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Review

A Review of the Impact of Battery Degradation on Energy Management Systems with a Special Emphasis on Electric Vehicles

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Abstract: The increasing popularity of electric vehicles (EVs) has been attributed to their low-carbon and environmentally friendly attributes. Extensive research has been undertaken in view of the depletion of fossil fuels, changes in climatic conditions due to air pollution, and the goal of developing EVs capable of matching or exceeding the performance of today's internal combustion engines (ICEs). The transition from ICE vehicles to EVs can reduce greenhouse gases significantly over a vehicle's lifetime. Across the different types of EVs, the widespread usage of batteries is due to their high power density and steady output voltage, making them an excellent energy storage device (ESD). The current downsides of battery-powered electric vehicles include long recharge times, the impact of additional strain on the grid, poor societal acceptance due to high initial costs, and a lack of adequate charging infrastructure. Even more problematic is their short driving range when compared to standard ICE and fuel cell EVs. Battery degradation occurs when the capacity of a battery degrades, resulting in a reduction in travel range. This review article includes a description of battery degradation, degradation mechanisms, and types of degradation. A detailed investigation of the methods used to address and reduce battery degeneration is presented. Finally, some future orientation in terms of EV research is offered as vital guidance for academic and industrial partners.

Keywords: lithium-ion; batteries; energy management system; electric vehicle; energy storage devices; degradation; microgrid; 4IR enabling technologies

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1. Introduction

Energy management systems (EMS) are highly optimized automated systems that take field-measured energy data, analyze it, and then make it available to end-users via visuals and online monitoring tools [1]. By studying EMS, experts in energy management can grasp the system's state in real-time and ensure that the system works effectively through reasonable adjustments, improving productivity, energy balance, and comprehension of the energy demand and consumption situation. As a result, the EMS ecosystem efficiently reduces load energy consumption and pollutant emissions [2]. An EMS utilizes energy scheduling technologies to ensure that end-users maximize the energy saving potential of energy storage devices (ESDs).

Smart homes and electric automobiles are two examples of loads in the EMS ecosystem. The development of electric vehicles was aided by advancements in battery and motor technology. An EV can act as both a load and a distributed energy resource for the microgrid (MG) [3]. An EV is propelled by an electric motor and powered by stored energy in the batteries. EVs stand in stark contrast to conventional internal combustion engine (ICE) automobiles. In addition to this, they generate zero-emission and are significantly more environmentally beneficial than vehicles fuelled by liquid petroleum gas [4–6]. In addition, EVs use less fuel and produce less noise than cars fuelled by gasoline. ICE vehicles have more moving parts than electric vehicles, which results in more frequent maintenance needs. Oil changes, tune-ups, or timing adjustments are not required when there is no engine or exhaust. Over the last decade, EVs have awakened much interest as one of the most favorable ways to reduce greenhouse gas (GHG) emissions. Additionally, they generate a more hygienic and calmer environment. The growing demand for global fossil fuels and their steady depletion has fuelled the early adoption of EVs. Furthermore, EVs have a particular advantage in terms of integration flexibility, which translates into increased transportation performance. EVs can incorporate a variety of energy sources, including fuel cells, solar panels, regenerative braking, ultra-capacitors and supercapacitors (SCs), and others [5].

The following EV variants have been produced and are currently being explored for improvement: the Battery EV (BEV), Hybrid EV (HEV), Plug-In Hybrid EV (PHEV), Range Extender EV (REEV), and Fuel Cell EV (FCEV) [7–10]. An HEV is propelled by an ICE and an electric motor. Vehicle propulsion requires chemical energy, which the ICE provides through its combustion chamber [11]. A BEV obtains all of its power from the grid and has batteries on board for energy storage only. The manufacture of batteries for BEVs consumes a lot of energy and emits many GHGs [12]. PHEVs are hybrid cars that combine the benefits of electric vehicles and traditional cars. This allows them to improve fuel efficiency while avoiding the mileage anxiety that comes with electric cars [13,14]. PHEVs have electric propulsion systems that work with conventional ICEs to make them more efficient. They can be charged at home or work. This means that secondary energy sources can help keep the ICEs in hybrid powertrains running at their best all the time, which improves both the vehicle's dynamics and performance. REEVs are viewed as a viable solution to short-range electric vehicles and high costs. The auxiliary power unit (APU) is used in a REEV to provide additional energy to support the primary battery in propulsion. The APU is mounted to the EV as a trailer [15,16]. FCEVs are EVs that utilize compressed hydrogen fuel as the primary source of power [10], resulting in significant reductions in GHG emissions [17].

Unique characteristics distinguish each type of EV: the ESDs (batteries, fuel cells, ultra-capacitors, SCs, and flywheels), the energy source, electric range, power units, and regenerative braking characteristics. Despite technological breakthroughs and EV subsidies, such as low operating costs and access to renewable energy, the general adoption of EVs has been gradual, with retail purchases dominating the EV industry [18–20]. The most significant hindrances to their adoption include expensive investment costs, greater upfront purchase costs, and short driving ranges, resulting from EVs' critical weakness—their battery. Additionally, charger compatibility, charging infrastructure availability, grid capacity, and car costs all pose significant challenges to the implementation and global acceptance of EV vehicles. The ESD system, particularly the batteries, must meet specific requirements regarding safety, charging and discharging rates, energy, and power density for the efficient operation of an EV [21–24]. Currently, batteries have several disadvantages, including low energy density, considerable weight, and high cost. Even with ongoing research into battery development, the current roadblock to the full embrace of EVs is the issue of battery degradation [24]. An evaluation of the attributes associated with each type of EV is provided in Table 1.

The electric vehicle's battery degradation results in high investment costs and a limited operating range. Lithium-ion (Li-ion), lead-acid, nickel/metal-hydride batteries, and ultra-capacitors can be used in HEVs, PHEVs, and EVs. Because of their relatively low rate of self-discharge while being stored, lithium-ion batteries are frequently used in electric vehicles (EVs). This is in contrast to the other battery technologies that have been utilized in the creation of EVs [8,25]. Additionally, they offer appropriate power density and a high energy density. However, despite their robustness, they suffer from a reduced life cycle, as evidenced by the depreciation of the battery life [26].

Table 1. Different types of EVs and their characteristic features [11].

	Braking Mechanism	Motor	Battery	ICE	Fuel Cells
BEV	Applicable	Electric motor	Battery	Not Applicable	Not Applicable
PHEV	Applicable	Electric motor	Battery	Driving the wheel	Fossil fuel cell
HEV	Applicable	Electric motor	Battery	Applicable	Fossil fuel cell
FCEV	Applicable	Electric motor	Battery	Not Applicable	Fuel cell + Hydrogen tank
REEV	Applicable (Partially)	Electric motor	Battery	Applicable (Generating power)	Not Applicable

Many researchers have attempted to solve the problem of EV battery degeneration. In [27], the central research concerns regarding lithium-ion batteries that were focused on included capacity estimation, battery sorting, remaining battery life, battery circuit modeling, and SOC techniques, while the merits and downsides of battery sorting were also discussed. In addition [28], presents a concise summary of many areas of LIB safety and an overview of thermal runaway, with a particular focus on the consequences of mechanical, electrical, and thermal abuse. The authors investigated various methods for enhancing cell safety, such as those involving cell chemistry, cooling, and balancing. They also described existing safety standards and the subsequent testing that corresponds to them.

None of these reviews has taken a comprehensive approach. While charging and discharging cycles undoubtedly reduce practical battery life, the factors that must be considered for the complete theoretical and practical modeling of a battery's degradation have not been addressed to the expected extent due to the enormously complex mathematical modeling of the electrolytic process. EV adoption will be delayed until a viable strategy to overcome the hurdles can be devised.

An EMS enhances the power output of numerous ESD sources, such as the battery and supercapacitor, providing essential power while optimizing certain cost functions in the EV, such as fuel consumption, battery life, emissions, and driving control. ESDs can be categorized broadly into mechanical energy storage systems, electrical energy storage systems, and chemical energy storage systems. Typical examples include the flywheel, compressed air, superconducting magnetic energy storage, supercapacitor, Li-ion batteries, and fuel cells.

Therefore, this article addresses the degradation mechanisms of batteries used in EMS, focusing on EVs. Additionally, the literature on battery deterioration will be analyzed to consider the scope of previous work, identify areas of inadequacy, and determine what may be carried out to improve the EV. The advantages and disadvantages of various electric vehicle technologies will also be discussed. Given the focus on electric vehicles (EVs) and the strategies for a smooth transition away from the usage of fossil fuels in transportation, we shall attempt to answer the following questions:

- What are the overall factors contributing to degradation in batteries?
- What methods have been used to reduce the degradation of batteries in EVs?
- What is the way forward in handling the problem of battery degradation as far as the EMS is concerned?

This paper is presented in the following sections: Section 2 presents the procedure used to identify and select existing literature for this article. Section 3 describes battery degradation and reports on the consequences of battery degeneration. Section 4 considers the many methodologies described in the literature for modeling and simulating battery degradation. Section 5 provides a systematic evaluation of studies highlighting the degradation of the battery as an essential component of an electric vehicle's EMS. The literature is then summarized in Section 6, followed by some proposed future research directions and priorities before concluding in Sections 7 and 8, respectively.

