IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 30 March 2023, accepted 24 April 2023, date of publication 27 April 2023, date of current version 4 May 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3271287

TOPICAL REVIEW

Battery Degradation in Electric and Hybrid Electric Vehicles: A Survey Study

LAXMAN TIMILSINA[1], (Graduate Student Member, IEEE), PAYAM R. BADR[1], PHUONG H. HOANG[2], GOKHAN OZKAN[1,3], (Senior Member, IEEE), BEHNAZ PAPARI[1,4], (Senior Member, IEEE), AND CHRISTOPHER S. EDRINGTON[1], (Senior Member, IEEE)

[1]Real-Time COntrol and Optimization Laboratory (RT-COOL), Holcombe Department of Electrical and Computer Engineering, Clemson University, Clemson, SC 29634, USA
[2]Operation Technology Inc., Irvine, CA 92618, USA
[3]Dominion Energy Innovation Center, Clemson University, North Charleston, SC 29405, USA
[4]Department of Automotive Engineering, Clemson University, Greenville, SC 29607, USA

Corresponding author: Laxman Timilsina (ltimils@clemson.edu)

This work was supported by the Simulation-Based Reliability and Safety Program (SIMBRS) for modeling and simulation of military ground vehicle systems, under the Technical Services Contract W56HZV-17-C-0095 with the U.S. Army DEVCOM Ground Vehicle Systems Center (GVSC).

ABSTRACT The lithium-ion batteries used in electric vehicles have a shorter lifespan than other vehicle components, and the degradation mechanism inside these batteries reduces their life even more. Battery degradation is considered a significant issue in battery research and can increase the vehicle's reliability and economic concerns. This study highlights the degradation mechanisms in lithium-ion batteries. The aging mechanism inside a battery cannot be eliminated but can be minimized depending on the vehicle's 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 paper explains the detailed degradation mechanism inside the battery first. Then, the major factors responsible for the degradation and their effects on the battery during the operation of electric vehicles are discussed. Also, the different techniques used to model the degradation of a battery and predict its remaining life are explained in-depth, along with the techniques to abate the aging process. Finally, this study focuses on the research gaps, difficulties in predicting the lifetime, and reducing the degradation mechanism of a battery used in electric vehicles.

INDEX TERMS Battery degradation, battery life prediction, charging and discharging rates, degradation abatement, electric vehicle, hybrid electric vehicle, lithium-ion battery, remaining useful life.

ACRONYM

BEV	Battery Electric Vehicle.
BMS	Battery Management System.
DoD	Depth of Discharge.
EM	Energy Management.
EOL	End of Life.
ESS	Energy Storage System.
EV	Electric Vehicle.
GHG	Green House Gases.
HEV	Hybrid Electric Vehicle.
ICE	Internal Combustion Engine.
INL	Idaho National Laboratory.
LAM	Loss of Active Materials.
LFP	Lithium Iron Phosphate.
LLI	Loss of Lithium Inventory.
PHEV	Plug-in Hybrid Electric Vehicle.
RUL	Remaining Useful Life.
SC	Supercapacitor.
SEI	Solid Electrolyte Interphase.
SNL	Sandia National Laboratory.
SoC	State of Charge.
SoH	State of Health.
V2G	Vehicle-to-Grid.

The associate editor coordinating the review of this manuscript and approving it for publication was Chandan Kumar.

I. 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]. Reference [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 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 [5]. 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 [6], [7], [8].

The EVs, whether battery electric vehicles (BEV) or other kinds of EV, 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 [9]. 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 compares these ESS in terms of energy density and power density, whereas figure 2 compares with broad parameters based on the data provided by [10] and [11], respectively.

Lithium-ion (Li-ion) and Nickel-metal hydride (NiMH) batteries are lighter and have a greater energy density compared to lead-acid batteries, which can be analyzed in figures 1 and 2. However, lead-acid batteries are more affordable and react more quickly to current fluctuations than other battery types. Lead-acid batteries are used in a wide range of applicationsÂ due to their robustness, affordability, inherent safety, and temperature tolerance, as seen in Figure 2.

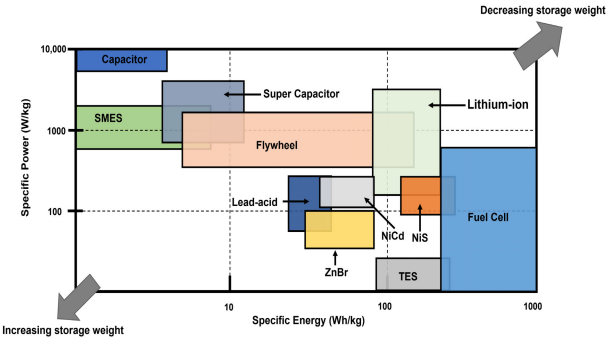


FIGURE 1. Comparison between various ESS in terms of energy density and power density.

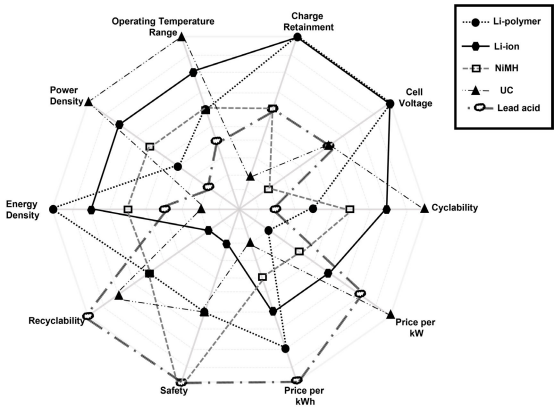


FIGURE 2. Comparison of attributes of various ESS [11].

SCs are also used in automotive applications to increase the power density of ESS as they have a higher energy density, as shown in figure 1. SCs are electrochemical capacitors that offer a better power density than conventional storage devices. With a longevity of up to 500,000 cycles, a rapid rate of charge/discharge, low internal resistance, little heat loss, and strong reversibility, SCs provide several benefits over batteries [10]. Moreover, SCs have an efficiency cycle of about 90% compared to batteries' efficiency cycle of about 80% [10]. Due to these mentioned advantages, the demand for SCs are increasing, and they can be used in parallel to achieve better performance for the ESS. SCs help to improve the vehicle's efficiency and reduce the peak current in the battery pack by supplying the load. This helps to increase the battery's lifetime, ultimately decreasing the operational cost of the EV. However, as a standalone ESS, SCs do not provide high energy density as the amount of energy stored per unit weight of SCs is only around 5-9 Wh/kg, while a Li-ion battery can store approximately 130-140 Wh/kg [10].

Fuel cells have high energy density than other ESS; instead, they are rarely used in EVs. The fuel cell manufacturing cost is expensive, which can cost more than ICE engines [12]. Also, it is challenging to store hydrogen gas at room temperature and pressure in vehicles. They are flammable and require a continuous supply of fuel. Flywheels

TABLE 1. Technical performance of battery types used in EV.

Battery Type	Lead-acid	Ni-Cd	NiMH	Li-ion
Energy density (Wh/kg)	30-50	45-80	60-120	110-160
Power density	180	150	250-1000	1800
Nominal voltage	2 V	1.25 V	1.25 V	3.2-3.7 V
Overcharge tolerance	High	Moderate	Low	Very low
Self-discharge	Low	Moderate	High	Very low
Operating temperature	-20°C to -60°C	-40°C to -60°C	-20°C to -60°C	-20°C to -60°C
Cycle-life	200-300	1500	300-500	500-1000
Charging efficiency	50-95%	70-90%	65%	80-90%
Self-discharge rate	5%.month^{-1}	20%.month^{-1}	30%.month^{-1}	3-10%.month^{-1}

can supply energy for longer and have a bigger energy storage capacity than capacitors. On the other hand, capacitors have a faster energy delivery rate and a higher efficiency potential than flywheels [11]. Compared to batteries, flywheels are more robust, do not experience depth-of-discharge problems, and have a rapid energy storage and delivery capacity. Nonetheless, flywheels often cost more than batteries, particularly in more compact applications. Also, because of their mechanical components, flywheels need extra maintenance. Similar to other energy sources, safety is a significant consideration when utilizing flywheels. To ensure safety, measures such as employing containment vessels in case of rotor failure, designing the flywheel to avoid flying apart, and monitoring the dynamic behavior of the flywheel are implemented [11]. Hence out of different ESS, currently the battery, is the most popular choice for energy storage in EVs because of its high energy density, compact size, and reliability [13].

In automotive applications, different types of batteries with different attributes have been used. Lead-acid batteries have been in use since the 1900s due to their ruggedness, low cost, inherent safety, and temperature tolerance [14]. During overcharging, lead-acid batteries lose water due to hydrogen production at the positive electrode [15]. To mitigate this problem, distilled water is added to lead-acid batteries. Current collectors in these batteries are made of lead, leading to low energy density, and the lead is prone to corrosion when exposed to a sulfuric acid electrolyte. Due to these issues and disadvantages like significant charging time and heavyweights, lead-acid batteries are now obsolete in EV applications. Lead-acid batteries are still widely used in cost-sensitive applications where low energy density and short cycle life are not a concern, ruggedness and abuse tolerance are required, such as automotive starting, lighting, and battery-powered uninterruptible power supplies (UPS).

NiMH batteries replaced lead-acid batteries in EVs as they have an energy density twice as more as that of lead-acid, as seen in figures 1 and 2. Also, the components of NiMH are harmless to the environment and could be recycled [10]. NiMH batteries are safer to operate at high voltage, have a wide operating temperature, and are more resistant to overcharge and discharge than lead-acid batteries. NiMH batteries use excess energy to split and recombine water during overcharging, making them maintenance-free. However, during high charge rates or fast charging, a large amount of heat is generated, which causes cell rupture due to the accumulation of hydrogen. If the battery is over-discharged, the cell can be reversely polarized, leading to capacity reduction. The performance of these batteries is not satisfactory at low temperatures [15]. Based on the information presented in figures 1 and 2, it can be inferred that, in addition to their energy and power density, NiMH batteries have a longer charging time, are susceptible to memory effect, and are less recyclable, which have a greater negative impact on the environment.

The most promising choice among existing battery technologies applicable to EVs is 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 be analyzed from figures 1 and 2 and as summarized by table 1 which are extracted from [16]. 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. 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) [11], [15].

The battery is a critical component of an electric vehicle, and being one of the most expensive components, it must be thoroughly vetted and operated [17], [18]. The major challenge for the auto industry is to reduce the battery cost and increase its operating life cycle [19]. To achieve the economic viability of an EV, it is required to have a long battery lifespan. The battery's lifetime depends on how it has been operated, and is a complex process to find it out [20]. Battery degradation is one of the limiting factors in battery lifetime; therefore, this mechanism must be thoroughly investigated and reduced in order to extend the battery's lifespan. To understand the degradation mechanism of a battery, a Li-ion battery is considered, which is a commonly used bat-

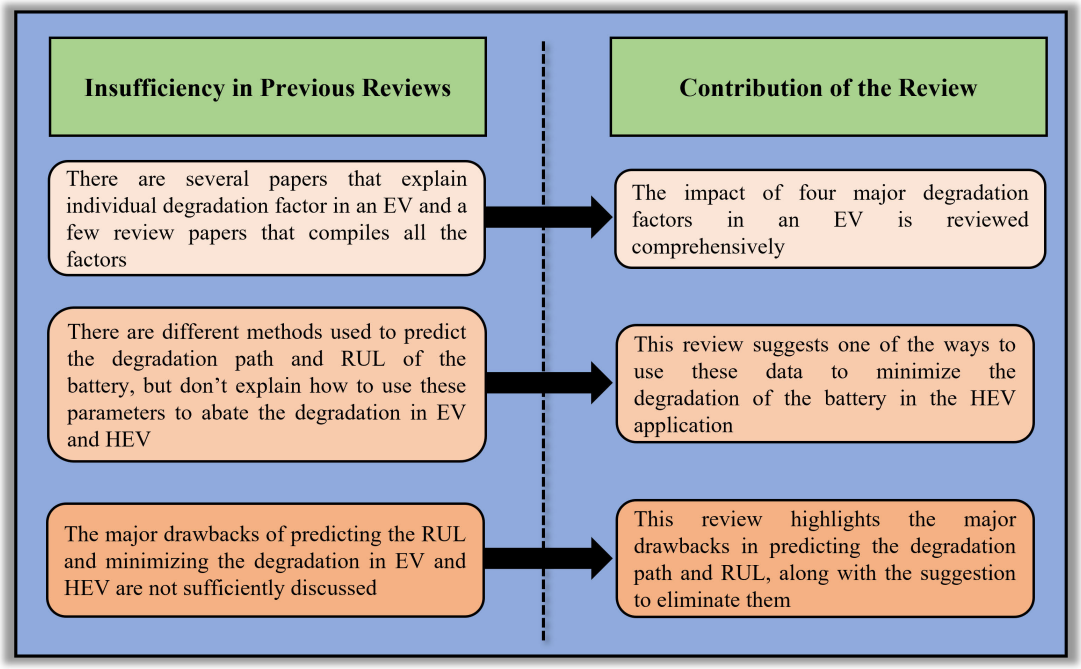


FIGURE 3. Existing drawbacks with the contributions of the paper.

tery in EV applications and has various advantages over other batteries. The Li-ion battery is a complex system to understand, and the aging mechanism is even more complicated. A single factor does not cause capacity and power fading but involves several processes and interactions. To analyze the decline in battery capacity, there should be a fundamental understanding of the operation of the battery.

A Li-ion battery is one of the advanced battery technology that uses lithium ions as a key component of its electrochemistry. Li-ion battery cell consists of a positive electrode (cathode), a negative electrode (anode), a separator, and an electrolyte. The electrolyte facilitates Li-ions to travel between the electrodes, while the separator separates the positive and negative electrodes, preventing shorting between them [21], [22], [23]. The positive electrode materials are transition metal oxides containing lithium, a type of ceramic. Li-ions must diffuse freely throughout the crystal structure in order to use these materials as a positive electrode for Li-ion batteries [24]. The primary negative electrode materials used in Li-ion batteries are graphite and hard carbon. Graphite is used extensively in these batteries because of its superior discharge profile compared to hard carbon [24]. Similarly, the separator is a thin microporous membrane made of polyolefin placed between the positive and negative electrodes to prevent contact and enable Li-ions to pass through [25]. Studies [26], [27], [28], [29], [30], [31], [32] have explained in detail the operating principle of a Li-ion battery, its components, requirements, and parameters of the components to be used, and the type of materials that have been used and researched for making different components of a Li-ion battery.

During the discharging process of a Li-ion battery, lithium atoms in the negative electrode are separated from their electrons [33]. These lithium ions travel from the negative electrode via the electrolyte to the positive electrode, where they recombine with their electrons and become electrically neutral. The tiny structure of Li-ion makes it possible to pass through a micro-permeable separator. Also, during charging, the opposite phenomenon occurs where the Li-ion moves from the positive side positive electrode to the negative side negative electrode [34]. Li-ion batteries may have a very high voltage and charge storage per unit mass and volume due to lithium's tiny size (third only to hydrogen and helium). From the initial charge, lithium ions react with the solvents of the electrolyte to form a layer known as Solid Electrolyte Interphase (SEI), whose formation plays a vital role in the degradation of the battery [11] and will be discussed in detail further.

This paper presents a review of today's knowledge on the degradation of Li-ion batteries. To provide a strong foundation for subsequent research, this paper tries to identify distinct elements that cause battery aging in EV applications as far as they are known from the literature. The remainder of this paper is organized as follows. Section II describes the implementation of the review methodology. Section III explains in detail different aging mechanisms inside a Li-ion battery, along with their causes and effects. Then the factors that give rise to these aging mechanisms in EVs are reviewed in Section IV. Section V explains different techniques used to model the degradation and predict the remaining useful life (RUL) of a battery. It also elaborates on how these pieces of

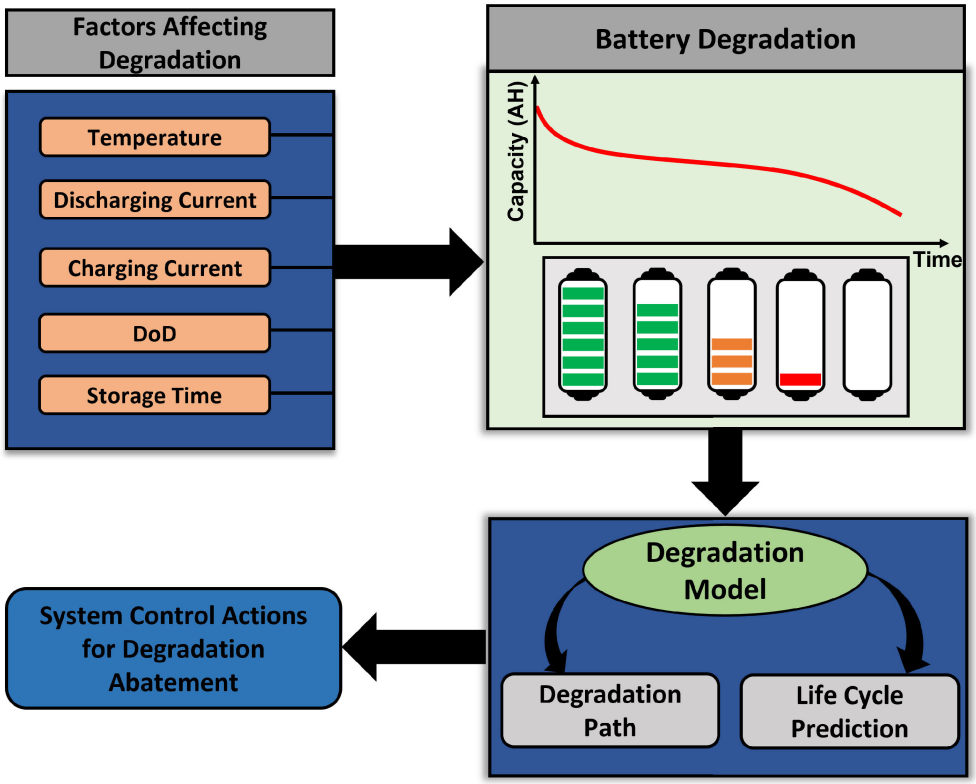


FIGURE 4. Overall orientation of paper in graphical form.

information can be used to abate battery degradation. Finally, Section VII concludes this paper with current research gaps and some recommendations. The figures used in this paper are replotted from several studies to have a clearer view, which is cited in the text along with the descriptions.

II. REVIEW METHODOLOGY

EVs and HEVs have gained significant attention in recent years due to their potential to reduce dependence on fossil fuels and improve air quality. However, one of the major concerns with these vehicles is the degradation of their batteries, which can significantly impact their performance and (RUL). This review aims to analyze the state-of-the-art studies on battery degradation in EV and HEV applications, with the goal of assisting in battery degradation modeling, prediction of RUL, and abatement of degradation.

The review process was conducted using articles published in reputable journals such as IEEE, Nature, Elsevier, Springer, and several conference publications. A total of 225 articles were selected based on their content, impact factor, citation count, and review process. The articles were analyzed to identify the factors that influence battery degradation and how these factors can be utilized to anticipate the degradation path and RULof the battery.

The review found several factors influence battery degradation, including temperature, current, and SoC. These factors can be utilized to anticipate the degradation path and RULof the battery. However, there hasn't been a lot of research on the abatement of degradation for EV and HEV applications and an approach to minimizing degradation with the above-mentioned parameters. This review provides a comprehensive analysis of the current state of knowledge on battery degradation in EV and HEV applications. It highlights the factors that influence battery degradation and how they can be utilized to anticipate the degradation path and RULof the battery. Additionally, it suggests an approach to minimizing degradation with the above-calculated parameters. The overall contribution of this paper is highlighted in figure 3, and the presentation of contents in this review paper is shown in figure 4.

III. BATTERY DEGRADATION

The battery's lifetime is the length of time it will take to meet the demands of a particular application. In EV applications, the battery's lifecycle is short compared to other components and is considered reliable until it reaches 80% of its initial capacity [35], [36]. A long battery life is necessary for an EV to be economically viable since the battery costs 30% of the price of an EV [37], [38]. The lifetime of a battery depends on its operation and how fast it degrades, which is a complex mechanism [20]. Battery degradation is one of the limiting factors in battery lifetime; therefore, this mechanism must be thoroughly investigated and reduced in order to extend the battery's lifetime. Two prominent metrics used to assess

the level of battery degradation are capacity fade and power fade. The use of EVs and HEVs for intense cycling results in the degradation of lithium-ion batteries, leading to a gradual decline in their capacity to store energy and deliver power. This is commonly known as capacity fade, and power fade.

- Capacity fade refers to the reduction in the energy storage capacity of a cell caused by its degradation. A capacity fade emerges as a gradual decline in the amount of battery capacity that can be discharged throughout a battery's lifespan. It is crucial because it depicts the decline in an electric vehicle's usable range.
- Power fade is defined as the decrease in cell power resulting from an increase in cell resistance due to the effects of aging. It is the gradual reduction in a battery's power capacity caused by a steady increase in the battery's cell impedance over time. Power fade is essential for applications in automobiles since it determines how much power the battery can deliver without lowering vehicle speed or activating an engine or power extender.

During cycling, side reactions occur in the battery system, and an amount of recyclable active particles irreversibly precipitates in the form of an insoluble SEI file. In addition, the degradation of electrolytes and contact loss between the electrode and the current collector also contribute to the increase of cell resistance. Finally, aged batteries display a reduction in the ability to store energy and deliver power; performance metrics correlate with a loss in capacity and an increase in internal resistance. During battery cycling, side reactions take place in the system, precipitating a certain amount of recyclable active particles as an insoluble SEI, which cannot be recovered. Moreover, the degradation of the electrolyte and the loss of contact between the electrode and the current collector further contribute to an increase in cell resistance. Ultimately, batteries that have undergone aging exhibit a decline in their capacity to store energy and deliver power, with performance metrics correlated with a decrease in capacity and an increase in internal resistance. To understand the degradation mechanism of a battery, a Li-ion battery is examined since it is a commonly used battery in EVs and has various advantages over the other batteries, as discussed in Section I. Once the battery has been manufactured, it will start to degrade, and different phases of this mechanism are shown in figure 5 [39].

The Li-ion battery is a complex system to understand, and the aging mechanism is even more complicated. A single factor does not cause capacity and power to fade away but involves several processes and interactions [41], [42]. Battery degradation is determined by different mechanisms and processes depending on the components and chemistry within them. Due to the complex, nonlinear, and path-dependent nature of battery degradation, the aging mechanisms are challenging to analyze and mitigate [43], [44]. According to study [42], the aging trajectories of lithium-ion batteries are categorized as linear, sublinear, or superlinear, which are displayed as capacity vs. cycle number or something

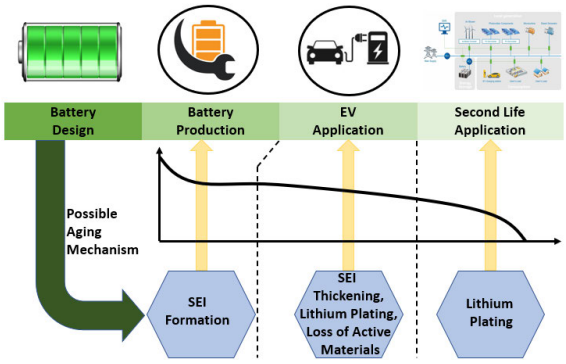


FIGURE 5. Different phases of battery degradation during its lifetime.

comparable. Battery aging trajectories are frequently linear or sublinear [45], [46]. Sublinear degradation is commonly considered to be due to side reactions like SEI growth, which grows nearly with the square root of time or cycle number due to its self-passivating nature. While this degradation is mainly unavoidable, the decelerating degradation rate is a fortunate property for long-lifetime applications. However, the degradation of superlinear batteries is also frequently noticed. They go by several names in different battery literature as knee [47], rollover failure [45], nonlinear aging [48], sudden death [49], saturation [50], second-stage degradation, or two-phase degradation [51], capacity plunge [52], or drop-off [53]. In addition, knees present difficulties for precise onboard state-of-health estimation because batteries with identical states of health could have different remaining useful lives. Avoiding or delaying knees is essential to ensuring long battery lifetimes.

