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Health-aware Control for Health Management of Lithium-ion Battery in a V2G Scenario

Mônica S. Félix[1], John J. Martinez-Molina[2], Christophe Bérenguer[3], Chetan S. Kulkarni[4] and Marcos E. Orchard[5]

[1,2,3] *Univ. Grenoble Alpes, CNRS, Grenoble INP*, GIPSA-lab, 38000 Grenoble, France*
monica.spinola-felix@grenoble-inp.fr
john.martinez@grenoble-inp.fr
christophe.berenguer@grenoble-inp.fr

[4] *NASA Ames Research Center (KBR, Inc), Moffett Field, CA 94043, USA*
chetan.s.kulkarni@nasa.gov
[5] *CASE - Univ. of Chile, Santiago, Chile*
morchard@u.uchile.cl

ABSTRACT

In response to the urgent need to combat climate change and reduce greenhouse gas emissions, the transition towards renewable energy sources such as solar and wind power is indispensable. However, the intermittent nature of these sources poses significant challenges to the stability of power grids. Battery Energy Storage Systems (BESS) offer a viable solution, and there is potential for Electric Vehicles (EVs) to serve as energy reservoirs, thereby bolstering grid stability through Vehicle-to-Grid (V2G) technology. While V2G holds promise, concerns persist regarding the longevity of batteries, particularly with the additional demand from charging and discharging cycles. To address these concerns, this study introduces a health-aware control strategy for V2G service scenarios. By employing feedback control mechanisms to adjust degradation rates, the strategy aims to effectively manage battery aging. Simulation outcomes of a V2G scenario with random input sources illustrate the efficacy of this proposed approach, demonstrating its potential applicability in practical settings where battery health needs to be managed. In summary, this research contributes to the advancement of health-aware strategies for an interconnected grid where electric vehicles participate as energy sources, with a primary focus on optimizing battery health management while fulfilling grid demands. Future efforts will concentrate on refining optimization strategies and integrating control methodologies with state estimators to ensure the performance of the approach on embedded battery health management systems.

1. INTRODUCTION

In the face of climate change and the urgent need to reduce global greenhouse gas (GHG) emissions, the transition to non-fossil fuels and renewable energy sources is crucial. While photovoltaics and wind power energy are promising solutions, their intermittent nature poses a challenge to the stability of the power grid. In solving this problem, Battery Energy Storage Systems (BESS) are proving to be a crucial component in ensuring a consistent energy supply. In parallel, the proliferation of Electric Vehicles (EVs) offers the opportunity to use their batteries as energy storage units, which can act as an energy buffer during the day reinforcing the stability of the power grid.

The concept of using EV as energy storage known as Vehicle-to-Grid (V2G) offers advantages, but also pose some challenges. According to (Didier et al., 2021) a fleet of 15% electrified cars in France in 2030 would mean an energy stock of 25GWh throughout the day, equivalent to 20% of the daily average production of the French renewable energy grid in 2020. Another notable benefit is the potential for users to recoup their investment by participating in grid-level demand response programs. However, the use of batteries, particularly EV batteries, raises concerns about their longevity as these batteries are more often used in a "two-shifts" operation. The impact on battery life has direct financial and environmental implications and therefore justify efforts to find V2G strategies that take battery health into account.

A well- known solution is to use the grid operator as an intelligent conductor, requesting energy from multiple energy sources to ensure the effectiveness of grid distribution while reducing the cost of multiple sources, including the cost of battery aging. An overview of such an approach that uses optimized scheduling methods to control the power grid including V2G application is discussed in (Collath, Tepe, Englberger, Jossen, & Hesse, 2022). However, it is important to note some limitations of this solution, such as a generalized modeling of battery degradation and the non-consideration of aging-related changes in electrical behavior. An additional challenge lies in the prediction of degradation behavior, a task that remains difficult even with the improved accuracy of data-driven methods.

With recent advancements in online estimation methods for determining the state of health in individual battery packs, the feasibility of health management has expanded to the battery management system (BMS) level. The overall objective is to ensure optimal discharge using adaptive control algorithms to alleviate stress factors and manage the aging process throughout the operational lifespan of electric vehicles, accounting for varying conditions. Recent studies have shown the benefits of implementing a health management controller in wind turbines (Kipchirchir, Do, Njiri, & Söffker, 2023). Using a feedback controller framework can effectively mitigate the degradation process and regulate the end-of-life of these systems using control laws and dynamic models to adapt or reconfigure operational processes. It is expected that incorporating this approach into battery-powered applications can also bring benefits as the aging process in can be efficiently managed.

In this sense, this article presents a health-aware control (HAC) strategy to address battery aging by considering the dynamical interaction between operational and stress variables (e.g. state of charge and temperature). The approach is based on the modulation of the degradation-rate using a feedback controller, as proposed in (Félix, Martinez, & Bérenguer, 2023), in a V2G scenario. For this purpose, a novel dynamic model is first proposed that models the degradation-rate as a function of identified stress factors in response to operational demands. As presented in (Pelletier, Jabali, Laporte, & Veneroni, 2017), the stress factors and effects in battery aging are closely interrelated and an optimal control behavior is not obvious. In addition, the discharge process does not behave linearly and suffers from the fluctuations of aging mechanisms. Therefore, based on the proposed model, a control design is also presented that incorporates robust techniques to handle uncertainties inherent in the degradation modeling and randomness induced by the system operation.

