Method to Embed Behavioral Battery Model in Predictive Energy Management Systems

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***Abstract*—In the context of battery use in an energy system, accurate degradation models are crucial to improve economic efficiency, because these models help to ensure that the cost of degradation is lower than the benefits of using the battery. This paper proposes a novel method to integrate a complex empirical degradation model of a lithium-ion battery into the optimization of an Energy Management System (EMS). The model uses relaxed nonlinear equations of a multi-factor degradation model that are based on empirical test data. This approach allows the degradation model to be included in an optimization framework and to monitor the State-of-Health (SoH) of the battery.**

The paper presents a case study where the proposed degradation model is applied in an arbitrage scenario to evaluate the benefits of the model in the optimization process. The results show that even a simple degradation model yields a positive benefit of 6,250 EUR/MWh/year, while a more complex model can achieve up to 10,000 EUR/MWh/year. These findings demonstrate the efficacy of the proposed model in achieving efficient battery use in an energy system.

***Index Terms*—Lithium-ion batteries, MILP optimization, battery degradation, MPC, McCormick relaxation.**

I. Introduction

The increasing share of renewable energy in the electricity mix comes with challenges to store and supply electricity when it is needed. Lithium-ion batteries are a promising solution for short-term storage to cope with the stochastic nature of renewable energy sources. Indeed, batteries can buffer electrical energy and perform price arbitrage or grid support services. These services can generate revenue for the battery owner, but they have to be managed properly to minimize the degradation of the battery and maintain performance.

When possible, an Energy Management System (EMS) that manages batteries should avoid regimes that cause high degradation. On one hand, this can be done simply by restricting the power range or the State-of-Charge (SoC) range of the battery. On the other hand, there exists complex degradation models that can be used to predict the degradation a battery will experience under various operating conditions, but are not easily usable in real-time optimization contexts.

There are different types of battery degradation models available depending on the level of accuracy required and the complexity that can be afforded [1]. The most basic model is the Full Equivalent Cycles (FEC) to failure, which estimates battery lifetime by comparing the number of cycles performed to a maximal number before End-of-Life (EoL). However, this model ignores multiple parameters that influence degradation, such as temperature, SoC, and C-rate [2]. Empirical models are more accurate and take into account multiple parameters but are chemistry-dependent and require time-consuming development. Semi-empirical models incorporate physics-based equations along with empirical data and are more accurate than empirical models [3], [4]. Electrochemical models are the most accurate but too complex for optimization frameworks and are used primarily for designing new cells or as a reference for other models.

The goal of this work is to integrate an accurate battery degradation model in an energy management system that relies on model predictive control (MPC) to plan the operation of the system. MPC is a popular optimal control technique used to minimize a cost function over time through finite receding horizon optimization. It is particularly useful in energy management applications as it allows to manage complex systems, while directly incorporating constraints and forecasts (e.g. of weather). In this work, we aim for a Mixed-Integer Linear Programming (MILP) formulation for the optimization problem, as it provides a good expressive power on the one hand and can be solved efficiently using open-source solvers [5]. The main challenge we will face is to simplify nonlinear degradation models to fit this framework. Relevant studies with a similar approach are detailed next.

An additive empirical model was proposed in [6], taking into account four factors influencing degradation: the Depth-of-Discharge (DoD), SoC, the current I and the temperature T. The contributions of those factors were added together, which helped to linearize the model. However, the DoD was calculated between consecutive time-steps only rather than on full cycles, which largely under-estimates the impact of larger DoD. Also, the degradation measurements for each parameters were obtained from datasets of different studies that investigated different battery chemistry. As the battery degradation is very dependent on the battery chemistry, their model and results should be taken with caution.

A cumulative empirical model was proposed in [7], taking into account DoD, SoC and C-rate. The effect of the C-rate was estimated with a piece-wise affine (PWA) function, while

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the DoD and SoC were combined in a cumulative function allowing to capture their nonlinear effect on degradation. This approach required specific degradation data to be developed which limits its replicability and lacked confirmation against a validated degradation model, but had the advantage of being already linear so compatible with a MILP optimization framework.

Our work differs from the existing literature as it is based on an open-source degradation model called SoXery [8] developed based on extensive real-world testing. Moreover, we are able to approximate this multi-factor model while controlling the accuracy of the approximation through the use of PWA functions and McCormick relaxations, leading to approximation errors of only a few percents in the case study considered.

The rest of the paper is structured as follows: the methodology is presented in Section II to present the SoXery degradation model and the integration of the proposed degradation model in the optimization framework. Section III presents a case study exploring a scenario where a battery performs arbitrage on the grid energy prices. Finally, section IV presents the outcomes of the study and possible future work.