Figure 6 shows the different degradation mechanisms in a Li-ion battery cell, where the information provided by [40] and [54] were used to draw this figure. General deterioration is influenced by the side reactions, structural changes, and altering chemical compositions. Loss of lithium inventory (LLI) [41], loss of active materials (LAM) [41], and loss of electrolyte [53], [55] are the three primary degradation modes identified in the battery aging mechanism [56]. Side reactions at the electrode/electrolyte interfaces, which permanently consume cyclable lithium and produce resistive layers of lithium oxides in the cell, are the primary cause of degradation [54]. The capacity of the cell is reduced (capacity fade) because these Li-ions are no longer cyclable for the intercalation process. Another prominent reason for degradation is the LAM due to electrode delamination, metal dissolution, particle isolation, structural disorder, and film formation [40]. Graphite exfoliation, electrode particle cracking, and dead lithium obstructing the active site pathway reduce the active mass on the negative electrode [57]. Similarly, transition metal dissolution, structural disordering, and electrode particle cracking reduce the active mass of the positive electrode [40], [58], [59], [60]. Electrolyte loss is another key source of deterioration; accumulated lithium on

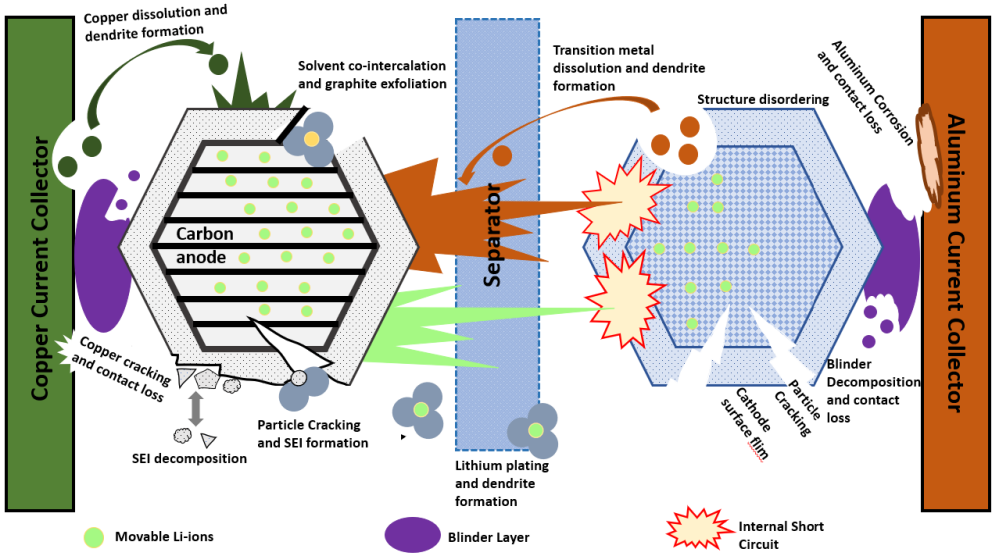


FIGURE 6. Degradation mechanism in Li-ion battery cells [40].

the negative electrode surface interacts with the electrolyte and consumes it [53], [61]. At the end of the battery's life, the reduction of the electrolyte content results in capacity and power fading. The increase in resistance caused by passive film development of the lithium oxides and electrical disconnects between the electrode subcomponents are additional sources of degradation. The most detrimental aging mechanisms impacting graphite anode electrodes are SEI film growth, binder decomposition, and irreversible plating [62]. All these degradation mechanisms can be broadly divided into the following categories:

A. LOSS OF FREE LITHIUM IONS

Lithium ions move from the negative electrode to the positive electrode during discharging and from the positive electrode to the negative electrode during charging in the presence of an electrolyte. While moving from negative electrode to positive electrode and vice-versa, the free Li-ions are consumed by parasitic reactions like SEI formation, decomposition reactions, and lithium plating. Due to these reactions, free Li-ions are no longer available for cycling between the positive and negative electrode, resulting in capacity fade and power fade [54]. Two major issues that consume Li-ions during the aging mechanism are described as follows.

1) SOLID ELECTROLYTE INTERPHASE

SEI is usually a protective layer formed on the surface of a negative electrode with unique properties that are permeable for lithium cations but impermeable for other electrolyte components and electrons. Typically, SEI layer protects the electrolyte component from further reduction and the charged electrode from corrosion [55]. Li-ions and other small species can pass through the resultant SEI layer, while bigger species cannot interact with the negative electrode. However, by restricting Li-ion transport and resisting volume changes within the graphitic layers of the negative electrode, the SEI layer can slow down intercalation kinetics at the electrode/electrolyte interface. The SEI layer may break as a result of such a volume change, further exposing the active material in the graphite to reduction processes. The restricted transportation of lithium ions will increase charge-transfer resistance within the battery cell. Also, the consumption of electrolytic compounds decreases charge-transfer capabilities and increases cell impedance.

During the operation of the battery, this SEI layer affects the battery performance in terms of reversible capacity, Coulombic efficiency, and cycling stability [63]. When Li-ions move from negative electrode to positive electrode and vice-versa, they react with the electrolyte to form an additional layer of SEI at the negative electrode making the SEI layer unstable and increasing its thickness [64]. This layer grows with time or the number of charging and discharging cycles. When there is chronic charging and discharging of a battery, there is frequent movement of free lithium ions which eventually increases the size of the SEI layer. Due to this, a large number of lithium ions get trapped in this layer and ultimately decrease the battery's capacity [65]. As the thickness of this layer increases, the battery's internal resistance also increases. This SEI layer's growth rate is higher at the early age of the battery and decreases as this layer becomes stable, which can be seen in figure 7 from [66]. During the initial 400 cycles, the SEI experiences significant growth. However, after this point and until the battery reaches 80% of its capacity (i.e., EOL), the SEI growth is at a constant rate. When the battery reaches its end of life (EOL), again, the growth of this layer increases rapidly [66], which is not shown in the figure. The SEI formation is believed to be the significant factor affecting the battery cycle life as it consumes

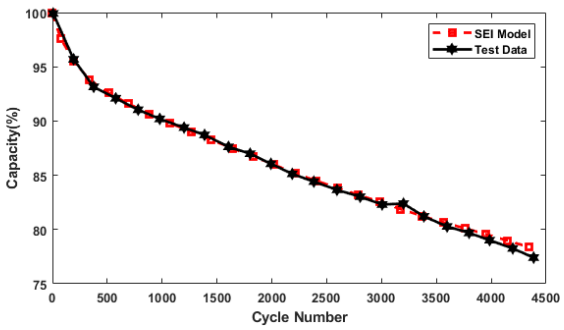


FIGURE 7. Fitting of SEI model from the degradation curve [66].

the free movable lithium ions and provides resistance to the movement of these ions [53], [67].

High operating temperatures that drive the kinetics of the exothermic parasitic process might increase SEI formation. Furthermore, elevated temperature can change the SEI into lithium salts that are less permeable to lithium ions. On the other hand, a low-temperature operation can reduce the excess lithium ions present at the interface due to slower ion transit, limiting SEI development. Operating the battery at low SoC (i.e., $< 20\%$) or at high SoC (i.e., $>80\%$) can further promote SEI growth because of the increased potential gradient between the active material and the electrolyte. Also, the high charging current can accelerate the growth of the SEI layer due to the high amount of electrons and Li-ions present at the interface.

Study [66] developed a model for the formation of SEI film inside a battery cell and is given by (1). Here, L is the battery life, α_{sei} is the portion of charge capacity irreversibly consumed, $f_{d,1}$ is the life lost in one unit of time. The detailed calculation of all these parameters is provided in [66].

$$L = 1 - \alpha_{sei} e^{-N\beta_{sei} f_{d,1}} - (1 - \alpha_{sei}) e^{-N f_{d,1}} \tag{1}$$

2) LITHIUM PLATING

Lithium plating is a well-known and innately destructive aging mechanism in Li-ion batteries. It is the deposition of metallic lithium on the graphite negative electrode surface [68]. Lithium plating is considered severe because it not only promotes degradation but also negatively impacts the battery's safety [69]. From a safety perspective, lithium plating in Li-ion batteries can be dangerous as it may result in thermal runaway. This can cause the battery to overheat, catch fire, or even explode. During lithium plating, the electrolyte in the battery is reduced and deposited onto the negative electrode's surface, creating a coating of metallic lithium. Due to this, the battery may experience a short circuit that might result in a thermal runaway. This can cause the battery to heat up rapidly and produce gases that could cause the battery to rupture or explode [69], [70].

Low operating temperatures, high SoC, high charge currents/ fast charging, and high cell voltage are some of the fundamental causes that give rise to lithium plating [54]. While operating the battery at low temperatures, the SEI layer's ability to diffuse lithium is reduced, which enhances the concentration of lithium ions at the electrode/electrolyte interface. Usually, during fast charging, the Li-ions can deposit on the surface of the negative electrode instead of being intercalated between the graphite's atomic layers [71]. These deposited Li-ions can be reversible or irreversible. The irreversible portion of Li-ions reacts with electrolytes to form a secondary layer of SEI that increases the thickness of this layer and increases the internal resistance of the battery cell [70]. Since the free Li-ions are captured to form the SEI layer, it also decreases the energy density of the battery cell. The irreversible portion accelerates the capacity fade, and in the severe case, the accumulated Li-ions might form a dendrite [72]. The formation of lithium dendrites during the lithium plating can cause the tearing of the separator, subsequent short circuits, and instant battery failure. On the other hand, the reversible portion can cause lithium stripping, which is the process where the deposited Li-ions with an electrical contact on the negative electrode interface experience a charge transfer reaction into the electrolyte and then re-intercalate into the negative electrode [42]. This process occurs throughout the discharge or rest period [73], [74]. Lithium plating is also likely to occur when the capacity of the two electrodes is unbalanced or when the positive electrode is physically bigger than the negatively charged electrode [75]. When the electrodes are unbalanced, it promotes lithium plating by polarizing the negative electrode to low potentials. Lithium deposits build up on the negative electrode's edges when the positive electrodes are bigger [42].

The harsh operating conditions, such as high C-rates, charging at a high SoC, and charging at low temperatures, give rise to lithium plating [76], [77], [78]. Due to these harsh conditions, charge transfer kinetics in the electrolyte and solid-state diffusion is delayed, leading the negative electrode potential to fall below the potential of lithium metal, allowing lithium plating to occur. At low temperatures, the power and energy densities of Li-ion batteries are lowered, especially during the charging process, due to three key factors: 1. low ionic conductivity in the electrolyte; 2. poor lithium-ion solid diffusivity in the electrode; 3. slow charge transfer rate [79], [80]. Similarly, a high SoC is a condition where the current continues to flow to the battery even though the battery is already full [81]. At such conditions, it is easier for Li-ion to concentrate on the negative electrode surface and exceeds the maximum allowable limit reaching a saturation level. While doing so, dendrite structures are seen in the cells that penetrate the porous separator, resulting in micro-internal short-circuit [82]. The results from [83] show how to avoid lithium plating, which can be achieved by using the battery at increased temperature, low currents, and SoC.

B. LOSS OF ACTIVE MATERIALS

When the battery is used for multiple cycles, there will be a point where there is no active mass of negative electrode and

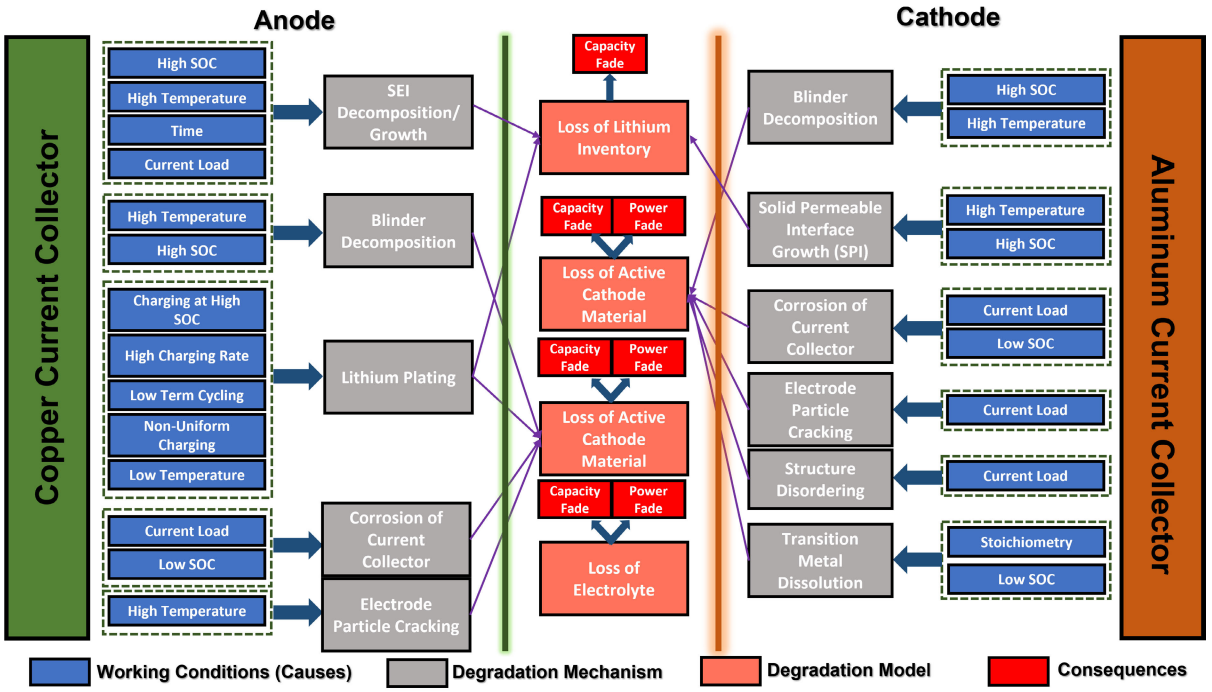


FIGURE 8. Cause and effect of degradation mechanisms and associated degradation modes [40].

positive electrode for the insertion of lithium due to particle cracking, blocking of active sites by resistive surface layers, and structure disordering. These are the phenomenon that causes capacity and power to fade [54]. Depending on the level of lithiation and the afflicted electrode, LAM can be categorized into four groups [41].

- First, the origin of LAM can be the separation of the active material grains from the electrode's ionic or electronic conduction network [84]
- The second is the transition metal's dissolution into the electrolyte solution [85]
- The third is a change in the composition of the electrode [86], and
- The fourth is a modification to the crystal structure of the active material that decreases the degree of lithiation [87].

The LAM is primarily responsible for the degradation of positive electrodes. The structural disordering of the oxide, the dissolving of the metallic ions, and surface modifications such as fracture are examples of the physical degradation of the active materials. High voltages and temperatures increase the electrolyte's disintegration of the oxide particles, raising the impedance. The dissolved species can either move through the electrolyte to interact with the negative electrode SEI, or they can precipitate into new phases on the positive electrode. In either case, the LAM is responsible for lowering the capacity of the positive electrode, which ultimately reduces the cell's capacity. Also, the insertion and extraction of Li-ions put stress and strain on the active material, which leads to micro-cracking. However, due to the bulk amount of active materials, only a minor aging mechanism is expected to occur. The volume change of graphite during Li-ion penetration and removal is not considered significant (typically in the range of 10% or less), and only a minor negative impact on the material's reversibility is expected as a consequence [88]. The structural changes can cause mechanical stress on C-C bonds resulting in cracking or some other structural damage which will have a minor impact on cell aging. But due to solvent co-intercalation, electrolyte reduction inside graphite, and/or gas evolution inside graphite, graphite exfoliation, and graphite particle cracking would most likely result in fast electrode deterioration [88].

Figure 8 shows different working conditions of a Li-ion battery and the degradation mechanism associated with that operating condition along with its effect in a graphical form which is a summary of details provided in studies [40] and [54].

IV. FACTORS AFFECTING BATTERY DEGRADATION

The degradation of a Li-ion battery can be characterized by a decrease in capacity over repeated charge and discharge cycles. Capacity is the amount of electrical charge the battery can store when fully charged. For batteries, 80% of the initial capacity is referred to as the point after which it tends to exhibit an exponential decay of capacity and is considered an unreliable power source after this point for EVapplication [89]. One issue that always comes with battery is self-discharging. Self-discharging means the battery

experiences a loss of energy even when it is in an inactive state. It is due to the chemical reactions inside the battery, even though there is no connection between the electrodes. Because of self-discharging, batteries initially have less than a full charge in their first cycle. Generally, the self-discharge for lithium batteries is minimal compared with other types of batteries, about 5% in the first 24 hours and around 1%-2% per month [90].

Besides this self-discharge, a battery's capacity is decreased due to the successive and complex set of dynamic chemical and physical processes that slowly reduce the number of mobile lithium ions and other factors discussed in section III. High current rates, high discharge conditions, and extreme operating temperatures are the most common factors which puts a lot of stress on the battery of EVs [89]. In order to minimize the degradation mechanism and ensure the long-term lifecycle of a battery, the degradation behavior must be thoroughly analyzed.

Once the battery is in use, the degradation process begins, and there are two types of aging mechanisms: calendar aging and cycling aging. Calendar aging occurs when the battery is in rest condition; there are no continuous charging and discharging cycles. Cycling aging occurs when the battery is used and depends on the frequency of charging and discharging cycles. Calendar aging begins shortly after the batteries are made and progresses over time, whereas cycling aging occurs when the battery is employed and depends on its operating conditions.

In modern Li-ion batteries, the main issue in calendar aging is the formation of the SEI layer on the negative electrode [91], [92], [93], [94]. SEI formation is accelerated at high levels of temperature and SoC that gives rise to the impedance of the battery resulting in lower activation energy [95], [96], [97], [98], [99]. The capacity loss of the battery when stored at a different level of SoC can be calculated using a semi-empirical equation (2) proposed by [100] and [101] with the value of the parameter provided by the study [102].

$$Q_{loss} = \alpha_1.exp(\beta_1.T^{-1}).\alpha_2.exp(\beta_2.SoC).t^{0.5} \quad (2)$$

In this model, t is the storage time in days, T is the storage temperature, and $\alpha_1, \beta_1, \alpha_2$, and β_2 are the fitting parameters. Using this model, the capacity fade of the battery when stored for a long period of time at different storage SoC can be calculated and is shown in figure 9 [101]. The capacity fade is calculated by varying the SoC from 20% to 100% at a constant temperature of $25°C$. For an equal temperature of $25°C$, the capacity loss is not the same at different SoC. The amount of ions on the electrode is given by SoC. A high SoC implies large potential disequilibrium at the electrode/electrolyte interface, which stimulates chemical reactions. Clearly, it can be concluded from the figure that the capacity loss of the battery goes on increasing as the storage SoC of the battery is increased, which is also verified in [103] and [104].

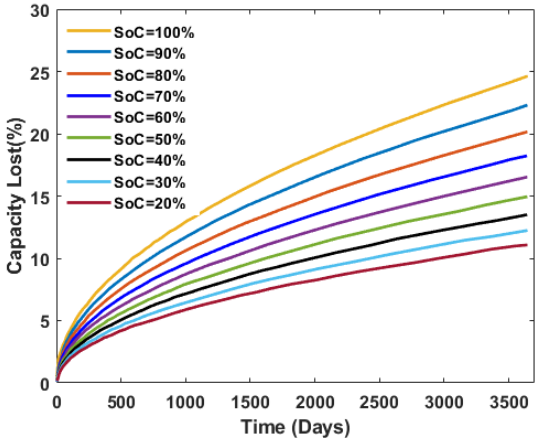


FIGURE 9. Effect of SoC on calendar aging [101].

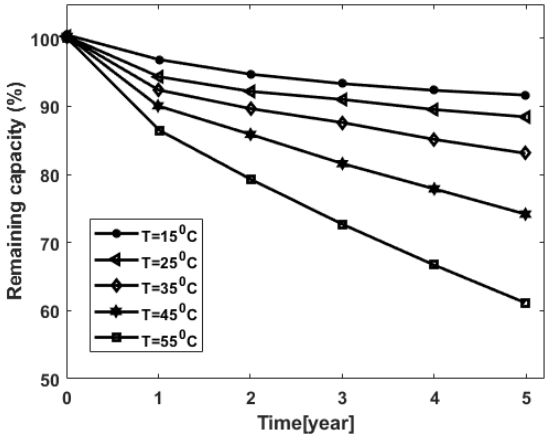


FIGURE 10. Effect of temperature on calendar aging [66].

Similarly, the effect of temperature on the calendar aging of a battery is investigated in [66], and its result is shown in figure 10. The battery is stored at five different temperatures from $15°C$ to $55°C$, keeping the SoC at 50%. Looking at the figure, it can be inferred that as the temperature increases, the capacity loss of the battery also increases. Study [105] has derived a mathematical model represented by (3) to find the capacity loss of a battery cell due to temperature, SoC, and time individually during calendar aging. $k_{temp,Q_{loss}}$ denotes the influence of temperature, σ denotes the influence of SoC, and t denotes the influence of time.

$$Q_{loss}(T, \sigma, t)[\%] = k_{temp,Q_{loss}}.(\sigma).\sqrt{t} \quad (3)$$

The temperature influence factor $k_{temp,Q_{loss}}$ can be modeled using Arrhenius equation as given by (4). Arrhenius equation is generally used to model the dependency of temperature on the aging of battery as done in studies [106], and [107]. The value of $k_{ref,Q_{loss}}$ can be calculated by dividing the measured value of Q_{loss} at the end of the aging study from the test point

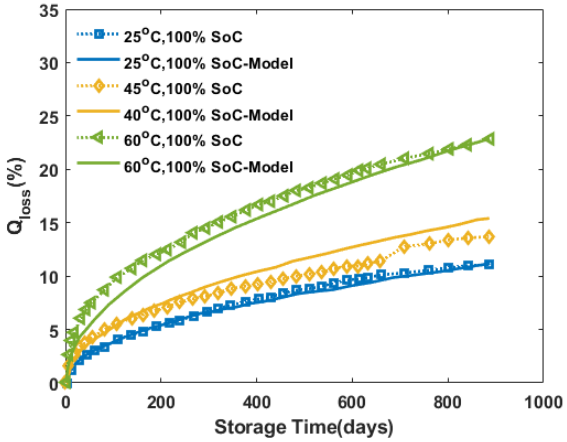


FIGURE 11. Impact of temperature on calendar aging based on experimental data and developed model [105].