The effectiveness of the approach is evaluated through simulations with a degraded battery model that simulates electrical and thermal dynamics, taking into account variations in critical factors such as increments on the internal resistance and reduction on the battery capacity induced by the ageing process and affecting battery autonomy. To demonstrate practical applicability, the article includes a case study of a simulation of in V2G scenario, integrating uncertainties and random elements to highlight the advantages of the approach in real-life. The results initiate a discussion on the benefits of the approach and its limitations of implementing HAC to V2G and further applications.

Accordingly, Section 2 presents the electrical circuit model of a battery subject to degradation and the proposed model of aging behavior. Section 3 describes the design of a feedback control approach to regulate the degradation-rate. Section 4 shows the results obtained by implementing such a health-aware controller at the BMS level of a V2G application. Conclusions and future perspectives are discussed in Section 5.

2. System model of a degraded battery

2.1. Equivalent circuit model

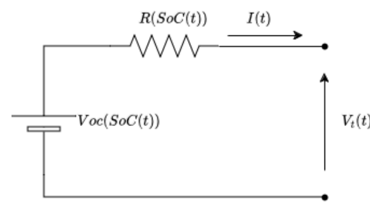


Figure 1. A simplified equivalent circuit model of the battery.

Figure 1 illustrates an equivalent circuit model of a lithium battery simplifies the complex electrochemical processes within the battery into a basic electrical behavior (Pelletier et al., 2017). It includes a voltage source $V_{oc}(k)$ representing the open-circuit voltage, internal resistance R to account for losses within the battery, both dependent of the State-of-Charge (SoC) usually expressed by a parameter $SoC(k)$ to track the available capacity of the battery. This model also incorporates a capacity element C modeling the battery's charge storage capability, and the flow of current $i(t)$ through the battery during charge-discharge cycles. Let us represent such equivalent circuit model as follows:

$$SoC(k+1) = SoC(k) - T_s \frac{I(k)}{(3600 \cdot C_n)} 100 \cdot \gamma(k) \ , \quad (1)$$

$$V_t(k+1) = aV_t(k) + (1-a)E(k) \ , \quad (2)$$

$$\text{with } E(k) = V_{oc}(SoC(k)) - R_n(SoC(k)) \cdot I(k) \cdot \gamma(k) \ . \quad (3)$$

In such model the dynamics of SoC is modeled using Coulomb counting of Eq.1, a function of the charge-discharge current rate $I(k)$ and counting sampling T_s, whereas the behavior of terminal voltage $V_t(k)$ follows Eq. 2 that is driven by a filter parameter a, and V_{oc} and R_n that are functions of the current $SoC(k)$.

2.2. Aging mechanism

In the equivalent circuit model, the state-of-charge and terminal voltage fluctuate in response to the current rate $I(k)$ ($I(k) < 0$ during discharging). Moreover, the charge-discharge behavior is intricately linked to the battery's aging process.

While aging stems from physical-chemical factors, its effects are reflected in electrical characteristics such as capacity fading and increasing internal resistance (Barré et al., 2013). This relationship suggests that these characteristics are influenced by an aging parameter, denoted here as γ. Specifically, the capacity $C(k)$ decrease and resistance $R(k)$ increase can be expressed as functions of γ:

$$C(k) = \frac{C_n}{\gamma(k)} \tag{4}$$

$$R(k) = R_n(SoC(k)) \cdot \gamma(k) \ , \tag{5}$$

where C_n and R_n are the nominal value for capacity and internal resistance.

For simplicity, let us consider γ to be equivalent in both effects, as they pertain to the same aging process. This framework sets the stage for developing a degraded battery model, just as introduced in (Martinez, Félix, Kulkarni, Orchard, & Bérenguer, 2024), where $\gamma = 1$ represents a new battery. During each discharging and charging mission, γ tends to increase until it reaches a maximum value of $\gamma = 2$, indicating that the battery can no longer operate.

2.3. Degradation extended model

As an electrochemical process, charge-discharge behavior incurs energy losses and generates thermal effects. This behavior is externally influenced by ambient temperature $T_{\text{amb}}(k)$ and the Joule effect, which produces heat ($T_{\text{Joule}}(k)$) when the current rate is non-zero. The thermal model can be described by Eq. 6, where c_0 is the inertial parameter of the thermal behavior, and $T_{\text{Joule}}(k)$ is defined by Eq. 7, incorporating factors such as c_1, $R_n(SoC(k))$, $I(k)$, and $\gamma(k)$.

$$T(k+1) = c_0 T(k) + (1 - c_0)\left(T_{Joule}(k) + T_{amb}(k)\right), \tag{6}$$

$$T_{Joule}(k) = c_1 R_n(SoC(k)) I(k)^2 \gamma(k) \tag{7}$$

How γ increases is an important research topic. In this matter, it is known that the increased current generates heat and accelerate degradation by promoting the dissolution of the electrode material and the breakdown of the electrolyte, thus we propose a model for the increase in γ based on the same influences as heating:

$$\gamma(k+1) = c_3 R_n(SoC(k)) I(k)^2 \gamma(k) \tag{8}$$

While this model remains an assumption and approximation, it is crucial for simulating the aging process responsible for increased resistance and decreased capacity. A similar approach to finding a degradation growth model is presented in (Brown et al., 2009) for electro-mechanical actuator applications. Also, this sheds light on which variables of the charging-discharging process could be considered as relevant factors for making decisions regarding aging acceleration.

