Real-Time Degradation Abatement Framework for Energy Storage System in Automotive Application using Data-Driven Approaches

Laxman Timilsina
ltimils@clemson.edu

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Dr. Christopher S. Edrington, Committee Chair
Dr. Johan H. Enslin
Dr. Yingjie Lao
Dr. Behnaz Papari
Dr. Gokhan Ozkan

Abstract

The increasing popularity of electric vehicles (EVs) is driven by their compatibility with sustainable energy goals. However, the decline in the performance of energy storage systems, such as batteries, due to their degradation puts EVs and hybrid electric vehicles (HEVs) at a disadvantage compared to traditional internal combustion engine (ICE) vehicles. The batteries used in these vehicles have limited life. The degradation of the battery is accelerated by the operating conditions of the vehicle, which further reduces its life and increases the reliability and economic concerns for the vehicle's operation.

The aging mechanism inside a battery cannot be eliminated but can be minimized depending on the vehicle's operating conditions and different control mechanisms that can alter the operating conditions. Different operating conditions affect the aging mechanism differently. Knowing the factors and how they impact battery capacity is crucial for minimizing degradation. This dissertation presents the detailed degradation mechanism inside the battery and the major factors responsible for the degradation, along with their effects on the battery during the operation of EVs. Then, to abate the degradation mechanism, a prognostic-based control framework (PBCF) for HEVs is proposed. Also, this framework reduces the overall cost of operating HEVs by taking into account the degradation of the energy storage systems. The strategy utilizes a degradation forecasting model of energy storage systems to predict their degradation paths. Analytical and data-driven approaches are used to find the degradation path of the energy storage systems as follows:

- Markov Chain Model
- Neural Network Model

These two models employ distinct datasets to validate the feasibility of the proposed strategy. The predicted degradation rate is then used to control the HEV via its energy management

(EM) system in order to reduce the degradation of energy storage systems. During the simulation, three distinct operating scenarios are developed to observe their effects on battery degradation and the response of the proposed control strategy PBCF.

Dedication

I dedicate this work to my parents, who never had the opportunity to attend university themselves but worked tirelessly throughout their lives to provide the best education for their two children. My endeavors are overshadowed by the immense sacrifices they undertook to secure us a quality education. Their unwavering support and dedication have been my inspiration.