II. Methodology

A. Empirical Stress-based Model

SoXery [8] is an open-source battery degradation simulation model, based on an empirical stress-based degradation model [9]. The degradation equation were developed on experimental tests on lithium-ion cells with a Lithium Nickel Manganese Cobalt (NMC) oxide on the positive side, acting as the positive terminal. Soxery was developed in the frame of the IEA Open Source Energy Storage Models project [10].

The State-of-Health (SoH) of a battery at time t is defined as:

$$SoH(t) = \frac{Q_{max}(t)}{Q_{max,0}} \cdot 100\% \tag{1}$$

where $Q_{max}(t)$ the maximal capacity of the battery at time t and $Q_{max,0}$ its initial maximal capacity, both in [Ah].

The SoH decrease is modeled with two components: the calendar ageing D_{cal} that is happening continuously at all times, and the cycle ageing D_{cyc} that occurs only while the battery is cycled. The SoH after N time-steps is forecasted as:

$$SoH(N) = SoH_0 - \sum_{t=1}^{N} D_{cal}(t) - \sum_{hc=1}^{n_{hc}} D_{cyc}(hc) \tag{2}$$

where the calendar ageing is calculated at each timestep t and the cycle ageing is calculated for each half-cycle hc.

Each degradation component is based on a reference Degradation Rate (DR) multiplied by Stress Factor (SF) equations for every influencing parameter. Calendar ageing has a linear SF for SoC and exponential SF for temperature and is found by multiplying those two SF equations by the reference DR for calendar ageing and by the time elapsed. On the other hand, cycle ageing has nonlinear SFs for C-rate, SoC, DoD and temperature, where the average value is considered over the half-cycle. As a result, four nonlinear SF equations are calculated and multiplied by the reference charging or discharging DR, and by the DoD of the half-cycle hc considered.

$$D_{cyc} = DR_{ref} \cdot SF_{Crate} \cdot SF_{SoC} \cdot SF_{DoD} \cdot SF_T \cdot DoD_{hc} \tag{3}$$

B. Simplifications of the Model

The empirical stress-based model presented above is nonlinear and must be adapted to fit the MILP modeling framework. We make the following assumptions.

- A constant SF for temperature is calculated at 25°C. This is because the battery dynamic model considered in the MPC problem currently does not include a thermal model to forecast the temperature of the cells,
- The cycle degradation is calculated at every time step (except for DoD as explained later), instead of each half-cycle. This is because extracting half-cycles in the optimization is complex and nonlinear. This makes no difference for linear SFs, but introduces errors for nonlinear ones.

As a result, calendar ageing depends on the SoC only, which has a linear SF, making it compatible with the MILP optimization framework:

$$D_{cal}(t) = DR_{cal,ref}(A \cdot SoC(t) + B)\Delta t \tag{4}$$

The cycle ageing is more complex as it depends on the C-rate, SoC and DoD. We observe that the C-rate is the dominant factor for degradation. Therefore, a basic SoH model has first been developed accounting only for the C-rate in cycle ageing. The cycle ageing DR (in %SoH loss per Half Equivalent Cycle (HEC)) is multiplied by the C-rate for the timestep (in HEC per hour) to give the %SoH loss per hour, shown in figure 1. This DR can then be multiplied by the time-step in hour to get the cycle ageing component:

$$D_{cyc}^{simple}(t) = DR_{cyc,ref} \cdot SF_{Crate}(t) \cdot C_{rate}(t) \cdot \Delta t \tag{5}$$

It can be approximated with a PWA function as illustrated in Fig. 1 with four pieces. The negative and positive C-rates represent charging and discharging, respectively. This simple model assumes that the SoC and DoD do not influence the cycle ageing, yielding SF values of 1 for those factors.

Next, a more complex SoH model has been developed, which includes the impact of SoC and DoD on cycle ageing. The cycle SF for SoC is a linear function and it is considered at each time step.

The DoD is considered differently. If it is considered at each time step, cycles with large DoD will be broken down in multiple smaller DoD, and since the SF for DoD is nonlinear (quadratic in our case), this would cause an underestimation of the impact of DoD (this is the case in [6]). We propose to consider in the MPC the maximum SoC range over the horizon of optimization to approximate the DoD. This is not perfect as there can be multiple cycles of different DoDs over

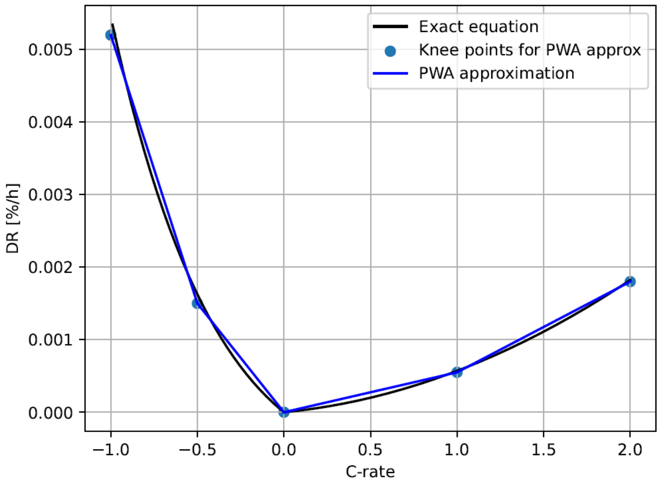

Fig. 1. Cycle Degradation Rate, for 60% DoD around 50% SoC

the optimization horizon, but typically not many for a horizon of one to a few days. This may lead to some overestimation, but this is clearly preferable as it will properly account for the nonlinear impact of DoD. Finally, the cycle SF for DoD is a quadratic function, it is approximated with a PWA function.