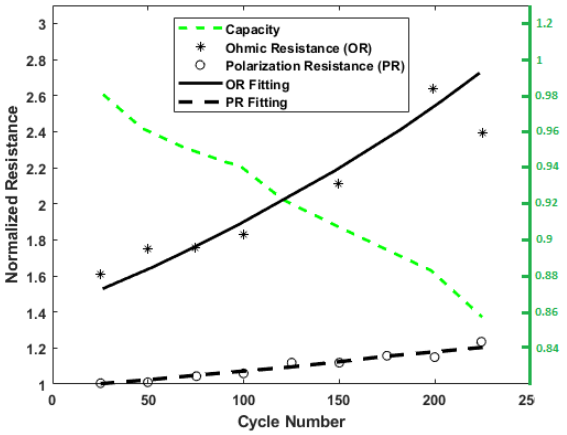


FIGURE 12. Change in parameters of battery with cycle count [112].

with $T = 25°C$ and SoC= 100%.

$$k_{temp,Q_{loss}} = k_{ref,Q_{loss}}.exp\left(-\frac{E_{a,Q_{loss}}}{R}\left(\frac{1}{T}-\frac{1}{T_{ref}}\right)\right) \quad (4)$$

The impact of temperature on the capacity loss based on the experimental data and developed mathematical model is shown in figure 11. This figure is plotted based on the experimental data and (3) and (4) provided in [105]. The analysis from this study and figure 11 concludes that the storage of batteries at high temperatures results in higher capacity loss. Also, the result of one year study of a 2.3 Ah graphite/lithium-iron phosphate (LFP) cell under storage conditions at $25°C$ and $45°C$ was presented in [108]. The result found that the aging was sensitive to temperature, and the battery cell operated at $45°C$ had capacity loss up to four times more than the battery cell operated at $25°C$. This capacity fade was dominated by the loss of cyclable Li-ions along with a minor loss of graphite active material.

Several studies have been conducted on Li-ion batteries at various operating temperatures, charging and discharging current rates, and DoD or SoC to determine their impact on battery aging. All these factors have a different impact on the battery that accelerate the aging mechanism. Knowing these factors and how they affect battery capacity is vital for minimizing battery capacity loss. One common parameter associated with all these factors that has a severe impact on battery degradation is internal resistance [109], [110], [111]. The change in internal resistance with the change of aforementioned parameters is examined in detail in [112]. The resistance in a Li-ion battery can be divided into two categories, ohmic resistance (OR) and polarization resistance (PR) [112], [113]. The first one includes electrolyte materials resistance, electrolyte resistance, separator resistance, and contact resistance, whereas the second is the resistance caused by polarization in the electrochemical reaction [114]. The change in these resistances with the increase in cycle number, along with the capacity fade, is shown in figure 12 [112]. It can be analyzed from this figure that with the increase in cycle number, both the resistances (OR and PR) of the battery increases, whereas the battery's capacity starts to decline. There are several factors that stimulate battery degradation, which is already summarized in figure 8, where different causes of degradation are shown along with their effects on the battery. It is a demanding task to predict the remaining lifetime of a battery due to the complex nature of the degradation process. However, to ensure reliable operation and timely maintenance, it is essential to determine the remaining lifetime of a battery.

The most common factors that affect the battery capacity and give rise to degradation are [164]:

- [1] Temperature
- [2] Discharging current
- [3] Charging current
- [4] Depth of Discharge (DoD)

These parameters have impacts depending on the mode of operation of the battery. If the battery is stored for some time, then the temperature and SoC of the battery have a great impact on the degradation of the battery. When the battery is in operation, all these factors have different effects on the battery and result in degradation. The battery in EVs is subjected to various stresses due to high current rates, deep discharge conditions, and operating temperatures. Table 2 provides a summary of the impact of these factors on the degradation of the battery, along with the corresponding references that were used to investigate their effects. The subsequent subsections delve into a detailed discussion of these factors.

A. TEMPERATURE

Temperature is a crucial factor that significantly impacts the health, performance, cycle lifetime, and safe operation of Li-ion batteries [165]. As the temperature in the battery changes, the chemical reaction inside the battery changes. One of the positive impacts of higher temperature on the battery is that it increases the performance and storage capacity of the battery [165]. This is because the electrolyte conduc-

TABLE 2. Factors Affecting Battery Degradation (with references).

Factors	Affects	Causes	Reference
High Temperature	Anode	Mechanical instability due to decomposition of blinder Growth in SEI layer and decrease in accessible surface area due to SEI growth Electrolyte decomposition resulting in loss of cyclable lithium and further SEI growth Parasitic side reactions exposing fresh graphite to electrolyte and increased SEI growth Phase change in active material due to metal dissolution	[55], [66], [89]–[101], [104]–[117]
	Cathode	Increase in phase changes in active material Blinder decomposition Increase in phase changes in active material Loss of cyclable lithium and gas evolution due to oxidation of electrolyte	[66], [67], [89]–[101], [104]–[114], [117]–[119]
Low Temperature	Anode	Lithium plating during charging at high SoC	[55], [79], [80], [120], [121]
High Current Rates	Anode	Metallic lithium plating and subsequent electrolyte decomposition by metallic lithium SEI growth at locations where Li metal is exposed to electrolyte Contact LAM particles and particle cracking due to volume changes Expose of fresh graphite to the electrolyte and further SEI growth	[8], [55], [89], [90], [117], [122]–[150]
	Cathode	Transition metal dissolution Active material crumbling Volume changes and tensile compressive stresses causing particle cracking	[8], [55], [90], [117], [122]–[126], [135]–[139], [141], [143]–[150]
High DoD	Both Anode and Cathode	Particle cracking due to mechanical stress caused by volume changes Contact LAM particles due to volume change during cycling	[55], [89], [112], [117], [151]–[159]
High SoC	Both Anode and Cathode	Blinder formation Electrolyte decomposition	[117], [160]
	Anode	Lithium plating at high charging rates	[55], [161]
	Cathode	Current collector corrosion	[117], [160]
Low SoC	Both Anode and Cathode	Blinder formation Electrolyte decomposition	[117], [160]
	Anode	Current collector corrosion	[162], [163]
	Cathode	Transition metal dissolution	[160]

tivity increases, and the electrode wetting characteristics are improved at higher temperatures [166]. When the temperature was raised from 25°C to 45°C in [165], the maximum storage capacity rose by 20%. However, this increase in capacity comes at a cost, reducing the battery's longevity. Similarly, the operation of the battery under low temperatures is not favorable as it leads to faster aging of the battery [167].

The effect of temperature on different components of the battery is the reason behind the degradation. The study of the impact of high temperatures on lithium batteries from [168] concludes that a blinder layer is formed on the positive electrode's surface, resulting in poor Li-ion intercalation. Also, the change in the composition of the SEI layer depends on the operating temperature, which is different at different operating temperatures [169]. The X-RAY analysis in this study showed that the capacity loss is mainly related to the SEI film growth on the negative electrode. The elevated temperature escalates the formation of the SEI layer on the negative electrode [170]. The formation of the SEI layer was the main contributor to the increase in the cell's internal resistance [171]. This decreases the performance of the battery by reducing its efficiency. Similarly, Lithium plating and subsequent interaction with the electrolyte, resulting in the loss of cyclable lithium, is the most common aging mechanism at low temperatures [121].

A 2.2Ah, 26650 $LiFePO_4$ cell with a carbon negative electrode was tested under the different operating conditions like temperature, DoD, and discharging current rates in [154]. To increase the accuracy of the experiment, two cells were tested at each of the conditions, which include six different temperatures: -30°C, 0°C, 15°C, 25°C,45°C, and 60°C, five levels of DoD: 90%, 80%, 50%, 20%, and 10% and four discharge current rates: C/2, C, 6C, and 10C. The cut-off voltage taken for the test cycle was 3.6V and 2V. The battery cell's end of life (EOL) is defined as a failure to deliver the required capacity before reaching a cell voltage of 2.0V [154]. Figure 13 extracts a portion of the experimental result of the lifecycle count of battery cells in a matrix table. The effect of temperature and DoD on the lifecycle of a battery cell can be analyzed from this matrix table. Due to the insufficient and

	Temperature (°C)												
DoD(%)	-30		0		15		25		45		60		C-Rate
90	1	1	2242	2240	2144	2130			1796	1661	754	518	
80	1	1	2520	2520	2390		2439	563	2120	2123	1011	1006	
50	13	15	3976	3965	3827	3804			3387	3317	3355	3963	C/2
20	2662	4979	9625	9652	9234		4711	2211	8374	8379	9801	9821	
10	9678	12082	18579	18534	18067	17940			16235	16571	19098	19385	

FIGURE 13. Test matrix for cycle life study.

missing data on discharging current rates in this experiment, the impact of discharge current on the lifecycle of the battery cell cannot be evaluated as proposed by the paper. The number in each cell of the figure denotes the number of cycles completed by the cell. The red highlighted box indicates that the battery has reached its EOL, the green box indicates that the battery cells are still being tested, and the grey box is empty, stating that the data at those conditions were not obtained. The effect of different parameters (temperature, DoD, and discharge rates), shown at the boundaries of the table, on the battery can be analyzed from these data.

To see the impact of temperature on the cycle count of the battery, any row in figure 13 can be analyzed. For the first row, the DoD of the battery is 90% (which means the SoC of the battery is reduced by 90%, can be from 100% to 10% or from 90% to 0%), discharged at a constant rate of C/2. The cycle count of the battery cell is 1 at -30°C, which is the lowest and increases as the temperature rises. The cycle count is 2240 at 0°C and stays in this range till 25°C. When the temperature is raised over 25°C, the cycle count starts to decrease. At 60°C, the cycle count is reduced to 518 for the second cell used in the experiment. Based on these results, it can be deduced that the battery's capacity reduces as the operating temperature differs from the ambient temperature.

In [165], the maximum charge storage capacity is investigated at four different temperatures from 25°C to 55°C. The result from the study is extracted and replotted, shown in figure 14 and table 3. Valuable information regarding the impact of temperature and cycle number on the degradation rate of the battery can be deduced from these data. The degradation rate depends not only on the cycle number but also on the battery cell's temperature [172]. The degradation rate or capacity loss of the battery cell at each temperature should be the same if the temperature does not affect capacity fading; however, this is not the case, as seen in figure 14. It shows that, with the exception of a dip at 55°C, the degradation rate (Q_m) increases with temperature. As mentioned previously, temperature improves the battery's performance temporarily by raising its capacity. But as seen from this figure, it also accelerates the degradation rate of Q_m. This is due to the acceleration of the degradation mechanism of irreversible capacity loss at elevated temperatures [132]. The decrease in capacity of the battery after 45°C is due to the increase of degradation of the components in a Li-ion battery i.e., a positive electrode, a negative electrode, and an electrolyte [116]. This study [165] reveals that the degradation of each component of a Li-ion battery temperature has the largest impact on the degradation rate of the Warburg element (resistance and capacitance) with cycling, followed by the cell impedance. When the operating temperature increased from 25°C to 55°C, the degradation rate of maximum charge storage increased from 4.22% to 13.24%. Similarly, the degradation rate of the Warburg element resistance increased from 49.4% to 584.07% (which was the largest increase), and the cell impedance increased from 33.64% to 93.29% after 260 cycles. Hence, the change in all these degradation parameters is the reason for the decrease in the capacity of the battery after 45°C.

As the temperature and cycle number increase, the percentage loss of capacity of the battery cell also increases, and the exact value of the capacity loss in percentage is shown in table 3. The battery cell with a cycle number count of 50 operated at 25°C has the minimum capacity fade of 0.79%. When the operating temperature was raised, it was observed that the battery cell operated at 55 °C had more than double, i.e., 1.86 percent capacity loss when measured at the exact cycle count of 50. A maximum capacity loss of 13.24% was observed at a cycle count of 250 and an operating temperature of 55°C in this experiment, concluding that battery capacity loss rises as cycle count increases. This irreversible capacity loss with cycle aging is linked to one or more of the following: insertion electrode structural changes, electrolyte decomposition, active materials dissolution, phase changes in the insertion electrode, and passive film formation over electrodes and the current collector surface [132], [173].

The influence of operating temperature, discharge current rates, and DoD on lithium iron phosphate-based battery was also investigated in [89]. The tests were carried out at four distinct temperatures: 40°C, 25°C, 0°C, and -18°C, with the results displayed in figure 15. Unlike the previous study done in [154], this study shows an apparent effect of temperature on the lifecycle count of the battery. When the operating temperature is at ambient temperature (25°C), the cycle count of the battery is maximum at 2600. The cycle count of the battery diminishes as the temperature increases over this point. It was found to be 1850 at 45°C, and the cycle count continues to plummet as the temperature rises. The instability of the SEI causes the battery's lifespan to decline beyond 25°C

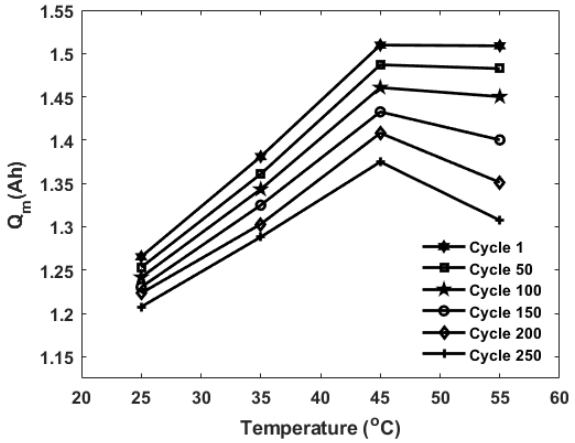


FIGURE 14. Capacity of battery cell as a function of temperature [165].

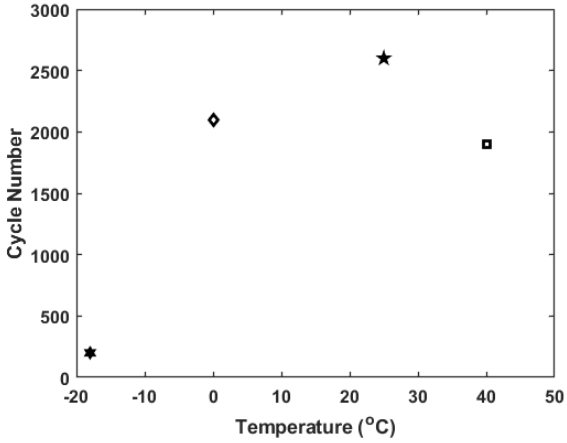


FIGURE 15. Effect of temperature on lifecycle count of a battery cell.

TABLE 3. Degradation percentage at different cycle number and temperature [165].

Cycle Number	Degradation Percentage			
	25°C	35°C	45°C	55°C
50	-0.79%	-1.37%	-1.40%	-1.86%
100	-1.72%	-2.62%	-3.05%	-4.07%
150	-0.26%	-3.93%	-5.01%	-7.29%
200	-3.29%	-5.55%	-6.70%	-10.48%
250	-4.22%	-6.57%	-8.74%	-13.23%

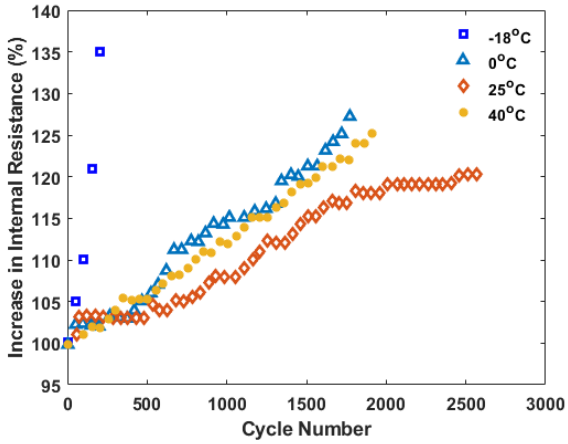


FIGURE 16. Variation of internal resistance at different temperatures [89].

because the SEI layer consumes free Li-ions during each charge cycle, reducing the number of free Li-ions available to represent the battery's capacity. Also, with the instability of SEI and the increase in its thickness, the internal resistance of the positive electrode surface will increase, and there will be a mismatch in the electrochemical process of the battery, due to which the lifecycle of the battery decreases [166]. As the temperature drops below the ambient temperature, the battery's cycle count will also start to decrease. The cycle count was lowered to 2070 when the temperature reached 0Â°C, around 20% decrease in cycle count. The battery's life cycle is substantially reduced when the temperature drops beyond this point; at -18°C, the cycle count was found to be 200.

A rigorous analysis of 18650 model Li-ion cells at low temperatures was done in [145] to identify why the life cycle count of the battery falls so drastically at negative temperatures. The temperature was decreased from 25°C to -40°C. The overall cell impedance increases by more than ten times, going from 25°C to -40°C. Also, the cells' energy and power density data at 25°C and -40°C were compared. At 25°C, energy and power density were found to be around 800 $W1^{-1}$ and 100 $Wh1^{-1}$, respectively, whereas those at -40°C were reduced to 100 $W1^{-1}$ and 5 $Wh1^{-1}$. The increase in cell impedance and poor battery performance is mostly due to an increase in the cathode-electrolyte interface's interfacial resistance [145]. Also, [174] concludes that the root cause for the degradation at low temperatures is the growth of SEI, which is aggravated by irreversible metallic lithium deposition, especially in graphite negative electrodes.

These experiments indicate that when the battery's temperature deviates from the ambient temperature, the performance of the battery slumps, as does the battery's lifespan [175]. The deviation from ambient temperature raises the internal resistance of the battery, which further aids in increasing the battery's temperature and speeds up the aging process [116]. Figure 16 shows the percentage increase in internal resistance at various temperatures replotted from [89]. The increase in internal resistance is more pronounced at -18°C, which is the electrical reason behind the poor performance of the battery at extremely low temperatures.

A battery's ohmic resistance equivalent model was developed in [112] to compute the ohmic resistance of a Li-ion battery in real-time by gathering data experimentally and using the recursive least square technique. The internal resistance at four different temperatures 20°C, 30°C, 40°C, and 50°C was observed, which is shown in figure 17. The outcome was the same as before, except this time, the increase in internal

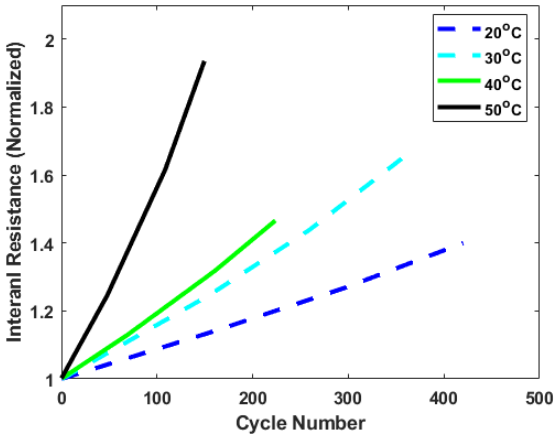


FIGURE 17. Variation of internal resistance at different temperatures [112].

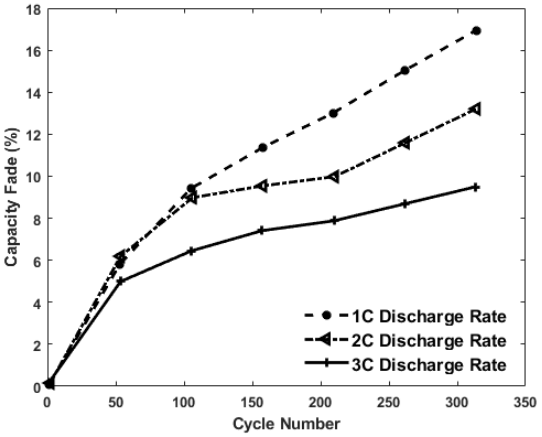


FIGURE 18. Capacity fade under different discharge current rates [131].

resistance was assessed as a normalized number rather than a percentage. The value of internal resistance increases as the working temperature rises, with $20°C$ having the lowest value and $50°C$ having the greatest value for any cycle count in this investigation.

B. DISCHARGING CURRENT

The discharge current is the amount of current at which the battery is being discharged. The discharge current rate is expressed as Q/h rate, where Q is rated battery capacity, and h is discharge time in hours. Sometimes discharge and charge rate is defined as C-rate, where 1C rate means that the discharge/charge current will discharge/charge the entire battery in 1 hour. The cycle count of a battery depends on the rate at which the battery is discharged. Numerous literature [127], [128], [129], [130] state that the discharge rate greatly impacts the performance and different amounts of discharge current have a different impact on the degradation of the battery.

To investigate the inherent property of the battery, [132] carries out a thorough analysis of the Sony US 18650 Li-ion battery at different discharge current rates. This study concludes that higher the amount of discharge current, the degradation of battery is faster due to three primary reasons: loss of secondary material, loss of primary material, and difference of rate capability [131]. This is verified by conducting a number of cycle life tests at 1C, 2C, and 3C discharge current rates. All the batteries should have a similar capacity at each cycle number if the discharge current rate does not affect the capacity of the battery. Nevertheless, as shown in figure 18, this is not the case where the capacity fade diverges at different cycles. There is no vast difference up to the first 50 cycles, but the capacity of the battery fades away depending on the discharge rate after this point. With a 3C amount of discharge current rate, the battery loses 16.9% of its initial capacity, whereas, with a 2C and 1C amount of discharge current, the battery loses 13.2% and 9.5% of its initial capacity.

The primary reason behind this higher capacity fade is the increase in loss of secondary material (i.e., carbon) at higher C-rates [131]. In the third case of this study, when C-rate was 3C, out of the total capacity loss of 16.9% of the whole cell, 10.6% of the capacity loss was due to the carbon electrode material alone. This increase in capacity fade at a higher discharge current for the carbon material was correlated to the increase of the internal resistance [132]. Hence, one way to reduce the capacity fade in a battery is by reducing the amount of discharge current that is fed by the battery to the load [133].

A separate experiment was conducted in [89] to find the life cycle count of a battery at different discharge rates. Here the battery's EOL is taken as 80% of the initial capacity, also defined by the standard ISO 1205-2. The battery cells were discharged at four different discharge current rates of 1C, 5C, 10C, and 15C. Figure 19 shows the curve with the remaining capacity of a battery and the number of cycles at different discharge current rates with a reference line of 80% of the initial capacity, drawn to indicate the EOL of the battery cells. As expected, the battery cell discharged at a low current (i.e., 1C-rate) has a maximum cycle count of 2900. As the discharge current rate increases, the battery's cycle count starts to decrease, as seen in the figure. The battery cells operated at 5C, 10C, and 15C, have cycle counts of 2060, 1100, and 559, respectively.

The capacity fade of the battery under high discharge current is again correlated to the increase in internal resistance [176]. Studies [89] and [132] analyzed the deviation in the internal resistance of a battery. They found that with the increase in discharge current, there is an increase in internal resistance, which increases the temperature of the battery and further decreases the capacity of the battery. This effect of change in internal resistance with the change in discharge current is further verified in [112], [140], and [177]. To see how the internal resistance changes with change in discharge

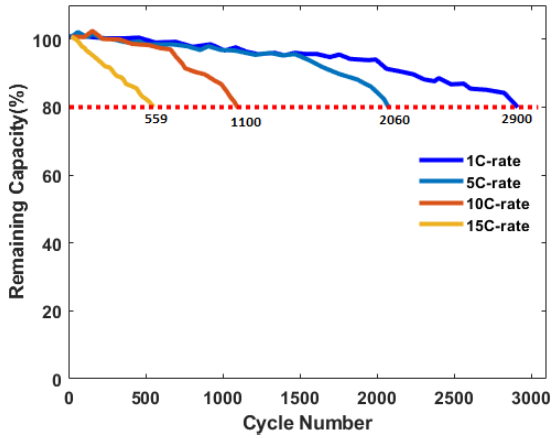


FIGURE 19. Remaining Capacity versus cycle life at different discharge current rates [89].

