# Impact of Battery Degradation on Energy Management Systems

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The increasing popularity of electric vehicles (EVs) has been attributed to their low-carbon and environmentally friendly attributes. Given the depletion of fossil fuels and changes in climatic conditions due to air pollution, extensive research has been undertaken to develop EVs capable of matching or exceeding the performance of today's internal combustion engines (ICEs). Transitioning from ICE vehicles to EVs can significantly reduce greenhouse gases over a vehicle's lifetime. Across the different EV types, the widespread usage of batteries is due to their high power density and steady output voltage, making them excellent energy storage devices (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 compared to standard ICE and fuel cell EVs. This situation is further compounded through battery degradation, which gradually reduces the capacity of a battery.

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

## 1. 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 conditional upon driving, storage, and charging/discharge cycles. In a battery, degradation is unavoidable and can occur slowly or quickly [1]. 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 can be subjected to before it reaches either its capacity loss or its resistance increase threshold [2][3]. Understanding battery degradation is essential to designing high-performance batteries that can be used in various applications. Analysis of a Lithium-ion (Li-ion) battery's health is typically conducted by looking at its internal resistance and maximum functional capacity [4].

From this perspective, the most common degradation mechanisms in a battery are the following: the formation of solid electrolyte interphase (SEI) layers, lithium plating, particle fracture, positive electrode structural decomposition, and negative electrode particle fracturing, which is visible in negative electrodes [5]. During cycling, Li-ion intercalation is accompanied by diffusion-induced stress that causes electrode material deformation, cracking, pulverization, and fracture. Li-ion intercalation manifests as lithiation or delithiation [6][7]. As a result, the open circuits render the active electrode plate incapable of Li-ion storage [8]. 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 [9].

Battery degradation in terms of the main causes, degradation mechanism, degradation mode, and their consequences is now further discussed. Interaction between the five basic degradation mechanisms outlined above results in many secondary degradation pathways. The negative electrode is affected by graphite exfoliation, island creation for the negative electrode, dendrite production, and SEI decomposition. Similarly, the positive terminals are adversely affected due to island development in the positive electrode, positive SEI growth, nickel–lithium site exchange, transition metal dissolution [10], and $O_2$ dissolution.
A combination of the primary degradation mechanism and the secondary degradation routes leads to an extra set of secondary degradation events such as pore obstruction, electrolyte breakdown, and electrolyte loss. Since the invention of Li-ion batteries, graphite has dominated anode materials due to its unrivaled combination of low cost, abundance, high

energy density, power density, and extremely long cycle life. However, when graphite is chemically exfoliated in the presence of oxidants, graphite exfoliation occurs because oxygen atoms overcome the connection between graphene particles. Due to the significant change in volume caused by the Li-alloying process, electrodes have a short cycle life and need to be replaced frequently.

Over a limited period, lithium dendrites can 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, typical in 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 [11][12][13][14][15].

An SEI layer is a passivation and protective surface layer that is formed on the negative electrode by depositing 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 [16][17][18][19].

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 the performance, durability, and safety of Li-ion batteries. Due to the closeness of graphite electrodes to Li-ions, graphite anodes are more vulnerable to lithium plating. On the other hand, hard carbons and lithium titanate anodes are less vulnerable to lithium plating [20][21][22].

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 battery charging or discharging, 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 [6]. The loss of structural integrity may decrease electric conductivity, in the process reducing the battery's capacity [23][24]. 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, marked operationally as capacity or as power fading.

A sketch of the degradation mechanism is presented in [5]. Three significant 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 [5][25][26]. Cycle aging (caused by use) and calendar aging (due to the passage of time) are the two most common types of battery deterioration pathways that disclose degradation mechanisms (resulting from storage) [5][27]. The aging mechanism that contributes to the degradation process of Li-ion batteries manifests in different forms; this is presented in **Table 1**.

**Table 1.** Degradation mechanisms and noticeable signs associated with each mechanism [5][28][29][30][31].

| 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** | **Fracture of particles in both electrodes and particle isolation.** |
| **Thermal coupling** | **Reaction rate increases with higher temperature.** |

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 [26][32]. Batteries in storage can also degrade due to various chemical mechanisms, including the limited thermal stability of storage materials and the corrosion of metal electrodes. The latter manifests as silver oxide in silver-zinc batteries, lead in lead-acid batteries, and lithium in lithium/thionyl chloride batteries [33]. 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 [34][35], Li-ion batteries, and sodium-ion batteries [36]. 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 [3][28].
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.

# 2. Literature-Based Methodologies for Battery Degradation Cost Minimization

## 2.1. Degradation Minimization Technique Based on Stochastic Optimization

Performance-based Energy Management Systems (EMS) emphasize 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. The degradation cost can be reduced by resolving this objective function, which may involve single or multiobjective functions.

A real-time predictive energy management strategy (PEMS) for plug-in hybrid electric vehicles is proposed in [37] 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 a 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 State of Charge (SoC) and State of Health (SoH for PEMS design was developed and constructed mathematically. The system for charging and discharging is represented by an equivalent circuit model 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. 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 [2]. 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 cells and hybrid storage energy systems, can be utilized for any hybridized system, regardless of the storage device combination [38]. The equations consider the control target: fuel usage, electricity costs for battery charging and discharging, and the cost of corresponding battery degradation. The penalty-based continuation/generalized minimal residual (C/GMRES) algorithm determines the projected engine power command in real-time. 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. [38], 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 research, 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 [39], 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 research concludes that overlooking the battery degradation cost provides a false feasibility report regarding the optimal operating cost calculation for the EV.