- Laxman

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Nomenclature

BEV Battery Electric Vehicle

BMS Battery Management System

CAN Controller Area Network

CAN-H CAN High

CHIL Controller-Hardware-In-the-Loop

CAN-L CAN Low

DF Degradation Forecasting

DLC Device Level Control

DoD Depth of Discharge

DoE Department of Energy

DNN Deep Neural Network

DP Dynamic Programming

DRTS Digital Real-time Simulator

ECU Electronic Control Unit

EM Energy Management

EoL End of Life

ESS Energy Storage System

EV Electric Vehicle

FEV Full Electric Vehicle

FL Forecasting Layer

FNN Feedforward Neural Network

HEV Hybrid Electric Vehicle

HF Hybridization Factor

HIL Hardware-in-the-Loop

HMI Human-Machine Interface

ICE Internal Combustion Engine

Li-ion Lithium ion

LSTM Long Short Term Memory

NN Neural Network

NiMH Nickel-Metal Hydride

NS Numerical Simulation

PBCF Prognostic-based Control Framework

PHEV Plug-in Hybrid Electric Vehicle

PM Power Management

PMP Pontryagin's Minimum Principle

RT-COOL Real-Time Control and Optimization Laboratory

RNN Recurrent Neural Network

RUL Remaining Useful Life

SNL Sandia National Laboratory

SoC State of Charge

SoH State of Health

V2G Vehicle-to-Grid

V2V Vehicle-to-Vehicle

Chapter 1

Introduction

The fluctuating cost of non-renewable energy resources, concern over global greenhouse gas emissions, and rigorous rules and regulations for vehicle emissions have prompted research toward clean and green transportation systems [1]. [2] provides data that shows the transportation sector accounts for a larger share of overall energy consumption (i.e., 26%). This consumption is attributable to the millions of conventional automobiles that use internal combustion engine (ICE), which run on fossil fuels (petroleum products) and emit carbon dioxide, hydrocarbon, sulphur oxides, and carbon monoxide as a byproduct. These gases give rise to the pollution that is hazardous to both the environment and living organisms and contributes to the production of greenhouse gases (GHG), which have a significant impact on global warming. In 2020, CO_2 emission from energy consumption in the United States was found to be 4.6 billion metric tons (Bmt) (decreased by 11% from 2019 due to the impact of COVID-19) [3]. Petroleum consumption accounted for 45% of CO_2 emissions and about 77% of petroleum CO_2 emissions occurred in the transportation sector [3]. Also, light and medium vehicles (weighing up to 26,000 pounds) contribute heavily to GHG emissions (more than 80%) as per the report provided by the United States Environmental Protection Agency (EPA) [4]. The extensive depletion of fossil fuels, issues related to global warming, and erratic rise in the price of these fossil fuels have given rise to the development of distributed energy resources [5], along with the Electric Vehicles (EVs). Such vehicles have a positive effect on the environment by reducing gas emissions and deviating toward clean and green technology as demanded by modern society [6]. As a result, more EVs, hybrid electric vehicles (HEVs), and plug-in hybrid electric vehicles (PHEVs) are being produced and used day-by-day as alternatives to conventional vehicles powered by ICEs. [7, 8, 9].

The EVs, whether battery electric vehicles (BEVs) or other kinds of EVs, are considered next-generation transportation that uses alternative energy storage systems (ESSs) to replace or in conjunction with ICE. For this transportation to gain popularity and replace conventional ICE vehicles, the ESS must maintain high capacity and power capabilities along with safe operation for more than ten years [10].

The selection of an appropriate ESS for an HEV or full electric vehicle (FEV) is influenced by several factors. Figure 1.1 provides an overview of critical considerations while choosing an ESS. The cost of the ESS has a direct impact on the overall vehicle cost, constituting around 30% of the total vehicle cost [11]. Thus, a lower cost for the selected ESS results in a more economical vehicle. The size of the chosen ESS directly influences the vehicle's design. It is essential to consider the size of the ESS, as the overall size of the HEV depends on it. Given the weight and volume constraints within the vehicle, an ESS with a smaller size and weight is the most suitable option. Another crucial criterion is the lifecycle of the ESS. Different ESS technologies have varying lifecycles, and selecting a system with a longer lifetime is advantageous for HEV/FEV applications. As the vehicle operates under high speeds and extreme conditions, it is crucial for the selected ESS to withstand these demanding operating conditions and operate safely. Power density and energy density are critical metrics determining the selection of an ESS. Higher power and energy densities make a particular ESS more suitable for EV applications. These metrics measure the ability of the system to deliver power and store energy efficiently.

It is important to note that finding an ESS that meets all of these criteria is challenging. Therefore, trade-offs are inevitable, and a specific ESS is chosen to fulfill the majority of these criteria, considering the specific requirements of the vehicle.

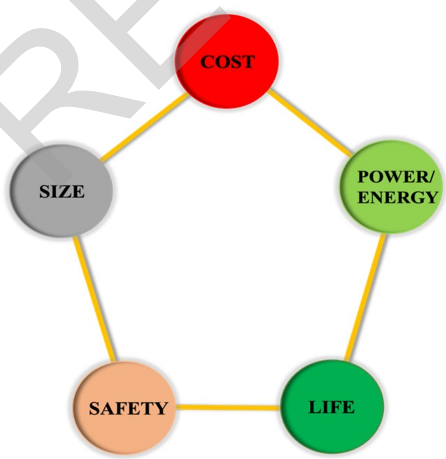

Figure 1.1: Important metrics for a ESS in HEV/FEV.