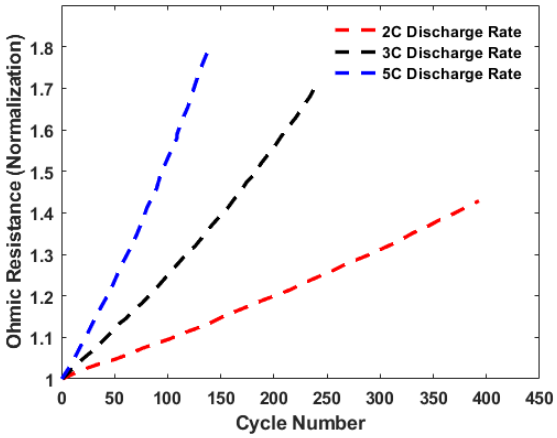


FIGURE 21. Increase of ohmic resistance at different discharge currents [112].

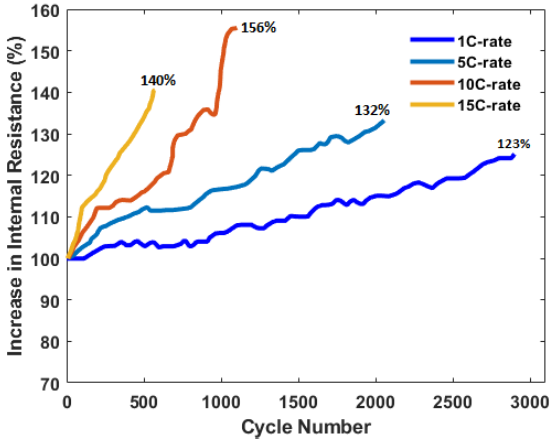


FIGURE 20. Increase of internal resistance at different discharge currents [89].

current rate, the percentage change in internal resistance were measured in [89] and is shown in figure 20. The battery cell that was discharged at 1C-rate, has the lowest percentage increase in the internal resistance of 123% after completing around 2800 cycles. As the amount of discharge current increases, the percentage increase in internal resistance increases, which can be seen in the figure. The battery cell discharged at 5C-rate had a 132% increase in resistance after 2000 cycles. Similarly, the percentage increase in internal resistance was found to be maximum for a 15 C-rate until 500 cycles, but after this point, the increase in internal resistance was maximum for 10 C-rate with 156%. Similarly, the change in ohmic resistance (OR) of a Li-ion battery used in a vehicle was investigated in [112] for different C-rates of 2C, 3C, and 5C, which is depicted in figure 21 for various cycle numbers. The result from this study is the same as concluded from [89]. The only difference is that this study provides the increase in resistance as a normalized value instead of a percentage increase. The increase in normalized resistance is minimum for 2C-rate and maximum for 5C-rate. The figure shows the value of ohmic resistance for the battery cells after completing 100 cycles. The battery cells discharged at 2C, 3C, and 5C-rate have ohmic resistance of 1.08 ohm, 1.26 ohm, and 1.55 ohm, respectively.

Also, Li-ion battery cells were tested by a manufacturer to monitor the capacity fade at different discharge current rates of 0.2C, 0.5C, 1C, and 2C, which were used in studies [90] and [135]. At a constant temperature of 37Â°C, the cells were charged and drained between 3V and 4.1V, with 2 samples obtained for 0.2C, 14 for 0.5C, 5 for 1C, and 3 for 2C to get a more robust result. Out of different samples, one sample for each discharge current rate is shown in figure 22 to have a clear view. As observed, the battery cell discharged at 2C-rate has the least cycle count between 150-200 cycles. As the battery was discharged more gently, i.e., at a lower discharge current rates, the cycle count of the battery cell increased. At 1C-rate, the cycle count was between 300-350, and for 0.5C-rate and 0.2C-rate, the cycle counts were higher, whose data were not acquired in the experiment but can be predicted from the path shown in the figure. As a result, as in prior experiments, the amount of discharge current affects the life cycle significantly, and the cycle life of the battery begins to diminish as the discharge current increases.

In study [178], a 2.7 Ah commercial Li-ion battery (Panasonic NCR18650PF) employing $Li(Ni_xCo_yAl_z)O_2$ as the positive electrode was used to investigate the discharging characteristics and heat generation behaviors. This study shows the effect of both the temperature and amount of discharge current on the degradation of the battery. The behaviors were studied under two different thermal conditions: constant temperature and near-adiabatic. Due to the influence of heat created by the battery with insulating techniques, the battery surface temperature rises gradually during the discharging process. It becomes more noticeable with higher discharging rates, shown in figure 23. Aside from the impact of discharge current, this rise in temperature at a high

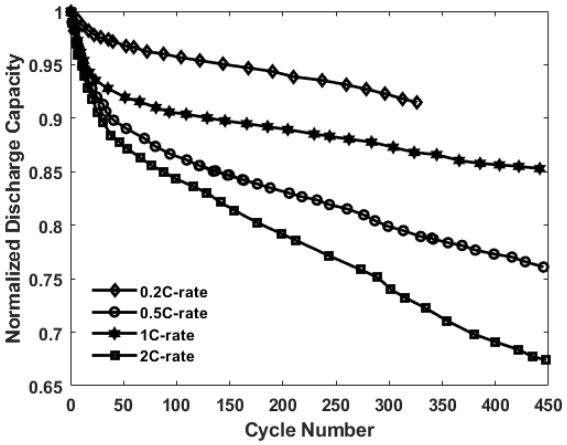


FIGURE 22. Discharge capacity testing at different discharge current rates.

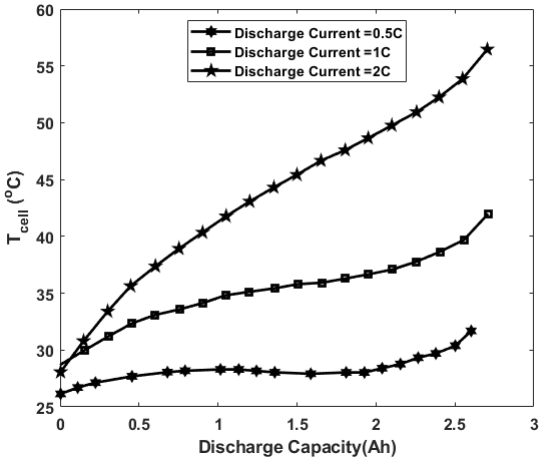


FIGURE 23. Variation of temperature under near adiabatic condition [178].

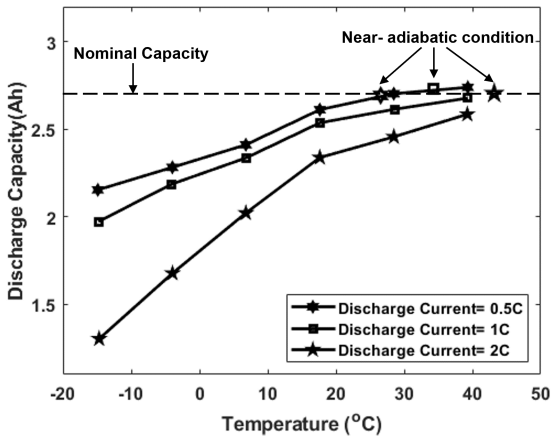


FIGURE 24. Discharge capacities of battery at two thermal conditions [178].

discharge current will further aid in the aging mechanism. It can be concluded, from figure 24, that as the discharge temperature is reduced from 20°C to 10°C for a particular discharging rate, the discharging capabilities decline substantially, especially for higher discharge rates. Using a discharge temperature of 10°C as an example, the discharging capacities at 0.5 C, 1 C, and 2 C are 79.6 %, 73 %, and 48.2 % of the rated capacity of 2.7 Ah battery cell, respectively. Also, there is only a slight decrease in the discharging capacity in the temperature range of 20°C to 40°C. The variation in discharging capacity between 20°C and 40°C, especially for a 0.5 C discharging rate, is just 0.133 Ah, or 4.9% of the claimed capacity of 2.7 Ah battery cell. It is worth noting that higher temperature (40°C in this study) can cause fast battery capacity deterioration as the number of cycles rises, despite the fact that the available capacity of Li-ion batteries increases at higher temperatures [136], [137], [138].

C. CHARGING CURRENT

Most EVs and commercial batteries have been using the concept of fast charging [179]. Vehicle charging time is a crucial factor in the adoption of EVs. Long charging time, usually more than 30 minutes, strongly reduces the sales of EVs [180]. This is because it increases waiting time in the queues, which acts as a barrier to EVadoption [181]. This is why all EVmanufacturing companies are shifting towards fast or ultra fast-charging systems for their vehicles [182]. The U.S. Department of Energy has classified charging of electric vehicles into three levels:

- Level 1 is regular charging, which happens when the charge power is less than 5 kW,
- Level 2 is fast charging, which occurs when the charge power is between 5 kW and 50 kW, and
- Level 3 is super-fast charging, which occurs when the charge power is higher than 50 kW [183], [184].

An off-board charger is used for Level 3 charging, which means the charger is located outside the car. Because of the high-power charging levels of Level 3 charging, carrying the requisite power electronics onboard is unfeasible owing to space limits. To overcome this limitation and reduce the mass, a Level 3 charge usually conveys the DC power to the vehicle, whereas Level 1 and Level 2 charging usually have onboard electronic converters that allow AC energy transmission [185].

Most EVs use Level 2 chargers, and Level 3 chargers are in the adoption phase. With the use of an AC level 2 charger, the LLI and LAM in the negative electrode were found to be the primary aging modes in the cells in the study [139]. These fast-charging technologies can help to increase EV adoption but can have a serious impact on the battery. Hence, there should be a better understanding of the effects of fast charging on Li-ion batteries [140], [149]. Studies [141], [142], [143], [144] investigated the effect of fast charging on Li-ion batteries and observed a more robust capacity fade at higher charging rates. Also, fast charging at a low temperature has a negative impact on the battery [8], [150]. Several failure modes were noted at a high charging current rate after the postmortem analysis of the cells, like lithium plating, graphite exfoliation,

jelly-roll deformation, active materials crumbling, aluminum corrosion, and an abnormal SEI formation [145], [146]. The capacity loss is mainly due to the lithium plating that causes irreversible loss of cyclable lithium [147]. Under high charge current or fast charging, heat generation within the cell accelerates the side reactions [148]. Lithium plating, ohmic heat, and increase in impedance are significant issues during fast charging that deteriorates the battery faster [149]. The studies of X-ray diffraction analysis (XRD), transmission electron microscopy (TEM), and scanning electron microscope (SEM) on the individual electrodes done in [123], indicate that the capacity fade during rapid charging and discharging of the battery can be correlated to two leading causes. First, the formation of the defects such as cation disorder and cracks in positive electrode's active material $LiCoO_2$. Second, the continuous increase in the passive film thickness on the negative electrode is due to the reduction of the electrolyte.

Also, overcharging a battery is another issue during the operation of EVs. Paper [124] investigates the overcharge-induced capacity fading behavior of 20Ah commercial pouch Li-ion batteries with NCM + LMO as a positive electrode and graphite as a negative electrode. A prognostic/mechanistic model and incremental capacity analysis were used to investigate the capacity deterioration process (ICA). This model was used to calculate the LAM in the positive and negative electrodes and the LLI at various overcharge phases. The analysis shows no noticeable capacity degradation until overcharged to 120% SoC. Above this SoC, LLI occurs as a result of lithium deposition, with LAM in the $Li_yMn_2O_4$ of the composite positive electrode [125]. The thickening of the SEI film is confirmed by the increase in internal resistance. When the battery is overcharged above 140% SoC, LAM occurs in both the positive and negative electrode. Also, due to the electrolyte oxidation, the battery starts to swell. When the battery was overcharged to 150% or more SoC, the battery cell started to rupture, with all the stored energy released instantly due to an internal short circuit, and pinholes on the separator surface were observed after dissembling the batteries.

To clearly understand the effect of charging current rates on the lifecycle count of a battery cell, many life cycle tests were carried out at a constant charge current of 1.25C, 2.5C, 4C, 7C, and 10C in the study [89]. The effect of the charge current rate is similar to that of the discharge current rate; the higher the amount of current rates, the lower the lifecycle count of the battery [126]. Figure 25 shows that when the battery was charged at 1.25 C-rate, it had a 2950 lifecycle count; however, when the charging rate was increased, the cycle count started to decline rapidly. The battery had 1607, 660, 567, and 414 cycle counts at 2.5C-rate, 4C-rate, 7C-rate, and 10C-rate, respectively. Hence, continuously charging a battery at a high current rate decreases the life cycle of the battery drastically [122].

Similarly, a 25Ah battery was utilized to examine the effect of charging current in [147], where cycling was performed between 20% and 80% of SoC and discharged at a constant

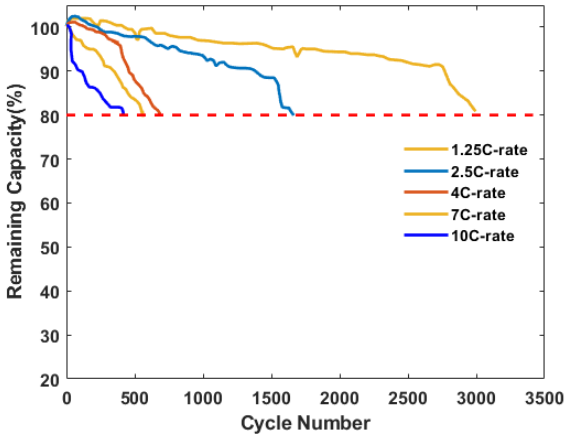


FIGURE 25. Change of capacity versus number of cycles at different charge current rates [89].

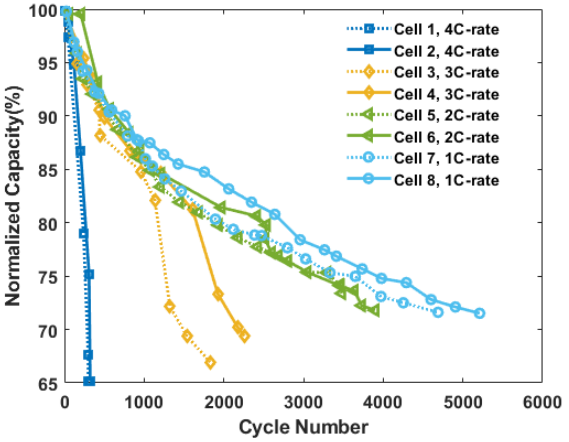


FIGURE 26. Capacity fade at different charge currents vs cycle count [147].

rate of 1C (25A). The battery was charged at four different charging current rates of 1C, 2C, 3C, and 4C (25A, 50A, 75A, and 100A). Two cells were operated at each charging current rate to ensure that the tests were as reliable as possible. Figure 26 shows the capacity fade in eight battery cells experimented on in this study. The two battery cells charged at a 4C rate had the highest capacity reduction than those charged at other rates. These two cells reach their EOL in less than 500 cycles. Similarly, the battery cell-8 charged at 1C- rate had the least capacity loss among these cells. The increase in capacity fade at higher charging current is due to more loss of free lithium ions as the SEI layer grows thicker with the increasing charging current. Also, there will be lithium plating at a higher charge current and an accelerated material loss [147]. The increase in the thickness of the SEI layer and lithium plating increases the battery's internal resistance, as shown in figure 27.

D. DEPTH OF DISCHARGE

The DoD is the portion of electrical charge discharged or charged during a cycle with respect to the maximum possible

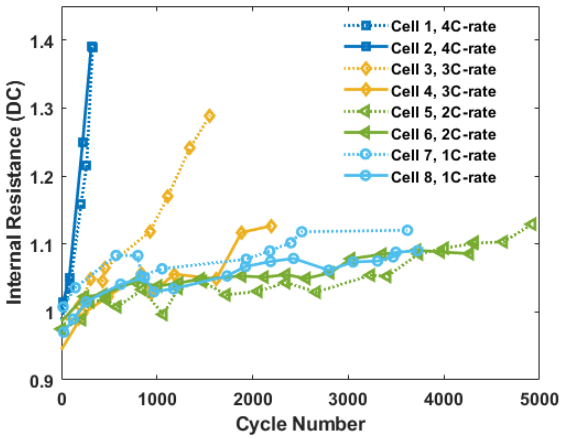


FIGURE 27. Internal resistance at different charge currents vs cycle count [147].

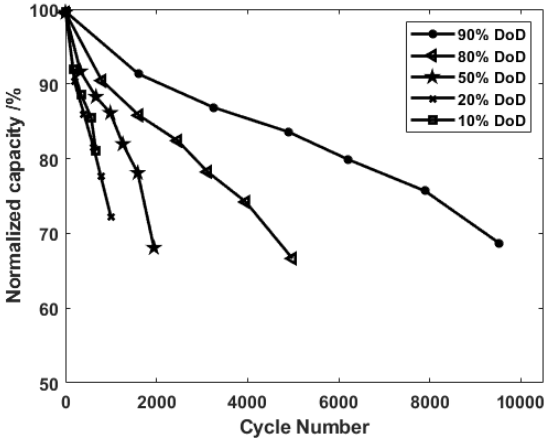


FIGURE 28. Change of cycle number at different DoD at constant temperature of 60°*C* [154].

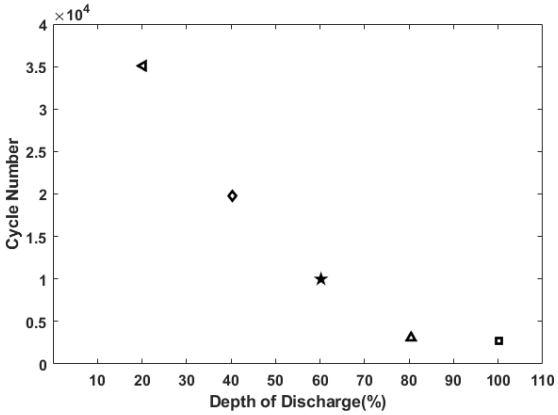


FIGURE 29. Change of cycle number with different DoD [89].

charge that a battery can hold. Or, in simple words, it is the percentage of battery capacity (rated capacity) to which a battery is discharged. Generally, the withdrawal of at least 80% of battery capacity is referred to as a deep discharge [89], [159]. A higher DoD indicates higher discharge of the battery, accelerating the battery aging and increasing the battery life cycle cost [151]. The study [152] finds that the deep discharging of batteries used in PHEV for bulk energy services during vehicle-to-grid (V2G) operation led to the annual replacement of battery packs across all EV charging regimes. Nevertheless, when compared to PHEV, charged opportunistically at home or worked, the battery pack was replaced once in 3 years. This concludes that the regular deep discharge of the battery can reduce the life span by more than one-third. These phenomena are mainly due to the degradation of a positive electrode and growth of the SEI layer [153].

The influence of DoD on the capacity fading of the battery can be examined using the data acquired in research [154], shown in figure 13. Looking at a constant C-rate of C/2 at any temperature, it can be seen that the battery's cycle count is more when it is discharged less. For example, at 15Â°C, when the battery is discharged 90% (i.e., from 100% SoC to 10% SoC), the cycle count is 2144. However, when the battery is discharged by 10% (i.e., from 100% SoC to 90% SoC), the cycle count is 18067. The cycle count of the battery reduces as the battery is depleted deeper, suggesting that the battery's capacity diminishes. Figure 28 replicates the data from the test matrix shown in figure 13, showing how the capacity of a lithium battery fades when it is discharged at different DoD at a constant temperature of 60°C and a constant discharge current rate of $C/2$. The reduction in capacity for the battery cell discharged at 10% DoD is minimum and found to have a cycle count of more than 6000 if 80% of the initial capacity is considered EOL of the battery cell. As the DoD is increased, the capacity fade goes on increasing. The reduction in capacity is found to be maximum for the battery cells that were deeply discharged (i.e., 80% and 90% DoD). The cycle count was found to be around 1000 for these DoD.

In [89], the life cycle of various battery cells was compared at different DoD, and it was found that the cycle count was not fixed. To look at a clear view of the battery performance at different SoC levels, a series of cycle life tests were conducted at different DoD at a room temperature of 20-25°C and is shown in figure 29. Here one cycle count means the SoC of the battery cell is reduced by 100%, which can be one time from 100% to 0% or five times from 100% to 80%. When the battery was discharged at 20% DoD, i.e., from 100% to 80%, the battery's cycle life was found to be 34957. As the DoD was increased to 40%, i.e., from 100% to 60%, the cycle life of the battery cell decreased to 19985. Similarly, when the battery was fully discharged (100% DoD), i.e., from 100% to 0%, the cycle life of the battery was only 2600. As a result, if the DoD is higher, the battery will degrade faster and have a shorter lifespan. Study [155] also concludes the same effect by conducting an experiment on a 60Ah Li-ion battery.

The change in DoD in a Li-ion battery cell can be electrically linked with the change in internal resistance. The

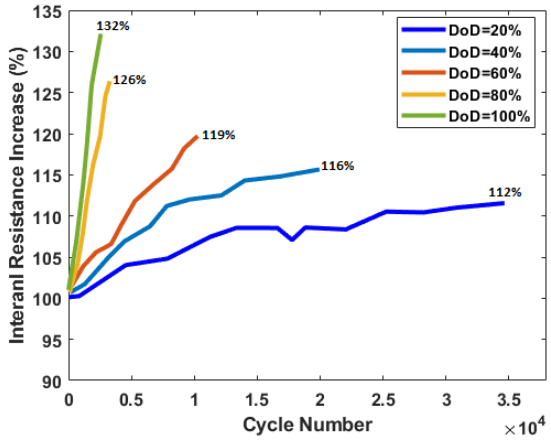


FIGURE 30. Increase of internal resistance versus cycle at different DoD [89].

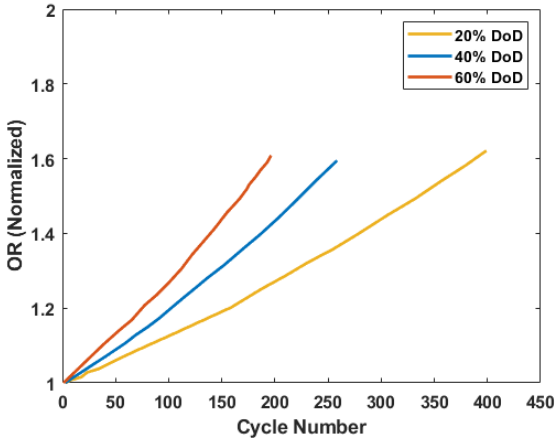


FIGURE 31. Increase of internal resistance at three different DoD [112].

internal resistance of the battery increases with the degree of DoD, which is shown in figure 30 from the study [89]. The percentage increase in internal resistance is lowest for the battery cell that was discharged at 20% DoD, which was found to be 112%. In contrast, the battery cell that was fully discharged (100%) had the highest percentage increase in the internal resistance of 132%. The higher the DoD, the higher the increase in internal resistance, which further assists in the battery's aging mechanism, which is further verified in [156], [157], [158]. Similarly, in [112], the influence of various DoD (20%, 40%, and 60%) on the battery's internal resistance was examined. The result from this experiment is the same as described previously and is shown in figure 31. The resistance of the battery goes on increasing as the cycle count increases. When the battery is discharged at 60%, it has the highest ohmic resistance, whereas when discharged at 20%, the ohmic resistance is the lowest.

