constraints of 30% to 80 % have a peak MPGe of 55, which is 1.5 MPGe less than the peak 56.5 MPGe, but the peak effective Ah-throughput of 70 significantly less than the peak value of 120 Ah-throughput.

Figure 4.9(a) shows the MPGe versus equivalence factor. The MPGe increases with increasing equivalence factor until reaching the maximum at an equivalence factor of 3.2. MPGe then decreases to the minimum. This combined drive cycle has mostly city driving, which has a higher MPGe than the other two combined drive cycles. Again, the higher MPGe occurred at SOC constraints with lower SOC constraint 20% before the MPGe peak, and lower constraint of 40% after the peak MPGe. Comparing with Figure 4.8(a), the SOC constraints from 20% to 70% and 30% to 70% have the peak battery damage but not the peak MPGe. Since most city driving uses lots of battery operation, the battery aging is worse than the other two combined drive cycles. At SOC constraints from 40% to 70%, for example, the MPGe has a peak at an equivalence factor of 3.2 with a MPGe value of 74 which is 1 MPGe less than the peak value. The effective Ah-throughput has the peak value at 3.2 and the peak value of 61, which is less than the peak of 89 for SOC constraints 30% to 70% and 20% to 70%. In addition, SOC constraints of 40% to 70% is one of the lowest Ah-throughput when the vehicle utilizes more engine only operation (at equivalence factors greater than 3.2).

Figure 4.9, (a): MPGe versus equivalence factor for different SOC constraints in CD1; (b) Effective Ah-throughput versus equivalence factor for different SOC constraints in CD1

The effect of SOC constraints and the ECMS penalty factor on battery aging have been evaluated. Appropriately selecting the SOC constraints in ECMS can significantly save battery life. The SOC constraints also effect the fuel consumption, and a tradeoff exists between battery life and fuel consumption. Information to evaluate this tradeoff is explicitly displayed in this work. Note that different constraint values and ECMS penalty factors are suggested for different types of driving, for instance, city verses highway.

In summary, most previous ECMS studies have focused on selecting the penalty factor to optimize fuel economy. This section shows that changing the SOC constraints in ECM effects the energy management strategy of the vehicle by limiting the operation range of battery, and, therefore, both the fuel economy and the battery lifetime.

4.3 Effect of low temperature

Joris' paper in [75][76][77] has conducted battery performance tests under different discharge current, and temperatures. The battery model used in this section has been modified to match Joris' battery, so that the testing data could be used. Per Jori's testing data, the temperature effects on battery performance are the reduction of capacity and the increase of the internal resistance. As discussed previously in this section, these facts are caused by lithium plating on anode when battery is under low temperatures.

The battery used in this feature is a lithium-ion battery cell with nominally rate voltage 3.3 volts and 100 Ah capacity. The working voltage of this battery cell is from 2.5 volts fully discharged and 3.8 volts fully charged. The testing Joris conducted is under temperature 25 °C, 0 °C, -10 °C and -20 °C. Since Joris used constant discharge current for these testing, an interpolating battery model based on various of testing data are conducted. Which include data points of depth of discharge versus voltage and internal resistance under different discharge rate and temperatures.

Table 4.5. Vehicle Simulation Parameters

Specifications	Honda Civic
Configuration	Mild Parallel
Vehicle mass	1279 Kg
Engine max Torque	120 Nm @ 3500rpm
E-motor max Torque	62 Nm @ 1500rpm
Battery cell capacity	100 Ah @ 25 °C
	83.3 Ah @ 0 °C
	70.8 Ah @ -10 °C
	61.1 Ah @ -20 °C
Battery Initial SOC	60%
SOC Constrains	50% ~ 70%

Table 4.5 showed the vehicle configuration used in this section. Simulations are based on a validated model of the Honda Civic Hybrid, and the Lithium ion battery LiFePO4 used in [75][76][77]. The external air temperature is considered as constant during each simulation.

The equivalence factors (EF) chosen to show the SOC trajectories variation at different temperatures which:

- EF =1.1 ; mostly EV Only mode (makes electric energy cheap)
- EF =2 ; strong EV operation mode
- EF =2.5; hybrid mode with more EV operation

- EF =3 ; hybrid mode with more engine operation
- EF =3.5 ; strong engine operation mode
- EF =4 ; mostly engine only mode (makes electric energy expensive)

The plots of the SOC trajectories under the temperatures mentioned in Table 4.5 are shown in Appendix, Figure A1, A2, and A3.

Figure 4.10 shows the battery state of health, which is defined in Section 3, Equation (3.22) and the MPGe versus the penalty factors for different external air temperatures. The lower temperature has caused lower battery state of health and less MPGe. The battery has more capacity in higher temperature, which allows for a smaller penalty factor. A smaller penalty factor leads to consuming more electric energy than fuel energy which gives an improved MPGe.

Figure 4.10, The UDSS HWFET UDSS drive cycle, along with equivalent fuel economy and battery state of health trajectories in ECMS penalty factors from 1 to 4.5 at temperature 25 °C, 0 °C, -10 °C and -20 °C.

Figure 4.11, The UDSS HWFET US06 drive cycle, along with equivalent fuel economy and battery state of health trajectories in ECMS penalty factors from 1 to 4.5 at temperature 25 °C, 0 °C, -10 °C and -20 °C.

Comparing Figure 4.10 and Figure 4.11 shows at low temperatures, a higher equivalence factor yields a better MPGe. This is caused by battery capacity being larger when temperature is higher. The larger battery capacity will be able to provide enough energy for the drivecycle. Otherwise, a smaller battery capacity will require more engine operation to assist achieving the power demand

From Figure 4.10 and Figure 4.11 in battery aging, the aging cost is similar when the penalty factor is between 2.3 to 2.8. However, the MPGe in this range have significant differences. For example, in Figure 2 at 25 °C, MPGe is around 100 mpg and the penalty factor are at 2.3. At 85 mpg the penalty factor is 2.8. But the battery SOH is varying between 95.5% to 95.6% (at these penalty factors). In Figure 4.11 at -20 °C, fuel economy is approximately 63 mpg when the penalty factor is around 2.7. Then at 61 mpg, the penalty factor is around 2.3. But the battery SOH is around 97% when the penalty factor is around 2.7. The SOH was also at 97% when penalty factor was around 2.3. When penalty factor is in hybrid region, then the MPGe becomes independent of SOH in the same temperature. When the penalty factor is between 2.8 and 3.3, vehicle operated within the battery SOC constrains, and battery is in transition from charge depleting to sustaining. During this transition, battery SOC changes more smoothly, it caused less battery aging damage and the battery SOH increases rapidly in lower temperatures, but changes in fuel economy are negligible.

From Figure 4.10, 4.11 and 4.12, when the penalty factor becomes greater than 3.5, the lower temperatures yields better fuel economy. This is because a battery with reduced needs less engine operation to charge the battery. When the penalty factor is between 2.8 and 3.5, the fuel economy at all temperatures are almost similar. This is because the vehicle can operate within the battery capacity limit in this region. When the penalty factor is between 3.5 and 4.5, the lower temperatures yield better fuel economy. This is because at lower temperatures, less fuel is needed to charge the battery.

Figure 4.12, The US06 HWFET SC03 drive cycle, along with equivalent fuel economy and battery state of health trajectories in ECMS penalty factors from 1 to 4.5 at temperature 25 °C, 0 °C, -10 °C and -20 °C.

In Figure 4.10, 4.11 and 4.12, the worst SOH is yields by penalty factor at 1.1 at most cases. This is because the big discharge cycle when vehicle operates in EV only mode. When

battery SOC reached the lower constraints, vehicle switched to engine only mode. This caused the best MPGe not having the worst SOH in above simulations.

To draw a conclusion, the effects of environmental temperatures and the ECMS penalty factor on battery aging have been evaluated. Lower temperatures will result in worse battery aging and less battery capacity which consequently affects the fuel economy. The results presented in this paper showed that different battery temperatures will require different penalty factors in ECMS to have the best fuel economy.

Comparing the results for all the combined drive cycles, a common phenomenon was found:

- Lower temperatures resulted in having worse fuel economy. This is a direct consequence of reduction in battery capacity.
- Lower temperatures resulted in having the worse battery aging. This is because the reduced battery capacity required more rapid charge-discharge cycles.
- Under the same temperature, the penalty factor which yields the best fuel economy does not result in having the worst battery aging.
- Lower temperatures required more engine operation to make up for the battery capacity shortage at lower temperature.
- Battery capacity reduction at low air temperature damages the battery life. But more engine operations at low air temperature will compensate the battery capacity reduction and improves the battery aging.

The simulations show that the effect of temperature is independent of driving cycles. Since the battery temperature can significantly affect the battery capacity and battery internal resistance, therefore effected the ECMS performance.

4.4 Simple rule-based control

In literature, two main methods are introduced for the energy management (EM) of plug-in hybrid electric vehicles (HEVs) [88-91][93-95]: Blended discharge (BD) strategy and charge-depletion charge-sustaining (CDCS) strategy. The main difference between these two methods is a constraint on using the fuel energy when battery is fully charged. This constraint, affects the trajectory of the battery state of charge (SOC) for each of these 2 strategies, as shown in Fig. 1.