There are several ESSs available in the market. Flywheel, fuel cell, supercapacitor (SC), and battery are the most common ESS, which have their own inherent properties. Figure 1.2 compares these ESS in terms of energy density and power density, whereas Figure 1.3 compares with broad parameters based on the data provided by [12] and [13], respectively. Fuel cells exhibit higher energy density compared to other ESS; however, they are seldom used in HEVs. This is primarily due to the expensive manufacturing cost of fuel cells, which surpasses that of internal combustion engines [14]. Additionally, storing hydrogen gas at room temperature and pressure in vehicles poses challenges, as hydrogen is flammable and necessitates a continuous fuel supply. Supercapacitors excel in power density but fall short in terms of energy density for EV applications. Among the available ESS options, batteries currently dominate as the preferred choice for energy storage in EVs. This is attributed to their high energy density, compact size, and reliability [12].

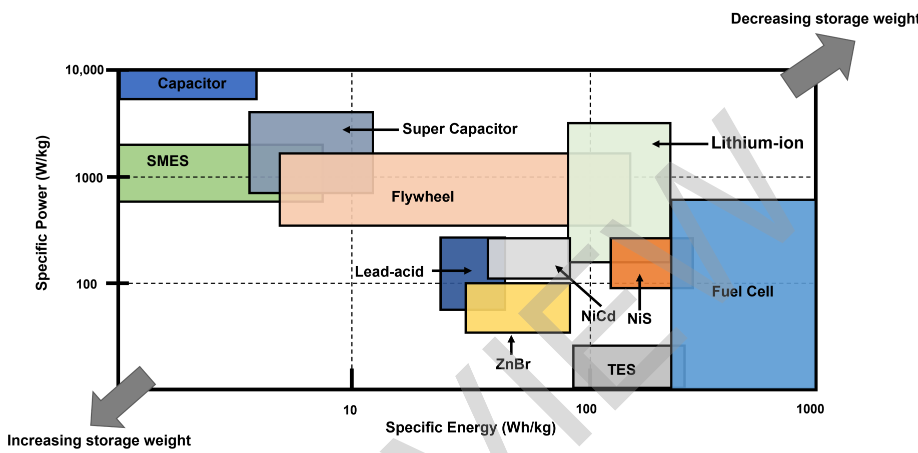

Figure 1.2: Comparison between various ESS in terms of energy density and power density [15].

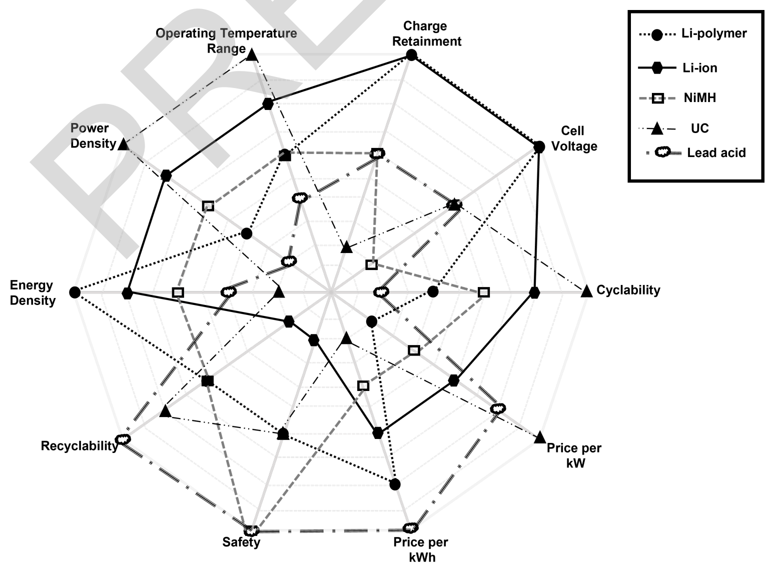

Figure 1.3: Comparison of attributes of various ESS [15].