Note that as the model is posed, an increase in γ increases the acceleration of the aging process itself, similar to how increased temperatures in degraded batteries increase the degradation of the batteries themselves. In addition, a significant increase in γ can lead to instability of T.

3. Problem formulation

This work focus on the application of health-aware discharging for power sale to the grid, known as V2G or V2Market. In this application, there are three main concerns:

1. Supplying the grid with enough energy stored in the battery in order to stabilize it.
2. Monetizing the time the car spends parked in the parking lot without charging.
3. Yet, taking into account the cost of battery degradation since discharging counts as a cycle in the battery's lifespan.

As explained in (Reniers, Mulder, Ober-Blöbaum, & Howey, 2018), when purchasing stored energy, the grid offers a value per kWh correlated with intermittent sources (e.g., solar and wind) availability. Energy prices fluctuate stochastically due to the stochastic behavior of these resources. A grid operator manages participation percentages and demand for each source to optimize production, considering costs, including batteries degradation. This optimization is reviewed in (Collath et al., 2022). While grid demand is generated, users aim to monetize their parked time without charging. Such profitability can be determined by:

$$R = \sum_{k=0}^{t_f} P(k) \times \text{Price}(k) \tag{9}$$

Here, $P(k)$ represents the power sold at discrete time step k, which can be measured by:

$$P(k) = V_t(k) \times I(k) \tag{10}$$

With power demand and price previously established, maximizing profitability becomes a matter of ensuring that $P(k)$ closely matches the power demand and maximizing the discharging interval t_f.

Despite the potential for monetizing a parked car, it is important to acknowledge that there is a cost associated with battery degradation when discharging. This degradation ultimately shortens the battery's lifespan, leading to decreased performance and necessitating eventual battery replacement. Let us consider this cost as the accumulated degradation over the discharging mission:

$$D = \gamma(t_f) - \gamma(0) \quad (11)$$

To proceed with a solution, let us consider the following:

- The power demand profile (i.e., $P_{grid}(k)$) is pre-defined on an hourly basis, and the power sold never exceeds the power demand ($P(k) \leq P_{grid}(k)$).
- The battery experiences degradation during discharge, as described by Eq. 8. The initial degradation index γ is estimated online using algorithms such as the one proposed in (Didier et al., 2021) or (Martinez et al., 2024).
- The initial State of Charge (SoC) is known and may be lower than the maximum capacity, while a minimum battery SoC is specified and consistently lower than the initial SoC, as represented by:
$$SoC_{\text{min}} \leq SoC(k) < SoC(0) \leq 100\%$$
- The maximum duration for which the vehicle remains parked, selling energy, is predefined as follows:
$$k \leq t_{\text{max}} \sim U(t_1, t_2)$$
- The terminal voltage remains consistently above a safe minimum ($V_t(k) > V_{\text{min}}$).

Figure 2 illustrates the proposed V2G service scenario with battery health management control acting as a discharging auxiliary system. It is assumed that SoH and SoC estimations are available and provided by a BMS.

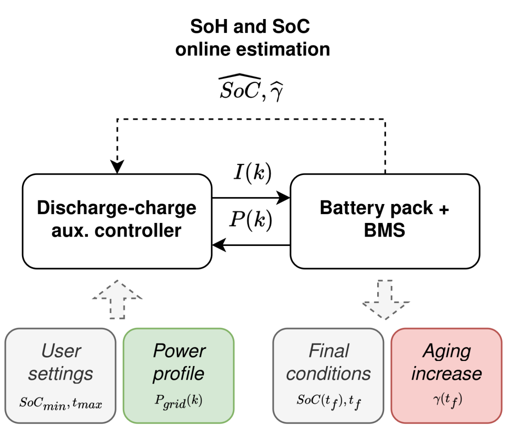


Figure 2. Illustration of Power-sale discharging mission.

3.1. Discharging strategies

The sale of vehicle energy can have numerous strategies. The first and simplest strategy is to manage the delivery of energy to exactly match the grid demand, only stopping the discharge when any of the restrictions (i.e. SoC_{min}, t_{max}, or V_{min}) are triggered. However, this strategy is not optimized, as it does not prioritize maximizing profitability or minimizing degradation costs. Therefore, we can assume other strategies that act on the current rate to maintain power close to demand, while at the same time, avoiding excessive degradation or deliberately degrading to manage battery lifespan. Here we are assuming that the grid is supplied by several other vehicles, and that its stability will not be affected if $P(k) < P_{grid}$.