In CDCS strategy once SOC falls below a certain threshold, the strategy switches from charge-depletion mode to charge-sustaining mode. In charge-depletion, the constraint is on activating the engine. Thus, vehicle propulsion power is mostly provided by the battery and engine is allowed to be turned on only if the battery alone cannot deliver the requested power by the driver [88-91]. In charge-sustaining mode, the constraint is on SOC range. Thus, the propulsion power is provided by both fuel and battery while maintaining SOC within a certain range.

Figure 4.13, Typical trajectories of battery SOC for BD and CDCS strategies. In comparison with BD, CDCS is constrained to not consume fuel when battery SOC is high.

BD strategy relies on prior information of drivecycle and is free of the CDCS constraints [90][93][94]. Therefore, engine is allowed to be turned on at any time, if it is determined that using fuel will improve the overall fuel economy. In addition, unlike CDCS, the SOC range in BD strategy is not limited to a narrow range and can vary from 100% to SOC_L (see Figure 4.13).

When the drivecycle is unknown, CDCS strategy is a good solution for the energy management of plug-in HEVs [17][89-91]. For instance, for short trips that can be travelled all in electric only mode, CDCS strategy yields the best fuel economy without any prior information about the drivecycle. However, for longer trips, CDCS eventually enters charge-sustaining mode and is forced to turn on the engine for maintaining the battery SOC in an admissible range. However, if the entire drivecycle is known in advance, the optimal trajectory of SOC and engine operating conditions for achieving the best fuel economy can be determined at the beginning of the trip. This technique is used for BD strategy [90][93][94]. In BD strategy, since the optimal trajectory of SOC and engine conditions for the whole trip is known in advance, there is no need for charge-depletion or charge-sustaining modes. As a result, with regard to fuel economy, the performance of BD strategy is expected to be better than CDCS strategy.

To compare BD and CDCS strategies, the global optimal solution of each strategy needs to be found for different drive cycles. To find the global optimal solution, the energy consumption minimization strategy (ECMS) technique is employed. Using ECMS for CDCS strategy is subject to more constraints than using ECMS for BD strategy. As a result, the global optimal solution found by ECMS for CDCS is expected to be different than optimal solution found for BD strategy.

The model of a plug-in parallel hybrid electric vehicle was developed in Simulink. The powertrain configuration of simulated vehicle is shown in Figure 4.14. The developed model was validated by a plug-in parallel hybrid truck that is designed and assembled at Hybrid Electric Vehicle Enterprise at Michigan Technological University.

The vehicle model and also driver's model was first developed in AMESim environment

with 23 dynamic states and the controller was developed in Simulink. Using AMESim interface with Simulink, it is possible to control the plant model in AMESim with commands from controller model in Simulink. Optimal controllers, such as ECMS, also need a simple version of plant model to search and find the optimal action, before applying the optimal control command to the plant. As a result, a similar model of the vehicle with 2 dynamic states (battery state of charge and vehicle speed) was developed in Simulink to be used at the heart of optimal controller (ECMS in this study). The simpler model in Simulink was validated with the advanced AMESim model using identical control action trajectories.

Figure 4.14, Powertrain configuration of simulated plug-in parallel HEV

Some of the key parameters of simulated HEV are presented in following Table 4.6. The vehicle forward simulation only considers the longitudinal dynamics of the vehicle for each drivecycle.

Figure 4.15, Left: The BSFC map and maximum Torque of simulated engine (LC-9);
Right: The efficiency map and maximum nominal Torque at different Voltages for simulated electric-motor in Simulink model of plug-in parallel HEV

For the electric motor, the efficiency map shown map shown in Figure 4.15 was used to find the optimal operating points of the electric motor. The map is acquired from Remy HVH250 motor datasheet which was installed in the Hybrid electric truck. The simulation considers the motor torque drop due to decrease in battery voltage, as the battery is discharged during the simulated drivecycle. In addition, the installed inverter that controls

the electric motor is simulated by a constant efficiency to account the energy loss in the inverter.

Table 4.6: Characteristics of the Simulated Plug-in Parallel HEV

Parameter	Value
Battery Energy	7 kWhr
Battery Max Power	134kW discharge, 66kW charge
Battery Nominal Voltage	330 V
Engine Max Torque	454 Nm @ 4000 rpm
E-Motor Nominal Power	55KW@2500rpm, 315Nm@2200rpm
Vehicle Frontal Area	3.3 m ²
Vehicle Mass (kg)	2500 kg
Transmission Ratios	2.95, 1.94, 1.34, 1, 0.63
Final Drive Ratio	3.73

As was discussed previously, CDCS strategy has more constraints than BD strategy: CDCS is constrained to not consume fuel in charge-depletion mode (assuming the battery and electric motor can provided the requested power) and then, limit SOC variations within a certain range once it enters charge-sustaining mode. As a result, while both CDCS and BD strategies are subject to constrains (3.6) and (3.23) to (3.26) defined previously in Section 3.1 and 3.3, the following addition constrains are applied to CDCS strategy in this study:

$$\begin{cases} CD \text{ mode: } \dot{m} = 0 \text{ if } x(t) > SOC_{Max} \text{ and } P_{em,max} \geq \frac{P_D}{\eta_{trs}} \\ CS \text{ mode: } SOC_{Min} \leq x(t) \leq SOC_{Max} \end{cases} \quad (4.3)$$

In (4.3), enforcing $\dot{m} = 0$ during charge depletion mode ensures the engine will not be turned on by CDCS strategy.

Due to additional constraint (4.3) that CDCS is subject to, the optimal solution of CDCS and BD strategies will not be the same. A fair comparison of CDCS and BD strategies is achieved by finding the optimal fuel economy of each strategy while both strategies consume equal amount of electric energy (start and end with similar battery SOC's).

For CDCS strategy in charge-depletion mode it can be shown that the λ^* is when the equivalence facotr is at its lower bound in (3.46):

$$\lambda^* = \frac{1}{Q_{lhv}} \quad (4.4)$$

where Q_{lhv} is the fuel lower heating value (J/g). For CDCS, in charge-sustaining mode, the optimal value of equivalence factor λ^* is unknown. Thus, different values of λ are tested to find the set of candidates $\lambda_{CS} = \{\lambda_{CS1}, \lambda_{CS2}, \dots, \lambda_{CSn}\}$ that maintain SOC within a desired range, while not letting SOC to reach the bounds defined in (3.27). Each of λ values in the candidate set is associated with a different final SOC in charge-sustaining mode (CS).

Similarly, for BD strategy, different values of λ are tested to find the set of candidates $\lambda_{BD} = \{\lambda_{BD1}, \lambda_{BD2}, \dots, \lambda_{BDn}\}$ for λ^* . Now, the λ values on both λ_{CS} and λ_{BD} sets are compared with regard to the battery final SOC. The optimal λ^* value for each strategy is the one that yield similar final SOC. For instance, suppose λ_{CS2} in CDCS yields a final SOC of 60%, and λ_{BDn} in BD also yields the same final SOC, i.e. 60%. Then, λ_{CS2} is λ^* for CDCS strategy in charge-sustaining mode and λ_{BDn} is λ^* for BD strategy.

Knowing λ^* values for each of CDCS and BD strategies, the optimal fuel economy and battery effective aging were calculated for different drive cycles. The simulation results are discussed in next section.

For all simulations, the battery initial SOC is set to 95%. For CDCS strategy, the range of SOC variations in charge-sustaining mode is set to 50% to 70%. Figure 4.16 represents the trajectories of battery SOC and also the effective Ah for both CDCS and BD strategies on UDDS drivecycle. Note that the effective Ah is a measure of damage to battery life. It can be observed that around the time 200s, Ah suddenly increases for CDCS controller.

Figure 4.16, Trajectories of battery SOC and effective Ah (a measure of damage to battery life) on UDDS drivecycle.

This sudden damage to the battery life around the time 200s can be explained by sudden high discharge current, as shown in Figure 4.16. CDCS controller in charge-depletion mode allows a high battery discharge current to avoid turning the engine on while providing requested propulsion power. Note that CDCS is not violating the battery discharge current limits. But, this figure shows that to prolong the battery life, additional constraint is required for the battery current in charge-depletion mode. Same conclusion can be made from Ah curve during HWFET and US06 drive cycles, as shown in Figure 4.17 and 4.18.

Results show that in both city and highway drive cycles, BD performance is better than CDCS in terms of battery ageing. Note that the cost function of BD has no term for

penalizing the damage to battery life. Nonetheless, BD is less harmful than CDCS strategy for battery life.

Figure 4.17, Battery Current during UDDS drivecycle.

Figure 4.18, Trajectories of battery SOC and effective Ah (a measure of damage to battery life) on HWFET drivecycle

Observing the effective Ah in figures, shows that most damage to battery life in CDCS strategy happens during the charge-depletion mode. In this mode, engine is allowed to operate only if the battery and electric motor cannot provide the requested propulsion power. In other words, in charge-depletion mode, the propulsion power is expected to be provided by battery only. Thus, high discharge current is typical and justified during the charge-depletion mode of CDCS strategy. As can be observed from Ah trajectories, the high discharging current during the charge-depletion mode has the major role in damaging the battery useful life.

Figure 4.19, Trajectories of battery SOC and effective Ah (a measure of damage to battery life) on US06 drivecycle

Two existing techniques for the energy management of plug-in HEVs, i.e. CDCS and BD strategies, were evaluated with regard to battery aging for a plug-in parallel HEV. BD strategy yields better fuel economy due to prior knowledge of entire drivecycle. It was observed that BD strategy is less harmful for battery aging than CDCS strategy.