There are different types of batteries with different specifications. Lead acid batteries have been in use since the 1900s due to their durability, affordability, inherent safety features, and tolerance to temperature variations [16]. However, overcharging of these batteries leads to water loss as hydrogen is produced at the positive electrode [17]. The use of lead as current collectors in these batteries results in low energy density and susceptibility to corrosion when exposed to a sulfuric acid electrolyte. As a result, lead-acid batteries are not commonly employed in automotive applications due to their extended charging time and heavy weight, in addition to these concerns. Nevertheless, lead-acid batteries still find wide usage in cost-sensitive applications where low energy density and limited cycle life are not significant factors. These applications prioritize ruggedness and tolerance to abuse. Examples of such applications include automotive starting systems, lighting applications, and battery-powered uninterruptible power supplies (UPS).

NiMH (Nickel-metal hydride) batteries replaced lead-acid batteries in EV applications due to their higher energy density, which is twice that of lead-acid batteries. Additionally, the components of NiMH batteries are environmentally benign and can be recycled [12]. NiMH batteries offer improved safety features compared to lead-acid batteries, as they can operate at higher voltages, have a wide operating temperature range, and are resistant to overcharging and discharging. However, one drawback of NiMH chemistry is its relatively high self-discharge rate. When overcharged, NiMH batteries utilize excess energy to split and recombine water, making them maintenance-free [17]. Nevertheless, if these batteries are charged at excessively high rates, hydrogen buildup may occur, leading to cell rupture due to the generation of excessive heat. Over-discharging can also result in reverse polarization of the cell, causing a reduction in capacity. Furthermore, NiMH batteries exhibit unsatisfactory performance at low temperatures [17].

The most promising choice among existing battery technologies applicable to EVs is lithium-ion (Li-ion) batteries, which are also now regarded as the best option for developing future-generation EVs. Li-ion batteries are emerging as the best fit for EVs as they have a higher energy density than any other battery technologies, higher power density, good high-temperature performance, and, most importantly, are lighter and smaller than other batteries, which can also be seen in Figures 1.2 and 1.3, respectively. These batteries have high energy-to-weight ratios, no memory effect, and a low self-discharge, due to which they are replacing NiMH batteries. They can operate in a wide range of state of charge (SoC) while maintaining a long cycle life [18]. Also, the operating voltage of Li-ion batteries is high (3.7V on average). The only disadvantage compared with NiMH batteries is that they require a protection circuit or battery management system (BMS) and are expensive [13, 17]. However, the cost of Li-ion battery production for a large number of HEVs is less than that of NiMH battery which is shown by Figure 1.4 [13].

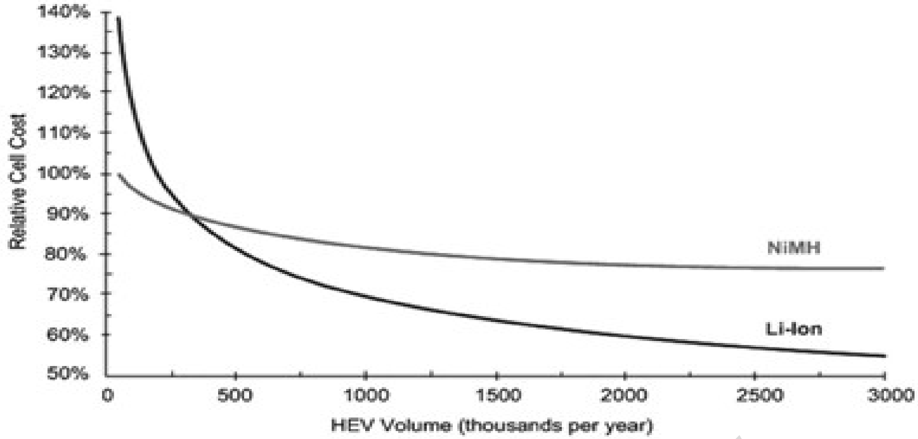

Figure 1.4: NiMH and Li-ion HEV cell cost as a function of vehicle production volume [13].