V. LIFECYCLE PREDICTION OF BATTERY AND DEGRADATION ABATEMENT

The battery's health in EVs must be closely monitored and predicted in real time for reliable operation and timely maintenance of the vehicle [186]. In recent years, there has been significant improvement in estimating the life of a battery using different degradation models. They can be classified into different categories where the literature [187], [188], [189] groups the methods into three main categories

1) Model-based approach,
2) Data-driven approach, and
3) Hybrid approach.

The model-based approaches are based on physics-based modeling of degradation behavior, in which an empirical model is built to represent the system's diminishing path based on the real diffusion phenomenon. This model demonstrates the degrading behavior of a battery using a combination of algebraic and differential equations or an empirical equation. Since the deterioration of the battery is nonlinear, predicting long-term performance can be rugged [190]. The main drawback of this model is its lack of flexibility and parametrization difficulty. It can easily lead to poor model design due to a lack of prior understanding of the system. To construct a robust model, the designer must have a proper understanding of the numerous aspects of the system, including mechanical, electrical, electronic, chemical, and other physical characteristics.

Data-driven approaches (commonly known as black-box models) are based on empirical observations with little or no understanding of the underlying processes. This method depends heavily on evaluating data from the process; therefore, designers do not need to gain a thorough, domain-specific grasp of the background process to use it. The data-driven method uses statistical theories or machine learning techniques to derive a model from measured data. This method creates a mathematical model from data gathered in the lab through large-scale testing under various aging circumstances, rather than utilizing a specific physical-based model, and forecasts the battery's deterioration trajectory. It has lately become the most popular method since it is more adaptable and practical and removes the need for sophisticated physics-based models. These models are self-adaptive, model-free, and have the ability to learn from previous data on their own. Data-driven approaches include techniques such as artificial intelligence, statistical analysis, Wiener process, and signal processing [54].

The data-driven approaches rely heavily on data; therefore, the model's accuracy and effectiveness are mainly determined by the data quality. Unbalanced data, for example, might lead to decision-making bias (also known as overfitting and underfitting) in a model. In essence, if a large amount of relevant data is readily accessible, a data-driven strategy would be beneficial. However, in the absence of this data, the application of a data-driven strategy would be limited. Recently the concept of featured-based data-driven models has been widespread. In this technique, certain features are retrieved from the voltage and current during the preprocessing stage using knowledge about the behavior of the cell's physical properties. Then, these attributes are used as a input to the algorithm used in the process. This method has the

advantage of producing less complex inputs by preprocessing the raw data that is supplied for the input. Studies [191], [192], [193] have used this concept of feature-based data-driven models to predict the RUL of the battery. Also, the study [194] explains the concept of generating synthetic data that are equivalent to the actual battery data for the data-driven approach. The generated datasets were compared to the battery's actual behavior, which yielded identical results. These large synthetic datasets can be used to train algorithms for data-driven approaches and diagnoses. As a result, these datasets can help evaluate various algorithms and enhance these techniques.

Similarly, the hybrid method incorporates the strengths of both model-based and data-driven models. This method is useful when there is limited or biased data, as the data-driven method can lead to imprecise forecasts or wholly misleading outcomes. In battery life estimation, hybrid techniques that combine model-based and data-driven methods to produce accurate forecasts have become a hotspot of study. The main advantage of this method is that it can extrapolate beyond the training data more precisely than the data-driven method. The use of this approach in studies [195], [196], [197] demonstrated promising results. The only issue to adopt this approach is lack of openly available field data, which should be validated with the results obtained from lab data [198]. All these three methods are summarized in figure 32, and the papers that use these techniques to predict the degradation of batteries are provided in table 4.

As discussed in section IV, various factors give rise to the degradation of the battery. Each factor has a different impact on the aging mechanism. The cycle life experiment conducted under one operating condition for a battery may not be valid for other operating conditions making it difficult to predict the RUL of the battery. To conduct experiments at continuously varying operating conditions would cost years of testing, causing such experiments to become infeasible. The development of precise battery performance and life prediction models would be hampered by the absence of comprehensive experimental data. However, despite the lack of degradation data, several types of studies have been conducted on accurately forecasting the cycle life of a battery. A dynamic battery degradation capacity model based on a semi-empirical equation has been used in several studies like [66], [154], [199], [200]. In this model, the effect of four parameters are considered, which are time, temperature, DoD, and discharge current rate. This semi-empirical model is based on the original formula of the Arrhenius degradation model shown in (5). Here, Q_{loss} is the percentage of battery capacity loss, A is the pre-exponential factor, Ea is the activation energy, 78.06 (J), R is the gas constant, 8.314 J/mol/K, T_{bat} is the absolute temperature of battery(K), Ah is the Ah-throughput, z is the time factor, C_{Rate} is the battery discharge rate, B is the compensation factor of C_{Rate}

$$Q_{loss} = Ae^{-\left(\frac{E_a+B.C_{RATE}}{RT_{bat}}\right)}(A_h)^z \tag{5}$$

According to the cumulative damage theory, the capacity fade model of the battery illustrated by the aforementioned equation can be utilized to predict battery degradation [201]. The dynamic degradation model's discrete formula is given by (6) as done in [202].

$$Q_{loss,p+1} - Q_{loss,p} = \Delta A_h z A^{\left(\frac{1}{z}\right)} e^{\left(-\frac{E_a+B*C_{RATE}}{RT_{bat}}\right)} (Q_{loss,p})^{\frac{z-1}{z}} \tag{6}$$

Here, $Q_{loss,p}$ and $Q_{loss,p+1}$ are the accumulated battery capacity loss at instantaneous time t_p and t_{p+1}, and ΔA_h is the Ah-throughput from t_p and t_{p+1}, which can be found by using (7)

$$\Delta A_h = \frac{1}{3600}\int_{t_p}^{t_p+1} |I_{bat}|\, dt \tag{7}$$

Study [200] derived an equation to find the remaining cycle number of the battery (N), which is obtained by combining the capacity loss model and Ah-throughput equation provided above and is shown in (8).

$$N = \left(\frac{Q_{Loss}}{A.e^{\left(-\frac{E_a+B*C_{RATE}}{RT_{bat}}\right)}}\right)^{\frac{1}{z}} \frac{1}{Q_{max}.DoD} \tag{8}$$

Using the above equations for the capacity loss and cycle number calculation with the help of experimental data, the study [200] successfully calculated the degradation path of the LFP battery. The degradation of the battery at different operating conditions (DoD and discharge current rate) was calculated and compared with the actual data. About 2000 sets of experimental cycle data of a commercial LFP battery were used to create and validate the degradation and life prediction model. Here, 80% of these data were used to develop the degradation model, and 20% were used to validate the accuracy of the developed model. The absolute mean percentage error of the developed degradation and life prediction model was found to be about 13%. The degradation of the LFP battery cell using the degradation model for three different operating conditions is shown in figure 33. Using the battery under harsh conditions (fully discharging it at a high rate, i.e., 2C) results in fast degradation and quickly reaches its EOL. However, the life of the battery can be extended by using it gently, reducing the discharging current rates and deep discharge of the battery. When the battery was discharged at a 1C rate at 60% DoD, it had a longer serving life than the one discharged completely at a 2C discharge rate. Similarly, the battery discharged with 40% DoD at a 0.4C rate had the highest serving life among these three operating conditions.

A. BATTERY DEGRADATION MODEL, ENERGY MANAGEMENT, AND OPTIMIZATION STRATEGY

Battery safety and reliability are crucial for the operation of EVs. The fundamental restriction of Li-ion-based EV batteries is aging since the battery goes through a complicated degradation process throughout the operation of the vehicle.

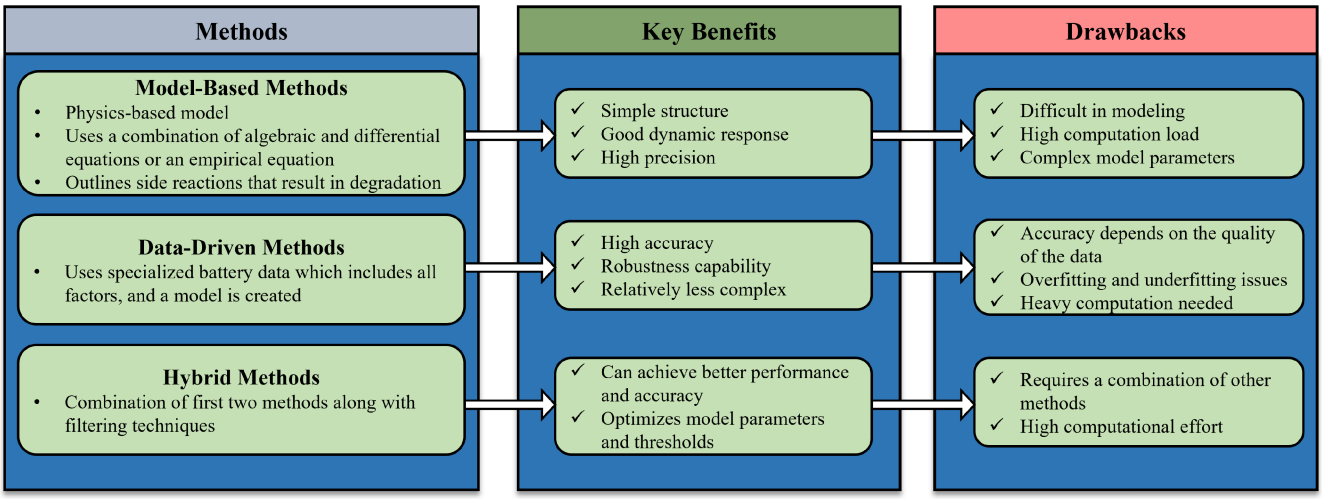


FIGURE 32. Methods for modeling battery degradation.

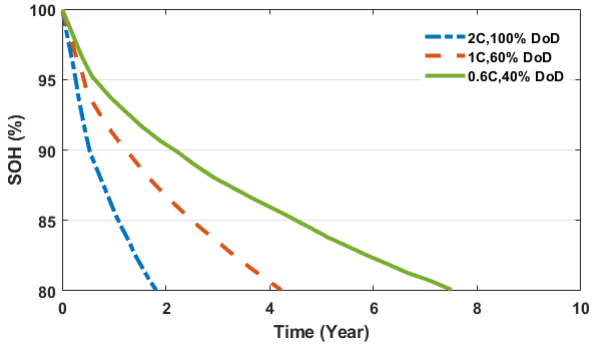


FIGURE 33. SOH of battery at different operating conditions [200].

The degradation occurs over time, resulting in a lower driving range due to reduced capacity. The operating conditions or factors giving rise to degradation are explained in detail in section IV. Battery states, battery aging, driving behavior, and environmental conditions are all possible, relevant elements influencing EV usage and energy consumption. The expensive energy capacity, which accounts for a large portion of the entire cost of an EV, and the restrictive driving environment, which limits the performance and acceptance of EVs, are two concerns in the battery application. As a result, minimizing the degradation through precise modeling, extending battery life, and optimizing battery capacity and energy management (EM) are the primary objectives for maximizing EVlifetime value. One of the most challenging tasks in modeling the degradation trend of an EVbattery is identifying the factors that contribute to it. The major factors leading to degradation are already explained, and these factors have a different impact on the battery, making it challenging to establish a degradation model through existing methods. The diversity and number of research literature on battery degradation give useful information that analyzes EV battery aging mechanisms, impacts, and features. Several researchers studied the approaches used to simulate the degradation mechanisms in EV batteries based on the explored factors.

The integration of precise degradation models with a battery management system maximizes battery capacity while guaranteeing that operations are optimized for battery lifespan. Model-based prediction of battery states such as SoC, SoH, and RULis possible with BMS. It evaluates and quantifies the evolution of EVbattery electrical performances and precisely predicts their RULin real-world operation. The use of an accurate degradation model in BMS assists in maintaining cells and battery packs by maintaining appropriate operational voltage and temperature ranges, assuring safe operation, extending battery service life, and keeping batteries in good health. The integration of degradation models into BMS allows EVbatteries to be used to their greatest capability and life expectancy before being replaced.

In EVs, combining precise degradation models and effective EM techniques can potentially extend battery life. Several research suggested optimization strategies considering battery deterioration models for the best battery size, DoD, and EM in EVs. Considering the battery degradation model and the battery degradation cost as a critical component in determining the operational costs of the EVbattery can achieve economic viability during vehicle operation. Hence, an optimized EVEM technique that accounts for battery degradation model and capacity loss simultaneously can successfully deal with dynamic EVoperations and extend battery lifespan, which is explained in detail as follows.

The battery's degradation path can be calculated using (5)-(6), and its remaining lifespan can be calculated using (8). A similar concept of calculating the battery's capacity loss and RUL can reduce the battery's capacity loss and increase its lifetime. While doing so, the battery's degradation cost can be minimized, ultimately reduces the vehicle's operating cost. This concept was implemented in the study [37], where the degradation of the battery in an HEV was reduced using a prognostic-based control strategy. The degradation path of

TABLE 4. Methods to Predict the Degradation of Battery (with references).

Methods	Modeling Techniques	Advantages	Drawbacks	Reference
Model-based	Equivalent circuit models	Simple structure Good dynamic response Considers the aging mechanism to some extent (i.e., describes the growth in internal resistance)	Requires expensive equipment ECM structure defines the prediction accuracy Model error increases continuously EIS test accelerates the aging process	[190], [203]–[205]
	Electrochemical models	High precision Quantify the aging state inside the battery High generalization ability	Difficult to identify the parameters Designer must have a proper understanding of the system No accurate internal aging mechanism	[206]–[209]
	Empirical models	Simple mathematical structure Fast performance calculations Wide applicability	External factor affects the accuracy Operating condition affects the accuracy There is no physical model Model parameters need to be updated	[96], [210]–[212]
Data-Driven	Statistical models	Simple to use High accuracy No complexity involved Easy to identify model parameters Good real-time performance	Requires comprehensive data Model update efficiency is poor Sensitive to the quality and quantity of data Lack of robustness and long-term accuracy	[213]–[216]
	Machine learning models	Robust High accuracy Can model non-linear systems Strong learning ability	Accuracy depends on the data quality High computational complexity Requires signification amount of training data	[217]–[222]
Hybrid	Combination of model-based and data-driven methods	Can achieve better performance and accuracy Optimizes model parameters and thresholds	Increases complexity High computational load	[223], [224]

the battery was calculated from the historical data conducted in the lab provided by Sandia National Laboratory (SNL) and minimized the degradation by changing the control algorithm of EM. The degradation of the battery was calculated using the Markov chain model, where four different states of the battery were defined to predict its degradation path. Also, a load-dependent model was used to model the degradation of the other components used in HEV. Depending upon the degradation of the battery and other components of the vehicle, the degradation forecasting layer interacts with the EM layer, which reallocates the power between battery and ICE, so as to reduce the degradation of the battery. This process was validated on an HEV with ICE and a battery as power-generating sources. The system was operated for 100 drive cycles, and the simulation results are shown in figures 34 and 35.

These figures show that the prognostic-based control strategy implemented in this study successfully reduced the degradation costs of HEV's components by $11.94 while running the vehicle for 100 drive cycles. However, the fuel cost was increased by $6.879. This is due to the action of EM. To reduce the degradation of the battery, EM changes its configuration and allocates more power to ICE, and reduces the power to be supplied by the battery. While doing so, the fuel consumption is increased, but it helps to reduce the degradation of the battery and the overall cost of operation of HEV. The overall cost of the vehicle is reduced by $5.066 while running the vehicle for 100 drive cycles only. Figure 35 clearly illustrates the decrease in battery degradation path with the implementation of prognostic-based control during the operation of HEV. From this figure, it can also be seen that there is no change in the degradation path of ICE, which states that the life of ICE is long compared to the battery.

VI. RESEARCH GAPS AND FUTURE RECOMMENDATION

The battery being one of the critical and expensive components of the EV, it is necessary to conduct detailed research on the performance and the factors affecting their performance [18]. The operation of the battery under harsh operating conditions makes its life shorter and needs to be replaced much faster, resulting in the uneconomical operation of EVs. Battery degradation is a complex phenomenon that involves several electrochemical side reactions in the anode, cathode, electrolyte, and separator. It is critical to investigate degradation behavior, identify the causes that have the most impact on the battery, and minimize the impact of these factors in order to extend the battery's longevity. Furthermore, knowing the battery degradation behavior allows for an accurate

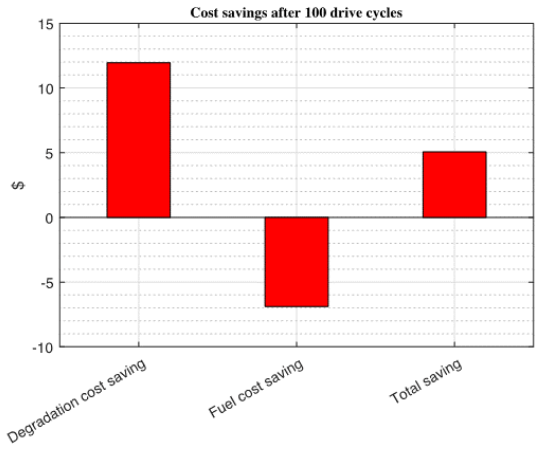


FIGURE 34. Cost saving using prognostic based control framework [37].

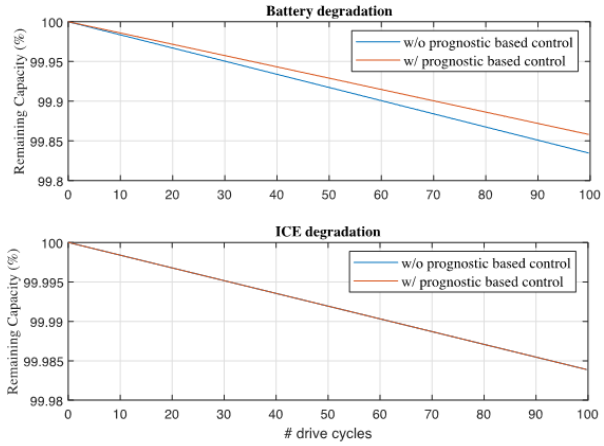


FIGURE 35. Battery degradation abatement [37].

estimation of the battery's remaining lifetime under various operating conditions. This is critical for the BMS to ensure reliable operation and timely maintenance, as well as for the second-life applications of the batteries.

There have been several studies on the investigation of the life cycle of a battery. The main challenge is to develop a proper degradation model and implement it. Different models developed until now use model-based, data-driven, or a combination of these two approaches, known as a hybrid approach, as explained in section V. These methodologies can be used to anticipate the degradation path and identify the battery's remaining life based on correct historical data and degradation models. These parameters can aid in the dependable functioning of the vehicle and lower the operating cost by minimizing battery deterioration as done in [37] and is explained in detail in section V. However, this study has several limitations, such as it was carried out for HEV, where two power sources are available to supply the power demanded by the vehicle. The algorithm of power dissipation and battery degradation estimation would be entirely different for full EVs. This study uses data from a laboratory for degradation calculation instead of actual HEV or EVbattery data. Also, the algorithm that is used to calculate the degradation of battery is Markov's chain model, which has several disadvantages, such as it assumes that the present state only determines the future state and ignores other factors, it believes that the data-generating system is static and has a tendency to overfit data and produce unreliable results when faced with new data, there is difficulty modeling complex non-linear relationships, which can result in incorrect prediction, and it needs to compute the transition matrix, which slows the computational process.

However, this study can be a reference for future research on the abatement of battery degradation in HEVs and EVs. This research has shown a way to reduce battery degradation by creating a degradation forecasting layer in HEV which can communicate with the EM layer. Depending upon the degradation of the battery, the EM reallocates the power dissipation between the power generating sources.

Also, there has been the development of several algorithms for the prediction of battery degradation. Machine learning techniques have been used successfully and efficiently in predicting the degradation path. Study [225] is a perfect example that uses a model-free deep reinforcement learning (DRL) method to optimize the battery energy arbitrage considering an accurate battery degradation model. However, this study calculates the degradation of batteries used as energy storage in a grid. But, this advanced control algorithm can also be used to predict the degradation of batteries used in EVs in real-time more efficiently.

Besides these issues, another main issue in the prediction and abatement of battery degradation in EVs is the limited amount of battery data. Several institutes like NASA Ames, the University of Maryland, Stanford University, and Hawaii Natural Energy Institute provides the battery data that are conducted in the lab. Nevertheless, access to actual battery data used in EVs is limited. Nissan provided the battery cell data used in the 2013 Nissan Leaf model, which is the only EV manufacturer to publicly make its battery cell data available. However, these data are also limited as they only provide the charging, discharging, and HPPC tests data which can be used to model the equivalent circuit of the battery cell precisely but are limited in predicting the degradation path and remaining life. Also, maximum research carried out under different degradation models is developed on limited data but under well-designed lab datasets and controlled test circumstances.

It is essential to include field data to develop a comprehensive understanding of how cells age in actual working environments. Obtaining data under real working conditions is another additional challenge. The EV users have uncontrolled working conditions, less accurate sensors, data collection and storage issues, and infrequent access to validation checks. If sufficient battery data is accessible, together with their driving patterns, a more accurate prognosis of the battery's remaining life and deterioration can be made, setting a new standard for vehicle reliability in the automobile industry.

Based on the previous sections discussed in this review, there is still a wide range of challenges in the prediction and abatement of battery degradation in EV applications. We outline the following key tasks and prospective research directions in order to better perform future investigations.

- To accurately estimate battery health and RUL, detailed degradation mechanism investigations at various stages are required. Most degradation studies are done at the cell level and are based on a single stress factor, which is not conducive to a complete knowledge of battery breakdown involving inconsistency. As a result, degradation tests at the cell and pack levels that encompass several stress variables, such as factors mentioned in section IV, are required.
- There has been the development of several accurate offline degradation models which can update dynamically to become self-improving. However, this is not the case for the online or real-time scenario. The use of a self-learning algorithm in real-time is recommended for accurate battery health and RUL prediction.
- SoH values are commonly employed in developing degradation models as training data. In the literature, these SoH values are recognized as accurate. However, in a real-world environment, training data is often calculated using estimation methods, where degradation models are applied onboard and updated online. This might lead to some errors in the estimations, which can influence the overall efficacy of the degradation model. Therefore, an accurate estimation algorithm that is robust when handling input data uncertainty should be used to develop effective degradation models.
- The development of large-scale open-source databases for battery performance and lifecycle count for EV applications. There are minimal data on batteries that are used in EV applications. To create a degradation model, there should be sufficient data, as explained in table 4. With access to a large database, accurate models can be created by training and assessing multiple models, which ultimately results in an accurate prediction of the battery's RUL and degradation path.
- The development of scalable algorithms or software that combines data-driven methods with model-based methods (i.e., hybrid approach) for predicting the degradation path of battery and remaining life. Ridgetop Group is one example of this scenario, which has developed cellSage and ARULE software in collaboration with Idaho National Laboratory (INL) that can predict the degradation path, State of Health (SoH), and RUL of a battery being monitored. Such an open-source database of batteries and software that can predict the degradation and RUL can directly be used in the research to develop more precise algorithms to minimize the degradation and increase the serving life of the battery.