CDCS strategy, on the hand, is more common for real-time applications where the strategy is divided to two phases: charge-depletion mode and charge-sustaining mode. In charge-depletion, the propulsion power is provided by battery power. This is because the drivecycle is unknown and thus, it is reasonable to discharge a full-charged battery instead of consuming fuel. However, simulation results show that this technique damages the battery useful life. In comparison with BD, the damage to battery life by CDCS is about 4% more, in average.

With regard to battery aging, results verify that the main reason for poor performance of CDCS strategy is the battery fast discharging rate during the charge-depletion mode. Note that CDCS strategy is employed for real-time applications where the drivecycle is unknown, *a priori*. Thus, if preserving the battery life is a goal, then the real-time energy management should allow engine to operate during the charge-depletion mode in case battery discharge current is too high.

Battery SOH is a function of rate of change in battery SOC. Therefore, by limiting steep reduction in SOC during charge-depletion mode, one can reduce damage to battery SOH. This new rule is named as: Limit Steep SOC Reduction (LSSR) during charge-depletion mode, or briefly, LSSR rule. The LSSR rule can be implemented modifying (4.3) to:

$$CD \text{ mode: } \dot{m} = 0 \text{ if } x(t) > SOC_{Max} \text{ and } P_{em,max} \geq \frac{P_D}{\eta_{trs}} \text{ and } \Delta SOC \leq \zeta \quad (4.5)$$

where ζ is the threshold for acceptable rate of reduction in SOC. If during charge-depletion mode $\Delta SOC > \zeta$, then engine has to be turn ON. The above expression for LSSR rule is suitable for rule-based controllers if one desires to implement CDCS strategy with a rule-based controller. Since this paper is employing ECMS for realization of CDCS strategy, an alternative for LSSR rule is to modify the ECMS cost function during charge-depletion mode, i.e., (4.5), as follows:

$$H = \dot{m}_{fuel}(\mathbf{u}(t), P_D(t)) + \lambda(t, x) P_{bat,C}(x(t), u(t)) + 100L \quad (4.6)$$

where L is defined as:

$$\begin{cases} L = 0, & \text{if } \Delta SOC \leq \zeta \\ L = \Delta SOC, & \text{if } \Delta SOC > \zeta \end{cases} \quad (4.7)$$

The penalty factor for L in (4.7) is intentionally chosen to be a big value, so that ECMS would enforce LSSR rule by making the cost of violating LSSR rule very high. The value of ζ should be chosen by experiments or simulations based on HEV configuration. For the simulated plugin HEV in this paper, $\zeta = 0.1$ is found to be suitable.

Since battery aging effect can only be more obvious in long-term driving. New combined drive cycles are identified in Table 4.7 with considerations of simulating generic driving behaviors.

Table 4.7, Drive cycles definition

Drivecycle name	abbreviation
NEDC SC03 US06 HWFET	CD1
UDDS HWFET US06	CD2
US06 SC03 HWFET	CD3
US06 US06 HWFET UDDS	CD4

The method to calculate the total cost during a trip is proposed as

$$Fuel\ Cost = \frac{CD\ Distance}{MPGe} \cdot Fuel\ Price \quad (4.8)$$

The battery cost is calculated from

$$Battery\ Cost = (1 - SOH) \cdot Battery\ Replacement \quad (4.9)$$

assuming the price for gasoline is \$3 per gallon and the cost to replace the battery pack is \$207 per 1kWh battery [83] plus a \$200 replacement labor cost, where the utility price for charging the battery has been ignored.

As shown in Table 4.8, the LSSR rule improved the battery aging in CDCS control strategy. Which lowered the cost for each CD defined in Table 4.7.

In summary, the majority of damage to battery life for CDCS strategy compared to BD happens during the fast discharging in charge-depletion mode. Therefore, when future

drivecycle is unknown, it is useful to prohibit battery high discharge current by turning the engine ON during charge-depletion mode. This will limit the damage to battery life. This result can be used in real-time rule-based control strategies to define a new rule for charge-depletion mode, as follows: If battery discharge current goes above a certain threshold during the charge-depletion mode, then the rule-based controller should turn the engine on to assist the electric motor and decrease the battery discharge current.

Table 4.8, Simulation Results for Different drive cycles

Drive cycle	BD Control strategy			CDCS Control Strategy without LSSR Rule			CDCS Control Strategy with LSSR Rule		
	Δ SOH (%)	MPG	Cost (\$)	Δ SOH (%)	MPG	Cost (\$)	Δ SOH (%)	MPG	Cost (\$)
CD1	0.349	118	9.54	0.426	108	11.36	0.399	103	10.78
CD2	0.330	143	8.82	0.331	140	8.85	0.304	138	8.25
CD3	0.344	271	8.85	0.401	239	10.21	0.373	219	9.59
CD4	0.398	80	11.24	0.541	73	14.67	0.408	63	11.42

5. Battery Aging Optimal Control Problems

Section 4.1 analyzed the relationship between equivalence factor, fuel economy and battery aging. And showed that battery lifetime can be significantly extended by selecting an equivalence factor that yields a slight decrease in fuel efficiency from the maximum. Selecting equivalence factors to extend battery life will decrease the lifecycle cost of vehicle operation.

As mentioned in [82], the battery size, described by the available battery energy capacity, will affect the energy management of the HEV. In previous section 4.2 and 4.3, we also observed that the change of battery capacity due to state of charge constraints or environment temperature changes significantly influence ECMS performance. Therefore, the ratio between battery pack energy capacity and fuel contained energy is considered when developing the cost function.

Section 4.4 used a simple rule-based control in charge-depletion mode will improve the cost during a trip for a HEV truck. This section will be focusing on improving the cost of battery aging by adding the battery aging term to the ECMS cost function in charge-sustaining mode.

Section 3.3 introduced upper and lower bounds on the equivalence factor λ^* , which are independent of drive cycle and depend only on the average efficiency values of the powertrain components. This section will add the battery aging term as a cost buffer in the ECMS, and show that ECMS is still optimal with the battery aging term added to the cost function. In addition, the bounds on the equivalence factor are shown that it will still be applicable with the battery aging term included. Lastly, aging ECMS CESO is introduced and implemented. It is verified that battery aging is improved significantly by using the new Aging ECMS algorithm.

5.1 Aging ECMS

The optimal control that minimizes the total fuel consumption with consideration of battery aging degradation is written as:

$$u^* = \underset{u}{\operatorname{argmin}} \left\{ \int_0^{tf} \dot{m}_{\text{fuel}}(x, u) + k \cdot \dot{A}h_{\text{eff}}(\sigma, I_{\text{bat}}) dt \right\} \quad (5.1)$$

where k is the aging coefficient yields a compromise between fuel consumption and battery aging. And again, $\dot{m}_f$ is the fuel mass flow rate in gram/s, $\dot{A}h_{\text{eff}}$ is the rate of effective Ah-throughput, x is the state variable defined as state of charge, u is the vector of control actions, u^* is the optimized control action, σ is the severity factor defined in Equation (3.18), and I_{bat} is the battery cell current. The control problem is subject to following the constraints defined in equation or inequalities (3.24)(3.25)(3.26)(3.27). Which guarantees that all constraints will not be violated by the control action u , driver's demanded power will be satisfied by u , the state Equation of the system is defined and within the limited bounds.

According to [74], the fundamental lemma of the calculus of variations, the Hamiltonian Equation can be optimized by solving the costate variable, which will minimize the cost function defined in Equation (5.1).

$$H = \dot{m}_{fuel}(u(t), P_D(t)) + k \cdot \dot{A}h_{eff}(x(t), u(t)) + p(t) \cdot \dot{x}(x(t), u(t)) \quad (5.2)$$

The derivative of effective Ah-throughput is obtained from Equation (3.21):

$$\dot{A}h_{eff}(t) = \sigma(I_c(t), T_{cell}(t), x(t)) \cdot |I_{bat}(t)| \quad (5.3)$$

Substituting Equation (3.26) and (5.3) into Equation (5.2) yields the Hamiltonian:

$$H = \dot{m}_{fuel}(u(t), P_D(t)) + k \cdot \sigma(I_c(t), T_{cell}(t), x(t)) \cdot |I_{bat}(t)| - p(t) \cdot \frac{P_{bat,c}(x(t), u(t))}{Q_{bat}V_{bat,oc}(x(t))} \quad (5.4)$$

where $p(t)$ is the co-state, and it is defined as:

$$\begin{aligned} \dot{p}(t) = -\frac{\partial H}{\partial x} = & -k \cdot \frac{\partial \sigma(I_c(t), T_{cell}(t), x(t))}{\partial x} \cdot |I_{bat}(t)| \\ & -k \cdot \sigma(I_c(t), T_{cell}(t), x(t)) \frac{\partial}{\partial x} |I_{bat}(t)| \\ & + p(t) \cdot \frac{\partial}{\partial x} \frac{P_{bat,c}(x(t), u(t))}{Q_{bat} \cdot V_{bat,oc}(x(t))} \end{aligned} \quad (5.5)$$

$V_{bat,oc}$ is almost constant in charge-sustaining mode [84][85][86] within the SOC constraints defined in Equation (3.27), therefore, the last 2 terms in Equation (5.5) are independent of state variable x

$$\begin{cases} \frac{\partial}{\partial x} |I_{bat}(t)| = \frac{\partial}{\partial x} \frac{P_{bat,c}(x(t), u(t))}{V_{bat,oc}(x(t))} = 0 \\ \frac{\partial}{\partial x} \frac{P_{bat,c}(x(t), u(t))}{Q_{bat} \cdot V_{bat,oc}(x(t))} = 0 \end{cases}$$

Therefore,

$$\dot{p}(t) = -k \cdot \frac{\partial \sigma(I_c(t), T_{cell}(t), x(t))}{\partial x} \cdot |I_{bat}(t)| \quad (5.6)$$

As shown in Figure 5.1, according to [60][73], when the environmental temperature is around 20 °C and the C-rate in this work is around 3-C, within the SOC constraints defined in (3.27), the derivative of the severity factor with respect to SOC is approximately zero, thus

$$\dot{p}(t) = -\frac{\partial H}{\partial x} \approx 0 \Rightarrow p^* \text{ is constant} \quad (5.7)$$

Hence, a constant value for the costate p still yields the global optimal solution, as long as the constraints defined in (3.27) are met.