1.1 Need of HEV

HEVs are those vehicles that utilize multiple energy sources to provide propulsion power. There are various types of HEVs based on this concept, including engine and fuel cell, battery and fuel cell, engine battery and capacitor, battery and flywheel, and battery and battery hybrids [19]. HEVs, powered by alternative sources and enabled by high-efficiency electric motors and controllers, offer a clean, efficient, and environmentally friendly transportation solution. They create a clean environment and reduce operating costs compared to gas-powered vehicles. Significant advancements in power electronics technology have enhanced the reliability and efficiency of HEVs [20, 21, 22].

The most common type of HEV combines an ICE and an electric motor to propel the vehicle. Depending on the way the ICE and motor contribute to the vehicle's transmission, HEVs can be classified into different architectures, such as series hybrids, parallel hybrids, series-parallel hybrids, and complex hybrids.

The Series HEV is a straightforward hybrid vehicle design where the ICE is not directly connected to the drivetrain. Instead, the engine's output is converted into electricity through a generator. This generated electricity is then used either to charge a battery or to power an electric motor that drives the vehicle's wheels. In this configuration, three propulsion devices are employed: the engine, the motor, and the generator [20]. One of the main advantages of this design is the flexibility it offers due to the absence of a direct connection between the wheels and the ICE. This allows for easy control of power distribution to each wheel and simplifies traction control. However, a drawback of this type of HEV is the requirement for separate motor-generator sets. The combined efficiency of these sets is generally lower than that of a conventional transmission [23]. In this dissertation series HEV is used to verify the proposed strategy.

In addition to the vehicle architecture, HEVs can be categorized based on the desired level of hybridization. The cost of an HEV under these categories is influenced by the capacity of ESS utilized in the vehicle. The concept of hybridization factor (HF), as introduced in [23], allows for the classification of HEVs on a spectrum between HF=0 (representing an ICE vehicle) and HF=1 (representing an FEV). The hybridization factor (HF) can be expressed as a measure of power supplied by the ICE and motor as

$$HF = \frac{P_{EM}}{P_{EM} + P_{ICE}} \tag{1.1}$$

where, P_{EM} = Peak power of electric motor and P_{ICE}= is the peak power of ICE.

According to this hybridization factor, that determines the amount of electric power fed by an electric motor, HEV can be classified into the following categories:

- Micro Hybrid
- Mild Hybrid
- Full Hybrid

PHEVs (Plug-in Hybrid Electric Vehicles) share similarities with conventional hybrid vehicles, incorporating both an engine and an electric motor. These vehicles can recharge their batteries through regenerative braking or using the engine. However, there are key distinctions that set PHEVs apart from regular HEVs. The primary difference lies in the presence of an additional charging port on the PHEV. This port allows the battery to be charged from an external power supply, granting the vehicle the ability to be plugged in. Furthermore, PHEVs typically possess higher-capacity batteries compared to their HEV counterparts. This larger battery capacity enables PHEVs to travel significantly longer distances using the electric motor alone, providing enhanced electric-only driving capabilities.

FEVs or HEVs are considered viable solutions to reduce petroleum consumption and GHG emissions. While FEVs may be the preferred option over HEVs for this purpose, their adoption can face challenges for three primary reasons: infrastructure support, battery supply, and public assurance during the transition from ICE vehicles to FEVs. The lack of infrastructure support for FEVs poses a significant hurdle. The establishment of numerous charging stations in various locations is necessary, requiring the expansion and modernization of electrical grids to ensure a reliable power supply to these stations. Additionally, the shift to FEVs necessitates extensive supply chains for ESSs, particularly batteries. The mining and transportation of minerals for these batteries can be a logistical challenge, especially considering the dominance of China in lithium battery supply chains. Public confidence in shifting from ICE to FEVs is another important consideration. Range anxiety, stemming from concerns about the limited range of FEVs due to battery degradation, often raises apprehension among consumers. Overcoming this anxiety and assuring the public about the reliability and convenience of FEVs is crucial for their widespread adoption.