In the scope of this study, we consider two control strategies:

1. Find the appropriate current $I(k)$ at time k that facilitates discharge in a manner that SoC achieves its minimum by time $tf = t_{max}$, i.e. $SoC(t_{max}) = SoC_{min}$. This strategy optimizes the utilization of parked time and the current, a key factor influencing degradation.
2. Find the optimal current $I(k)$ at time k that allows the degradation rate to follow a predefined reference $\Delta\gamma_{ref}$, ensuring a desired growth rate by time $t_f = t_{max}$, i.e. $\gamma(t_{max}) - \gamma(0) = \Delta\gamma_{ref}$.

The first strategy emphasizes managing the discharge duration. If the discharge time is shorter than the parking duration, the current is adjusted to meet the objective. This approach ultimately influences degradation growth through effective time management.

On the other hand, the second strategy prioritizes degradation effects. It involves tracking a desired γ growth rate either to meet a predefined lifespan or to meet a optimize a value γ^d derived from an optimization problem involving power sold and γ growth rate.

As discussed in (Collath et al., 2022), BESS technology that addresses only issues 1 and 2 of the previously formulated problem does not account for degradation costs over time, reducing the profitability of V2G usage. The two strategies proposed here aim to address the third issue. The first strategy involves mitigating the impact of current on aging increase during discharge, while the second strategy focuses on regulating the degradation-rate by reconfiguring discharge across multiple cycles. Both strategies will inevitably affects the performance of energy delivery to the grid, reducing the profit per discharge. However, this reduction can lead to a significant improvement in battery life. By designing an optimal controller for both strategies, we try to find the best compromise for this trade-off.

3.2. Control framework

For the design of the controller, we consider the system to be controlled written in a discrete-time state-space representation:

$$x_{k+1} = A(\rho_k)x_k + B(\rho_k)u_k + E(\rho_k)d_k\,, \quad (12)$$

with respect to the state vector defined as $x_k \in \Re^n$, the control input variable $u_k \in \Re^m$ and the disturbance input of $d_k \in \Re^p$. The variability of the system is determined by a varying parameter vector ρ_k. When the varying parameter ρ_k is bounded and it belongs to a convex polytopic region Ω_ρ limited by N vertices of the polytopic set $\theta \in \Omega_\rho \subset \Re^L$ defined by ρ_k boundaries. Then, we can write ρ_k as a convex combination of vertices $\theta^{(i)}$ as follows:

$$\rho_k = \sum_{i=1}^{N} \alpha_k^{(i)} \theta^{(i)} \,, \tag{13}$$

where $\alpha_k^{(i)} \geq 0$ and $\sum_{i=1}^{N} \alpha_k^{(i)} = 1$.

Such a modeling approach is known as polytopic modeling, which enables the construction of robust control designs by guaranteeing stability within the boundaries of the convex set. Since the system is subject to variations due to stochastic disturbances in discharge conditions or changes over time in γ due to aging, this approach will ensure stability for all variable conditions that the discharging process and its dynamics face.

3.2.1. SoC rate control design

According to Eq. 1, SoC decreases dynamically as follows:

$$SoC(k+1) = SoC(k) + SoC'(w(k)) \tag{14}$$

Here, $w(k)$ represents the decision variable that can be adjusted to solve a control problem, specifically a tracking reference problem. To address this problem, we introduce an integrator error tracking $z(k)$ to be minimized. The system to be stabilized is thus defined as:

$$w(k+1) = u(k) \tag{15}$$

$$z(k+1) = z(k) + T_s \cdot (\widehat{SoC}'(w(k)) - SoC'_{ref}(k)) \tag{16}$$

where $u(k)$ represents the control decisions at each sample k, with T_s as the decision rate. $SoC'_{ref}(k)$ is the desired decrease rate of SoC. The linear decrease behavior of $SoC(k)$ imposes a desired rate given by:

$$SoC'_{ref}(k) = \frac{SoC_{min} - \widehat{SoC}(k)}{t_{max} - k} \tag{17}$$

where t_{max} and SoC_{min} are the maximum discharging time and the minimum SoC chosen by the user. $\widehat{SoC}(k)$ can be estimated through online algorithms such as presented in (Didier et al., 2021) with a higher sampling rate.

By choosing the current rate adjustments as the decision variable $w(k)$, we obtain

$$SoC'(w(k)) = \frac{-T_s \cdot 100}{(3600 \cdot C_n)} \gamma(k)(I_{\text{grid}}(k) + w(k)).$$

Now we can define the system matrix as follows:

$$A_k = \begin{bmatrix} 0 & 0 \\ T_s \cdot \rho(k) & 1 \end{bmatrix} \text{ and } B_k = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \,, \tag{18}$$

where $x(k) := [w(k) \; z(k)]$ and $\rho(k) = \frac{-T_s \cdot 100}{(3600 \cdot C_n)} \gamma(k)$, with $\rho(k) \in [\rho_{\text{min}}, \rho_{\text{max}}]$ imposed by minimum and maximum values of γ and nominal capacity.