Defining $\lambda = -p(t)/(Q_{bat}V_{bat,oc}(x))$, the Hamiltonian Equation can be written as the ECMS cost function with an additional term that penalizes battery aging:

$$H = \dot{m}_{fuel}(u(t), P_D(t)) + k \cdot \dot{A}h_{eff}(x(t), u(t)) + \lambda \cdot P_{bat,C}(x(t), u(t)) \quad (5.8)$$

From (5.7), the optimal value of λ is a constant[17][87].

Figure 5.1, Sensitivity of severity factor map with respect to SOC [60]

5.11 Aging coefficient k

The battery capacity affects the performance of the optimal EMS as discussed in section 4. We have shown that the optimal equivalence factor λ is a constant. Since the co-state $p(t) = -\lambda \cdot Q_{bat} \cdot V_{bat,oc}(x)$ will be changed if the battery capacity Q_{bat} is changed according to temperature, battery aging, or physical constraints. On the other hand, in ECMS, the battery term is used as an energy buffer [68], and the aging term is being considered as an additional weight added to the battery cost. Therefore, the aging coefficient k needs to be correlated to the co-state. Thus, the aging coefficient k needs to consider the variation of battery capacity to balance the weight/cost which aging term added to the battery. The energy capacity ratio is then defined

$$k_R = R_{Energy,Cap} = \frac{E_{useful,bat}}{E_{useful,fuel}} = \frac{E_{bat,cap} \cdot \eta_{bat}}{E_{fuel,cap} \cdot \eta_{eng}} \quad (5.9)$$

represents the relative energy contribution of the battery and the fuel. Less battery capacity results in a smaller hybridization ratio of the HEV, i. e., a smaller relative energy contribution of the battery compared to the fuel. This results in battery fading having a smaller effect on performance. Also, a smaller battery pack is less expensive compared to

the entire vehicle. Therefore, it is expected that k should scale with the energy capacity ratio. Simulations presented later in the paper will bear out this assumption.

The optimal control is obtained by minimizing the Hamiltonian in Equation (5.8) at every point in time [74]. Therefore, we need to minimize a linear combination of the power used and the fading power of the battery. The power used includes both the power in the fuel and the power out of the battery. Insight into the relative contribution of these terms can be obtained by rewriting the optimal control problem in terms of energy (and including the energy out of the battery):

$$u^* = \underset{u}{\operatorname{argmin}} \{a \cdot E_{bat,f} + E_{loss}\} \quad (5.10)$$

where $E_{Bat,f}$ is the equivalent battery energy capacity lost due to battery fading, E_{loss} is the total powertrain lost energy during the trip, and $a = a_0 \cdot k_R$ is proportional to k . Note that a is used here because the change of variables in the cost function results in a different value. But, a is still a weighting factor that provides a tradeoff between battery fading and powertrain efficiency. Note that a is a constant in this work, but could be adaptively adjusted due to battery capacity variation (fading) and temperature change in future work.

The powertrain lost energy is:

$$E_{loss} = E_{fuel} + E_{bat,C} - E_D \quad (5.11)$$

where E_{fuel} is the energy contained in the fuel consumed, $E_{bat,C}$ is the battery chemical energy consumed, and E_D is the driver demanded energy. So, the optimal control problem can be given as:

$$u^* = \underset{u}{\operatorname{argmin}} \{a \cdot E_{bat,f} + E_{fuel} + E_{bat,C} - E_D\} \quad (5.12)$$

Energy is the integral of power, so

$$u^* = \underset{u}{\operatorname{argmin}} \left\{ \int_0^{t_f} (P_{fuel} + P_{bat,C} + a \cdot \dot{A}h_{eff} \cdot V_{ocv} \cdot 3600 - P_D) dt \right\} \quad (5.13)$$

where P_D is the demanded power which is not controllable. Therefore:

$$\begin{aligned} u^* &= \underset{u}{\operatorname{argmin}} \left\{ \int (P_{fuel} + P_{bat,C} + a \cdot \dot{A}h_{eff} \cdot V_{bat,oc} \cdot 3600) dt \right\} \\ &= \underset{u}{\operatorname{argmin}} \left\{ \int (\dot{m}_{fuel} \cdot Q_{lhv} + P_{bat,C} + a \cdot V_{bat,oc} \cdot 3600 \cdot \dot{A}h_{eff}) dt \right\} \end{aligned} \quad (5.14)$$

Defining:

$$k_0 = \frac{3600 \cdot V_{bat,oc}}{Q_{lhv}} \quad (5.15)$$

$$k = a_0 \cdot k_R \cdot k_0 \quad (5.16)$$

where k_0 is for unit conversion. Therefore:

$$u^* = \operatorname{argmin} \left\{ \int \left(\dot{m}_{fuel} + \frac{1}{Q_{lhv}} P_{bat,c} + k \cdot \dot{A}h_{eff} \right) dt \right\} \quad (5.17)$$

The values of k with different battery capacities are shown in Table 5.1.

Table 5.1, Value of k IN DIFFERENT BATTERY PACK SIZE,
HONDA CIVIC IMA 13.2 GALLONS FUEL TANK

Battery Capacity	Value of k
1 kWh battery pack	0.0064
2 kWh battery pack	0.0129
4 kWh battery pack	0.0258

As shown in Table 5.1, the value of k is relatively small as expected. Since battery aging has been considered as a long term factor as comparing to the instantaneous energy usage from fuel and battery in the cost function.

5.12 Bounds of the aging ECMS Equivalence Factor

Finding the optimal equivalence factor, in general, requires solution of a two-point boundary value problem which requires that the driver's demanded power for the whole drive be available at the start of the drive. But, comparing Equation (5.17) and (5.8) we see that $\lambda = 1/Q_{lhv}$. Also, we expect that fuel usage is minimized by maximizing the use of the battery when ignoring the state of charge constraints. Therefore, we expect that $\lambda = 1/Q_{lhv}$ will maximize the use of the electric motors. This behavior is confirmed by the simulations which show that this equivalence factor results in the battery SOC quickly reaching the lower bound SOC_L . A smaller λ makes the battery energy even less valuable. Therefore, the optimal value of

$$\lambda_{opt} = \lambda_{Min} = \frac{1}{Q_{lhv}} \leq \lambda \quad (5.18)$$

When the ECMS equivalence factor is large, the penalty for using electrical power is high and ECMS tends to charge the battery up to $SOC = SOC_H$. In this case, the vehicle operates in fuel only mode for most of the trip. When SOC is at the upper bond, the control action u is

$$\left. \begin{array}{l} x = SOC_H \\ P_D > 0 \end{array} \right\} \Rightarrow u \in \{u_{eom}\} \cup \{u_{bom}\} \cup \{u_{hm}\} \quad (5.19)$$

where u_{eom} is the control action in engine only mode, u_{bom} is in battery only mode, and u_{hm} is in hybrid mode. Then, the Hamiltonian Equations for these modes are shown below

$$H(u_{eom}^*) = \dot{m}_{fuel}(u_{eom}^*, P_D) + k \cdot \dot{A}h_{eff}(x, u_{eom}^*) \quad (5.20)$$

$$H(u_{bom}^*) = \lambda P_{bat,c}(x, u_{bom}^*) + k \cdot \dot{A}h_{eff}(x, u_{bom}^*) \quad (5.21)$$

$$H(u_{hm}^*) = \dot{m}_{fuel}(u_{hm}^*, P_D) + \lambda P_{bat,C}(x, u_{hm}^*) + k \cdot \dot{A}h_{eff}(x, u_{hm}^*) \quad (5.22)$$

where u^* represents all the admissible control actions. When λ approaches infinity, then based on Equation (5.8), the ECMS will never discharge the battery, because the cost of using the battery will always be higher than the cost of using fuel. Consequently, the vehicle will always be in engine only mode for any $P_D > 0$, and the SOC will stay at the upper limit since the battery is charged by Engine.

$$\left. \begin{array}{l} x = SOC_H \\ \gg \frac{1}{Q_{lHV}} \end{array} \right\} \Rightarrow \left\{ \begin{array}{l} P_D > 0 : H(u_{eom}) < H(u_{bom}^*) \\ \text{and} \\ P_D > 0 : H(u_{eom}) < H(u_{hm}^*) \end{array} \right. \quad (5.23)$$

Therefore, this large value of λ cannot be optimal for any drivecycle. An upper bound for λ^* can be obtained by decreasing of λ until use of the electric motors becomes feasible. For instance, the battery only mode and the hybrid mode will also have chance to be operate optimally.

$$\left. \begin{array}{l} x = SOC_H \\ \lambda = \lambda_{Max} \end{array} \right\} \Rightarrow \left\{ \begin{array}{l} P_D > 0 : H(u_{eom}) > H(u_{bom}^*) \\ \text{or} \\ P_D > 0 : H(u_{eom}) > H(u_{hm}^*) \end{array} \right. \quad (5.24)$$

The inequalities above shows that the upper bond of λ should allow battery discharging to be optimal. So $\lambda_{Max} = \min(\lambda_{Max1}, \lambda_{Max2})$, where λ_{Max1} is the upper bond λ value during battery only mode, λ_{Max2} is the upper bond λ value during hybrid mode.