2. Approach to Literature Review

The subject of this review study, battery degradation in relation to EMS, was approached using a methodical literature review strategy. Through theoretical synthesis of the field and its subfields, this strategy attempts to provide collective insights into the area. Initially, a systematic search was undertaken. The search was carried out with the help of the Science Research Assistant (SRA). Using SRA, essential information on any web page, including lengthy scientific papers, can be quickly retrieved. Subsequently, any keyword on any web page can be efficiently searched for in scientific journals via tabs such as general science publishers (Elsevier, Hindawi, Taylor & Francis, Springer, Wiley); medicine, agriculture, chemistry, and biology (Nature); physics, mathematics, technology, computer science (arXiv, CiteSeerX, IEEE, DPLP); and metasearch (Google scholar, +journal, +research, and news).

The keywords used in the search were "degradation" and "electric vehicles", among others. "Degradation of batteries", "Degradation of fuel cells", and "Energy management system" were among the search terms used later. Following that, a thorough review of the literature identified during the search was carried out. It was important to summarize and present the findings from such detailed review work in a meaningful way. The initial findings prompted a search for additional literature that elaborated on the factors that cause degradation in storage systems. The definitions for different degradation models, such as the semi-empirical and electrochemical models, were also investigated to ensure a comprehensive literature search that would provide an accurate state-of-the-art representation of the most significant factors. By removing book chapters and internet pages, the number of articles discovered decreased. Only conference proceedings, articles, publications in the press, and review papers were displayed in the search results. A final list of articles for the review was compiled, with each article focusing specifically on the interaction between electric vehicles and battery degradation.

3. Key Assumptions and Equations

In modeling the degradation of a lithium battery, several parameters such as the battery State of Charge (SOC), ambient cell temperature, depth of cycling C-rate, ampere-hour throughput, and ampere-hour-count are considered. The SOC limits (minimum and maximum), calendar aging, and cyclical aging are necessary to find out how healthy a battery is and its expected lifetime, the latter two being the critical parameters for identifying the performance degradation of a battery [29]. It is also assumed that any battery used in the drive cycle, with or without additional energy sources such as supercapacitors or fuel cells, will have been used and must be recharged. In addition, it is reasonable to assume that the capacity of the battery to complete a required driving cycle is available before it reaches the End-of-life (EOL). This, in turn, significantly impacts how the battery charges and discharges. This is carried out while considering SOC, which is typically set between a minimum and maximum value of 0.2 to 0.9, respectively. Systems for managing batteries are also installed to control the battery's operating temperature. Another central assumption is that the energy at a particular period is a function of the energy at the previous time, $t-1$, and loss in the capacity at the same time. This is denoted mathematically in Equation (1):

$$E_{Bat(t)} = E_{Bat(t-1)} + Q_{Bat(t-1)} \tag{1}$$

where $E_{Bat(t)}$ is the energy at present, $E_{Bat(t-1)}$ is the energy at $(t-1)$, and $Q_{Bat(t-1)}$ is the loss experienced at $(t-1)$.

The CB_{Rated}, the battery rated capacity, is assumed to be established by the ratio between the current in the battery, I_{Bat}, and the charge in the battery, Q_{Bat} [30]. After that, it is possible to estimate the SOH of the battery using Equation (2).

$$\text{SOH} = \frac{CB_{Max}}{CB_{rated}} \times 100\% \tag{2}$$

where CB_{Max} is the maximum releasable battery capacity, while CB_{Rated} is the battery rated capacity which reduces over time giving rise to CB_{Max}. A high CB_{Rated} and a higher depth of discharge (DOD) accelerate the degradation of lithium batteries. The relationship between DOD and CB_{Rated} is expressed mathematically in Equation (3) [31]:

$$t \approx \frac{2N \times \text{DOD}}{CB_{rated}}. \tag{3}$$

Another parameter that is important in simulating how a Li battery degrades is the DOD. The SOC's numerical complement is called the DOD. It could be considered the battery power that has been used up before a new charging phase begins. This can be expressed as (100 − SOC) % or (1 − SOC) [32], where SOC is the state of charge. The relationship between the SOC and CB_{Rated} is described by the expression in Equation (4) [33]:

$$\text{SOC}_t = \left| -\frac{1}{CB_{rated}} \right|. \tag{4}$$

The SOC can be seen as designating the upper limit and is expressed as the difference between the upper and lower cutoff SOC [34]. This is expressed in Equation (5) as:

$$\text{SOC}_{\min(lower)} \leq \text{SOC}(t) \geq \text{SOC}_{\max(upper)}. \tag{5}$$

The minimum and maximum values are assumed and limited to a specific limit to prevent overcharge and overdischarge of the battery. In simplifying the expression for DOD, the DOD at an instantaneous time, t, can be introduced, involving the rated battery energy capacity, $E_{BEC(t)}$, and the charging and discharging energy capacity of the battery $E_{CDEC(t)}$. This is described in Equation (6):

$$\text{DOD}(t) = \frac{\left(E_{BEC(t)} - E_{CDEC(t)}\right)}{E_{BEC(t)}}. \tag{6}$$

SOC over a step k can also be expressed in Equation (7) as follows: [35]:

$$\text{SOC}_{(k+1)} = \text{SOC}_{(k)} - \frac{I_{Bat}\Delta t}{Q_{Bat(t=0)}} \tag{7}$$

where Δt is the discretization time interval between initial time and final time. This can be represented mathematically as equal to $t_{(n+1)}$ minus $t_{(n)}$. This can be expanded further in Equation (8) to be:

$$\text{SOC} = 100\% - \frac{\int I_{Bat} dt}{Q_{Bat}} \tag{8}$$

where Q_{Bat} is the initial capacity of the battery at a given time, t, I_{Bat} is the current of the battery, Δt is the discretization time interval, and SOC(k) is the present time.

Different approaches can be deployed when charging the battery in an EV. Such approaches include multi-stage constant current charging, high rate constant charging, and the multi-stage constant current constant voltage approach. The charging time of the current profile is determined by the cutoff voltage, $V_{cut\text{-}off}$, and the corresponding current associated with each phase represented by $Ic(i)$ to $Ic(n)$, where i to n represent the number of profile phases.

$V_{cut-off}$ is the prescribed lower-limit voltage at which battery discharge is considered fully complete. The relationship between the cutoff voltage and battery capacity can be expressed as follows in Equation (9):

$$V_{cut-off} = \frac{h}{CB_{rated\_lt}} \tag{9}$$

where h is the size of the battery.

The power matching strategy is central to the best performance of the hybrid power train. Among the factors to be checked when trying to ensure a proper power matching strategy is the degree of hybridization. With the DoH, the EV can be powered by the battery and supplemented by other power supply sources. It is also possible that the EV can be powered by the other power supply sources and supplemented by a battery source. The relationship is depicted in Equation (10) below [36]:

$$\mathrm{DoH} = \frac{P_{BS}}{P_{BS} + P_{AES}} \tag{10}$$

where P_{BS} is the battery's maximum capacity, and P_{AES} is the capacity associated with any other energy source in the FCHEV. Since the capacity is equal to the energy stored, Equation (10) can be expressed as follows in Equation (11):

$$\mathrm{DoH} = \frac{Q_{BS}}{Q_{BS} + Q_{AES}}. \tag{11}$$

If DoH is greater or less than 0.375, this can be expressed mathematically as follows [37] in Equation (12):

$$\begin{array}{c} 0 \leq \mathrm{DoH} \leq 0.375 \\ 0.375 \leq \mathrm{DoH} \leq 1 \end{array} \tag{12}$$

The energy used in an EV at any time, t based on the DoH is assumed to be modeled using Equation (13):

$$p(t) = \left\{ \begin{array}{l} x, \forall\ \mathrm{DoH} > 0.375 \\ y, \forall\ \mathrm{DoH} < 0.375 \end{array} \right\} \tag{13}$$

where $p(t)$ is the energy source for the FCHEV at any instant, t, and x is higher energy density battery and low fuel cell, while y is high power fuel cell and low battery capacity. These come into play when either of the energy sources cannot sustain the entire journey.

Since batteries have a finite amount of energy that can be used until a limit is reached, this limit is the EOL, which is assumed to be 80 percent of the initial battery capacity. This loss cannot be reversed. In contrast, battery energy is commonly restored by the "recharging process." The relationship between the nominal or rated capacity of the battery and E_{ol} can be described in Equation (14) as follows [38]:

$$E_{ol} = 0.8 \times CB_{rated} \tag{14}$$

where CB_{rated} is the useable battery capacity and E_{ol} is the end-of-life level.

4. Battery Degradation

A battery's capacity to store energy and deliver power decreases over time, making it unsuitable for applications that call for high-capacity batteries. Battery degradation is a well-known consequence of battery use and is known to be conditional upon driving, storage, and charging/discharge cycles. In a battery, degradation is unavoidable and can occur slowly and quickly [39]. Battery degradation cannot be discussed holistically without first considering battery life. Battery life is frequently measured using two inter-reliant metrics: calendar life and cycling life. The calendar life of a battery is the number of years it is predicted to last. In contrast, the term "cycling life" refers to the anticipated number of charge–discharge cycles that the battery will be subjected to before it reaches either its capacity loss or its resistance increase threshold [40,41]. Understanding battery degradation is essential to designing high-performance batteries that can be used in various applications. Analysis of a Li-ion battery's health is typically conducted by looking at its internal resistance and maximum functional capacity [42].