The potential research gaps or problems and suggestions associated with the batteries used in EVs or HEVs from the research point of view are explained in detail above. The following points summarize the steps and suggest a way to abate the degradation mechanism of a battery used in EVs and HEVs.

1) An open-source database system for the battery used in EVs or HEVs: This step involves creating a database system that can be accessed by researchers, manufacturers, and other stakeholders to collect and share data related to the batteries used in EVs or HEVs. By making this information publicly accessible, researchers can better understand the factors contributing to battery degradation.
2) An accurate algorithm that can predict the degradation path of the battery in real-time: This step involves developing an algorithm that can accurately predict how a battery will degrade over time. By doing so, researchers and vehicle operators can identify when a battery is likely to fail and take preventative measures to avoid it.
3) Development of control techniques or algorithms to minimize the battery's degradation path without compromising the vehicle's performance: This step involves the development of novel methods like control techniques or algorithms that can optimize the use of the battery without compromising the vehicle's performance. For example, the algorithm can limit the stress placed on the battery during acceleration or deceleration to reduce degradation
4) Continuous monitoring of the battery's health: This step involves regularly monitoring the battery's health to identify any signs of degradation or damage. By doing so, manufacturers can take corrective actions before the battery fails, reducing the risk of safety issues and minimizing the cost of replacing the battery.

VII. CONCLUSION

This review article systematically presents state-of-the-art battery degradation in EVand HEV applications. It presents a comprehensive classification of factors responsible for battery degradation and their consequences at different phases of life described in the literature. This paper focuses on the many physical and chemical changes that occur during battery degradation, then goes into detail on how various operating circumstances such as temperature, discharge current rate, charge current rate, and DoD affect the capacity and lead to degradation. The impact of the harsh working circumstances coming from a different set of fields is thoroughly discussed based on the findings of the literature.

In this study, section III explains the different degradation mechanisms that occur inside a battery. Different causes that give rise to these mechanisms and their effects are explained in detail. Then section IV explains different operational conditions that affect the battery's lifespan. It can be noted that battery behavior and degradation are fairly complex processes that depend on their operating condition and

environment. Due to this reason, it is crucial to have in-depth knowledge about the degradation behavior and the factors that have the utmost effect on the battery so that the effect of these factors can be minimized to increase the lifespan of the battery. Moreover, it's difficult to model this complicated phenomenon as different factors have different impacts on the degradation path of the battery.

The development of battery degradation models is crucial from a research perspective to identify ways to enhance battery performance and lengthen the life of the batteries. With the knowledge of battery degradation behavior and factors giving rise to it, a degradation model can be developed accurately at various operating conditions, which will be essential for the BMS to ensure reliable operation and timely maintenance of the EVs. The different techniques to develop a degradation model are explained in section V, along with their comparisons. Over the years, there has been a significant advancement in modeling battery degradation and estimating health and RUL. Recently, machine learning algorithms in degradation prediction have been used widely as they offer a non-intrusive approach with minimal computation and high accuracy when taking into account the scalability and time-frame concerns of battery deterioration. However, these algorithms in battery health and RUL estimation have gaps and face several challenges, which are summarized in the same section. This section further explains the technique to use the information from degradation models, i.e., degradation path and RUL for degradation abatement in EVand HEV applications with the help of EM.

Finally, section VI explains the research gaps that exist in this field. It is worth mentioning that there lies an interesting research avenue in integrating separate works discussed in this paper. The different factors responsible for the degradation of the battery can be used to model an accurate degradation behavior which can give SoH and RUL. Looking at the degradation path, if the battery is degrading fast, the operating scenario for an EV/HEV can be changed in real-time so as to minimize the degradation. Through this paper, the authors hope that anyone interested in the degradation abatement of batteries used in EV/HEV applications can benefit from this survey. Also, we hope this review will benefit several researchers in developing different degradation abatement techniques in EVs and improving degradation modeling by including different stress factors mentioned in this paper.

REFERENCES

[1] C. C. Chan, "The state of the art of electric and hybrid vehicles," *Proc. IEEE*, vol. 90, no. 2, pp. 247–275, Feb. 2002, doi: 10.1109/5.989873.

[2] UEI Administration. *Monthly Energy Review, Table 2.1*. Accessed: Nov. 1, 2022. [Online]. Available: https://www.eia.gov/energyexplained/use-of-energy

[3] UEI Administration. *Monthly Energy Review*. Accessed: Nov. 1, 2022. [Online]. Available: https://www.eia.gov/todayinenergy/detail.php?id=48856

[4] UEP Agency. *U.S. Transportation Sector Greenhouse Gas Emissions 1990-2020*. Accessed: Jan. 16, 2022. [Online]. Available: https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions

[5] K. Jorgensen, "Technologies for electric, hybrid and hydrogen vehicles: Electricity from renewable energy sources in transport," *Utilities Policy*, vol. 16, no. 2, pp. 72–79, 2008.

[6] I. Irena, "Global renewables outlook: Energy transformation 2050," Int. Renew. Energy Agency, Abu Dhabi, Tech. Rep., 2020. [Online]. Available: https://www.irena.org/publications/2020/Apr/Global-Renewables-Outlook-2020

[7] Industry Steering Committee, "Electric vehicle technology roadmap for Canada: A strategic vision for highway-capable battery-electric, plug-in and other hybrid-electric vehicles," Natural Resour. Canada, Ottawa, ON, Canada, Tech. Rep., 2009.

[8] A. Tomaszewska, Z. Chu, X. Feng, S. O'kane, X. Liu, J. Chen, C. Ji, E. Endler, R. Li, L. Liu, and Y. Li, "Lithium-ion battery fast charging: A review," *ETransportation*, vol. 1, Aug. 2019, Art. no. 100011.

[9] Z. J. Zhang, W. Fang, and R. Ma, "Brief review of batteries for XEV applications," *eTransportation*, vol. 2, Nov. 2019, Art. no. 100032.

[10] M. A. Hannan, F. A. Azidin, and A. Mohamed, "Hybrid electric vehicles and their challenges: A review," *Renew. Sustain. Energy Rev.*, vol. 29, pp. 135–150, Jan. 2014.

[11] S. M. Lukic, J. Cao, R. C. Bansal, F. Rodriguez, and A. Emadi, "Energy storage systems for automotive applications," *IEEE Trans. Ind. Electron.*, vol. 55, no. 6, pp. 2258–2267, Jun. 2008.

[12] J. Wang, H. Wang, and Y. Fan, "Techno-economic challenges of fuel cell commercialization," *Engineering*, vol. 4, no. 3, pp. 352–360, Jun. 2018.

[13] D. N. How, M. A. Hannan, M. H. Lipu, and P. J. Ker, "State of charge estimation for lithium-ion batteries using model-based and data-driven methods: A review," *IEEE Access*, vol. 7, pp. 136116–136136, 2019.

[14] P. Lailler, J.-F. Sarrau, and C. Sarrazin, "Comparative study for '36 V' vehicle applications: Advantages of lead-acid batteries," *J. Power Sources*, vol. 95, nos. 1–2, pp. 58–67, 2001.

[15] X. Fan, B. Liu, J. Liu, J. Ding, X. Han, Y. Deng, X. Lv, Y. Xie, B. Chen, W. Hu, and C. Zhong, "Battery technologies for grid-level large-scale electrical energy storage," *Trans. Tianjin Univ.*, vol. 26, no. 2, pp. 92–103, Apr. 2020.

[16] K. E. Aifantis, S. A. Hackney, and R. V. Kumar, *High Energy Density Lithium Batteries*. Hoboken, NJ, USA: Wiley, 2010.

[17] P. H. Hoang, G. Ozkan, P. R. Badr, C. S. Edrington, and B. Papari, "An online degradation forecasting and abatement framework for hybrid electric vehicles," SAE Int., Troy, MI, USA, Tech. Paper 2021-01-0161, pp. 1–6, 2021, vol. 2021, doi: 10.4271/2021-01-0161.

[18] J. Belt, C. Ho, and H. David, "Long term combined cycle and calendar life testing of Johnson controls saft HP-12LC lithium ion cells," in *Proc. ECS Meeting Abstr.* Bristol, U.K.: IOP Publishing, Aug. 2008, p. 550.

[19] K. Liu, X. Hu, Z. Yang, Y. Xie, and S. Feng, "Lithium-ion battery charging management considering economic costs of electrical energy loss and battery degradation," *Energy Convers. Manage.*, vol. 195, pp. 167–179, Sep. 2019.

[20] X. Han, M. Ouyang, L. Lu, J. Li, Y. Zheng, and Z. Li, "A comparative study of commercial lithium ion battery cycle life in electrical vehicle: Aging mechanism identification," *J. Power Sources*, vol. 251, pp. 38–54, Apr. 2014.

[21] K. Xu, "Nonaqueous liquid electrolytes for lithium-based rechargeable batteries," *Chem. Rev.*, vol. 104, no. 10, pp. 4303–4418, Oct. 2004.

[22] Q. Wang, L. Jiang, Y. Yu, and J. Sun, "Progress of enhancing the safety of lithium ion battery from the electrolyte aspect," *Nano Energy*, vol. 55, pp. 93–114, Jan. 2019.

[23] Q. Li, J. Chen, L. Fan, X. Kong, and Y. Lu, "Progress in electrolytes for rechargeable li-based batteries and beyond," *Green Energy Environ.*, vol. 1, no. 1, pp. 18–42, Apr. 2016.

[24] G. Pistoia, *Lithium-Ion Batteries: Advances and Applications*. Oxford, U.K.: Newnes, 2013.

[25] V. Deimede and C. Elmasides, "Separators for lithium-ion batteries: A review on the production processes and recent developments," *Energy Technol.*, vol. 3, no. 5, pp. 453–468, May 2015.

[26] J. B. Goodenough and Y. Kim, "Challenges for rechargeable Li batteries," *Chem. Mater.*, vol. 22, pp. 587–603, Feb. 2010.

[27] N. Nitta, F. Wu, J. T. Lee, and G. Yushin, "Li-ion battery materials: Present and future," *Mater. Today*, vol. 18, no. 5, pp. 252–264, 2015.

[28] C. De Las Casas and W. Li, "A review of application of carbon nanotubes for lithium ion battery anode material," *J. Power Sources*, vol. 208, pp. 74–85, Jun. 2012.

[29] A. Yoshino, "Development of the lithium-ion battery and recent technological trends," in *Lithium-Ion Batteries*. Amsterdam, The Netherlands: Elsevier, 2014, pp. 1–20.

[30] J. Locke, "Silicon nanowires for high energy lithium-ion battery negative electrodes," Ph.D. thesis, Univ. Southampton, Southampton, U.K., 2015.

[31] F. H. Gandoman, J. Jaguemont, S. Goutam, R. Gopalakrishnan, Y. Firouz, T. Kalogiannis, N. Omar, and J. Van Mierlo, "Concept of reliability and safety assessment of lithium-ion batteries in electric vehicles: Basics, progress, and challenges," *Appl. Energy*, vol. 251, Oct. 2019, Art. no. 113343.

[32] Y. Ko, S. Lee, C. H. Kwon, S. W. Lee, and J. Cho, "Interfacial design and assembly for flexible energy electrodes with highly efficient energy harvesting, conversion, and storage," *Adv. Energy Mater.*, vol. 11, no. 27, Jul. 2021, Art. no. 2002969.

[33] F. Savoye, P. Venet, M. Millet, and J. Groot, "Impact of periodic current pulses on Li-ion battery performance," *IEEE Trans. Ind. Electron.*, vol. 59, no. 9, pp. 3481–3488, Sep. 2012.

[34] N. Sato, "Thermal behavior analysis of lithium-ion batteries for electric and hybrid vehicles," *J. Power Sources*, vol. 99, nos. 1–2, pp. 70–77, Aug. 2001.

[35] O. Erdinc, B. Vural, and M. Uzunoglu, "A dynamic lithium-ion battery model considering the effects of temperature and capacity fading," in *Proc. Int. Conf. Clean Electr. Power*, Jun. 2009, pp. 383–386.

[36] K. Smith, T. Markel, G.-H. Kim, and A. Pesaran, "Design of electric drive vehicle batteries for long life and low cost," in *Proc. Accelerated Stress Test. Rel. (ASTR), IEE Workshop*, 2010, pp. 6–8.

[37] P. H. Hoang, G. Ozkan, P. Badr, L. Timilsina, and C. Edrington, "A prognostic based control framework for hybrid electric vehicles," SAE Int., Troy, MI, USA, Tech. Paper 2022-01-0352M, 2022, vol. 2022, doi: 10.4271/2022-01-0352.

[38] I. Boudway and B. Hyperdrve. (2020). *Batteries for Electric Cars Speed Toward a Tipping Point*. [Online]. Available: https://www.bloomberg.com/news/articles/2020-12-16/electric-cars-are-about-to-be-as-cheap-as-gas-powered-models

[39] X. Han, L. Lu, Y. Zheng, X. Feng, Z. Li, J. Li, and M. Ouyang, "A review on the key issues of the lithium ion battery degradation among the whole life cycle," *eTransportation*, vol. 1, Aug. 2019, Art. no. 100005.

[40] C. R. Birkl, M. R. Roberts, E. McTurk, P. G. Bruce, and D. A. Howey, "Degradation diagnostics for lithium ion cells," *J. Power Sources*, vol. 341, pp. 373–386, Feb. 2017.

[41] M. Dubarry, C. Truchot, and B. Y. Liaw, "Synthesize battery degradation modes via a diagnostic and prognostic model," *J. Power Sources*, vol. 219, pp. 204–216, Dec. 2012.

[42] P. M. Attia, A. Bills, F. B. Planella, P. Dechent, G. Dos Reis, M. Dubarry, P. Gasper, R. Gilchrist, S. Greenbank, D. Howey, and O. Liu, "'Knees' in lithium-ion battery aging trajectories," *J. Electrochem. Soc.*, vol. 169, no. 6, 2022, Art. no. 060517.

[43] P. H. Hoang, G. Ozkan, P. R. Badr, L. Timilsina, B. Papari, and C. S. Edrington, "Integrating degradation forecasting into distribution grids' advanced distribution management systems," *Int. J. Electr. Power Energy Syst.*, vol. 150, Aug. 2023, Art. no. 109071.

[44] M. Dubarry, G. Baure, and A. Devie, "Durability and reliability of EV batteries under electric utility grid operations: Path dependence of battery degradation," *J. Electrochem. Soc.*, vol. 165, no. 5, pp. A773–A783, 2018.

[45] X. Ma, J. E. Harlow, J. Li, L. Ma, D. S. Hall, S. Buteau, M. Genovese, M. Cormier, and J. R. Dahn, "Editors' choice—Hindering rollover failure of Li[$Ni_{0.5}Mn_{0.3}Co_{0.2}$]O_2/graphite pouch cells during long-term cycling," *J. Electrochem. Soc.*, vol. 166, no. 4, pp. A711–A724, 2019.

[46] P. M. Attia, W. C. Chueh, and S. J. Harris, "Revisiting the $t^{0.5}$ dependence of SEI growth," *J. Electrochem. Soc.*, vol. 167, no. 9, Jan. 2020, Art. no. 090535.

[47] P. Fermín-Cueto, E. McTurk, M. Allerhand, E. Medina-Lopez, M. F. Anjos, J. Sylvester, and G. dos Reis, "Identification and machine learning prediction of knee-point and knee-onset in capacity degradation curves of lithium-ion cells," *Energy AI*, vol. 1, Aug. 2020, Art. no. 100006.

[48] S. Atalay, M. Sheikh, A. Mariani, Y. Merla, E. Bower, and W. D. Widanage, "Theory of battery ageing in a lithium-ion battery: Capacity fade, nonlinear ageing and lifetime prediction," *J. Power Sources*, vol. 478, Dec. 2020, Art. no. 229026.

[49] D. Müller, T. Dufaux, and K. P. Birke, "Model-based investigation of porosity profiles in graphite anodes regarding sudden-death and second-life of lithium ion cells," *Batteries*, vol. 5, no. 2, p. 49, Jun. 2019.

[50] X. Lin, J. Park, L. Liu, Y. Lee, A. M. Sastry, and W. Lu, "A comprehensive capacity fade model and analysis for Li-ion batteries," *J. Electrochem. Soc.*, vol. 160, no. 10, pp. A1701–A1710, 2013.

[51] M. Dubarry, G. Baure, and D. Anseán, "Perspective on state-of-health determination in lithium-ion batteries," *J. Electrochem. Energy Convers. Storage*, vol. 17, no. 4, Nov. 2020, Art. no. 044701.

[52] R. Fang, P. Dong, H. Ge, J. Fu, Z. Li, and J. Zhang, "Capacity plunge of lithium-ion batteries induced by electrolyte drying-out: Experimental and modeling study," *J. Energy Storage*, vol. 42, Oct. 2021, Art. no. 103013.

[53] J. S. Edge, S. O'Kane, R. Prosser, N. D. Kirkaldy, A. N. Patel, A. Hales, A. Ghosh, W. Ai, J. Chen, J. Yang, and S. Li, "Lithium ion battery degradation: What you need to know," *Phys. Chem. Chem. Phys.*, vol. 23, no. 14, pp. 8200–8221, 2021.

[54] X. Hu, L. Xu, X. Lin, and M. Pecht, "Battery lifetime prognostics," *Joule*, vol. 4, no. 2, pp. 310–346, Feb. 2020.

[55] J. Vetter, P. Novák, M. R. Wagner, C. Veit, K. C. Möller, J. O. Besenhard, M. Winter, M. Wohlfahrt-Mehrens, C. Vogler, and A. Hammouche, "Ageing mechanisms in lithium-ion batteries," *J. Power Sources*, vol. 147, nos. 1–2, pp. 269–281, Sep. 2005.

[56] R. V. Bugga and M. C. Smart, "Lithium plating behavior in lithium-ion cells," *ECS Trans.*, vol. 25, no. 36, pp. 241–252, Apr. 2010.

[57] C. Pastor-Fernández, K. Uddin, G. H. Chouchelamane, W. D. Widanage, and J. Marco, "A comparison between electrochemical impedance spectroscopy and incremental capacity-differential voltage as Li-ion diagnostic techniques to identify and quantify the effects of degradation modes within battery management systems," *J. Power Sources*, vol. 360, pp. 301–318, Aug. 2017.

[58] T. R. Tanim, E. J. Dufek, M. Evans, C. Dickerson, A. N. Jansen, B. J. Polzin, A. R. Dunlop, S. E. Trask, R. Jackman, I. Bloom, Z. Yang, and E. Lee, "Extreme fast charge challenges for lithium-ion battery: Variability and positive electrode issues," *J. Electrochem. Soc.*, vol. 166, no. 10, pp. A1926–A1938, 2019.

[59] F. Grimsmann, F. Brauchle, T. Gerbert, A. Gruhle, J. Parisi, and M. Knipper, "Impact of different aging mechanisms on the thickness change and the quick-charge capability of lithium-ion cells," *J. Energy Storage*, vol. 14, pp. 158–162, Dec. 2017.

[60] S. Ahmed, I. Bloom, A. N. Jansen, T. Tanim, E. J. Dufek, A. Pesaran, A. Burnham, R. B. Carlson, F. Dias, K. Hardy, and M. Keyser, "Enabling fast charging—A battery technology gap assessment," *J. Power Sources*, vol. 367, pp. 250–262, Nov. 2017.

[61] E. R. Logan and J. R. Dahn, "Electrolyte design for fast-charging Li-ion batteries," *Trends Chem.*, vol. 2, no. 4, pp. 354–366, Apr. 2020.

[62] P. Liu, J. Wang, J. Hicks-Garner, E. Sherman, S. Soukiazian, M. Verbrugge, H. Tataria, J. Musser, and P. Finamore, "Aging mechanisms of $LiFePO_4$ batteries deduced by electrochemical and structural analyses," *J. Electrochem. Soc.*, vol. 157, no. 4, p. A499, 2010.

[63] H. Wang, H. Wang, S. Chen, B. Zhang, G. Yang, P. Gao, J. Liu, X. Fan, Y. Huang, J. Lin, and Z. Shen, "A depth-profiling study on the solid electrolyte interface: Bis(fluorosulfuryl) imide anion toward improved K^+ storage," *ACS Appl. Energy Mater.*, vol. 2, no. 11, pp. 7942–7951, 2019.

[64] Y. Shan, L. Li, and X. Yang, "Solid-state polymer electrolyte solves the transfer of lithium ions between the solid–solid interface of the electrode and the electrolyte in lithium–sulfur and lithium-ion batteries," *ACS Appl. Energy Mater.*, vol. 4, no. 5, pp. 5101–5112, 2021.

[65] I. Laresgoiti, S. Käbitz, M. Ecker, and D. U. Sauer, "Modeling mechanical degradation in lithium ion batteries during cycling: Solid electrolyte interphase fracture," *J. Power Sources*, vol. 300, pp. 112–122, Dec. 2015.

[66] B. Xu, A. Oudalov, A. Ulbig, G. Andersson, and D. S. Kirschen, "Modeling of lithium-ion battery degradation for cell life assessment," *IEEE Trans. Smart Grid*, vol. 9, no. 2, pp. 1131–1140, Mar. 2018.

[67] M. Broussely, P. Biensan, F. Bonhomme, P. Blanchard, S. Herreyre, K. Nechev, and R. J. Staniewicz, "Main aging mechanisms in Li ion batteries," *J. Power Sources*, vol. 146, no. 1, pp. 90–96, 2005.

[68] X. Lin, K. Khosravinia, X. Hu, J. Li, and W. Lu, "Lithium plating mechanism, detection, and mitigation in lithium-ion batteries," *Prog. Energy Combustion Sci.*, vol. 87, Nov. 2021, Art. no. 100953.

[69] P. Arora, M. Doyle, and R. E. White, "Mathematical modeling of the lithium deposition overcharge reaction in lithium-ion batteries using carbon-based negative electrodes," *J. Electrochem. Soc.*, vol. 146, no. 10, p. 3543, 1999.

[70] N. Legrand, B. Knosp, P. Desprez, F. Lapicque, and S. Raël, "Physical characterization of the charging process of a Li-ion battery and prediction of li plating by electrochemical modelling," *J. Power Sources*, vol. 245, pp. 208–216, Jan. 2014.