Finally, we propose to calculate the decisions here using a feedback control law such as:

$$u(k) = -Kx(k). \tag{19}$$

To find the optimal control gain K that minimizes the error z, the system matrices are used to solve a robust Linear-Quadratic Regulator (LQR) problem (see Appendix A) with a Linear Matrix Inequality (LMI) solution.

3.2.2. Aging rate control design

According to Eq. 8, the increase of γ can be expressed as:

$$\gamma(k+1) = \beta(w(k))\gamma(k)$$

In line with the SoC rate control, $w(k)$ denotes the decision variable adjusted to solve a control problem, particularly a tracking reference problem, and an integrator error tracking $z(k)$ is also employed for minimization. The system to be stabilized is thus defined as:

$$w(k+1) = u(k) \tag{20}$$

$$z(k+1) = z(k) + T_s \cdot (\widehat{\beta}(w(k)) - \beta_{ref}(k)), \tag{21}$$

where $\widehat{\beta}(w(k))$ represents the estimated increase rate of γ, T_s is the control decision rate. β_{ref} denotes the current desired increase rate. The exponential growth behavior of γ imposes a desired rate given by:

$$\beta_{ref}(k) = \frac{1}{(t_{max} - k)} \ln\left(\frac{\Delta\gamma_{ref}^{(n)} + \hat{\gamma}(0)}{\hat{\gamma}(k)}\right) \tag{22}$$

where $\hat{\gamma}(0)$ is the estimated γ at the beginning of the cycle and $\hat{\gamma}(k)$ at each control calculation, t_{max} is the imposed maximum discharging interval, and $\Delta\gamma_{ref}$ is the chosen increase increment of the current cycle, which can be calculated in different ways; we propose calculating it based on the value desired of γ for a chosen number of cycles N as follows:

$$\Delta\gamma_{ref}^{(n)} = \frac{1}{2 * (N - (n-1))} \ln\left(\frac{\gamma_{ref}^{max}}{\hat{\gamma}(0)}\right) \tag{23}$$

n represents the current discharge cycle, while γ_{max} denotes the desired level of γ in cycle N. In this scenario, the vehicle is expected to operate in two shifts: during the day in the parking lot and the remainder of the day on regular routes, which counts as an additional full discharge. Although realworld usage may introduce random degradation during the vehicle's operational shift, we assume that the cumulative effect of these fluctuations does not surpass the degradation equivalent to two full discharges of the vehicle.

According to Eq. 8, the dynamic of β is defined by $\beta(w(k)) = c_3 R_n(SoC(k))(I_{grid}(k) + w(k))^2$. Now, the matrix of the system can be defined as:

$$A_k = \begin{bmatrix} 0 & 0 \\ T_s \cdot \rho(k) & 1 \end{bmatrix} \text{ and } B_k = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \quad (24)$$

where $x(k) := [w(k)\ z(k)]$ and

$$\rho(k) = 2 * c_3 R_n(SoC(k)) I_{grid}(k),$$

with $\rho(k) \in [\rho_{min}, \rho_{max}]$ imposed by minimum and maximum values of internal resistance and current rate imposed by the grid, and variations on c_3. For this strategy, we also propose utilizing a feedback control law

$$u(k) = -Kx(k),$$

where the control gain K is determined through a robust control LQR problem.

4. Results: V2G scenarios

The degradation battery model presented is used here to simulate an aging battery. The control framework is employed to achieve the objectives of the two different discharge strategies. Firstly, let us describe the simulation scenario used to obtain the results, and then analyze the outcomes of such approaches for battery health management.

4.1. System Description

In real-life scenarios, uncertainties are inherent in the aging process of systems. Various sources of randomness contribute to these uncertainties, stemming from factors such as internal resistance, open circuit voltage, and ambient temperature fluctuations. The interplay of these factors leads to diverse aging acceleration rates, ultimately resulting in varying the battery's lifespan.

The introduced degraded battery model is utilized to simulate the controlled system. The model's parameters, including internal resistance and open-circuit voltage as functions of SoC, are detailed in Appendix B.

The simulated scenario considers the stochastic nature of battery parameters and discharging conditions. The simulation parameters treated as stochastic sources are listed in Table 1.

These conditions vary randomly, as detailed in Table 1, and are subject to change with each simulation of the 20 consecutive days of V2G discharge. For example, Figure 3 outlines the user-defined parameters for each discharge event, including the minimum desired SoC (SoC_{min}) and the maximum discharge duration (t_{max}). These settings collectively determine when the discharge should halt, in conjunction with the minimum voltage, as elaborated in the preceding problem formulation.