From this perspective, the most common degradation mechanisms in a battery are the following: the formation of solid electrolyte interphase (SEI) layers, positive electrode structural decomposition, lithium plating, and negative electrode particle fracturing, which is visible in negative electrodes, whereas the positive electrode is influenced by particle fracture and by positive electrode breakdown [43]. During cycling, diffusion-induced stress associated with lithium ions (Li-ions) intercalation causes electrode material deformation, cracking, pulverization, and fracture, with Li-ions intercalation manifesting as lithiation or delithiation [44,45]. Consequently, the open circuits render the active electrode plate incapable of Li-ion storage [46]. Other contributing factors to stress include particle size, insertion and extraction rates, and solid-state diffusivity. The fragmentation of the electrode surface raises the electrical resistance, isolating the entire particle and directly contributing to capacity fade and, eventually, loss [47].

When the 5 basic degradation mechanisms outlined above interact, 13 secondary degradation pathways result. The negative electrode is affected by graphite exfoliation, island creation for the negative electrode, dendrite production, and SEI decomposition. The positive terminals are adversely affected due to island development in the positive electrode, positive SEI growth, nickel–lithium site exchange, transition metal dissolution [48], and O_2 dissolution. Over a limited period, it is possible for lithium dendrites to grow on a lithium anode when Li-ions are deposited on the anode from a non-aqueous liquid electrolyte, such as the type used in Li-ion batteries. Dendrites are formed when Li-ion batteries are plated rather than alloyed with their anode, which can be either silicon or graphite. The production of dendrites, which is common in both solid and liquid electrolytes, accelerates electrolyte degradation, produces a thermal runway, and among other consequences, results in an internal short circuit and capacity loss in the battery [49–53].

An SEI layer is a passivation and protective surface layer that is formed on the negative electrode by deposition of an electrolyte solution's reductive breakdown products on the surface of the negative electrode. A crucial function of the SEI layer is to prevent additional electrolyte breakdown while allowing Li-ions to pass through the layer. This is accomplished by its electron-insulating and ion-conducting capabilities [54–57]. Lithium plating on the graphite anode occurs as a side effect of Li-ions intercalation under severe charge circumstances, i.e., high charge rates and low charge temperatures. Such plated lithium is detrimental to Li-ion batteries' performance, durability, and safety. Due to the closeness of graphite electrodes to Li-ions, graphite anodes are more vulnerable to lithium plating. Hard carbons and lithium titanate anodes, on the other hand, are less vulnerable to lithium plating [58–60]. A Li-ion battery is composed of an electrolyte and two electrodes. Each electrode is composed of an atomic framework that contains a small amount of mobile lithium. During the charging or discharging of the battery, Li-ions are extracted from one electrode, migrate through the electrolyte, and are injected into the other electrode. At the same time, electrons move between the electrodes via an external metallic wire. When lithium is extracted or inserted, diffusion-induced stresses are applied to the electrodes, resulting in deformation and fracture [44]. The loss of structural integrity may decrease electric conductivity, reducing the battery's capacity in the process [61,62]. These degradation pathways result in five distinct cell-level regimes: loss of Li-ion inventory, impedance change, stoichiometric drift, and loss of active material at both electrodes, which is marked operationally as capacity or as power fading.

A sketch of the degradation mechanism is presented in [43]. Three major modes can quantify degradation: change in the ohmic and faradic resistances, change in active materials, and change in lithium inventory. These modalities reveal themselves as an increase in resistance, kinetic limitation, depletion of active materials, and depletion of lithium inventory [43,63,64]. The battery degradation pathways through which degradation mechanisms are revealed are typically divided into cycle aging (resulting from usage) and calendar aging (resulting from storage) [43,65]. The aging mechanism that contributes to the degradation process of Li-ion batteries manifests in different forms and this is presented in Table 2.

Frequent and intensive use of the battery causes rapid deterioration of its performance, requiring the battery system to be replaced after a few years at increased warranty costs [64,66]. Batteries in storage can also degrade due to various chemical mechanisms, including limited thermal stability of storage materials and metal electrodes' corrosion. Corrosion of metal electrodes manifests in silver oxide in silver–zinc batteries, lead in lead-acid batteries, and lithium in lithium/thionyl chloride batteries [67]. The performance of lithium metal rechargeable batteries also diminishes during use due to charging cycles and parasitic processes, such as interactions between lithium metal and the battery electrolyte in such batteries. In recent years, there has been a significant increase in the development of secondary batteries, including nickel-metal hydride batteries [68,69], Li-ion batteries, and sodium-ion batteries [70]. Examples of Li-ion batteries include lithium nickel cobalt aluminum oxide (NCA) batteries, Li-ion phosphate batteries, and Li-ion batteries with $Li_4Ti_5O_{12}$ anodes. Additional battery types include nickel-metal hydride and sodium-ion batteries [41,71]. Their rapid ascension can be attributed to their high power and energy densities, long cycle life, and improved efficiency. They have vast and diverse applications in energy systems, including bulk storage, peak shaving, frequency regulation, voltage support, and reserve capacity.

Table 2. Degradation mechanisms and noticeable signs associated with each mechanism [43,71–74].

Degradation Forms	Indications
Mechanical	Mechanical stress and deformation manifest in the form of external and internal stress. Automotive vibration in the form of Z-axis vibration of the cylindrical cells.
Chemical	Lithium plating during overcharge, operation at a low temperature, and high discharge.
Electrochemical	Side reactions, solvent dissolution, solid electrolyte layer growth and decomposition, and electrolyte oxidation.
Electrochemical and mechanical	Active site area loss due to cycling is better described with two processes: fracture of particles in both electrodes and particle isolation.
Thermal coupling	Reaction rate increases with higher temperature.

5. Modeling Approaches Used in Battery Degradation

Modeling battery degradation is a multi-parameter and highly non-linear process [75]. The parameters primarily affecting battery degradation include battery temperature, average state of charge (SoC), depth of charge, depth of discharge (DoD), variation of SoC, C-rate current, time, and the number of complete equivalent cycles (charge/discharge rate), voltage exposure, and current profile [76–81]. Batteries must be put through many expensive and time-consuming tests to ensure they are safe, to see how well they work, and how they will change over time.

5.1. Mechanistic Modeling

The mechanistic modeling approach has proven to be highly flexible and valuable for lithium-ion battery diagnosis and prognosis [82]. Diagnostic models are typically employed for classifying and identifying problems; prognostic models incorporate the dimension of time, adding a stochastic element through which the problem's conclusion is speculated or projected. Historically, battery diagnosis has been approached from two opposing perspectives. A common approach aims for maximal precision, which is achieved by applying several resources: post-mortem characterization and comprehensive modeling. Studying a single battery is time-consuming, expensive, and often harmful, so it cannot be used in the field. The second path, commonly utilized in deployed systems, is as resource-efficient as possible and is often limited to extrapolating how capacity and resistance have changed over time, which is not enough to predict things such as the state of health.

Applying theory and assumptions to any problem allows a mechanistic model to forecast what will occur in the real world. Two processes are engaged in the development of such models. To proceed, the mathematical equations must be written down. The second phase of model development is called a parametric investigation. This approach ensures that the computer-aided design and the simulation models are a good match [83]. Mechanistic models use theories to understand and predict what would happen in real-world models, so they have input–output links [84,85]. Battery degradation is modeled using mechanistic models. It is physical in nature and considers the following parameters: charge loss due to SEI generation, active material isolation, and lithium plating. It is possible to use an electrochemical model to simulate the behavior of a half-cell electrode, which can help figure out how the cell will charge and discharge. In [86], another example is simulating the evolution of the incremental capacity and differential voltage curves using an artificial, mechanistic model based on half-cell data gathered from studies or the literature. This methodology allows for identifying the electrode's role in cell degradation mode. Empirical models investigate real-world models to establish theories via observation and experimentation rather than through mechanical relationships, i.e., mathematically defined frameworks. This discipline of modeling has increased dramatically in popularity since the rise in popularity of sophisticated machine learning methodologies.

5.2. Semi-Empirical Modeling

Battery degradation can be modeled using semi-empirical battery degradation models, an approach of moderate complexity, moderate accuracy, and adequate scalability that has been developed incrementally by fitting equations and parameters to experimental data [34]. The described approach arrives at the simulated behavior from equations that accurately capture the underlying physical behavior. It is critical to emphasize that the equations underlying empirical models may be meaningless and are employed to simulate the battery's behavior, which is considered a black box. Empirical models are frequently constrained by the experimental data and hence unable to provide detailed insights into the electrochemical interactions occurring within the battery. An example of this technique is equivalent circuit models (ECMs), which simulate and define the electrical behavior of batteries through electronics circuit elements such as resistors, inductors, and capacitors. This method enables the prediction of the SoC and state of health of batteries for vehicle power and energy management control. Other models are simpler to develop and utilize because they are based on equivalent ECMs. They do not, however, connect these circuit parameters to physical qualities. Table 3 shows the differences between mechanistic and empirical models.

Table 3. Difference between the mechanistic and empirical model.