When $\lambda = \lambda_{Max}$ and $SOC = SOC_H$, λ_{Max1} is calculated having battery only mode be more efficient than engine only mode (have a smaller Hamiltonian):

$$\begin{aligned} & H(u_{eom}) > H(u_{bom}) \\ & \dot{m}_{fuel}(u_{eom}, P_D) + k \cdot \dot{A}h_{eff}(x, u_{eom}) \\ & > \lambda^* P_{bat,C}(x, u_{bom}) + k \cdot \dot{A}h_{eff}(x, u_{bom}) \\ & \lambda^* \leq \frac{\dot{m}_{fuel}(u_{eom}, P_D) + k \cdot \dot{A}h_{eff}(x, u_{eom}) - k \cdot \dot{A}h_{eff}(x, u_{bom})}{P_{bat,C}(x, u_{bom})} \end{aligned} \quad (5.25)$$

In engine only mode (λ is very large), there will be few (only when the batteries are required to meet drivers demand) opportunities to use battery power. Therefore, the cost of the aging term $k \cdot \dot{A}h_{eff}(x, u_{eom}) = 0$. In addition, when λ is relatively large, there is again limited opportunity to use the battery. So, $k \cdot \dot{A}h_{eff}(x, u_{bom})$ is approximately zero when λ is relatively large. Therefore, Equation (5.25) is approximately

$$\lambda^* \leq \frac{\dot{m}_{fuel}(u_{eom}, P_D)}{P_{bat,C}(x, u_{bom})} \quad (5.26)$$

Then

$$\lambda_{Max1} = \frac{\frac{P_D/\eta_{trs}(u_{eom}^*)}{Q_{lhv}\eta_{eng}(u_{eom}^*)}}{P_D/\eta_{trs}(u_{bom}^*)/\eta_{em}(u_{bom}^*)\eta_{inv}(u_{bom}^*)\eta_{bat}(u_{bom}^*)}$$

$$\Rightarrow \lambda_{Max1} = \frac{\bar{\eta}_{em}\bar{\eta}_{inv}\bar{\eta}_{bat}}{Q_{lhv}\bar{\eta}_{eng}} \quad (5.27)$$

where η_{trs} is the transmission efficiency, η_{eng} is the engine efficiency, η_{em} is the e-machine efficiency, η_{inv} is the inverter efficiency, and η_{bat} is the battery efficiency. And $\bar{\eta}$ is the average efficiency of the powertrain component.

The second inequality in (5.24) requires that,

$$\lambda^* \leq \frac{\dot{m}_{fuel}(u_{eom}, P_D) - \dot{m}_{fuel}(u_{hm}, P_D)}{P_{bat,C}(x, u_{hm})} \quad (5.28)$$

Therefore

$$\lambda_{Max2} = \frac{\frac{P_D/\eta_{trs}(u_{eom}^*)}{Q_{lhv}\bar{\eta}_{eng}(u_{eom}^*)} - \frac{P_D/\eta_{trs}(u_{eom}^*) - P_{em}(u_{hm}^*)}{Q_{lhv}\bar{\eta}_{eng}(u_{hm}^*)}}{\frac{P_{em}(u_{hm}^*)}{\bar{\eta}_{en}(u_{hm}^*)\bar{\eta}_{inv}(u_{hm}^*)\bar{\eta}_{bat}(u_{hm}^*)}}$$

$$\Rightarrow \lambda_{Max2} = \frac{\bar{\eta}_{em}\bar{\eta}_{inv}\bar{\eta}_{bat}}{Q_{lhv}\bar{\eta}_{eng}} \quad (5.29)$$

Therefore, the bounds of the equivalence factor for ECMS, given in Section 3, Equation (3.46), are still valid bounds for the equivalence factor in Aging ECMS.

5.2 Fixed equivalence factor simulation results

TABLE 5.2, Vehicle Specification Honda Civic IMA Parallel HEV

Vehicle Components	Vehicle Specification
Configuration	Mild Parallel Hybrid
Vehicle mass	1279 Kg
Engine max torque	120 N·m @ 3500 rpm
E-machine max torque	62 N·m @ 2200 rpm
Battery energy	1.003 KW.hr
	2.007 KW.hr
	4.001 KW.hr
Battery cell capacity	3.5 Ah
Battery initial SOC	68.5%
Battery SOC range	50% to 70%
Battery OCV	3.8 V
Initial temperature	20 °C

The Honda Civic IMA with the configuration shown in Figure 3.1 is used in this work. The detailed vehicle specifications are shown in Table 5.2. Three battery packs with 1 kWh, 2 kWh, and 4 kWh have been simulated to show the performance of the proposed ECMS with Aging consideration.

Figure 5.1, Combined drive cycles, vehicle speed, 1 kWh Fuel Economy Equivalent, 1 kWh Battery remaining State of Health. (a) CD1: UDSS+HWFET+UDSS; (b) CD2: UDSS+HWFET+US06; (c) CD3: US06+SC03+HWFET

Three types of Combined Drive-cycles (CDs) have been tested for each simulation. These CDs were created by appending standard drive cycles in a sequence, as follows:

- CD1: UDDS, HWFET, and UDDS
- CD2: UDDS, HWFET, and US06
- CD3: US06, SC03, and HWFET

These CDs simulate different types of daily driving behaviors, utilizing different percentages of highway, city, or country driving. Figure 5.1 shows the vehicle speed for these three CDs. Figure 5.1a includes the most of city driving with a total distance of 25.26 miles. Figure 5.1b includes a balance between city and highway driving with a total distance of 25.77 miles. Figure 5.1c includes the most highway driving with a total distance of 21.87 miles.

Figure 5.1 also shows the MPGe and battery remaining state of health (SOH) across all equivalence factors within the bounds. When $\lambda = 1/Q_{lhv}$, the aging ECMS operates in electric only mode, the battery discharges at the beginning of the drive cycle, and the SOC remains at the lower constraint. When $\lambda = 4/Q_{lhv}$, the aging ECMS operates in engine only mode, the battery charges at the beginning of the drive cycle, and the SOC remains at the upper constraint. Therefore, the MPGe is lower at the values close to the equivalence factor bounds.

When λ/Q_{lhv} equals around 2.5 to 3.5, the aging ECMS operates in more hybrid mode, which causes more battery damage (fast charging-discharging events) and provides better fuel economy. As shown in Figure 5.1, the aging ECMS algorithm significantly improves the battery SOH, especially at equivalence factors where the vehicle is operating in hybrid mode, for all three drive cycles. In addition, there is only a small fuel economy penalty all cases. Using 2 kWh and 4 kWh battery packs generated similar overall results.

TABLE 5.3
Optimal equivalence factor simulation results

Battery pack	Drive Cycle	General ECMS	Aging ECMS
		$\lambda^* \cdot Q_{lhv}$	$\lambda^* \cdot Q_{lhv}$
1 kWh	CD1	3.2	3
	CD2	2.7	3.1
	CD3	2.6	3.2
2 kWh	CD1	3.2	3.1
	CD2	2.8	3.2
	CD3	2.6	3.2
4 kWh	CD1	3.1	3.1
	CD2	2.8	3.1
	CD3	2.6	3.1

Table 5.3 and Table 5.4 shows the optimal penalty factor for each combined drive cycle with 1 kWh, 2 kWh and 4 kWh battery packs. The MPGe and remaining SOH of both

general ECMS and Aging ECMS are compared. The optimal equivalence factor which yields the best MPGe for both general ECMS and Aging ECMS are picked. As stated before, the MPGe has been picked to compare, because the causal ECMS and Aging ECMS algorithms cannot control the final SOC.

TABLE 5.4
Simulation results of the performance

Battery pack	Drive Cycle	General ECMS		Aging ECMS	
		<i>MPGe</i>	<i>SOH</i>	<i>MPGe</i>	<i>SOH</i>
1 kWh	CD1	75.70	99.859%	72.32	99.932%
	CD2	57.01	99.932%	57.29	99.937%
	CD3	54.04	99.956%	52.54	99.967%
2 kWh	CD1	80.35	99.947%	76.56	99.966%
	CD2	59.26	99.969%	59.63	99.968%
	CD3	56.51	99.977%	54.88	99.981%
4 kWh	CD1	88.05	99.976%	85.21	99.980%
	CD2	63.57	99.983%	64.12	99.982%
	CD3	61.61	99.985%	59.67	99.986%

As shown in Table 5.4, aging ECMS saved 0.073% of battery aging in a 25.26 miles drive which traded off from 75.7 MPGe to 72.32 MPGe. Assume the price for gasoline is \$3 per gallon and the cost to replace the battery pack is \$207 per 1kWh battery [83] plus a \$200 replacement labor cost. Table 5.5 shows the economic performance comparison between general ECMS and aging ECMS. Fuel cost showed in Table 5.5 is calculated based on

$$Fuel\ Cost = \frac{CD\ Distance}{MPGe} \cdot Fuel\ Price \quad (5.30)$$

The battery cost is calculated from

$$Battery\ Cost = (1 - SOH) \cdot Battery\ Replacement \quad (5.31)$$

The total cost comparison is shown in Table 5.6.