Table 1. Simulation parameters

Parameter	Value	Unit
T_{amb}	$\mathcal{N}(23, 3)$	°C
C_1	$\mathcal{N}(2.5, 10^{-2})$	Ah
R_{min}	$\mathcal{N}(0.02, 10^{-2})$	Ω
E_o	$\mathcal{N}(4.2, 10^{-2})$	V
$SoC(0)$	$\mathcal{N}(90, 10)$	%
ϵ_γ	$\mathcal{U}(2e-4, 12e-4)$	-
t_{max}	$\mathcal{N}(4, 1)$	h
SoC_{min}	$\mathcal{N}(10, 1)$	%
P_{grid}	$\mathcal{N}(175, 300)$	W

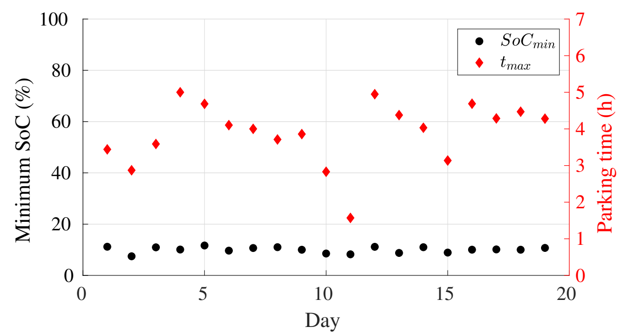


Figure 3. User settings for 20 days in consecutive discharge scenarios.

It is assumed that the battery operates in two shifts: during the day in the parking lot and the rest of the day on regular routes, which contributes to additional aging. Thus, at the start of each new day $n \in [1, N]$, the initial value of $\gamma^n(0)$ is defined as:

$$\gamma^{(n)}(0) = \gamma^{(n-1)}(t_f) + \epsilon_\gamma \ , \quad (25)$$

where $\gamma^{(n-1)}(t_f)$ represents the level at the end of the last discharging day, and ϵ_γ denotes a random positive additional increase.

Figure 4 displays, then, the initial SoC, $SoC(0)$, representing the battery's starting level upon arrival at the discharge station for the current shift. Additionally, it depicts the additional degradation factor since the last discharge, denoted as ϵ_γ.

Finally, the resulting discharge will depend on the discharging conditions, which will vary with each discharge event. The discharge halts once one of the stop conditions is met. Figure 5 showcases the outcomes of simulations of discharge scenarios without a discharge control. It illustrates diverse discharge histories observed over 20 consecutive days, emphasizing the system's variability influenced by the stochastic nature of battery parameters and discharging conditions.

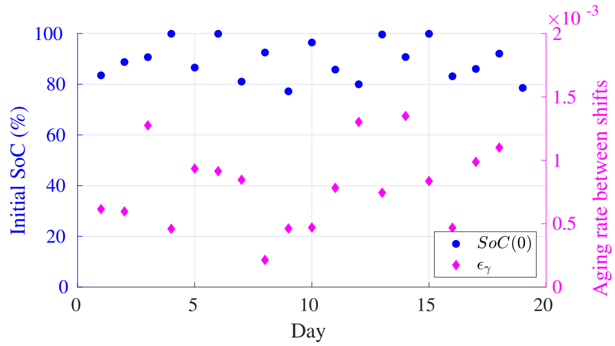


Figure 4. Initial conditions for 20 days in consecutive discharge scenarios.

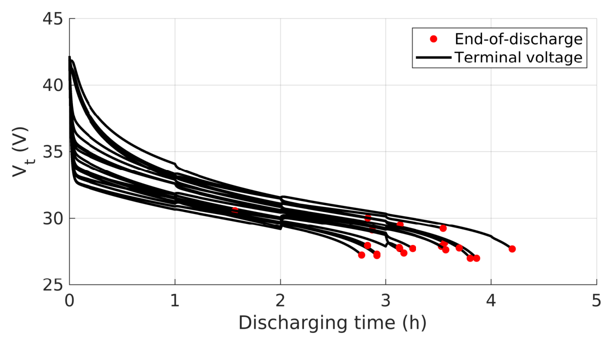


Figure 5. Simulated energy discharge for 20 days in consecutive discharge scenarios for a battery pack of 10 cells.

4.2. Control implementation

In this work, two control strategies are employed to mitigate battery aging, utilizing a feedback control $u(k)$ for the current rate, expressed as $I(k) = I_{\text{grid}} + w(k)$.

SoC Rate Control: For the implementation of the first strategy's control, Eq. (15) is utilized. Employing robust LQR techniques with the previously defined system matrices and simulation parameters, the resulting control gain K is determined as follows:

$$K = [0.011726,\ -70.399]. \tag{26}$$

The initial value for the integral action is calculated according to Eq. (15) as:

$$z_0 = \frac{w_0 + K(1)w_0}{-K(2)}. \tag{27}$$

where the initial decision parameter is chosen to be $w_0 = 0$. Note that, in practice, $w(k)$ is equivalent $u(k-1)$.

Aging rate control: For aging control, Eq. (20) is employed to minimize the reference tracking error. The rate adjustment is accomplished through a feedback control $u = -Kx(k)$, where K is also computed by solving a robust LQR problem with the provided model parameters, yielding the following values:

$$K = [0.9987,\ 5444.5]. \tag{28}$$

It is expected an aging rate reference to be determined according to Eq. (23) using the following parameters:

$$n \in [1, N],\ N = 20,\ \gamma_{\text{ref}}^{\text{max}} = 1.025.$$

Here, $\gamma_{\text{ref}}^{\text{max}}$ is the desired aging parameter value at the conclusion of 20 days, which is set to be lower than the expected value of standard discharging, but could be chosen to respect a prognostic and health management constraint.