Mechanistic Models	Empirical Models
The mechanistic model provides higher fidelity based on the first principle as it captures the loss of active material (LAM), loss of lithium inventory (LLI), and ohmic resistance increase (ORI) in its model.	It can only predict cell capacity because it does not consider correlated degradation such as LAM, LLI, and ORI, which distorts the predicted model result.
A mechanistic model is less computationally intensive compared to a model which is physics-based.	A substantial amount of training data is required to derive the fitting parameters and methods. This is prevalent in models powered by data.
It provides material insight and inference without trading off the accuracy and flexibility of the considered model.	Even though substantial resources are required, the result offers limited adaptability and applicability and cannot be easily adapted to real-life scenarios.
It is much more challenging to parameterize since it includes other modeling approaches.	It is easy to parameterize since it does not includes other modeling approaches.
Mechanistic models do not bind data availability, and a model developed for one application scenario may apply to another.	Experimental data imposes constraints on empirical models, and a model built for one application scenario may not apply to another.

5.3. Physics-Based Modeling

Several physics-based models use a set of partial differential equations (PDEs) linked together to model the battery's electrochemical and chemical interactions. These PDEs include vector calculus, electrochemical, thermal, and mechanical partial differential equations. This first principle approach provides critical insights and benchmarks for other approaches for modeling battery degradation [41]. The physical-based electrochemical degradation models for real-time monitoring of batteries are complex and computationally expensive [43]. Physical-based models, coupled with experimental validation, offer more insight into the operation of the batteries [87]. While providing full physics-based information for battery operation and appearing to be a time-saving measure, such models cannot account for all the phenomena that occur throughout a battery due to the incredible complexity of the equations involved. The complex modeling process and excessive computation intensity lessen their adoption and wide application [88,89]. It is difficult to establish a link between physical-based degradation and experimental results [90].

5.4. Electrochemical-Based Modeling

The model is established using electrochemical methods and is based on the internal physical and chemical interactions that occur within the battery during the charging and discharging process. An electrochemical model can predict how Li-ion cells work by considering the compounds' chemical properties and design parameters. In electrochemical-based modeling, the effects of various electrochemical reactions, most notably those at the electrodes and those in the electrolyte, are expressed as PDE and non-linear differential equations [91]. This approach enables the development of suitable but also efficient models that describe a system and reveal a combination of electrochemical and electrical principles. It also provides an accurate representation of what occurs inside the cell. Because of the benefits of electrochemical models, these are expected to replace the ECM in an advanced battery management system (BMS) which will observe and estimate the battery's states and properties as the battery ages [92,93]. In addition, this approach is significantly more adaptable than any other model-based approach while providing an excellent response when applied to diverse operational conditions and applications [94].

The lifeline battery modeling methodologies associated with the three modeling approaches include applicability, model complexity, physical–chemical knowledge, experimental data requirement, model accuracy, and computational effort. The characteristics of the different models and their degree of intensity [95] are presented in Table 4.

Table 4. Comparison of the different models.

Characteristics	Mechanistic Model	Semi-Empirical Model	Empirical Model
Applicability	*** (Applicable to the more comprehensive range of battery modeling).	*** (Applicable to the more comprehensive range of battery modeling).	* (Applicable to the minimum range of battery modeling).
Model Complexity	*** (Physics-based Electrochemical model from the first principle).	** (Performance Based modeling).	* (Black-box modeling).
Physical–chemical Knowledge	*** (Based on physical, mathematical, and chemical laws).	** (Following mathematical equation).	* (Trained with advanced algorithms).
Experimental data requirement	* (Moderate data required).	** (Extensive data needed).	*** (Big Data required).

Table 4. *Cont.*

Characteristics	Mechanistic Model	Semi-Empirical Model	Empirical Model
Model accuracy	*** (Highest level of accuracy).	** (Medium level of accuracy).	* (Lowest level of accuracy).
Computational effort	*** (Highly computational, especially with the mathematical aspect).	* (Moderate computation).	*** (Highly computation, especially with the simulation and advanced algorithm aspect).

*** Highest degree of intensity; ** Average level of intensity; * Minor level of intensity.

5.5. Hybrid Modelings

Hybrid models are models that incorporate both physics-based and data-driven elements. Data-driven models can also be constructed based on measured data to understand the system's behavior under consideration. Models deemed data-driven include empirical models, electrical circuit models, and neural network models, to name a few. Data-driven models rely solely on experimental data for feedback. In addition, they employ simple data-driven models with data-fitting equations. While data-driven modeling techniques can considerably reduce computation time, they lack trust in outcomes outside their calibration range [96].

6. Literature-Based Methodologies for Battery Degradation Cost Minimization

6.1. Degradation Minimization Technique Based on Stochastic Optimization

Performance-based EMS emphasizes the need to optimize the performance of an EMS in an EV by considering battery degradation and other aspects (associated parts and parameters) that can reduce overall costs. This optimization technique aims to find the variables that minimize or maximize the objective function while satisfying the constraints. By resolving this objective function, which may involve single or multiobjective functions, the degradation cost can be reduced.

A real-time predictive energy management strategy (PEMS) for plug-in hybrid electric vehicles is proposed in ref. [97] to coordinate fuel economy with battery lifetime. The engine-generator set (EGS), lithium-battery package, traction motor, and power inverter are the four components that make up the powertrain idea for plug-in hybrid electric vehicle. The EGS and the battery are both connected to the power inverter. The output of the power inverter is then connected to the EV using the driveline axle and the traction motor. Based on the longitudinal vehicle dynamics, this control-oriented model of battery SoC and SoH for PEMS design was developed and mathematically constructed. The system for charging and discharging is shown by a model of an equivalent circuit with an internal resistance of the first order.

This allows a variation in voltage and power flow to be established. A semi-empirical battery lifespan model based on a rechargeable lithium cell was used to quantify battery capacity loss.

Among other features, the PEMS comprises a velocity predictor used to correctly anticipate future drive velocity, an SoC reference generator, and an online optimization technique. The velocity predictor uses the neural network technique based on radial basis functions. The control objective was to minimize fuel consumption, electricity, and battery degradation cost minimization. In addition, a SOC tracking reference was introduced as part of the objective function. The physical constraints in the PHEV train include the engine's power, generator, current drawn from the battery, and the state of charge. The cost minimization problem is formulated to resolve the model predictive control (MPC) problem [40]. Multivariable and constrained issues in nonlinear and multivariable systems can be resolved by MPC while maintaining high degrees of robustness and stability. A high level of stability is commonly required while regulating and controlling the systems. Hybridization systems, such as fuel cell and hybrid storage energy systems, can be utilized for any hybridized system, regardless of the storage device combination [98]. The equations take into account the control target: fuel usage cost, the electricity costs for battery charging and discharging, and the cost of corresponding battery degradation. In real-time, the penalty-based continuation/generalized minimal residual (C/GMRES) algorithm determines the projected engine power command. This strategy is essential to alleviate the significant stress of the optimization procedure. The external penalty function instead of C/GMRES, which cannot handle inequality constraints, ensures that the powertrain's physical inequality limits are not exceeded.

In ref. [98], an EMS capable of implementing vehicle speed prediction and a predictive control mechanism was created. The fuel cell hybrid system was modeled to meet the vehicle's power demand under different labor conditions. In the article, the hybrid power system combines the fuel cell and battery. The batteries successfully handle poor dynamic responses in the fuel cell system. It is possible to conserve braking energy from the vehicle using the battery, and the battery can be recharged. The velocity speed predictor allows the speed predictor to be fed into a Markov-based connection to forecast and make decisions regarding the speed. A system response prediction is passed into the objective function via the dynamic vehicle model, coupled with historical and current data, allowing interaction between energy use and fuel cell degradation. An optimal solution is then fed into the EV's hybrid power system with the necessary constraints. This solution can also be modified as the system becomes operational. The speed prediction and offline dynamic programming were developed and utilized to solve and compare the model's performance.

An analogous predictive approach to EMS is also described in ref. [99], where battery degradation costs are analyzed with distinctive emphasis on active power charging, discharging, and providing reactive power service. The battery degradation capacity is a function of charging/discharging power. Once modeled, it is converted from the associated loss capacity to a cost term. Simulations are carried out in various EV operating scenarios, including charging alone, charging and discharging, and charging/discharging while providing reactive power service. The study concludes that overlooking the battery degradation cost provides a false feasibility report regarding the optimal operating cost calculation for the EV. The total cost minimization strategy, a low-cost energy management formula, was used to keep the total cost of three items as low as possible. The reduced costs include the energy used to recharge the battery, the damage to the battery, and the fuel used to generate electricity. This strategy is a derivative of the energy cost minimization strategy [100]. Since the dynamic programming (DP)-based solution needs information concerning the driving cycle, which is currently unavailable, the minimization problem was solved using Pontryagin's Minimum Principle (PMP).