[71] R. Chandrasekaran, "Quantification of bottlenecks to fast charging of lithium-ion-insertion cells for electric vehicles," *J. Power Sources*, vol. 271, pp. 622–632, Jul. 2014.
[72] S. Hein and A. Latz, "Influence of local lithium metal deposition in 3D microstructures on local and global behavior of lithium-ion batteries," *Electrochimica Acta*, vol. 201, pp. 354–365, May 2016.
[73] H. Wang, Y. Zhu, S. C. Kim, A. Pei, Y. Li, D. T. Boyle, H. Wang, Z. Zhang, Y. Ye, W. Huang, Y. Liu, J. Xu, J. Li, F. Liu, and Y. Cui, "Underpotential lithium plating on graphite anodes caused by temperature heterogeneity," *Proc. Nat. Acad. Sci. USA*, vol. 117, no. 47, pp. 29453–29461, Nov. 2020.
[74] S. J. Harris, A. Timmons, D. R. Baker, and C. Monroe, "Direct in situ measurements of Li transport in Li-ion battery negative electrodes," *Chem. Phys. Lett.*, vol. 485, nos. 4–6, pp. 265–274, Jan. 2010.
[75] T. Gao, Y. Han, D. Fraggedakis, S. Das, T. Zhou, C.-N. Yeh, S. Xu, W. C. Chueh, J. Li, and M. Z. Bazant, "Interplay of lithium intercalation and plating on a single graphite particle," *Joule*, vol. 5, no. 2, pp. 393–414, Feb. 2021.
[76] T. Guan, S. Sun, F. Yu, Y. Gao, P. Fan, P. Zuo, C. Du, and G. Yin, "The degradation of $LiCoO_2$/graphite batteries at different rates," *Electrochimica Acta*, vol. 279, pp. 204–212, Jul. 2018.
[77] L. Gireaud, S. Grugeon, S. Laruelle, B. Yrieix, and J.-M. Tarascon, "Lithium metal stripping/plating mechanisms studies: A metallurgical approach," *Electrochem. Commun.*, vol. 8, no. 10, pp. 1639–1649, Oct. 2006.
[78] H. Ge, T. Aoki, N. Ikeda, S. Suga, T. Isobe, Z. Li, Y. Tabuchi, and J. Zhang, "Investigating lithium plating in lithium-ion batteries at low temperatures using electrochemical model with NMR assisted parameterization," *J. Electrochem. Soc.*, vol. 164, no. 6, pp. A1050–A1060, 2017.
[79] D. Ouyang, Y. He, J. Weng, J. Liu, M. Chen, and J. Wang, "Influence of low temperature conditions on lithium-ion batteries and the application of an insulation material," *RSC Adv.*, vol. 9, no. 16, pp. 9053–9066, 2019.
[80] J. Jaguemont, L. Boulon, and Y. Dubé, "A comprehensive review of lithium-ion batteries used in hybrid and electric vehicles at cold temperatures," *Appl. Energy*, vol. 164, pp. 99–114, Feb. 2016.
[81] L. Zhang, Z. Zhang, P. C. Redfern, L. A. Curtiss, and K. Amine, "Molecular engineering towards safer lithium-ion batteries: A highly stable and compatible redox shuttle for overcharge protection," *Energy Environ. Sci.*, vol. 5, no. 8, pp. 8204–8207, 2012.
[82] D. Juarez-Robles, A. A. Vyas, C. Fear, J. A. Jeevarajan, and P. P. Mukherjee, "Overcharge and aging analytics of Li-ion cells," *J. Electrochem. Soc.*, vol. 167, no. 9, Jan. 2020, Art. no. 090547.
[83] M. Ecker, P. Shafiei Sabet, and D. U. Sauer, "Influence of operational condition on lithium plating for commercial lithium-ion batteries – electrochemical experiments and post-mortem-analysis," *Appl. Energy*, vol. 206, pp. 934–946, Nov. 2017.
[84] M. Kerlau, M. Marcinek, V. Srinivasan, and R. M. Kostecki, "Reprint of 'studies of local degradation phenomena in composite cathodes for lithium-ion batteries,'" *Electrochimica Acta*, vol. 53, no. 3, pp. 1385–1392, 2007.
[85] Y. Xia, Y. Zhou, and M. Yoshio, "Capacity fading on cycling of 4 VLi/$LiMn_2O4$ cells," *J. Electrochem. Soc.*, vol. 144, no. 8, pp. 2593–2600, Aug. 1997.
[86] H. Zheng, Q. Sun, G. Liu, X. Song, and V. S. Battaglia, "Correlation between dissolution behavior and electrochemical cycling performance for $LiNi_{1/3}Co_{1/3}Mn_{1/3}O_2$-based cells," *J. Power Sources*, vol. 207, pp. 134–140, Jun. 2012.
[87] N. Sharma, V. K. Peterson, M. M. Elcombe, M. Avdeev, A. J. Studer, N. Blagojevic, R. Yusoff, and N. Kamarulzaman, "Structural changes in a commercial lithium-ion battery during electrochemical cycling: An in situ neutron diffraction study," *J. Power Sources*, vol. 195, no. 24, pp. 8258–8266, Dec. 2010.
[88] G.-A. Nazri and G. Pistoia, *Lithium Batteries: Science and Technology*. Elsevier, 2008.
[89] N. Omar, M. A. Monem, Y. Firouz, J. Salminen, J. Smekens, O. Hegazy, H. Gaulous, G. Mulder, P. Van den Bossche, T. Coosemans, and J. Van Mierlo, "Lithium iron phosphate based battery—Assessment of the aging parameters and development of cycle life model," *Appl. Energy*, vol. 113, pp. 1575–1585, Jan. 2014.
[90] S. Saxena, Y. Xing, D. Kwon, and M. Pecht, "Accelerated degradation model for C-rate loading of lithium-ion batteries," *Int. J. Elect. Power Energy Syst.*, vol. 107, pp. 438–445, May 2019.
[91] M. Kassem and C. Delacourt, "Postmortem analysis of calendar-aged graphite/$LiFePO_4$ cells," *J. Power Sources*, vol. 235, pp. 159–171, Aug. 2013.
[92] E. V. Thomas, I. Bloom, J. P. Christophersen, and V. S. Battaglia, "Statistical methodology for predicting the life of lithium-ion cells via accelerated degradation testing," *J. Power Sources*, vol. 184, no. 1, pp. 312–317, Sep. 2008.
[93] A. Eddahech, O. Briat, E. Woirgard, and J. M. Vinassa, "Remaining useful life prediction of lithium batteries in calendar ageing for automotive applications," *Microelectron. Rel.*, vol. 52, no. 9, pp. 2438–2442, Sep. 2012.
[94] M. Dubarry, N. Qin, and P. Brooker, "Calendar aging of commercial Li-ion cells of different chemistries—A review," *Current Opinion Electrochem.*, vol. 9, pp. 106–113, Jun. 2018.
[95] M. Ecker, N. Nieto, S. Käbitz, J. Schmalstieg, H. Blanke, A. Warnecke, and D. U. Sauer, "Calendar and cycle life study of Li(NiMnCo)O_2-based 18650 lithium-ion batteries," *J. Power Sources*, vol. 248, pp. 839–851, Feb. 2014.
[96] I. Bloom, B. W. Cole, J. J. Sohn, S. A. Jones, E. G. Polzin, V. S. Battaglia, G. L. Henriksen, C. Motloch, R. Richardson, T. Unkelhaeuser, and D. Ingersoll, "An accelerated calendar and cycle life study of Li-ion cells," *J. Power Sources*, vol. 101, no. 2, pp. 238–247, Oct. 2001.
[97] B. Y. Liaw, E. P. Roth, R. G. Jungst, G. Nagasubramanian, H. L. Case, and D. H. Doughty, "Correlation of Arrhenius behaviors in power and capacity fades with cell impedance and heat generation in cylindrical lithium-ion cells," *J. Power Sources*, vols. 119–121, pp. 874–886, Jun. 2003.
[98] J. Shim, R. Kostecki, T. Richardson, X. Song, and K. A. Striebel, "Electrochemical analysis for cycle performance and capacity fading of a lithium-ion battery cycled at elevated temperature," *J. Power sources*, vol. 112, no. 1, pp. 222–230, 2002.
[99] R. B. Wright, C. G. Motloch, J. R. Belt, J. P. Christophersen, C. D. Ho, R. A. Richardson, I. Bloom, S. A. Jones, V. S. Battaglia, G. L. Henriksen, and T. Unkelhaeuser, "Calendar-and cycle-life studies of advanced technology development program generation 1 lithium-ion batteries," *J. Power Sources*, vol. 110, no. 2, pp. 445–470, 2002.
[100] E. Sarasketa-Zabala, I. Gandiaga, L. M. Rodriguez-Martinez, and I. Villarreal, "Calendar ageing analysis of a $LiFePO_4$/graphite cell with dynamic model validations: Towards realistic lifetime predictions," *J. Power Sources*, vol. 272, pp. 45–57, Dec. 2014.
[101] S. Pelletier, O. Jabali, G. Laporte, and M. Veneroni, "Battery degradation and behaviour for electric vehicles: Review and numerical analyses of several models," *Transp. Res. B, Methodol.*, vol. 103, pp. 158–187, Sep. 2017.
[102] E. Sarasketa-Zabala, I. Laresgoiti, I. Alava, M. Rivas, I. Villarreal, and F. Blanco, "Validation of the methodology for lithium-ion batteries lifetime prognosis," in *Proc. World Electric Vehicle Symp. Exhib. (EVS)*, Nov. 2013, pp. 1–12.
[103] S. Bashash, S. J. Moura, J. C. Forman, and H. K. Fathy, "Plug-in hybrid electric vehicle charge pattern optimization for energy cost and battery longevity," *J. Power Sources*, vol. 196, no. 1, pp. 541–549, Jan. 2011.
[104] J. Belt, V. Utgikar, and I. Bloom, "Calendar and PHEV cycle life aging of high-energy, lithium-ion cells containing blended spinel and layered-oxide cathodes," *J. Power Sources*, vol. 196, no. 23, pp. 10213–10221, Dec. 2011.
[105] M. Naumann, M. Schimpe, P. Keil, H. C. Hesse, and A. Jossen, "Analysis and modeling of calendar aging of a commercial $LiFePO_4$/graphite cell," *J. Energy Storage*, vol. 17, pp. 153–169, Jun. 2018.
[106] E. Prada, D. Di Domenico, Y. Creff, J. Bernard, V. Sauvant-Moynot, and F. Huet, "A simplified electrochemical and thermal aging model of $LiFePO_4$-graphite Li-ion batteries: Power and capacity fade simulations," *J. Electrochem. Soc.*, vol. 160, no. 4, pp. A616–A628, 2013.
[107] S. Grolleau, A. Delaille, H. Gualous, P. Gyan, R. Revel, J. Bernard, E. Redondo-Iglesias, and J. Peter, "Calendar aging of commercial graphite/$LiFePO_4$ cell—Predicting capacity fade under time dependent storage conditions," *J. Power Sources*, vol. 255, pp. 450–458, Jun. 2014.
[108] M. Safari and C. Delacourt, "Aging of a commercial graphite/$LiFePO_4$ cell," *J. Electrochem. Soc.*, vol. 158, no. 10, p. A1123, 2011.
[109] N. Ogihara, Y. Itou, T. Sasaki, and Y. Takeuchi, "Impedance spectroscopy characterization of porous electrodes under different electrode thickness using a symmetric cell for high-performance lithium-ion batteries," *J. Phys. Chem. C*, vol. 119, no. 9, pp. 4612–4619, Mar. 2015.
[110] T. Momma, T. Yokoshima, H. Nara, Y. Gima, and T. Osaka, "Distinction of impedance responses of Li-ion batteries for individual electrodes using symmetric cells," *Electrochimica Acta*, vol. 131, pp. 195–201, Jun. 2014.
[111] M. Ecker, J. B. Gerschler, J. Vogel, S. Käbitz, F. Hust, P. Dechent, and D. U. Sauer, "Development of a lifetime prediction model for lithium-ion batteries based on extended accelerated aging test data," *J. Power Sources*, vol. 215, pp. 248–257, Oct. 2012.

[112] X. Wei, B. Zhu, and W. Xu, "Internal resistance identification in vehicle power lithium-ion battery and application in lifetime evaluation," in *Proc. Int. Conf. Measuring Technol. Mechatronics Autom.*, 2009, pp. 388–392.

[113] M. Dubarry, V. Svoboda, R. Hwu, and B. Y. Liaw, "Capacity and power fading mechanism identification from a commercial cell evaluation," *J. Power Sources*, vol. 165, no. 2, pp. 566–572, 2007.

[114] D. J. Noelle, M. Wang, A. V. Le, Y. Shi, and Y. Qiao, "Internal resistance and polarization dynamics of lithium-ion batteries upon internal shorting," *Appl. Energy*, vol. 212, pp. 796–808, Feb. 2018.

[115] R. Kostecki and F. McLarnon, "Microprobe study of the effect of Li intercalation on the structure of graphite," *J. Power Sources*, vols. 119–121, pp. 550–554, Jun. 2003.

[116] T. Waldmann, M. Wilka, M. Kasper, M. Fleischhammer, and M. Wohlfahrt-Mehrens, "Temperature dependent ageing mechanisms in lithium-ion batteries—A post-mortem study," *J. Power Sources*, vol. 262, pp. 129–135, Sep. 2014.

[117] K. Uddin, S. Perera, W. Widanage, L. Somerville, and J. Marco, "Characterising lithium-ion battery degradation through the identification and tracking of electrochemical battery model parameters," *Batteries*, vol. 2, no. 2, p. 13, 2016.

[118] G. Sarre, P. Blanchard, and M. Broussely, "Aging of lithium-ion batteries," *J. Power Sources*, vol. 127, nos. 1–2, pp. 65–71, 2004.

[119] M. S. D. Darma, M. Lang, K. Kleiner, L. Mereacre, V. Liebau, F. Fauth, T. Bergfeldt, and H. Ehrenberg, "The influence of cycling temperature and cycling rate on the phase specific degradation of a positive electrode in lithium ion batteries: A post mortem analysis," *J. Power Sources*, vol. 327, pp. 714–725, Sep. 2016.

[120] G. M. Ehrlich, "Lithium-ion batteries," *Handbook Batteries*, vol. 3. New York, NY, USA: McGraw-Hill, 2002.

[121] M. R. Palacín, "Understanding ageing in Li-ion batteries: A chemical issue," *Chem. Soc. Rev.*, vol. 47, no. 13, pp. 4924–4933, 2018.

[122] T. Amietszajew, E. McTurk, J. Fleming, and R. Bhagat, "Understanding the limits of rapid charging using instrumented commercial 18650 high-energy Li-ion cells," *Electrochimica Acta*, vol. 263, pp. 346–352, Feb. 2018.

[123] J. Li, E. Murphy, J. Winnick, and P. A. Kohl, "Studies on the cycle life of commercial lithium ion batteries during rapid charge–discharge cycling," *J. Power Sources*, vol. 102, nos. 1–2, pp. 294–301, Dec. 2001.

[124] M. Ouyang, D. Ren, L. Lu, J. Li, X. Feng, X. Han, and G. Liu, "Overcharge-induced capacity fading analysis for large format lithium-ion batteries with $Li_yNi_{1/3}Co_{1/3}Mn_{1/3}O_2$+$Li_yMn_2O_4$ composite cathode," *J. Power Sources*, vol. 279, pp. 626–635, Apr. 2015.

[125] M. Dubarry, C. Truchot, and B. Y. Liaw, "Cell degradation in commercial $LiFePO_4$ cells with high-power and high-energy designs," *J. Power Sources*, vol. 258, pp. 408–419, Jul. 2014.

[126] X. G. Yang, G. Zhang, S. Ge, and C. Y. Wang, "Fast charging of lithium-ion batteries at all temperatures," *Proc. Nat. Acad. Sci. USA*, vol. 115, no. 28, pp. 7266–7271, Jul. 2018.

[127] A. Yang, Y. Wang, F. Yang, D. Wang, Y. Zi, K. L. Tsui, and B. Zhang, "A comprehensive investigation of lithium-ion battery degradation performance at different discharge rates," *J. Power Sources*, vol. 443, Dec. 2019, Art. no. 227108.

[128] M. R. Jongerden and B. R. Haverkort, "Battery aging, battery charging and the kinetic battery model: A first exploration," in *Proc. Int. Conf. Quant. Eval. Syst.* Cham, Switzerland: Springer, 2017, pp. 88–103.

[129] X. Xu, Z. Li, and N. Chen, "A hierarchical model for lithium-ion battery degradation prediction," *IEEE Trans. Rel.*, vol. 65, no. 1, pp. 310–325, Mar. 2016.

[130] F. Yang, D. Wang, Y. Zhao, K.-L. Tsui, and S. J. Bae, "A study of the relationship between Coulombic efficiency and capacity degradation of commercial lithium-ion batteries," *Energy*, vol. 145, pp. 486–495, Feb. 2018.

[131] A. Perez, V. Quintero, F. Jaramillo, H. Rozas, D. Jimenez, M. Orchard, and R. Moreno, "Characterization of the degradation process of lithium-ion batteries when discharged at different current rates," *Proc. Inst. Mech. Eng., I, J. Syst. Control Eng.*, vol. 232, no. 8, pp. 1075–1089, Aug. 2018.

[132] G. Ning, B. Haran, and B. N. Popov, "Capacity fade study of lithium-ion batteries cycled at high discharge rates," *J. Power Sources*, vol. 117, nos. 1–2, pp. 160–169, 2003.

[133] F. Sun, R. Xiong, H. He, W. Li, and J. E. E. Aussems, "Model-based dynamic multi-parameter method for peak power estimation of lithium–ion batteries," *Appl. Energy*, vol. 96, pp. 378–386, Aug. 2012.

[134] L. E. Downie, L. J. Krause, J. C. Burns, L. D. Jensen, V. L. Chevrier, and J. R. Dahn, "In situ detection of lithium plating on graphite electrodes by electrochemical calorimetry," *J. Electrochem. Soc.*, vol. 160, no. 4, pp. A588–A594, 2013.

[135] E. Cripps and M. Pecht, "A Bayesian nonlinear random effects model for identification of defective batteries from lot samples," *J. Power Sources*, vol. 342, pp. 342–350, Feb. 2017.

[136] Y. Wu, P. Keil, S. F. Schuster, and A. Jossen, "Impact of temperature and discharge rate on the aging of a $LiCoO_2$/$LiNi_{0.8}Co_{0.15}Al_{0.05}O_2$ lithium-ion pouch cell," *J. Electrochem. Soc.*, vol. 164, no. 7, p. A1438, 2017.

[137] J. Lindgren and P. D. Lund, "Effect of extreme temperatures on battery charging and performance of electric vehicles," *J. Power Sources*, vol. 328, pp. 37–45, Oct. 2016.

[138] A. Hausmann and C. Depcik, "Expanding the Peukert equation for battery capacity modeling through inclusion of a temperature dependency," *J. Power Sources*, vol. 235, pp. 148–158, Aug. 2013.

[139] T. R. Tanim, M. G. Shirk, R. L. Bewley, E. J. Dufek, and B. Y. Liaw, "Fast charge implications: Pack and cell analysis and comparison," *J. Power Sources*, vol. 381, pp. 56–65, Mar. 2018.

[140] S. C. Nagpure, B. Bhushan, S. Babu, and G. Rizzoni, "Scanning spreading resistance characterization of aged Li-ion batteries using atomic force microscopy," *Scripta Mater.*, vol. 60, no. 11, pp. 933–936, Jun. 2009.

[141] A. Laforgue, X.-Z. Yuan, A. Platt, S. Brueckner, F. Perrin-Sarazin, M. Toupin, J.-Y. Huot, and A. Mokrini, "Effects of fast charging at low temperature on a high energy Li-ion battery," *J. Electrochem. Soc.*, vol. 167, no. 14, Nov. 2020, Art. no. 140521.

[142] D. D. Patel, F. P. Tredeau, and Z. M. Salameh, "Temperature effects on fast charging large format prismatic lithium iron phosphate cells," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2010, pp. 1–4.

[143] R. Mathieu, O. Briat, P. Gyan, and J.-M. Vinassa, "Comparison of the impact of fast charging on the cycle life of three lithium-ion cells under several parameters of charge protocol and temperatures," *Appl. Energy*, vol. 283, Feb. 2021, Art. no. 116344.

[144] S. Mothilal Bhagavathy, H. Budnitz, T. Schwanen, and M. McCulloch, "Impact of charging rates on electric vehicle battery life," *Findings*, vol. 2021, pp. 1–5, Mar. 2021.

[145] G. Nagasubramanian, "Electrical characteristics of 18650 Li-ion cells at low temperatures," *J. Appl. Electr.*, vol. 31, no. 1, pp. 99–104, Jan. 2001.

[146] M.-T. Fonseca Rodrigues, V. A. Maroni, D. J. Gosztola, K. P. C. Yao, K. Kalaga, I. A. Shkrob, and D. P. Abraham, "Lithium acetylide: A spectroscopic marker for lithium deposition during fast charging of Li-ion cells," *ACS Appl. Energy Mater.*, vol. 2, no. 1, pp. 873–881, Jan. 2019.

[147] A. S. Mussa, A. Liivat, F. Marzano, M. Klett, B. Philippe, C. Tengstedt, G. Lindbergh, K. Edström, R. W. Lindström, and P. Svens, "Fast-charging effects on ageing for energy-optimized automotive $LiNi_{1/3}Mn_{1/3}Co_{1/3}O_2$/graphite prismatic lithium-ion cells," *J. Power Sources*, vol. 422, pp. 175–184, May 2019.

[148] V. Agarwal, K. Uthaichana, R. A. DeCarlo, and L. H. Tsoukalas, "Development and validation of a battery model useful for discharging and charging power control and lifetime estimation," *IEEE Trans. Energy Convers.*, vol. 25, no. 3, pp. 821–835, Sep. 2010.

[149] O. D. Momoh and M. O. Omoigui, "An overview of hybrid electric vehicle technology," in *Proc. IEEE Vehicle Power Propuls. Conf.*, Sep. 2009, pp. 1286–1292.

[150] A. Laforgue, X.-Z. Yuan, A. Platt, S. Brueckner, F. Perrin-Sarazin, M. Toupin, J.-Y. Huot, and A. Mokrini, "Comparative investigation of the impact of fast charging at low temperature on commercial Li-ion cells," *J. Power Sources*, vol. 524, Mar. 2022, Art. no. 231071.

[151] S. Xie, S. Qi, and K. Lang, "A data-driven power management strategy for plug-in hybrid electric vehicles including optimal battery depth of discharging," *IEEE Trans. Ind. Informat.*, vol. 16, no. 5, pp. 3387–3396, May 2020.

[152] J. D. K. Bishop, C. J. Axon, D. Bonilla, M. Tran, D. Banister, and M. D. McCulloch, "Evaluating the impact of V2G services on the degradation of batteries in PHEV and EV," *Appl. Energy*, vol. 111, pp. 206–218, Nov. 2013.

[153] J. R. Belt, C. D. Ho, C. G. Motloch, T. J. Miller, and T. Q. Duong, "A capacity and power fade study of Li-ion cells during life cycle testing," *J. Power Sources*, vol. 123, no. 2, pp. 241–246, Sep. 2003.

[154] J. Wang, P. Liu, J. Hicks-Garner, E. Sherman, S. Soukiazian, M. Verbrugge, H. Tataria, J. Musser, and P. Finamore, "Cycle-life model for graphite-$LiFePO_4$ cells," *J. Power Sources*, vol. 196, no. 8, pp. 3942–3948, Apr. 2011.