The smaller battery pack combined with more city driving saved the most total cost. This is because city driving requires the battery to be used more frequently for charging, discharging, regenerative braking and electric only operation. The smaller battery pack has smaller electric energy capacity compared to the energy capacity of the fuel tank. The smaller energy capacity requires more rapid changes in SOC, and quicker and more frequently charge discharge cycles. On the other hand, the total cost with the larger battery pack is less than with the smaller battery pack in the same drive cycle.

TABLE 5.5
Economic performance simulation results

Battery pack	Drive Cycle	General ECMS [\$]		Aging ECMS [\$]	
		Fuel Cost	Battery Cost	Fuel Cost	Battery Cost
1 kWh	CD1	1.001	0.574	1.048	0.277
	CD2	1.356	0.277	1.349	0.256
	CD3	1.214	0.179	1.249	0.134
2 kWh	CD1	0.943	0.325	0.990	0.209
	CD2	1.305	0.190	1.296	0.196
	CD3	1.161	0.141	1.196	0.117
4 kWh	CD1	0.861	0.247	0.889	0.206
	CD2	1.216	0.175	1.206	0.185
	CD3	1.065	0.154	1.100	0.144

TABLE 5.6
Economic performance total cost

Battery pack	Drive Cycle	General ECMS Total cost [\$]	Aging ECMS total cost [\$]	Percent saved
1 kWh	CD1	1.575	1.325	15.89%
	CD2	1.633	1.606	1.65%
	CD3	1.393	1.383	0.73%
2 kWh	CD1	1.269	1.198	5.52%
	CD2	1.495	1.493	0.13%
	CD3	1.302	1.312	-0.76%
4 kWh	CD1	1.107	1.095	1.12%
	CD2	1.391	1.391	0.01%
	CD3	1.219	1.243	-1.99%

Battery cost in CD1 is larger than in other drive cycles in both general ECMS and aging ECMS. However, the differences in CD1 of the battery cost are all smaller than other CDs in aging ECMS compare to general ECMS as shown in Table V. CD2 has the largest cost of all battery packs, which is because the relatively longer distance of this drive cycle and less MPGe caused by the higher percentage of highway driving. CD3 is the drive cycle with the highest percentage of highway drives, which resulted the least MPGe in both general ECMS and aging ECMS. With 2 kWh and 4 kWh battery packs and the CD3 drive cycle, the cost of general ECMS is less than the aging ECMS. This is because in highway driving, less battery power is used, and the aging ECMS is not able to implement many control actions. However, the remaining SOH in CD3 is higher than other drive cycles as shown in Table 5.6.

(a)

(b)

(c)

Figure 5.2. CD1 Performance, State of Charge, Severity Factor, State of Health and Battery temperature. (a) 1 kWh battery pack; (b) 2 kWh battery pack; (c) 4 kWh battery pack

Figs. 5.2, 5.3 and 5.4 shows the SOC variation, severity factor, SOH degradation, and battery temperature changes for 1 kWh, 2 kWh, 4 kWh battery packs in the three CDs. The optimal equivalence factor shown in Table 5.3 are picked and plotted.

(a)

(b)

(c)

Figure 5.3. CD2 Performance, State of Charge, Severity Factor, State of Health and Battery temperature. (a) 1 kWh battery pack; (b) 2 kWh battery pack; (c) 4 kWh battery pack

It is obviously in Figure 5.2 that the smaller battery pack has more rapid changes in State of Charge. In Figure 5.2(a), aging ECMS takes the action to reduce the rapid charge-discharge cycles around 1800 seconds, and the severity factor and SOH plots shows that general ECMS produced critical damage during this time. In addition, Temperature plots

also shows the temperature increases due to increased current. In Figure 5.2(b) and (c), the amount of output current is the same, but the increase capacity of the battery leads to a smaller variation in SOC. The rapid increase in power demand is still the same, however, the requested power per battery cell has been reduced.

(a)

(b)

(c)

Figure 5.4. CD3 Performance, State of Charge, Severity Factor, State of Health and Battery temperature. (a) 1 kWh battery pack; (b) 2 kWh battery pack; (c) 4 kWh battery pack

As shown in Figure 5.3 and Figure 5.4, aging ECMS attempted to save battery life by reducing the ripples of the state of charge, which can also be seen in the temperature curve. All temperature plots show that aging ECMS generated less heat than general ECMS, which is because the total amount of discharges out from the battery is less compared to general ECMS. Similarly, SOH is decreased by the rapid discharge of the battery around 1400 seconds in CD2 and 1200 seconds in CD3. According to Figure 5.1(b) and (c), this is caused by the rapid acceleration request from the driver. The battery has to provide a large amount of power to fully meet the demanded power from the driver.

From the simulation results, the performance of the aging ECMS algorithm significantly increased the battery life with little penalty to the fuel economy. The bounds on the equivalence factor presented should also be useful for designing new types of adaptive-ECMS algorithms that incorporate battery aging considerations.

5.3 Adaptive ECMS: CESO with battery aging

Section 5.1 and 5.2 introduced ECMS with fixed equivalence factor, as shown in section 5.2, the best performance equivalence factor lambdas are different for combined drive cycles which involved different amount of highway and city drives. Therefore, an adaptive law for equivalence factor need to be found to make the EMS drive-cycle independent. This section is introducing the aging CESO, which produced the optimal results without the knowledge of drive cycle.

On the other hand, since aging ECMS proposed in previous section also only considering the *SOC* hard constraints defined in Equation (3.27). There will still be a chance that the optimal EM strategy reject the desired optimal mode. In order to catch these energy saving opportunities as described in Section 3.4, soft bounds inside the hard bounds in (3.27) has been defined below.

$$SOC_L^{soft} \leq x(t) \leq SOC_H^{soft} \quad (5.32)$$

The Hamiltonian Equation with considering the cost of the soft constraints is then proposed.

$$H = \dot{m}_{fuel}(\mathbf{u}(t), P_D(t)) + k \cdot \sigma(I_c(t), T_{cell}(t), x(t)) \cdot |I_{bat}(t)| + p_1 \dot{x} + p_2 \dot{x}_2 \quad (5.33)$$

The following condition need to be satisfied with the costates p_1 and p_2 .

$$H(x^*, u^*, p^*, P_D) \leq H(x^*, u, p^*, P_D), \forall u \in U \quad (5.34)$$

Where the new state variable x_2 is defined based on the hard constraints in Equation (3.27).

$$\dot{x}_2 = (x - SOC_L^{soft})^2 S(x - SOC_L^{soft}) + (SOC_H^{soft} - x)^2 S(SOC_H^{soft} - x) \quad (5.35)$$

Where $S = 1$ if its argument is negative, otherwise $S = 0$. Which means, when $SOC_L^{soft} \leq x(t) \leq SOC_H^{soft}$, $\dot{x}_2 = 0$. Otherwise, $\dot{x}_2 = (x - SOC_L^{soft})^2$ when $x(t) < SOC_L^{soft}$ or $\dot{x}_2 = (SOC_H^{soft} - x)^2$ when $x(t) > SOC_H^{soft}$.

Finding the costates defined in (5.33)

$$\begin{aligned} \dot{p}_1^* = -\frac{\partial H}{\partial x} = & -p_1^* \frac{\partial \dot{x}}{\partial x} - p_2^* \frac{\partial \dot{x}_2}{\partial x} - k \cdot \frac{\partial \sigma(I_c(t), T_{cell}(t), x(t))}{\partial x} \cdot |I_{bat}(t)| - k \\ & \cdot \sigma(I_c(t), T_{cell}(t), x(t)) \frac{\partial}{\partial x} |I_{bat}(t)| \end{aligned} \quad (5.36)$$

$$\begin{aligned} \dot{p}_2^* = -\frac{\partial H}{\partial x_2} = & -p_1^* \frac{\partial \dot{x}}{\partial x_2} - p_2^* \frac{\partial \dot{x}_2}{\partial x_2} - k \cdot \frac{\partial \sigma(I_c(t), T_{cell}(t), x(t))}{\partial x_2} \cdot |I_{bat}(t)| - k \\ & \cdot \sigma(I_c(t), T_{cell}(t), x(t)) \frac{\partial |I_{bat}(t)|}{\partial x_2} \end{aligned} \quad (5.37)$$

Where $\dot{m}_{fuel}(\mathbf{u}(t), P_D(t))$ is independent of x and x_2 ; $\dot{x}$ defined in Equation (3.26) is independent of x and x_2 when x is within constraints defined in (3.27); from Equation (5.37), $\dot{x}_2$ is independent of x_2 and only depends on x . In addition, x_2 is defined only depend on x , since $I_{bat}(t)$ and $\sigma(I_c(t), T_{cell}(t), x(t))$ are independent of x within constraints (3.27), then $I_{bat}(t)$ and $\sigma(I_c(t), T_{cell}(t), x(t))$ are independent of x_2 . Therefore, (5.36) and (5.37) can be re-written to

$$\dot{p}_1^* = -\frac{\partial H}{\partial x} \approx -p_2^* \frac{\partial \dot{x}_2}{\partial x} \quad (5.38)$$

$$\dot{p}_2^* = -\frac{\partial H}{\partial x_2} = 0 \Rightarrow p_2^* = \text{constant} \quad (5.39)$$

$$\dot{\lambda}^* = \frac{p_2^*}{Q_{bat} V_{bat,oc}} \frac{\partial \dot{x}_2}{\partial x} \quad (5.40)$$

The battery absolute current and the aging severity factor are independent of the system state x . This factor guaranteed that the cost of battery aging defined in the cost function (5.1) or the Hamiltonian (5.33) has been monitored during the entire process independently, and when the aging cost is big, the aging term will penalty the battery usage with regardless of state of charge or system bounds.