Consequently, near-optimal performance is attained in real-time via the PMP, independent of driving cycle information. The powertrain model and optimization problem were altered to account for battery aging. Finally, it was proved that such a real-time technique is comparable to the benchmark for overall energy expenses. Authors in ref. [101] identify and evaluate battery capacity deterioration under a variety of SoC conditions, including the optimal way of charging, the worst possible way of charging, and the systematic manner of charging. These three methods were utilized to estimate the cost of battery capacity decline, with economic analysis and numerical examples being presented for each methodology. It was demonstrated that by modifying the charging pattern of electric vehicles, battery capacity degradation, which is a non-negligible and elastic component of the total cost, may significantly decrease. In ref. [102], the authors aim to reduce the cost of EV battery charging deterioration while meeting the battery charging characteristics of a park-and-charge system. The development of a practical charging system that incorporates the consequences of battery degradation into the EV charging scheduling problem was made possible using a battery degradation cost model to capture the characteristics of battery performance degradation while the battery is being charged. When designing the ideal EV charging scheduling scheme, the above battery degradation cost model was used to reduce the total battery deterioration cost to the absolute minimum. In order to tackle the linked optimization problem, a technique for allocating vacant resources and a dynamic power adjusting algorithm were proposed. Customers and charging operators would benefit from the findings, which revealed that the proposed method outperformed the competition in terms of battery deterioration cost minimization and peak power load reduction.

In ref. [33], another strategy for ensuring and lowering the energy cost of EVs and MGs was proposed, which described the hybridization of energy-source devices as a hybrid energy storage system (HESS). During the vehicle modeling process, two distinct power train designs were examined. The first is an electric power train with a single type of battery, while the second is made of HESS. The HESS comprises a direct parallel combination of a battery, a supercapacitor, and a DC/DC converter, which is missing in the first configuration. Using an internal resistance model, the energy storage system was theoretically calculated using the battery pack and supercapacitor. The engine and traction motor were also recreated using vehicle parts, demonstrating their contribution to the braking energy recovery required for charging the energy storage device. The driving cycle and charging pattern were also recognized and documented. In this case, the objective function involves the cost of battery deterioration and the total cost of plug-in hybrid electric buses (PHEB) equipped with a HESS consisting of lithium iron phosphate (LFP) batteries and SCs, was included. The optimization goal is to reduce the life-cycle cost, including fuel, power, battery, and supercapacitor costs, compared to the same life cycle. This is true for configurations A (two energy sources: engine and battery) and B (the engine and HESS). The optimization constraints are determined by each configuration's power and voltage and state constraints such as state of charge (related to the battery) and energy condition (associated with the supercapacitor). The 2D PMP strategy optimization technique is used to accelerate strategy creation, aid in online implementation, and reduce computing costs.

The cost of installing a single battery to achieve the same benefits was calculated and compared using an offline technique based on a semi-empirical battery-degradation model. As a result of the envisaged connectivity, battery life for all three energy sources (engine, battery, and storage capacitor) is expected to be extended. To determine the concept's practicality, the economic cost of the HESS system's life cycle was evaluated and compared to that of a bus with a single battery. While obtaining the required electric range with a single battery of appropriate power capacity is impractical, the suggested technique would result in a more excellent engine, battery, and SC control due to the HESS, reduced battery deterioration, and overall cost saving through PHEBs. On the other hand, using a single battery bus would increase fuel consumption and exacerbate battery deterioration. The battery would have to be replaced several times to keep the EV running for its entire service life, resulting in substantial maintenance expenditure.

It is necessary to account for battery degradation when calculating the operating costs of a battery energy storage system because the life of electrochemical battery cells is highly sensitive to the number of charge and discharge cycles the battery undergoes. This, in turn, is directly affected by how the battery is maintained and operated. Batteries degrade in numerous ways, and current models of battery degradation either do not match published calculations or do not adequately depict the actual mechanism of battery degradation. Sizing guides and energy management (EM) benchmarks of the HESS of battery-SC arrangements deployed in EV applications are presented in ref. [103]. The approach of HESS size optimization in order to minimize battery degradation and financial costs in EVs was explored. The optimal EM benchmarks that can minimize battery degradation were likewise presented, irrespective of the EM technique implemented. By decoupling the EM problem from the issues surrounding the HESS sizing, the factors of battery degradation and HESS sizing, which are inconsequential to the specifications of batteries and SCs, and the design parameters of EV, were highlighted. The semi-empirical model used in this work follows the Arrhenius Law.

In ref. [37], the authors optimized power matching algorithms by considering the cost of the hybrid system, the equivalent energy consumption of hydrogen fuel, and the cost of battery deterioration. The hybrid power train's structure, specifications, and configuration were identified to analyze the different degrees of hybridization of the fuel cell and battery energy storage system. The motor model, fuel cell model, battery model and configuration, battery degradation, and the elements that contribute to the degradation are all highlighted in the description. In order to solve this non-linear, multiobjective problem, a bionic optimization strategy based on particle swarm optimization (PSO) was applied, and the optimization variable, the degree of hybridization (DOH), was identified. To obtain the ideal degree of hybridization (DoH) values for various hybrid schemes and weighting factor groups, the particle swarm optimization (PSO) approach was used. Four groups of weighting factors were selected and used to improve the objective optimization function for each level of hybridization by this method. The weighting factors were also set up to evaluate the objective functions.

Finding an ideal DOH achieves a balance of cost, fuel usage, and battery aging. The optimization goal was separated into three parts: equivalent hydrogen consumption per 100 km, the cost of the hybrid energy storage system (battery and PEMFC), and battery capacity degradation. The optimization constraint is a one-dimensional parameter consisting of the particle velocity and position. In terms of the DOH, several approaches were utilized to share the required motor power between the PEMFC and the battery. The battery took over when the FC could not supply the requirement from the motor. Battery life was prolonged, energy consumption optimized, and powertrain costs lowered based on individual requirements, the multiobjective optimization applied, and the proper hybridization degrees of the provided hybrid powertrain.

A vehicle model proposed in ref. [30] was based on an existing vehicle that was initially a pure electric automobile. However, in order to increase its autonomy, a proton exchange membrane FC was added. A model that illustrates dynamic behavior was included when creating the objective function and limitations. Following that, an evaluation of the energy management system was performed to aid in measuring the damage caused to the battery during any profile, specifically the current profile, taking into account fuel economy and battery degradation. After completing the previous modeling, the high-efficiency hydrogen fuel cell used in the car was modeled with clear accommodation of the boost converter, which is helpful for power flow management between the fuel cell and the DC bus. The equivalent consumption minimization technique, an online EMS, was utilized with a comprehensive vehicle model to solve the local optimization problem. The control input or command flow for the vehicle can be computed. A weight factor ranging from 0 to 1 is significant in altering the performance of the suggested technique from maximum fuel economy to maximum fuel economy of the battery. The objective function was specified to accommodate fuel consumption and battery usage, and a single weight factor was also introduced. The control input, the change in fuel cell power, and the state vector are all limitations. The state vectors are the SoC, the battery current, and the power connected to the fuel cell. In addition, an additional optimal strategy though offline in nature, based on the dynamic programming strategy, was also employed.

A power management system that simultaneously accounts for fuel cell degradation and consumption and battery degradation was proposed and reported in ref. [104]. The simulation model considered for the fuel cell degradation model is based on the electrochemical active surface area (ECSA) loss. The platinum dissolution models, consisting of a comprehensive set of electrochemical equations, were used to build the ECSA degradation. Subsequently, the influence of ECSA decay on the polarization curve was investigated. The data from the ECSA decay model was then validated by comparing it to what was available in the literature. Only then was the lithium battery degradation modeled as a function of Ah throughput, a standard bus drive cycle in the optimization process. The objective function was designed to reduce the overall lifetime cost of the hybrid system by decreasing fuel cell use and optimizing fuel cell and battery lifetime. This is dependent on the power cell's SOC.

6.2. Degradation Minimization Technique Based on Stochastic Optimization and 4IR Enabling Tools

Another strategy utilized in the literature to lower the cost of battery degradation is to use single-objective or multiobjective stochastic optimization with artificial intelligence. Random variables emerge in the formulation of stochastic optimization problems that incorporate random objective functions or constraints. Almost every real-world problem has some degree of vagueness in its parameters. Historically, these uncertainties have been dealt with primarily by approximating them with projected values, which fail to generate robust results even when the most practical forecasting algorithms are used [37]. It is currently becoming more popular to monitor batteries and the accompanying battery deterioration costs utilizing the fourth industrial revolution (4IR) enabling technologies such as Blockchain, Big Data, machine learning, and the Internet of Things. There has already been significant research, development, and presentation of solutions relating to EMS, with an unusual emphasis on MG, EV, and other related areas. As the energy cost of an EMS with a particular focus on BMS continues to rise in the electric vehicle space, the application of the 4IR enabling technologies in this space [105], particularly in monitoring, evaluating, and albeit indirectly computing the total energy cost, is becoming increasingly important.

A Q-learning-based strategy in tabular form was proposed in ref. [106] to minimize battery degradation and energy consumption. The authors recommended and optimized two heuristic energy management strategies by combining the PSO algorithm with a Q-learning strategy, a comparative examination of four distinct energy management strategies. A baseline option was proposed that does not require the usage of an ultracapacitor, whereas two heuristic methods and a Q-learning method do. A genetic algorithm was used to validate the battery aging model against experimental data.

In ref. [107], a two-stage stochastic programming approach was used in a smart home application to reduce the cost of power procurement for a typical household. The stochastic choice variables represented the charge–discharge power of these components. An excellent analytical battery degrading cost model was used to account for the uncertainties resulting from the power generation of roof-mounted photovoltaic (PV) panels, household load demand, real-time electricity price, and other factors. In addition, an artificial neural network (ANN) was trained using historical time series data in order to develop the stochastic process model. Because of these uncertainties, various charging schemes were researched, including those with and without degradation cost, those with and without battery energy storage systems, and those uncoordinated. The susceptibility to different electric vehicle and battery energy storage systems and their charging rates was also investigated.