[155] T. Guena and P. Leblanc, "How depth of discharge affects the cycle life of lithium-metal-polymer batteries," in *Proc. 28th Int. Telecommun. Energy Conf. (INTELEC)*, Sep. 2006, pp. 1–8.
[156] C. H. Chen, J. Liu, and K. Amine, "Symmetric cell approach and impedance spectroscopy of high power lithium-ion batteries," *J. Power Sources*, vol. 96, no. 2, pp. 321–328, Jun. 2001.
[157] D. P. Abraham, J. L. Knuth, D. W. Dees, I. Bloom, and J. P. Christophersen, "Performance degradation of high-power lithium-ion cells—Electrochemistry of harvested electrodes," *J. Power Sources*, vol. 170, no. 2, pp. 465–475, Jul. 2007.
[158] Y. Zhang and C.-Y. Wang, "Cycle-life characterization of automotive lithium-ion batteries with $LiNiO_2$ cathode," *J. Electrochem. Soc.*, vol. 156, no. 7, p. A527, 2009.
[159] A. Millner, "Modeling lithium ion battery degradation in electric vehicles," in *Proc. IEEE Conf. Innov. Technol. Efficient Reliable Electr. Supply*, Sep. 2010, pp. 349–356.
[160] P. Arora, R. E. White, and M. Doyle, "Capacity fade mechanisms and side reactions in lithium-ion batteries," *J. Electrochem. Soc.*, vol. 145, no. 10, p. 3647, 1998.
[161] T. M. Bandhauer, S. Garimella, and T. F. Fuller, "A critical review of thermal issues in lithium-ion batteries," *J. Electrochem. Soc.*, vol. 158, no. 3, p. R1, 2011.
[162] X. Zhang, B. Winget, M. Doeff, J. W. Evans, and T. M. Devine, "Corrosion of aluminum current collectors in lithium-ion batteries with electrolytes containing $LiPF_6$," *J. Electrochem. Soc.*, vol. 152, no. 11, p. B448, 2005.
[163] S.-T. Myung, Y. Hitoshi, and Y.-K. Sun, "Electrochemical behavior and passivation of current collectors in lithium-ion batteries," *J. Mater. Chem.*, vol. 21, no. 27, pp. 9891–9911, 2011.
[164] E. Wood, M. Alexander, and T. H. Bradley, "Investigation of battery end-of-life conditions for plug-in hybrid electric vehicles," *J. Power Sources*, vol. 196, no. 11, pp. 5147–5154, 2011.
[165] F. Leng, C. M. Tan, and M. Pecht, "Effect of temperature on the aging rate of li ion battery operating above room temperature," *Sci. Rep.*, vol. 5, no. 1, pp. 1–12, Aug. 2015.
[166] K. Amine, J. Liu, and I. Belharouak, "High-temperature storage and cycling of C-$LiFePO_4$/graphite Li-ion cells," *Electrochem. Commun.*, vol. 7, no. 7, pp. 669–673, Jul. 2005.
[167] B. Ng, P. T. Coman, E. Faegh, X. Peng, S. G. Karakalos, X. Jin, W. E. Mustain, and R. E. White, "Low-temperature lithium plating/corrosion hazard in lithium-ion batteries: Electrode rippling, variable states of charge, and thermal and nonthermal runaway," *ACS Appl. Energy Mater.*, vol. 3, no. 4, pp. 3653–3664, Apr. 2020.
[168] L. Bodenes, R. Naturel, H. Martinez, R. Dedryvère, M. Menetrier, L. Croguennec, J.-P. Pérès, C. Tessier, and F. Fischer, "Lithium secondary batteries working at very high temperature: Capacity fade and understanding of aging mechanisms," *J. Power Sources*, vol. 236, pp. 265–275, Aug. 2013.
[169] L. Tan, L. Zhang, Q. Sun, M. Shen, Q. Qu, and H. Zheng, "Capacity loss induced by lithium deposition at graphite anode for $LiFePO_4$/graphite cell cycling at different temperatures," *Electrochimica Acta*, vol. 111, pp. 802–808, Nov. 2013.
[170] M. Dubarry, B. Y. Liaw, M. S. Chen, S. S. Chyan, K. C. Han, W. T. Sie, and S. H. Wu, "Identifying battery aging mechanisms in large format Li ion cells," *J. Power Sources*, vol. 196, no. 7, pp. 3420–3425, 2011.
[171] Y. Zhang, C.-Y. Wang, and X. Tang, "Cycling degradation of an automotive $LiFePO_4$ lithium-ion battery," *J. Power Sources*, vol. 196, no. 3, pp. 1513–1520, Feb. 2011.
[172] D. Zhang, B. S. Haran, A. Durairajan, R. E. White, Y. Podrazhansky, and B. N. Popov, "Studies on capacity fade of lithium-ion batteries," *J. Power Sources*, vol. 91, no. 2, pp. 122–129, Dec. 2000.
[173] W. He, N. Williard, M. Osterman, and M. Pecht, "Prognostics of lithium-ion batteries based on Dempster–Shafer theory and the Bayesian Monte Carlo method," *J. Power Sources*, vol. 196, pp. 10314–10321, Dec. 2011.
[174] C. Vidal, O. Gross, R. Gu, P. Kollmeyer, and A. Emadi, "XEV Li-ion battery low-temperature effects—Review," *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 4560–4572, May 2019.
[175] R. B. Wright, J. P. Christophersen, C. G. Motloch, J. R. Belt, C. D. Ho, V. S. Battaglia, J. A. Barnes, T. Q. Duong, and R. A. Sutula, "Power fade and capacity fade resulting from cycle-life testing of advanced technology development program lithium-ion batteries," *J. Power Sources*, vol. 119, pp. 865–869, Jun. 2003.
[176] D. Anseán, M. Dubarry, A. Devie, B. Y. Liaw, V. M. García, J. C. Viera, and M. González, "Operando lithium plating quantification and early detection of a commercial $LiFePO_4$ cell cycled under dynamic driving schedule," *J. Power Sources*, vol. 356, pp. 36–46, Jul. 2017.
[177] M. Kassem, J. Bernard, R. Revel, S. Pélissier, F. Duclaud, and C. Delacourt, "Calendar aging of a graphite/$LiFePO_4$ cell," *J. Power Sources*, vol. 208, pp. 296–305, Jun. 2012.
[178] Z. Lu, X. L. Yu, L. C. Wei, F. Cao, L. Y. Zhang, X. Z. Meng, and L. W. Jin, "A comprehensive experimental study on temperature-dependent performance of lithium-ion battery," *Appl. Thermal Eng.*, vol. 158, Jul. 2019, Art. no. 113800.
[179] C. Suarez and W. Martinez, "Fast and ultra-fast charging for battery electric vehicles – a review," in *Proc. IEEE Energy Convers. Congr. Expo. (ECCE)*, Sep. 2019, pp. 569–575.
[180] A. Hackbarth and R. Madlener, "Consumer preferences for alternative fuel vehicles: A discrete choice analysis," *Transp. Res. D, Transp. Environ.*, vol. 25, pp. 5–17, Dec. 2013.
[181] S. Carley, R. M. Krause, B. W. Lane, and J. D. Graham, "Intent to purchase a plug-in electric vehicle: A survey of early impressions in large U.S. cites," *Transp. Res. D, Transp. Environ.*, vol. 18, pp. 39–45, Jan. 2013.
[182] R. Collin, Y. Miao, A. Yokochi, P. Enjeti, and A. Von Jouanne, "Advanced electric vehicle fast-charging technologies," *Energies*, vol. 12, no. 10, p. 1839, May 2019.
[183] C. Dericioglu, E. Yirik, E. Unal, M. Cuma, B. Onur, and M. Tumay, "A review of charging technologies for commercial electric vehicles," *Int. J. Adv. Automot. Technol.*, vol. 2, no. 1, pp. 61–70, 2018.
[184] C. Botsford and A. Szczepanek, "Fast charging vs. slow charging: Pros and cons for the new age of electric vehicles," in *Proc. Int. Battery Hybrid Fuel Cell Electric Vehicle Symp.* Princeton, NJ, USA: Citeseer, 2009, pp. 1–9.
[185] J. Sears, D. Roberts, and K. Glitman, "A comparison of electric vehicle level 1 and level 2 charging efficiency," in *Proc. IEEE Conf. Technol. Sustainability (SusTech)*, Jul. 2014, pp. 255–258.
[186] Y. Zhang, R. Xiong, H. He, X. Qu, and M. Pecht, "Aging characteristics-based health diagnosis and remaining useful life prognostics for lithium-ion batteries," *eTransportation*, vol. 1, Aug. 2019, Art. no. 100004.
[187] S. M. Rezvanizaniani, Z. Liu, Y. Chen, and J. Lee, "Review and recent advances in battery health monitoring and prognostics technologies for electric vehicle (EV) safety and mobility," *J. Power Sources*, vol. 256, pp. 110–124, Jun. 2014.
[188] L. Wu, X. Fu, and Y. Guan, "Review of the remaining useful life prognostics of vehicle lithium-ion batteries using data-driven methodologies," *Appl. Sci.*, vol. 6, no. 6, p. 166, 2016.
[189] A. T. Stamps, C. E. Holland, R. E. White, and E. P. Gatzke, "Analysis of capacity fade in a lithium ion battery," *J. Power Sources*, vol. 150, pp. 229–239, Oct. 2005.
[190] K. Goebel, B. Saha, A. Saxena, J. R. Celaya, and J. P. Christophersen, "Prognostics in battery health management," *IEEE Instrum. Meas. Mag.*, vol. 11, no. 4, pp. 33–40, Aug. 2008.
[191] Z. Yun and W. Qin, "Remaining useful life estimation of lithium-ion batteries based on optimal time series health indicator," *IEEE Access*, vol. 8, pp. 55447–55461, 2020.
[192] J. Yang, B. Xia, W. Huang, Y. Fu, and C. Mi, "Online state-of-health estimation for lithium-ion batteries using constant-voltage charging current analysis," *Appl. Energy*, vol. 212, pp. 1589–1600, Feb. 2018.
[193] B. Chinomona, C. Chung, L.-K. Chang, W.-C. Su, and M.-C. Tsai, "Long short-term memory approach to estimate battery remaining useful life using partial data," *IEEE Access*, vol. 8, pp. 165419–165431, 2020.
[194] M. Dubarry and D. Beck, "Big data training data for artificial intelligence-based Li-ion diagnosis and prognosis," *J. Power Sources*, vol. 479, Dec. 2020, Art. no. 228806.
[195] D. Zhang, S. Dey, H. E. Perez, and S. J. Moura, "Remaining useful life estimation of lithium-ion batteries based on thermal dynamics," in *Proc. Amer. Control Conf. (ACC)*, May 2017, pp. 4042–4047.
[196] M. Aykol, C. B. Gopal, A. Anapolsky, P. K. Herring, B. van Vlijmen, M. D. Berliner, M. Z. Bazant, R. D. Braatz, W. C. Chueh, and B. D. Storey, "Perspective—Combining physics and machine learning to predict battery lifetime," *J. Electrochem. Soc.*, vol. 168, no. 3, Mar. 2021, Art. no. 030525.
[197] D. J. Tait, F. B. Planella, T. Damoulas, and W. D. Widanage, "Scalable multitask latent force models with applications to predicting lithium-ion concentration," in *Proc. NeurIPS*, 2020, pp. 1–13.

[198] V. Sulzer, P. Mohtat, A. Aitio, S. Lee, Y. T. Yeh, F. Steinbacher, M. U. Khan, J. W. Lee, J. B. Siegel, A. G. Stefanopoulou, and D. A. Howey, "The challenge and opportunity of battery lifetime prediction from field data," *Joule*, vol. 5, no. 8, pp. 1934–1955, Aug. 2021.

[199] Z. Song, H. Hofmann, J. Li, J. Hou, X. Han, and M. Ouyang, "Energy management strategies comparison for electric vehicles with hybrid energy storage system," *Appl. Energy*, vol. 134, pp. 321–331, Dec. 2014.

[200] L. Chen, Y. Tong, and Z. Dong, "Li-ion battery performance degradation modeling for the optimal design and energy management of electrified propulsion systems," *Energies*, vol. 13, no. 7, p. 1629, Apr. 2020.

[201] M. Safari, M. Morcrette, A. Teyssot, and C. Delacourt, "Life-prediction methods for lithium-ion batteries derived from a fatigue approach: I. Introduction: Capacity-loss prediction based on damage accumulation," *J. Electrochem. Soc.*, vol. 157, no. 6, p. A713, 2010.

[202] J. Ruan, B. Zhang, B. Liu, and S. Wang, "The multi-objective optimization of cost, energy consumption and battery degradation for fuel cell-battery hybrid electric vehicle," in *Proc. 11th Int. Conf. Power, Energy Electr. Eng. (CPEEE)*, Feb. 2021, pp. 50–55.

[203] A. Guha, A. Patra, and K. V. Vaisakh, "Remaining useful life estimation of lithium-ion batteries based on the internal resistance growth model," in *Proc. Indian Control Conf. (ICC)*, Jan. 2017, pp. 33–38.

[204] N. Laayouj and H. Jamouli, "Lithium-ion battery degradation assessment and remaining useful life estimation in hybrid electric vehicle," *Renew. Energy Sustain. Develop.*, vol. 2, no. 1, pp. 37–44, Jun. 2016.

[205] D. Z. Li, W. Wang, and F. Ismail, "A mutated particle filter technique for system state estimation and battery life prediction," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 8, pp. 2034–2043, Aug. 2014.

[206] G. Ning, R. E. White, and B. N. Popov, "A generalized cycle life model of rechargeable Li-ion batteries," *Electrochim. Acta*, vol. 51, no. 10, pp. 2012–2022, 2006.

[207] J. Li, L. Wang, C. Lyu, H. Wang, and X. Liu, "New method for parameter estimation of an electrochemical-thermal coupling model for $LiCoO_2$ battery," *J. Power Sources*, vol. 307, pp. 220–230, Mar. 2016.

[208] C. Lyu, Q. Lai, T. Ge, H. Yu, L. Wang, and N. Ma, "A lead-acid battery's remaining useful life prediction by using electrochemical model in the particle filtering framework," *Energy*, vol. 120, pp. 975–984, Feb. 2017.

[209] V. Ramadesigan, K. Chen, N. A. Burns, V. Boovaragavan, R. D. Braatz, and V. R. Subramanian, "Parameter estimation and capacity fade analysis of lithium-ion batteries using reformulated models," *J. Electrochem. Soc.*, vol. 158, no. 9, p. A1048, 2011.

[210] M. V. Micea, L. Ungurean, G. N. Carstoiu, and V. Groza, "Online state-of-health assessment for battery management systems," *IEEE Trans. Instrum. Meas.*, vol. 60, no. 6, pp. 1997–2006, 2011.

[211] K.-H. Tseng, J.-W. Liang, W. Chang, and S.-C. Huang, "Regression models using fully discharged voltage and internal resistance for state of health estimation of lithium-ion batteries," *Energies*, vol. 8, no. 4, pp. 2889–2907, Apr. 2015.

[212] J. Lu, L. Wei, M. M. Pour, Y. Mekonnen, and A. I. Sarwat, "Modeling discharge characteristics for predicting battery remaining life," in *Proc. IEEE Transp. Electrific. Conf. Expo (ITEC)*, Jun. 2017, pp. 468–473.

[213] B. Saha, K. Goebel, and J. Christophersen, "Comparison of prognostic algorithms for estimating remaining useful life of batteries," *Trans. Inst. Meas. Control*, vol. 31, nos. 3–4, pp. 293–308, 2008.

[214] B. Long, W. Xian, L. Jiang, and Z. Liu, "An improved autoregressive model by particle swarm optimization for prognostics of lithium-ion batteries," *Microelectron. Rel.*, vol. 53, no. 6, pp. 821–831, 2013.

[215] W. Gu, Z. Sun, X. Wei, and H. Dai, "A new method of accelerated life testing based on the grey system theory for a model-based lithium-ion battery life evaluation system," *J. Power Sources*, vol. 267, pp. 366–379, Dec. 2014.

[216] D. Wang, Y. Zhao, F. F. Yang, and K.-L. Tsui, "Nonlinear-drifted Brownian motion with multiple hidden states for remaining useful life prediction of rechargeable batteries," *Mech. Syst. Signal Process.*, vol. 93, no. 1, pp. 531–544, Sep. 2017.

[217] S. S. Y. Ng, Y. Xing, and K. L. Tsui, "A naive Bayes model for robust remaining useful life prediction of lithium-ion battery," *Appl. Energy*, vol. 118, pp. 114–123, Apr. 2014.

[218] T. Parthiban, R. Ravi, and N. Kalaiselvi, "Exploration of artificial neural network [ANN] to predict the electrochemical characteristics of lithium-ion cells," *Electrochim. Acta*, vol. 53, no. 4, pp. 1877–1882, 2007.

[219] R. Razavi-Far, M. Farajzadeh-Zanjani, S. Chakrabarti, and M. Saif, "Data-driven prognostic techniques for estimation of the remaining useful life of lithium-ion batteries," in *Proc. IEEE Int. Conf. Prognostics Health Manage. (ICPHM)*, Jun. 2016, pp. 1–8.

[220] A. Nuhic, T. Terzimehic, T. Soczka-Guth, M. Buchholz, and K. Dietmayer, "Health diagnosis and remaining useful life prognostics of lithium-ion batteries using data-driven methods," *J. Power Sources*, vol. 239, pp. 680–688, Oct. 2013.

[221] D. Liu, J. Zhou, D. Pan, Y. Peng, and X. Peng, "Lithium-ion battery remaining useful life estimation with an optimized relevance vector machine algorithm with incremental learning," *Measurement*, vol. 63, pp. 143–151, Mar. 2015.

[222] W.-A. Yang, M. Xiao, W. Zhou, Y. Guo, and W. Liao, "A hybrid prognostic approach for remaining useful life prediction of lithium-ion batteries," *Shock Vibrat.*, vol. 2016, pp. 1–15, Jan. 2016.

[223] H. Dong, X. Jin, Y. Lou, and C. Wang, "Lithium-ion battery state of health monitoring and remaining useful life prediction based on support vector regression-particle filter," *J. Power Sources*, vol. 271, pp. 114–123, Dec. 2014.

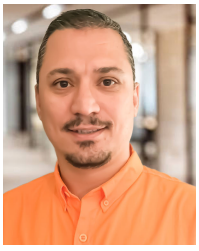
[224] X. Peng, C. Zhang, Y. Yu, and Y. Zhou, "Battery remaining useful life prediction algorithm based on support vector regression and unscented particle filter," in *Proc. IEEE Int. Conf. Prognostics Health Manage. (ICPHM)*, Jun. 2016, pp. 1–6.

[225] J. Cao, D. Harrold, Z. Fan, T. Morstyn, D. Healey, and K. Li, "Deep reinforcement learning-based energy storage arbitrage with accurate lithium-ion battery degradation model," *IEEE Trans. Smart Grid*, vol. 11, no. 5, pp. 4513–4521, Sep. 2020.

LAXMAN TIMILSINA (Graduate Student Member, IEEE) received the B.E. degree in electrical engineering and the M.Sc. degree in distributed generation in electrical engineering (with a focus on the improvement of the power qualities of an isolated microgrid) from the Institute of Engineering, Tribhuvan University, Nepal, in 2016 and 2019, respectively. He is currently pursuing the Ph.D. degree in electrical engineering with Clemson University, under the supervision of Dr. Christopher S. Edrington. He is a Graduate Research Assistant with the Real-Time COntrol and Optimization Laboratory (RT-COOL), Holcombe Department of Electrical and Computer Engineering (ECE), Clemson University. His research interests include electric vehicles, the integration of renewable energy, and smart grids.

PAYAM R. BADR is currently pursuing the Ph.D. degree (as a direct-entry candidate) in electrical engineering with a focus on multi-objective optimization and adaptive control systems with Clemson University. He is a Graduate Research Assistant with the Real-Time COntrol and Optimization Laboratory (RT-COOL), Holcombe Department of Electrical and Computer Engineering, Clemson University. His research interests include microgrids, ship power systems, energy system optimization, electrical machines, and real-time virtual prototyping. He is an IEEE Student Branch Committee Member of Clemson University.

PHUONG H. HOANG received the B.S. degree in control and automation engineering from the Hanoi University of Science and Technology, Vietnam, the M.S. degree in mechanical engineering from the Gwangju Institute of Science and Technology, South Korea, and the Ph.D. degree in electrical engineering from Clemson University. He is currently with the Optimization and AI Department, Research and Development Team, Operation Technology Inc. (ETAP), USA (a Schneider Electric Subsidiary). His main tasks at ETAP are to research, design, and develop new engines for ETAP software. His research interests include optimization for power systems, degradation forecasting, and machine learning.



GOKHAN OZKAN (Senior Member, IEEE) received the B.Sc. degree in electric education department from Marmara University, in 2006, the B.Sc. (as a valedictorian) and M.Sc. degrees from the Department of Energy System Engineering, Erciyes University, in 2014 and 2016, respectively, and the Ph.D. degree from the Department of Electrical and Computer Engineering, Florida State University, in 2019. He joined Clemson University, as a Postdoctoral Fellow, in 2020, where he has been a Research Assistant Professor with the Holcombe Department of Electrical and Computer Engineering, since 2021. He is currently a Research Lead with the Energy Innovation Center, North Charleston, SC, USA, and also the Manager with the Real-Time COntrol and Optimization Laboratory (RT-COOL). His main research interests include power systems and DER integration, model predictive control in power converters and drives, active thermal management and fault-tolerant control, distributed controls, power, and EM, real-time power distribution system modeling, simulation, co-simulations, and hardware-in-the-loop instantiation.

BEHNAZ PAPARI (Senior Member, IEEE) received the B.S. degree in electrical engineering from the University of Bushehr, Iran, in 2008, the M.Sc. degree in electrical engineering from the K. N. Toosi University of Technology, Iran, in 2011, and the Ph.D. degree in electrical and computer engineering from Florida State University, USA, in 2018. Prior to joining the Department of Automotive Engineering and Electrical and Computer Engineering, Clemson University, in Spring 2022, she was an Assistant Professor with the Department of Marine Engineering Technology, Texas A&M University, and an Assistant Professor of practice with the Energy Production and Infrastructure Center (EPIC), UNC Charlotte, for three years, where she taught at undergraduate and graduate levels. Her background is in power systems controls with an emphasis on modeling, analysis, planning, and AI-based optimization. Her current research interests include distributed controls and secure control frameworks under uncertainty, applications on energy system modeling, stochastic optimization, and electric vehicle, including electric and hybrid-electric, and ESSs.

CHRISTOPHER S. EDRINGTON (Senior Member, IEEE) received the B.S. degree in engineering from Arkansas State University, in 1999, and the M.S. and Ph.D. degrees in electrical engineering from the Missouri University of Science and Technology, in 2001 and 2004, respectively. From 2004 to 2007, he was an Assistant Professor of electrical engineering with the College of Engineering, Arkansas State University. From 2007 to 2019, he held the ranks of Assistant Professor, Associate Professor, and Full Professor of electrical and computer engineering with the FAMU-FSU College of Engineering and was the lead for the energy conversion and integration thrust with the Center for Advanced Power Systems, Florida State University. In 2019, he joined Clemson University, as the Warren H. Owen Distinguished Professor of electrical and computer engineering, where he leads the Real-Time COntrol and Optimization Laboratory (RT-COOL). He is the Associate Director for industry relations with the VIPR-GS Center, Clemson University. His research interests include modeling, simulation, optimization, and control of electromechanical drive systems, applied power electronics, integration of renewable energy, storage, and pulse power loads, and hardware in the loop (HIL) VV&A experimentation. He was a fellow of GAANN and IGERT.