Similarly, from Equation (5.40), the optimal equivalent is then independent to battery aging term, and only depends on p_2 and x_2 . Therefore, Section 3.4 from Equation (3.55) to (3.69) will be duplicated in the following to generate the adaptive law of the equivalence factor. Thus, the adaptive law for equivalence factor λ is the same as introduced in Section 3.4, which is shown below

$$\lambda(t) = \begin{cases} \mu, & SOC_L^{soft} \leq x(t) \leq SOC_H^{soft} \\ \mu - \left(\mu - \frac{1}{Q_{lhv}}\right) \left(\frac{\theta(t)}{\theta_{Max}}\right)^2, & x(t) > SOC_H^{soft} \\ \mu + \left(\frac{\bar{\eta}}{Q_{lhv}} - \mu\right) \left(\frac{\theta(t)}{\theta_{Max}}\right)^2, & x(t) < SOC_L^{soft} \end{cases} \quad (5.41)$$

In summary, as shown in Equation (5.41), the adaptive equivalence factor $\lambda(t)$ will be a constant when $SOC_L^{soft} \leq x(t) \leq SOC_H^{soft}$; it will be increased to leads the vehicle operates by more engine mode when the battery SOC turns low and the battery will be charged; otherwise, it will be decreased to leads the vehicle operates in more battery mode when battery SOC turns high. In ECMS-CESO, a reasonable μ has been proposed to maintain $\lambda(t)$ within the range defined in (3.46), which μ is set to the midpoint of this range: $\mu = (\bar{\eta} + 1)/(2Q_{lhv})$ as shown in Figure 3.5.

5.4 Aging CESO simulation results

The vehicle configuration and the combined drive cycle introduced in section 5.2 has been used in this simulation. The simulation results of the performance of aging CESO are shown in appendix from Figure A4 to A12, which include the detail trajectory of the vehicle speed, SOC, severity factor, remaining battery SOH, and battery pack temperature when using 1kWh, 2kWh and 4kWh battery packs compared to general CESO ECMS. Figure A13 to A21 showed equivalence factor variations in CESO ECMS with respect to vehicle speed, SOC trajectory, and severity factor for different combined drive cycles and different battery pack sizes.

The SOC trajectories, severity factors, SOH, and battery temperature for battery pack 1 kWh, 2 kWh and 4 kWh in CD1 are shown in Figures A4, A5 and A6. The general CESO ECMS caused more battery damage in the time period 1500 seconds to 2000 seconds by fast charging-discharging cycles, which aging CESO ECMS removed and saved battery life. Similarly, for CD2 and CD3 in Figures A7 to A12, general CESO ECMS caused more battery damage in the time period 1300 to 2100 seconds in CD2 and 1200 to 1800 seconds in CD3, because of the fast variation of SOC in general CESO ECMS. Aging CESO ECMS filtered out the fast charging-discharging cycles to save battery life. Which leads to better overall operating costs as shown in the Tables below.

Simulation results as shown from Figure A13 to A21 indicated that aging CESO compared to general CESO successfully avoided the unnecessary charge-discharge cycles in the combined drive cycles, and resulted better battery life with a traded off of acceptable penalty on equivalent fuel economy.

Table 5.7 showed the summary of the aging CESO simulation results compare to the general CESO. As shown in table 5.7, aging CESO has significantly improved the SOH compare to the general CESO in all combined drive cycles and all different battery packs with few or no penalties in equivalent fuel economy. In CD1, battery pack with 1kWh battery pack has the least MPGe and the battery remaining SOH, and battery pack with 4

kWh battery pack has the best MPGe and the most battery remaining SOH. This is because larger battery pack brings more capacity of the energy distribution, which the SOC will be more compatible before reaching the soft or hard constraints. And the least battery capacity resulted more rapidly charge-discharge cycles, which brings more damage to the battery. CD3 has the least MPGe and the most remaining battery life in all battery packs, which is because CD3 contained the most highway drives, which leads the EMS operates in more engine only mode to satisfy the demanded power.

Table 5.7, CESO simulation results of the performance

Battery pack	Drive Cycle	General CESO		Aging CESO	
		SOH [%]	MPGe	SOH [%]	MPGe
1 kWh Battery	CD1	99.901	75.49	99.934	74.24
	CD2	99.919	59.30	99.941	58.29
	CD3	99.936	56.05	99.942	55.28
2 kWh Battery	CD1	99.959	79.71	99.969	78.23
	CD2	99.966	60.95	99.973	60.52
	CD3	99.967	58.05	99.973	57.67
4 kWh Battery	CD1	99.979	86.41	99.981	84.30
	CD2	99.982	63.98	99.983	63.93
	CD3	99.984	61.15	99.984	61.28

Similar to Section 5.2, identify the price of gasoline as \$3 per gallon and the battery pack \$207 with a \$200 replacement cost of \$200. The cost for the combined drive cycles are identified according to Equations (5.30) and (5.31). The fuel cost and the battery cost are shown below in Table 5.8 below..

Table 5.8, CESO simulation results of the economic performance

Battery pack	Drive Cycle	General CESO [\$]		Aging CESO [\$]	
		Fuel Cost	Battery Cost	Fuel Cost	Battery Cost
1 kWh Battery	CD1	1.004	0.402	1.021	0.268
	CD2	1.304	0.328	1.326	0.240
	CD3	1.170	0.259	1.187	0.237
2 kWh Battery	CD1	0.951	0.251	0.969	0.193
	CD2	1.269	0.209	1.277	0.166
	CD3	1.130	0.201	1.138	0.166
4 kWh Battery	CD1	0.758	0.221	0.899	0.200
	CD2	1.208	0.183	1.209	0.177
	CD3	1.073	0.164	1.071	0.162

As shown in Table 5.8, CD1 produced the largest battery cost in all battery packs. This is because CD1 contained the most of city drives, which required the most regenerative braking. Therefore, the battery experienced the most charge-discharge cycles. CD2 has the

largest fuel cost, which is because the relatively longer distance of this drive cycle, and the more highway drives lead the EMS to operate in more engine only mode. Since aging CESO resulted better remaining battery SOH, the aging CESO battery cost shown in Table 5.8 are less than the general CESO battery cost. Table 5.9 compared the total cost compare between general CESO and aging CESO.

Most of the total cost shown in Table 5.9 indicated that aging CESO has saved money comparing to general CESO. The only exception is in CD1 when vehicle using 4kWh battery. The reason why money is not saved in this case is because that SOC variation is already slow, which does not cause much battery damage. And it actually improved the aging, and punished little in fuel economy. As shown in Figure A6 in appendix, the SOC variation for the 4kWh battery pack at CD1 in general CESO is already smooth, the aging CESO reduced the oscillation in the time range from 1500 seconds to 2300 seconds to improve battery aging, but this variation cost more fuel consumed. But, the 4kWh battery pack in CD1 is already generating the least cost compare to other CDs and battery pack combinations, and the cost will be reduced further with the drop of the fuel price.

Table 5.9, CESO simulation results of the total cost

Battery pack	Drive Cycle	General CESO	Aging CESO	Percent saved [%]
		Total Cost [\$]	Total Cost [\$]	
1 kWh Battery	CD1	1.406	1.289	8.297
	CD2	1.632	1.566	4.053
	CD3	1.430	1.424	0.413
2 kWh Battery	CD1	1.202	1.162	3.308
	CD2	1.478	1.444	2.311
	CD3	1.331	1.303	2.072
4 kWh Battery	CD1	0.979	1.099	-12.295
	CD2	1.391	1.386	0.381
	CD3	1.237	1.233	0.354

Table 5.10, compare aging ECMS and aging CESO simulation results of the total cost

Battery pack	Drive Cycle	Aging ECMS	Aging CESO	Percent saved [%]
		Total Cost [\$]	Total Cost [\$]	
1 kWh Battery	CD1	1.325	1.289	2.717
	CD2	1.606	1.566	2.491
	CD3	1.383	1.424	-2.965
2 kWh Battery	CD1	1.198	1.162	3.005
	CD2	1.493	1.444	3.282
	CD3	1.312	1.303	0.686
4 kWh Battery	CD1	1.095	1.099	-0.365
	CD2	1.391	1.386	0.359
	CD3	1.243	1.233	0.805

On the other hand, compare to Table 5.6, aging CESO has significantly reduce the total cost of a trip in most cases as shown in Table 5.10.