An ANN prediction model that can connect numerous properties of this battery type to improve battery performance was proposed in ref. [108]. Experimental samples, an upgraded Thévenin model, and MATLAB programs were used to train and test the ANN-Predictive model, which was then performed and again tested. When learning values are in between, this neural model can predict them and distinguish between expectations to learn and adapt information of varying qualities. This was followed by a discussion about non-linear arithmetical capacities, interfaces between information sources, yields for neural networks, and the corresponding Simulink model. The time and SoC are the model's information sources. The results are the average degradation function, degradation density function, cycle life, DoD, and capacity rate.

In ref. [109], a proposal was put forward for a battery degradation model that may be used to estimate capacity fading in an unbalanced battery operation. A number of essential concepts in battery degradation were considered in this model, including the Arrhenius connection and the formation of solid electrolyte interface films. The parameters for the study were derived from real-world data collected with a specific battery type. In addition, the suggested model and parameter tuning method can also be utilized to model Li-ion battery degradation in various batteries. An empirical DoD stress model was found to be the most accurate for the lithium manganese oxide battery cycle dataset utilized. Using multiple DoD stress models, the case study shows that the suggested deterioration model can be applied to Lithium–Iron–Phosphate and Lithium–Nickel–Manganese–Cobalt–Oxide batteries.

In ref. [110], a real-time approach for calculating and tracking battery degradation costs in EVs was proposed using a blockchain system. A critical factor for the efficient operation of an EV while monitoring battery degradation are decisions regarding charging and discharging. Based on the current state of the battery in an electric vehicle, the cost of the battery's initial degradation was calculated. At the same time, the EV range and age were the two additional factors examined. The battery degradation cost was calculated using battery specifications and constant tracking of the variables that affect battery energy capacity, which determine the economic cost for EV consumers involved in the vehicle-to-grid ecosystem. In addition, a cost-minimizing Mixed Integer Linear Program that accommodates degradation cost in its objective function was utilized to make the best decision as to when the EV connects to the grid. The battery degradation cost was updated at the end of each 24 h cycle based on the charging/discharging transactions conducted throughout the cycle and the temperature conditions. These transactions and battery degradation costs are stored in a consortium blockchain shared by all parties involved.

On the other hand, data-driven machine learning models have recently become more popular for estimating state and lifetime prediction because they can learn from data [111]. By examining published synthetic low-rate charge curves created by a mechanistic model for various thermodynamic degradation modes, the physical foundations of mechanistic models are merged with the power of machine learning. The investigation is performed on LFP, nickel manganese cobalt (NMC), and nickel cobalt aluminum batteries. Another approach that evaluates and estimates the effect and cost of battery degradation for a real-life application is discussed in ref. [112]. A new notion of traveled distance between two consecutive recharging events (CRE) was developed to characterize battery capacity degradation based on an analysis of large-scale electric taxi global positioning satellite (GPS) data. Using historical CRE readings from electric taxis, a box-plot-based statistical analysis method was provided to understand better battery aging and its effects on performance. This method was chosen because BMS data is unavailable in the public domain. The data in the experiments came from over four years of real-world EV taxi GPS data, which was used to evaluate battery performance and degradation in real-world EV operation. The result of the study proves that external circumstances, such as temperature, road conditions, and charging rate, will impact battery degradation in real-life EV use. A large volume of data has cleared the pathway for Big Data analytics in the EMS, especially the BMS. In ref. [113], the capabilities of Big Data analytics in BMS applications, emphasizing the properties of Big Data in intelligent BMS, Big Data software frameworks, sources, and infrastructure, were addressed. A feasible semi-empirical mathematical evaluation model, the extended wear density function (WDF), to be used to determine the remaining battery life was proposed in ref. [114]. In addition to analyzing the data, the authors developed an enhanced WDF model to create a more practical WDF. A transformation was performed to convert the measured operating temperature, current, and operating SoC values into coefficients for the extended WDF. The suggested data platform saves the measured data along with the parameters of the batteries. It is used to train the extended WDF model, which estimates battery degradation based on new experimental data with the same characteristics as the training data. The simulation results verify that the suggested extended WDF and data structure in the proposed platform are accurate.

Given that it is commonly recognized that power train modeling is a fundamental step in developing an effective and efficient EMS, the power source of the FC and lithium-ion battery is discussed in ref. [35]. The fuel cell manages the current flow to the DC bus when in operation, and the battery is directly connected to the DC bus. The required power for the engine, the input into the fuel cell hybrid car, is generated based on the vehicle's longitudinal dynamics. Because reinforcement learning is used for the EMS, state variables, and action space, utilizing the reward function to be optimized is critical in performing deep reinforcement learning. The state variables required, including vehicle speed, battery SOC, and FCS output power, are accommodated in the expression and input to the assessment network. The reward function equation considers how much fuel is used, how quickly the FC deteriorates, and how much hydrogen is used at each point in time.

A summary of work carried out in literature relating to battery degradation is presented in Table 5.

Table 5. Summary of findings from literature review [30,33,35,38,91,97,98,104,107,115–120].

Reference	Type of EV	Description	Pros	Limitations
[17]	FCEV	The cost minimization considers hydrogen consumption, hybrid cost of battery and fuel cell, and battery degradation while using PSO to find optimal DoH.	PSO used allows a fast convergence rate for an optimal solution. It can thus be employed to solve non-linear and multiobjective optimization problems.	The DoH is designed for each objective variable, i.e., prolonging battery life, reducing system cost, or reducing fuel consumption. Despite this, it has not been demonstrated whether it is possible to handle all the objective variables due to their varied weights.
[30]	FCEV	Heuristic EMS strategy.	The heuristic strategy might provide acceptable performance and lower the computational burden in real-time applications.	The solution might not be optimal. The decision made might be inaccurate.
[33]	PHEV	A semi-empirical model is used. The 2D PMP algorithm/strategy minimizes the system's life-cycle cost.	The bus service chosen for modeling the driving cycle and charging patterns around a fixed route, following the same route daily, makes the model simpler than using a passenger vehicle with an ever-changing route. The PMP strategy includes one more state variable and can be used in a real-time control situation. Computational costs are reduced due to the 2D PMP algorithm.	The mechanisms governing degradation are complex, non-linear, and strongly interrelated. They are susceptible to varying operational conditions; thus, practical analysis is complex. Variation in electrodes, electrolytes, and manufacturing processes significantly increases the difficulty level. Not all predominant mechanisms are considered in the study
[35]	FCEV	Powertrain system modeling with proton exchange membrane FC and Li-ion battery power sources is designed and modeled. Subsequently, a prioritized experience replay Deep Q-Network algorithm is applied.	The SoC in the analysis is kept at 0.7, resulting in less battery power. With the help of continuous training, the actions selected can bring about better rewards and stability in the system.	With the increasing number of layers comes the increased complexity associated with the training process.
[97]	PHEV	RBF-Neural network plus C/GMRES algorithm used for cost minimization.	Driving velocity can be predicted based on the algorithm used. Therefore, the potential for practical use is enormous. The C/GMRES algorithm is used to mitigate the burden associated with real-time optimization.	The extra penalty method used in handling inequality constraints, heuristic in nature, might only trade off precision for speed.

Table 5. *Cont.*

Reference	Type of EV	Description	Pros	Limitations
[103]	All EV types	HESS sizing is used to minimize battery degradation and financial cost using the DP approach.	This approach makes the decoupling of EMS from the HESS sizing problem realizable. Therefore, it is possible to minimize battery degradation regardless of the HESS size.	The decoupling of EMS from the HESS makes it impossible to investigate co-dependence and co-existing variables that EM and HESS share. The solution provided due to the isolation of each system might not be globally optimal.
[104]	FCEV	A deterministic DP algorithm uses a fuel cell degradation model based on electrochemical surface area (ECSA) loss and a battery capacity model (minimizing fuel consumption and maximizing fuel cell lifetime plus battery).	Other frameworks for fuel cell degradation mechanisms can be incorporated whenever available. Since the EMS is rule-based, it is easy to implement. Even though only one mechanism of the fuel cell was considered (degradation of the platinum catalyst), the possibility of converting other degradation mechanisms found in transient load into ECSA allows a more dynamic and accurate representation.	Drive cycles are representative of the typical urban transit system. This system does not accommodate the variability associated with personal cars that use different routes.
[107]	BEV	Two stochastic stage systems plus ANN are supplied with historical time series lag (Software based: GAMS + KNITRO Solver).	KNITRO Solver supports a wide range of linear and non-linear problems. The low level of SoC employed in the design limits the degradation rate.	When ANN produces a probing solution, it does not indicate why and how. This approach reduces trust and the ability to replicate such results within the network. There is no specific rule for determining the structure of ANN. The appropriate network structure is achieved through experience and trial and error.
[117]	HEV	Cost minimization using adaptive EMS based on dynamic source resistance splitting plus heuristic optimization using the quantum butterfly optimization algorithm.	It is simple to implement since it accommodates dynamic source conditions (battery and ultracapacitor). Through optimal sizing, the energy and power requirements are satisfied. The stress on the battery packs is alleviated; thus, the battery life is extended. High peak charging and discharging is avoided. With this, the incidence of current drain is reduced.	Even though an electrical model was investigated, it has been established that electrochemical models are advantageous as an accurate representation of what occurs in cells is revealed.
[119]	FCEV	Fuzzy logic-controlled EMS relies on the genetic algorithm. The cost of the battery, fuel degradation, and fuel consumption were considered part of the objective function.	The EMS system is formulated as an optimization problem, allowing the fuzzy controller to be tuned to objective functions.	Cycling ageing has been considered while avoiding calendar ageing. The rule-based EMS might not be optimal for driving scenarios experienced on the road. A single SoC value was used; it was unclear whether it was the minimum or maximum value.