Instead, 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 [40]. 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 [41] identify and evaluate battery capacity deterioration under various 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 modifying the charging pattern of electric vehicles may significantly decrease battery capacity degradation, which is a non-negligible and elastic component of the total cost. In [42], 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. [43], another strategy for ensuring and lowering the energy cost of  electric vehicles (EVs) and MGs was proposed by describing 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 involves an 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, including the total cost of plug-in hybrid electric buses (PHEB) equipped with a HESS consisting of lithium iron phosphate (LFP) batteries and SCs. The optimization goal is to reduce the lifecycle cost  for configuration A (two energy sources: engine and battery), compared to the life-cycle cost of configuration B (the engine and HESS). The optimization constraints are determined by each configuration's power and voltage and by state constraints such as the 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. Given that 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 [44]. The approach of HESS size optimization in order to minimize battery degradation and financial costs in EVs was explored. The optimal EM benchmarks that 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, as well as the design parameters of EV, were highlighted. The semi-empirical model used in this work follows the Arrhenius Law.

In ref. [45], 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 nonlinear, 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. The weighting factors were also set up to evaluate the objective functions.

Finding an ideal DOH requires achieving 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 PEMFC and 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. [46] was based on an existing vehicle that was initially a pure electric automobile. However, a proton exchange membrane FC was added to increase its autonomy. When creating the objective function and limitations, a model that illustrates dynamic behavior was included. Following that, an energy management system was evaluated 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 battery economy. 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 and 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 [47]. The simulation model considered for the fuel cell degradation model is based on the electrochemical active surface area (ECSA) loss. 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.

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

Another strategy utilized in the literature to lower battery degradation costs is using 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 to projected values, which fails to generate robust results even when the most practical forecasting algorithms are used [45]. 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 a strong 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 4IR enabling technologies in this space [48], 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. [49] 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, which involved a comparative examination of four distinct energy management strategies. A baseline option was proposed that does not require the usage of an ultracapacitor, in contrast to two heuristic methods and a Q-learning method. A genetic algorithm was used to validate the battery aging model against experimental data.

In ref. [50], 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 to develop the stochastic process model. Because of these uncertainties, various charging schemes were researched, including those with and without degradation cost and battery energy storage systems. Their 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 [51]. Experimental samples, an upgraded Thévenin model, and MATLAB programs were used to train and test the ANN-Predictive model, which was then implemented, and again tested. When learning values are implemented, this neural model can predict them and distinguish between expectations as to learning and adapting information of varying qualities. This was followed by a discussion about nonlinear arithmetical capacities, interfaces between information sources, yields for neural networks, and the corresponding Simulink model. The time spent and SoC is the model's information sources. The results are the average degradation function, degradation density function, cycle life, DoD, and capacity rate. In [52], 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 concepts essential to battery degradation were considered in this model, including the Arrhenius connection and the formation of solid electrolyte interface films. The parameters for the research 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. [53], 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 in terms of battery degradation are decisions regarding charging and discharging. The cost of the battery's initial degradation was calculated based on the current state of the battery in an electric vehicle. At the same time, the range and age of the EV 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 determining 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 decide when the EV should connect to the grid. The battery degradation cost was updated at the end of each 24 hr 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 [54]. 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 are discussed in ref. [55].
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. A box-plot-based statistical analysis method was provided using historical CRE readings from electric taxis to better understand 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 research showed that external circumstances, such as temperature, road conditions, and charging rate, will impact battery degradation in real-life EV use.

The availability of a large volume of data has cleared the pathway for using Big Data analytics in the EMS, especially the BMS. In [56], the capabilities of Big Data analytics in BMS applications were addressed, emphasizing the properties of Big Data in intelligent BMS, Big Data software frameworks, sources, and infrastructure. 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 [57]. 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 proposed 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 proposed platform's extended WDF and data structure 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 [58]. 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, optimizing the reward function is critical in performing deep reinforcement learning. The state variables required, including vehicle speed, battery SOC, and FCS output power, are accommodated in the assessment network's expression and input. 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 2**.

**Table 2.** Summary of findings from literature review [37][38][43][46][47][50][58][59][60][61][62][63][64][65][66].

| Reference | Type of EV | Description | Pros | Limitations |
|---|---|---|---|---|
| [67] | 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.<br>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.** |
| [46] | 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.<br>The decision made might be inaccurate.** |
| [43] | 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.<br>The PMP strategy includes one more state variable and can be used in a real-time control situation.<br>Computational costs are reduced due to the 2D PMP algorithm.** | **The mechanisms governing degradation are complex, nonlinear, and strongly interrelated.<br>They are susceptible to varying operational conditions; thus, practical analysis is complex.<br>Variation in electrodes, electrolytes, and manufacturing processes significantly increases the difficulty level.<br>Not all predominant mechanisms are considered in the study** |

| Reference | Type of EV | Description | Pros | Limitations |
| --- | --- | --- | --- | --- |
| [58] | 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.<br>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. |
| [37] | 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.<br>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, will trade-off precision for speed. |
| [44] | 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.<br>The solution provided due to the isolation of each system might not be globally optimal. |
| [47] | 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.<br>Since the EMS is rule-based, it is easy to implement.<br>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. |
| [50] | 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.<br>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.<br>There is no specific rule for determining the structure of ANN. The appropriate network structure is achieved through experience and trial and error. |
| [63] | 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).<br>Through optimal sizing, the energy and power requirements are satisfied.<br>The stress on the battery packs is alleviated; thus, the battery life is extended.<br>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. |

| Reference | Type of EV | Description | Pros | Limitations |
|---|---|---|---|---|
| [65] | 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.<br>The rule-based EMS might not be optimal for driving scenarios experienced on the road.<br>A single SoC value was used; it was unclear whether it was the minimum or maximum value.** |

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