4.3. Simulation results

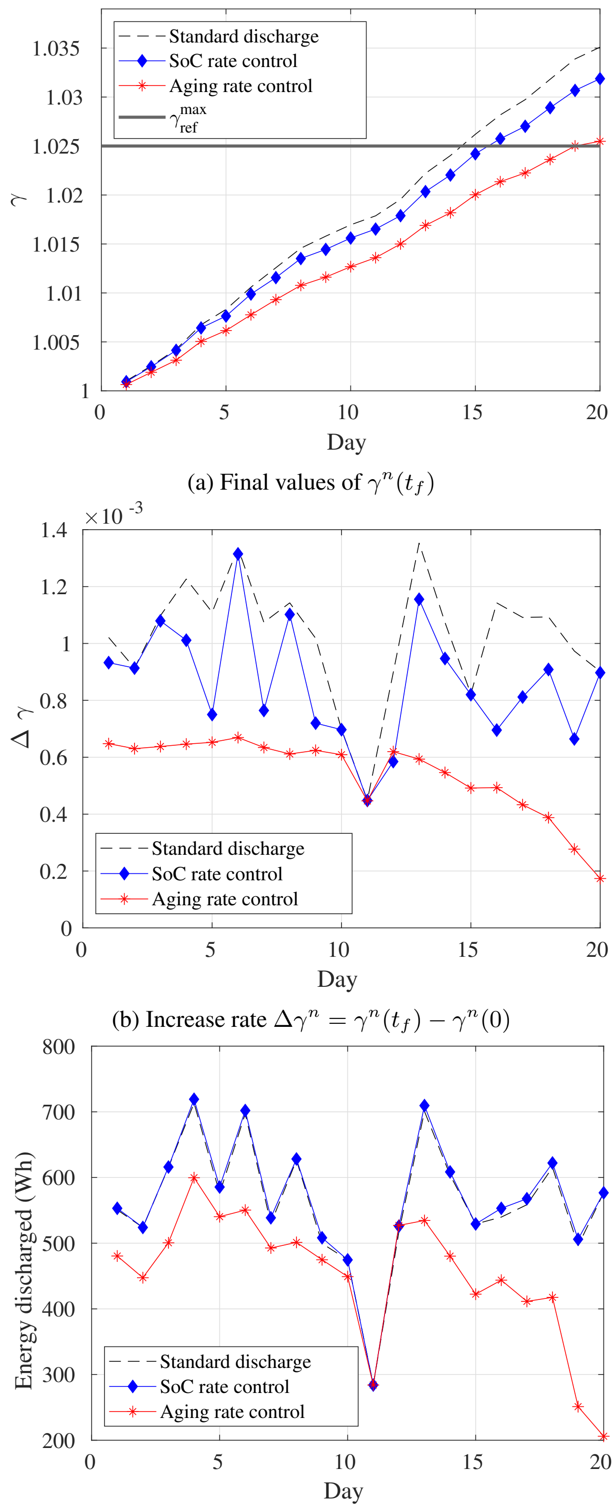
When implementing the control of the SoC decrease rate or the aging control (increase of γ) for the 20 consecutive days scenario, we obtain the respective aging curves of both strategies as shown in Figure (6a). Each day of discharging service resulted in an increase in the rate of γ and energy sold to the grid, as shown in Figure (6b) and Figure (6c), respectively.

The total energy sold through the SoC rate control strategy surpasses that of the γ rate control. This is because the latter prioritizes tracking the desired γ growth rate over maximizing energy discharged. In particular, SoC rate control surpasses standard discharge in total energy when it focuses utilizing the entire available discharge time. Moreover, when examining the aging rate, standard discharge emerges as the least favorable option. SoC rate control effectively mitigates aging by regulating the current rate, although it remains susceptible to random fluctuations determined by the discharge conditions. Conversely, aging rate control continuously adjusts the aging rate to achieve the required γ value by the end of the 20 cycles.

By considering 1.025 as the maximum γ rate (instead of $\gamma = 2$), the total energy sold by the battery in 20 days would be comparable to that of other strategies, as it undergoes more cycles below the maximum γ threshold. Additionally, aging rate control provides the advantage of effectively managing capacity fading. By considering the 20-day rate as a reference and considering the total aging interval ($\gamma = 2$), the battery can reach half of its maximum capacity in about 800 days with aging rate control, a level of certainty not achievable with the other strategies.