7. Summary of Findings from the Literature

An intelligently designed EMS is highly crucial for the complete embrace of EVs. This approach has massive implications for future development, especially when considering the degradation of batteries. Some offline and online EMS approaches provide reliable EV power management. While the offline approach requires precise future drive information prior to the journey, an online approach provides such information during any journey. The accuracy of the real-time online strategy still needs to be tested continuously, given that the offline EMS approach cannot be deployed in online applications. In order to reduce cost, an optimization strategy is used that relies on analytical or digital operation [60]. Optimization control can also be utilized to determine the best ways of applying EMS in the future. There are two types of optimizations: global optimization (GO) and real-time optimization (RTO). GO [61,62] is based on ascertaining what needs to change in the future and what needs to stay the same in order to cut costs in fixed driving cycles while maintaining the same performance. A typical example of GO is the DP. Transforming a multi-stage optimum decision problem into several single-stage optimal decision problems is a feasible solution strategy in optimization. Nevertheless, because of its high computing cost, DP can only be optimized offline for a defined driving cycle, making real-time control impossible [63]. Nonetheless, the GO control method is possible when used with linear programming, DP [63], stochastic DP, and genetic algorithms.

On the other hand, the PMP, the equivalent fuel consumption minimization strategy, the robust control approach, decoupling control, and optimal predictive control are all components of real-time optimization (RTO) [118]. An instantaneous computing burden makes real-time optimization control difficult to achieve [119]. Achieving optimum fuel usage in each real-time period is necessary for real-time optimization applications.

Both approaches depend on meta-heuristic and heuristic strategies to produce a near-optimal solution within minimal time and with minimal space computational cost [120]. Heuristic techniques are more suited for real-time applications because they provide adequate performance while requiring less computing effort [30]. Such optimization methods include mixed-integer, convex programming, linear programming, DP, the Markov decision process, PSO, fuzzy logic, stochastic optimization, predictive energy management, and equivalent consumption minimization. These problems are formulated using the listed optimization methods and built on the predictive control model, a dynamic model that efficiently controls the process while satisfying the ensuing constraints.

Another data-driven approach can be applied to the EMS while considering battery degradation. Some sensors have been deployed to track the usage and gradual loss of capacity in the process of generating data. Some data-driven approaches have manifested in using Blockchain, Internet of Things (IoT), Big Data analytics, etc., to help make informed decisions around the energy costs associated with the EV design. Artificial intelligence methods such as ANN, regression, correlation, and deep learning are currently being applied to understand better the phenomena linked to battery degradation. The summary of the literature survey is presented in Table 6.

Table 6. A summary of models and various approaches used in the literature.

Models	Characteristics	Approach	Merits
Mechanistic (mechanical relationships are used to develop theories)	Online (real-time) or offline approach. Single or multiobjective function. Single or multiple constraints. The preferred approach can involve the maximization or minimization of the objective function. Single or hybrid energy sources. An inequality constraints handler, such as an external penalty, can be applied in some cases.	Stochastic optimization (Optimization-based EMS): [30,33,97,117,121,122] The control approach is based on observed driving patterns or on expected future driving patterns. It is necessary to use an iterative procedure that includes an optimizer and a model (objectives, variables, and constraints).	High level of robustness and stability Multivariable and constraint problems. A globally optimal result can be realized. Provide causality missing from the machine learning approach
Empirical (By observing and experimenting, you can develop a theory.)	Diverse optimization techniques include PSO, genetic algorithms, Mixed-integer Linear programming, etc.	Stochastic optimization (Optimization-based EMS) + 4IR technologies, i.e., Blockchain, machine learning, Artificial intelligence (Learning-based EMS): [107] + (Rule-based EMS): [104,119,123] The rule-based approaches are built upon expert knowledge, intuition, and the retrieval of findings from GO techniques. (Hybrid based optimization): [35,124]	This approach enables the integration of mathematical modeling with the exploratory nature of observation and experiment. Without any prior knowledge or established rules, it is possible to select actions directly from states. Simple. Low computational burden. Ease of implementation.

8. Guide and Suggestions for Implementation

Any model that does not explicitly consider a battery aging factor, i.e., does not include a degradation model, will yield an inefficient cost-competitive model. Over the short term, the cost of degradation might not be readily seen. However, the consequences of degradation are undoubtedly seen over the extended term and impact on the profit obtained. Even if the electrochemical model represents the behavior of a real battery, semi-empirical or empirical models must be used to evaluate the variables. In most cases, it is difficult to obtain empirical data because the manufacturer does not provide this information. Data-driven approaches need to be introduced to complement the existing approaches for estimating battery degradation as precisely as possible. Such approaches can clarify the interdependencies between variables and parameters observed in the electrochemical, empirical, and data-driven approaches.

However, hybrid models incorporating both electrochemical and empirical approaches are available, such as the model developed by ref. [125], which incorporates lithium diffusion in the solid phase. This is in addition to the empirical Peukert's law [126], which employs electric lumped elements to simulate porous electrodes. With the use of modeling, it is possible to obtain a better understanding of physicochemical phenomena. Using the chemical features of the compounds and the design parameters, an electrochemical model may simulate the behavior of Li-ion cells. An artificial intelligence approach that establishes variable relationships can also confirm which variables have a relationship and which do not. Thus, semi-empirical and electrochemical approaches can then be brought together. In this way, a robust but scalable approach for estimating the degradation cost contribution to the whole EV ecosystem can be laid out. Even though the model's effectiveness is limited, and this approach is best described as imperfect because some variables, such as the kinetic rate constant, have no definite measure, this model is expected to produce viable results.

Batteries that use Li-ion technology can be used in everything from electric automobiles to large-scale energy storage. The materials utilized, the system architecture, and the operating conditions significantly impact how long these devices last. These factors have made it harder to operate battery systems in the real world. Combining this information with the development of machine learning methodologies to construct a digital twin for batteries becomes possible with a better understanding of battery degradation, modeling approaches, simulation tools, and the analytical approaches that may be used. Even though publications on this subject have appeared [127–129], more research into battery modeling, deterioration, and cost analysis over a short and extended period of economic implications is required. Such studies must translate from proposals to actual implementation and deployment in EMS. Such studies would shift perspectives and build a solid foundation for increasing the number of scientists and engineers who wish to make a significant contribution to intelligent BMS.

According to the literature, degradation cost is temperature-dependent, and temperature varies across geographical regions; thus, battery degradation costs are similarly location-based. As a result, it is critical to identify an optimal point of best fit that will guarantee accelerated degradation due to climatic factors such as temperature can be managed wherever the battery is used. To better understand Li-ion battery degradation, it is necessary to research both hot and cold temperature locations. Having a near-optimal point would reduce the overall cost of battery manufacturing and the degradation rate.

Dimensionality reduction (DR) is a data preparation technique used prior to modeling that minimizes the number of input variables in a dataset. It must, however, be performed following data cleansing and scaling and prior to training a predictive model. Increased input features frequently complicate predictive modeling tasks, a phenomenon referred to more broadly as the curse of dimensionality. With an excessive number of input variables, the performance of machine learning algorithms can suffer. High-dimensional statistics and DR techniques are commonly utilized for data visualization [130].

Nevertheless, similar strategies can optimize the fit of a classification or regression dataset in applied machine learning. Regression analysis is used to assess whether two variables have a relationship. Correlation demonstrates the link between two variables, whereas regression analysis demonstrates how one variable influences another. In the field of EMS, many features are associated with the simulation and modeling of battery degradation. It is commonly recognized that these models are overly complex. Utilizing the DR technique makes it possible to reduce the number of input characteristics. This results in a more concise, easily interpretable form that focuses the user's attention on the critical factors. The electrochemical model defines the physics of the underlying phenomena, which include ion diffusion, mechanical strain, charge transfer, and ion migration.

Furthermore, the inclusion of input characteristics or variables is required by empirical equations and representations of similar electric circuits. DR is relevant since the electrochemical, empirical, semi-empirical, and data-driven approaches all rely on a combination of input features. DR reduces the number of features in the dataset to only the most important ones, preserving as much information as possible while improving the model's overall performance. Because substantial amounts of data can sometimes cause poor performance in data analytics applications, some columns containing information are discarded. Despite the removal of some columns, the data characteristics remain relatively unchanged. The most widely used and accepted methods are backward elimination, forward selection, and random forests. DR techniques are used in the data analytics landscape. Backward elimination allows the fewest features to achieve the desired classification performance, whereas forward selection creates new features by combining existing ones. The set of features is correctly modified in the forward selection method.