Considering these factors, the transition to FEVs will require time and effort. In the meantime, HEVs emerge as a favorable solution. Current data support this notion, as shown in Figure 1.5, illustrating the different types of EV sales in the US from 2000 to 2021. According to the US Department of Energy (DOE) [24], more than 65% of the total EVs sold in 2021 were HEVs. Presently, around 74% of registered EVs in the US are HEVs, while PHEVs and FEVs make up 9% and 17%, respectively [24]. A notable observation from Figure 1.5 is that the number of EV sales has doubled from 2020 to 2021.

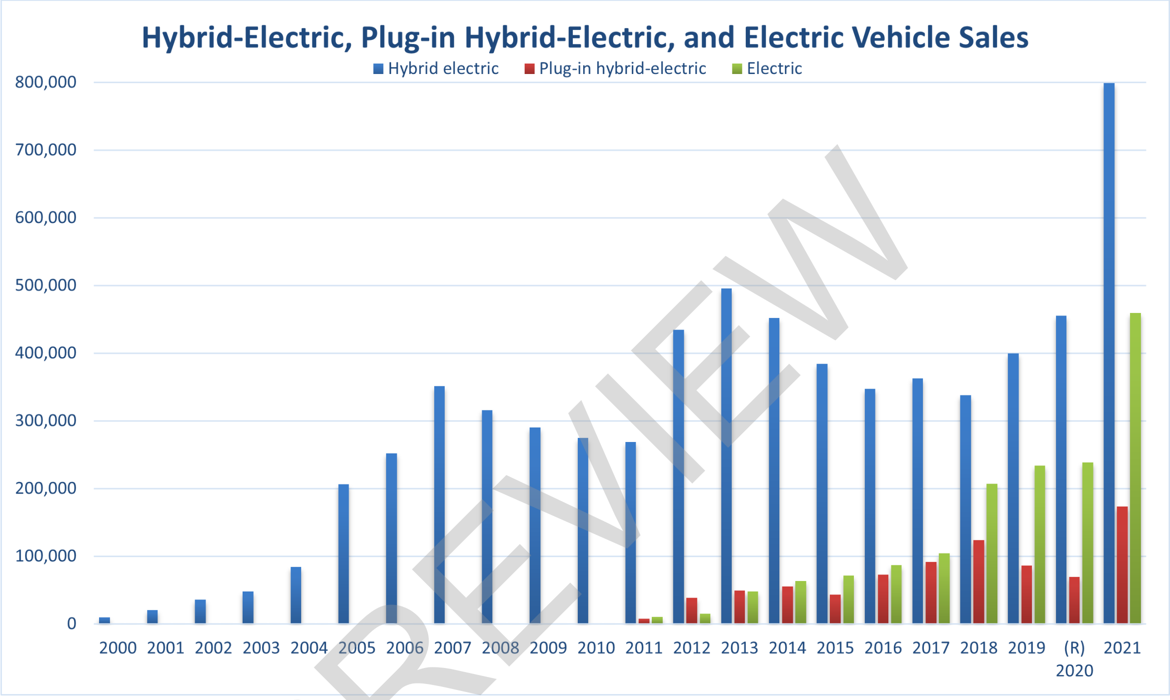

Figure 1.5: EV sales over the years [24].

1.2 Challenges in EVs/HEVs

The components used in a vehicle degrade with time due to the vehicle's operation. As a result, these components' output is compromised, which could make the vehicle's operation unreliable. One of these components is the ESS utilized in EVs and HEVs. Compared to a gasoline-powered car, the initial cost of an electrified vehicle is typically higher. Nearly 30% of the overall cost of the vehicle goes toward ESS [25]. The ESS degradation raises concerns regarding electrified vehicles' system dependability and viability. As a result, there will be a significant impact on economic goals from ESS deterioration.

The degradation of the battery results in a decrease in its capacity, and when the capacity drops