5. Conclusion

This work introduces two health-aware strategies for grid energy sales in a V2G service. The first strategy focuses on managing discharge to maintain the SoC above a specified minimum within the discharge interval, optimizing usage and



(a) Final values of $\gamma^n(t_f)$

(b) Increase rate $\Delta\gamma^n = \gamma^n(t_f) - \gamma^n(0)$

(c) Total energy discharged to the grid

Figure 6. Results of 20 days ($N = 20$) of discharging for power selling using different strategies.

mitigating stress factors like discharge current. This strategy embodies a basic approach, based on stress factor mitigation, offering a V2G service that considers aging process. The second strategy aims to regulate the aging increase rate during the discharge event to maintain the SoH below a specified maximum within the interval discharging days. Both strategies employ adaptive control of grid demand, designed with robust techniques and error minimization. Results show the first strategy reduces the final aging, represented by the stress factors index, while increasing total energy sold at the discharging end. Conversely, the second strategy prioritizes desired degradation increase rates, potentially compromising energy sold, but it succeeds in managing the aging process. Specifically, the degradation rate regulation strategy ensures that the aging factor reaches the desired level within the specified timeframe, which proves beneficial for lifetime control. Furthermore, it still ensures the sale of energy close to the standard discharge behavior. In summary, this paper's contributions include:

- Incorporating aging effects such as capacity decrease and resistance increase into the discharge behavior of a battery model.
- Health-aware discharging approaches using degradation-rate regulation and discharge-rate regulation.

Certainly, there is significant potential in incorporating SoH and SoC estimations integrated with closed-loop HAC frameworks to effectively manage battery health. Future work involves integrating control approaches with SoC an SoH estimation approaches to validate performance when used in conjunction, particularly in embedded applications. Furthermore, the utilization of other control optimization techniques, such as Model Predictive Control (MPC), to align with different objectives, such as charging process, is encouraged. An extension of this work could involve comparing it with alternative approaches addressing the same issue. Finally, this study lays the groundwork for a charging-discharging parking service with energy selling that integrates strategies for the management of battery lifetime.

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APPENDIX A - LQR PROBLEM

Consider a linear system represented in state-space form as:

$$\dot{x} = Ax + Bu$$

where x is the state vector, and u is the control input.

The Linear Quadratic Regulator (LQR) problem is a control strategy designed to create an optimal feedback controller for such linear systems while minimizing a quadratic cost function and stabilizing the system. The objective of the LQR problem is to minimize a quadratic cost function, defined as:

$$J = \int_0^\infty \left(x^T Q x + u^T R u\right) dt \tag{29}$$

Here, Q is a positive semidefinite weighting matrix that penalizes deviations of the state from its desired trajectory, and R is a positive definite weighting matrix that penalizes control effort or deviations of the control input from its desired values.

The optimal control law u is then determined to minimize Eq. 29 and stabilize the system. When the control law is defined as

$$u = -Kx$$

K is the optimal gain matrix found through a stability guarantee function equivalent to the Riccati Equation, which depends on the existence of a positive definite matrix P.

APPENDIX B - MODEL PARAMETERS

In battery discharging, the values of R_n and V_{oc}, as depicted in the equivalent model, vary as functions of $SoC(k)$. These variations can be expressed by the following equations:

$$R_n(SoC(k)) = M * \left(R_{min} + \frac{K_3}{SoC(k)} + \frac{K_4}{100 - SoC(k)}\right) \tag{30}$$

$$V_{oc}(SoC(k)) = M * \left(E_o - K_1 \ln\left(100 - SoC(k)\right) - \frac{K_2}{SoC(k)}\right) \tag{31}$$

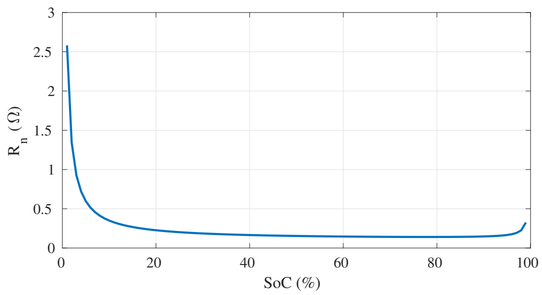
$$C_n = M * C_1 \tag{32}$$

Table 2 presents the parameters of the model used for simulation. These parameters are obtained using data from (Fricke, Nascimento, Corbetta, Kulkarni, & Viana, 2023).

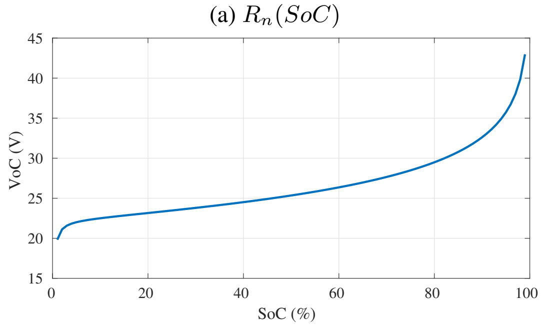
Table 2. Battery model parameters

Parameter	Value
M	10
T_s	0.02 s
a	$\exp\left(\frac{-T_s}{50}\right)$
c_3	10^{-8}
K_1	0.27
K_2	0.45
K_3	0.25
K_4	0.02

M is the number of cell in the battery pack. Obtained R_n and V_{oc} are illustrated in Figure 7.



(a) $R_n(SoC)$



(b) $V_{oc}(SoC)$

Figure 7. Nominal values of $R_n(SoC)$ and $V_{oc}(SoC)$ resulted from the considered model with mean mean parameters.