Solid-state batteries, a next-generation lithium-metal battery, are being developed with an eye toward electric vehicle powertrains. A small, ultra-compact solid-state battery would take up little room, significantly increase battery life, and enhance safety. Additionally, it would have better energy and power density and charge far faster than the standard and widely used Li-ion batteries found in smartphones, smartwatches, and electric vehicles [131]. Despite these merits, making solid-state batteries is a complicated and expensive science. Another limitation with solid-state batteries is the dendrites which are microscopic fissures that occur in the solid electrolyte while charging and discharging and which eventually become large enough to short-circuit the battery. No one has worked out how to do this affordably or sustainably. Thus, the foremost advancement in solid-state batteries is developing dendrite-resistant solid-state batteries. In view of the research review presented above, the authors in this paper propose the approach depicted in Figure 1 below. The approach in Figure 1 can be applied to any type of battery that has been developed for use in an electric vehicle or hybrid vehicle applications. The process is iterative to find an optimal solution that can slow down battery degradation.

According to Figure 1, the battery is developed with IoT capabilities to measure associated features surrounding the electrochemical parameters at least for two years and store the data. Subsequently, the data could be kept in the cloud, where it could be accessible to data scientists, engineers, and chemists researching ways to increase the battery's capacity. Due to the vast amount of data, DR techniques can be applied to minimize the number of features focused on or to discover the more minor and significant variables to the overall study. It will be possible to successfully execute the modeling and simulation of the battery once the DR technique stage has been completed. A model that allows for converting physical and electrochemical models into empirical models is essential, particularly when addressing the loss of capacity. It is possible that mathematical modeling will be a multiobjective problem requiring stochastic optimization to minimize the objective function. Once the set of unknowns or variables that control the objective function's value has been computed, the known variables can be reintroduced to optimize the battery manufacturing process. 4IR technologies provide an alternative or complementary approach to mathematical modeling [132]. In particular, machine learning offers an algorithmic solution to the multiobjective problem at the cost of computational power.

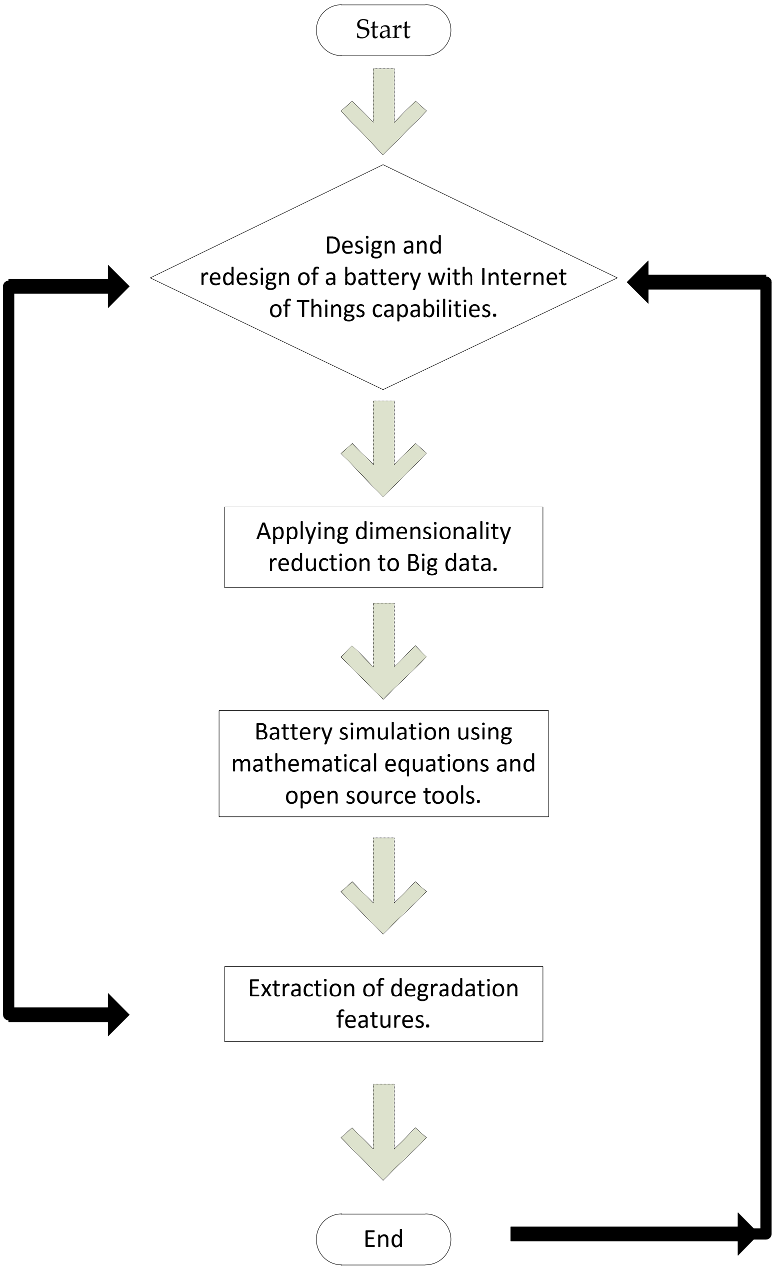

Figure 1. Iterative procedure for defining the parameters that are critical in determining the rate of degradation and, as a result, optimizing the performance of newly made batteries.

9. Conclusions

In this article, the deterioration mechanisms of batteries used in EMS, with emphasis on EVs, were examined. In addition, the literature that has attempted to lower energy costs in relation to the fundamental components of EVs, the MG, and the EMS was reviewed, and the current and applied battery deterioration models for the EMS were examined. This was carried out in terms of the hybridized system, widely used in the literature because of deficiencies associated with each ESD. The literature reported the overall elements that contribute to battery degradation. The various techniques for reducing battery degradation in EVs were identified. The fundamental assumptions and equations common to all battery models were identified and thoroughly addressed. In addition, the implications of each modeling approach and the repercussions of the various degradation mechanisms and patterns were explored. Finally, we proposed techniques for dealing with the issue of battery degradation with respect to EMS.

Despite the advances in the design of EVs and EMS, there are still some areas that are deficient and which can be considered for future development:

Parameterization: Recognizing defective cells before catastrophic failure, developing safer usage procedures, and creating materials to reduce degradation rates depends on understanding Li-ion battery degeneration. Insight into the physical world and ease of execution varies greatly among the methods utilized in this regard. The parameters of each degradation model have yet to be determined; hence there is no method for predicting such model parameters. It is vital to learn more about the interconnectedness of these degradation mechanisms and their effects rather than focusing only on the effects of deterioration.

Hydrogen storage technology: Despite the trend toward using hydrogen for EVs, which cuts consumption costs and carbon dioxide emissions, there is still a lack of storage technology due to the low volumetric energy density of hydrogen and its status as the lightest element. The onboard storage quantity is also easily flammable.

Charging Infrastructure: Providing the charging infrastructure for the millions of new electrified vehicles anticipated in the upcoming years may be more complicated than designing and manufacturing BEVs. Installing and maintaining chargers is costly. When utilizing electricity firms' institutional capacity to build and maintain networks, policies controlling the ownership of EV charging infrastructure utilities must be balanced to ensure successful and competitive markets. Additionally, the situation is compounded in that not all EV charging stations have grid access. At the same time, supraharmonics and harmonics can be seen in places where EVs are connected to the grid for charging, which causes the network to age and become unstable.

Battery Tech and the Transition to Solid State: transition from lithium to solid-state batteries: Even though most cars are powered by lithium-ion batteries, automakers are still trying to make solid-state batteries the industry standard. Solid-state batteries are easier to charge and may reach 80% of their capacity in 15 min. They also have excellent safety, compactness, and stability. In contrast to solid-state batteries, which keep 90% of their capacity after 5000 cycles, lithium-ion batteries start to degrade after 1000 cycles. For solid-state batteries to become practical for more extensive applications, such as EVs, hardware and technology must be scaled up. Such an update is costly. Solid-state lithium batteries are thought to be the best choice for the next generation of vehicle power batteries because they have high energy density and are very safe.

Energy harvesting methods: In order to reduce their reliance on power grids, EVs need to be incorporated into the mechanism for energy harvesting. Energy harvesting strategies need to be studied and explored from four perspectives: waste heat recovery from exhaust gas; mechanical energy recovery from braking, vibration, and shock; alternative fuels; integration of renewable energy sources. Such mechanisms would aid in powering vehicles in cases where the battery dies, so they can continue running during a disaster or crisis. For instance, networked police, fire, and ambulance services could coordinate their responses and services using the harvested energy.

EOL: Lithium-ion batteries, used in most commercial electric cars, reach their EOL at 80% of their initial capacity. When these batteries have lost almost 80% of their original power, they should be recycled. There are specific difficulties in creating EOL battery management systems and EV rules due to the anticipated increase in battery consumption over the next few years. These include a lack of information as to the number of defective batteries, battery kinds, the availability of technology, and recycled or remanufactured goods. Remanufacturing, recycling, and reuse are at least three of the EOL options for batteries that can lessen some of the environmental effects of disposing of Li batteries. If it is assumed there are no practical ways to dispose of and handle the enormous quantities of used batteries, severe environmental degradation, health issues, and resource depletion will unavoidably result. Techniques for utilizing used batteries, such as enabling an EV battery to be removed once it has passed its prime and repurposed as an energy storage system, are crucial. This would improve the grid's stability and dependability and accelerate the rate at which renewable energy can be integrated.

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