In summary, Section 5.1 and 5.2 introduces the aging ECMS control algorithm with a fixed equivalence factor. The Ah-throughput method has been used as the aging term in the ECMS cost function. Section 5.1 and 5.2 also demonstrates that the equivalence factor in this algorithm is a constant. In addition, it is shown that with the new aging term added to ECMS, the bounds on the equivalence factor remain the same as for ECMS. These bounds have been used in aging CESO to create the adaptive law of the equivalence factor.

Section 5.3 and 5.4 introduced aging CESO as the on-line HEV optimization strategy in charge sustaining mode, which is developed based on aging ECMS by adaptively control the equivalence factor within the SOC hard and soft constraints. The aging CESO ECMS optimal controller presented does not require prediction or knowledge of future driving actions, which is a causal controller for on-line applications. This advantage could save the vehicle cost regarding to the installation of sensors, GPS devices and high performance vehicle electronic control unit which are using for estimating the future knowledge of driving route.

The simulation results showed that with consideration of battery aging in CESO ECMS, comparing to the best performance of fixed equivalence factor shown in section 5.2, can significantly save the cost in a trip from either fuel economy or battery aging.

5.5 CESO in Charge-depletion mode and SHEV

The proposed CESO ECMS has been simulated using a charge-sustaining PHEV. However, the proposed work can, not only be applicable in the proposed vehicle type or operation mode, but also in charge depletion mode [88], or in series hybrid electric vehicles (SHEV) [92].

In section 5.1, it can be shown that for any type of HEV, regardless of the drivecycle, the optimal value of λ in the ECMS cost function (5.8), by minimizing the energy lost and battery fading shown in (5.17) is

$$\lambda^* = 1/Q_{thv} \quad (5.42)$$

The constraint (3.27) on SOC is defined for charge-sustaining mode only. However, the battery SOC is usually not constrained in charge-depletion mode, because the priority is to rely on battery energy [88][89]. During charge-depletion mode, the engine is only turned on when battery and electric motor cannot deliver the demanded power [90][91]. Charging the battery by using engine is not desired in this mode. Therefore, in a vehicle contained both charge depletion and charge sustaining (CDCS) modes, the adaptive law of CESO becomes (5.42) in charge depletion mode, and (5.41) in charge sustaining mode [88]. With aging consideration in charge-depletion mode, LSSR rule based control could be simply added to improve the battery degradation as shown in (4.6) and discussed in section 4.4.

In a SHEV, engine is only configured to re-charge the battery. A typical SHEV configuration is shown in Figure 5.5. For the SHEV, the power train power is defined as $P_{ptr} = P_D + P_{brk}$. Therefore, the e-motor power P_{em} becomes:

$$P_{em} = \frac{P_{ptr}(t)}{\eta_{trs}^n(r_{trs}(t))} = \frac{P_D(t) + P_{brk}(t)}{\eta_{trs}^n(r_{trs}(t))} \quad (5.43)$$

where η_{trs} is the total efficiency of the transmission, and r_{trs} is the gear ratio, and n is defined as:

$$n = \begin{cases} -1, & \text{braking/coasting } P_D(t) \leq 0 \\ 1, & \text{accelerating/cruising, } P_D > 0 \end{cases} \quad (5.44)$$

The electric power of the battery $P_{bat,E}$ is then defined according to Figure 5.5

$$P_{bat} = \frac{P_{ptr}(t)}{\eta_{em}^n \eta_{invt}^n} + P_{gn} = \frac{P_D(t) + P_{brk}(t)}{\eta_{em}^n \eta_{invt}^n} + P_{gn} \quad (5.45)$$

where η_{em} and η_{invt} are the power efficiency of the e-motor and the inverter. P_{gn} is the power of the generator, which is always non-positive ($P_{gn} \leq 0$). Therefore, equation (5.45) is equivalent to equation (3.5) for the SHEV configuration.

Figure 5.5. Typical configuration of a Series HEV

As shown in Figure 5.5, engine and generator are coupled mechanically. Therefore, the engine and generator can be combined and optimized based on P_{gn} . Thus, a known control of P_{gn} can be optimized offline by controlling the engine torque and speed for the minimum $\dot{m}_{fuel}$. Therefore, the optimal problem for SHEV is the same as the PHEV shown in (3.48) or (5.33) for CESO ECMS [92] or aging CESO ECMS presented in Section 5.3 and 5.4 in this brief.

6. Conclusion

This work has systematically introduced the CESO ECMS with aging consideration. Section 3 introduced the base-line PHEV using a LiFePO₄ battery pack, the Ah-throughput battery aging model, the general ECMS control strategy, and the CESO ECMS algorithm. As reviewed in Section 2, LiFePO₄ has been widely used in the automotive industry because of its safety and long life characteristics. The main aging characteristic of the LiFePO₄ battery is due to experiencing capacity loss rather than impedance growth. Therefore, it is more compatible with control oriented research on battery aging. The Ah-throughput method as a performance model, directly measures the battery damage by the measurement of the variation of SOC and C-rate. Therefore, the inputs of this battery aging model are SOC and C-rate, which are both real-time inputs. Thus, the Ah-throughput battery aging model is real-time implementable. ECMS and CESO ECMS are the base optimal control strategies on this work. Section 3 also introduced the ECMS optimal control problem and the bounds on the equivalence factor. The bounds of the equivalence factor have been further used to develop a real-time optimal control strategy which adaptively adjust the equivalence factor during a trip.

Section 4 first analyzed the effects of battery aging with different equivalence factor values, and proposed that battery lifetime can be significantly extended by selecting an equivalence factor that yields a slight decrease in fuel efficiency from the maximum. On the other hand, the SOC constraints and the temperature impacted the battery available energy capacity to the vehicle. This further influenced the vehicle performance in fuel economy and battery aging. Section 4 also analyzed these facts. A simple rule-based control is then implemented in charge-depletion mode. The simulation results showed that with simple rule-based control, vehicle operation cost could be significantly improved. This further motivates in adding a battery aging term in the charging-sustaining mode in ECMS.

The optimal control problem using ECMS with battery aging considerations is then introduced in Section 5. The proposed cost function has been proved to be optimal when the equivalence factor is a constant, and the bounds introduced in section 3 remain same. Battery aging cost has been considered as a buffer to the battery usage cost, therefore, the aging coefficient has been correlated to the co-state by using the battery energy capacity. The simulation results showed that aging ECMS has improved the cost during a trip comparing to general ECMS. ECMS with a fixed equivalence factor might miss energy saving opportunities. Therefore, CESO ECMS with battery aging intended to catch energy saving opportunities has been introduced in Section 5. The simulation results showed that compare to the fixed equivalence factor used in aging ECMS, aging CESO ECMS further improved the cost.

Appendix

A. SOC variation in temperature effects

Figure A1, The UDDS HWFET UDDS drive cycle, along with State of charge trajectories with selected ECMS penalty factors at temperature 25 °C, 0 °C, -10 °C and -20 °C.

Figure A2, The UDDS HWFET US06 drive cycle, along with State of charge trajectories in different ECMS penalty factors at temperature 25 °C, 0 °C, -10 °C and -20 °C.

Figure A3, The US06 HWFET SC03 drive cycle, along with State of charge trajectories in different ECMS penalty factors at temperature 25 °C, 0 °C, -10 °C and -20 °C.

B. CESO Performance

Figure A4, ECMS-CESO performance in UDDS HWFET UDDS combined drive cycle when using 1kW battery pack

Figure A5, ECMS-CESO performance in UDDS HWFET UDDS combined drive cycle when using 2kW battery pack

Figure A6, ECMS-CESO performance in UDDS HWFET UDDS combined drive cycle when using 4kW battery pack

Figure A7, ECMS-CESO performance in UDDS HWFET US06 combined drive cycle when using 1kW battery pack

Figure A8, ECMS-CESO performance in UDDS HWFET US06 combined drive cycle when using 2kW battery pack

Figure A9, ECMS-CESO performance in UDDS HWFET US06 combined drive cycle when using 4kW battery pack

Figure A10, ECMS-CESO performance in US06 SC03 HWFET combined drive cycle when using 1kW battery pack

Figure A11, ECMS-CESO performance in US06 SC03 HWFET combined drive cycle when using 2kW battery pack

Figure A12, ECMS-CESO performance in US06 SC03 HWFET combined drive cycle when using 4kW battery pack

Figure A13, UDDS HWFET UDDS combined drive cycle 1 kWh battery CESO performance

Figure A14, UDDS HWFET UDDS combined drive cycle 2 kWh battery CESO performance

Figure A15, UDDS HWFET UDDS combined drive cycle 4 kWh battery CESO performance

Figure A16, UDDS HWFET US06 combined drive cycle 1 kWh battery CESO performance

Figure A17, UDDS HWFET US06 combined drive cycle 2 kWh battery CESO performance

Figure A18, UDDS HWFET US06 combined drive cycle 4 kWh battery CESO performance

Figure A19, US06 SC03 HWFET combined drive cycle 1 kWh battery CESO performance

Figure A20, US06 SC03 HWFET combined drive cycle 2 kWh battery CESO performance

Figure A21, US06 SC03 HWFET combined drive cycle 4 kWh battery CESO performance

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