This results in the following equation for the complex cycle ageing degradation at the end of the horizon of N time-steps:

$$D_{cyc}^{complex}(N) = \sum_{t=1}^{N} [D_{cyc}^{simple}(t) \cdot SF_{SoC}(t)] \cdot SF_{DoD_{max}} \quad (6)$$

where the DoD_{max} is found as the maximal SoC range over the optimization horizon.

C. McCormick Relaxation

In the complex cycle ageing model (6), bilinear terms emerge from the multiplication of D_{cyc}^{simple} by SF_{SoC} and SF_{DoD}.

One popular technique to relax bilinear equalities is the McCormick relaxation [11]. This relaxation is done by replacing each bilinear term of the form $x \cdot y$ by an additional variable z, which is restricted by the four linear inequalities:

$$z \geq xy^L + x^L y - x^L y^L \quad (7a)$$
$$z \geq xy^U + x^U y - x^U y^U \quad (7b)$$
$$z \leq xy^L + x^U y - x^U y^L \quad (7c)$$
$$z \leq xy^U + x^L y - x^L y^U \quad (7d)$$

where x^L and x^U are, respectively, the lower and upper limits of the variable x, and y^L and y^U the lower and upper limits of y. Equations (7a) and (7b) represent two lower-bounding planes, while (7c) and (7d) represent two upper bounding planes, building a convex envelope around the exact surface $z = x \cdot y$.

However, with loose bounds of each of the variables x and y, the region described by (7) may be too large. As a result, the relaxation can lead to values of z far away from the exact value of $x \cdot y$, and hence to poor lower bounds on the original optimal value (dealing with a minimization problem).

To face this issue, the idea of partitioning the search domain by separating the range of one of the variables in sub-intervals has been proposed [12].

D. Tight Piecewise McCormick Relaxation

The tight piecewise McCormick relaxation consists in building piecewise under- and over-estimators of the variable z thanks to the use of additional variables and constraints. The following constraints are taken from the model [NF-12] of [12], for a partitioning of the x variable with N sub-intervals of equal size $d = (x^U - x^L)/N$. The equations were slightly rearranged for the implementation.

The variable x is found thanks to the binary variables $\theta(n)$ and the global differential variable Δx:

$$x = x^L + d \sum_{n=0}^{N-2} \theta(n) + \Delta x \quad (8)$$

$$0 \leq \Delta x \leq d \quad (9)$$

The N-1 binary variables $\theta(n)$, for $n = 0, ..., N-2$ are defined as follows:

$$\theta(n) = \begin{cases} 1 & \text{if } x \geq x^L + (n+1)d \\ 0 & \text{otherwise} \end{cases} \quad (10)$$

This condition is reformulated to be implemented in the optimization problem by specifying that $\theta(n)$ can be either 0 or 1, and taking the value 1 if $x - x^L - (n+1)d \geq 0$. By integrating $\theta(n)$ in this condition directly and normalizing by $(x^U - x^L)$ so that $\theta(n)$ does not exceed 1, we get the following constraint (instead of (10)):

$$\theta(n) \geq (x - x^L - (n+1)d)/(x^U - x^L), \text{ for } 0 \leq n \leq N-2 \quad (11)$$

The other condition on the $\theta(n)$ is that they are never increasing:

$$\theta(n) \leq \theta(n-1), \text{ for } 1 \leq n \leq N-2 \quad (12)$$

Then, the variable y is defined thanks to its lower bound y^L and a global incremental variable Δy as follows:

$$y = y^L + \Delta y \quad (13)$$

$$0 \leq \Delta y \leq y^U - y^L \quad (14)$$

As a result, substituting x from (8) and y from (13) into $z = xy$, we get the following constraint:

$$z = xy^L + x^L(y - y^L) + d \sum_{n=0}^{N-2} \overbrace{\theta(n)\Delta y}^{\Delta v(n)} + \overbrace{\Delta x \Delta y}^{\Delta z} \quad (15)$$

Defining the N-1 continuous variable $\Delta v(n) = \theta(n)\Delta y$, for $n = 0, ..., N-2$, the $\Delta v(n)$ are also never increasing (as are the $\theta(n)$), and are all bounded between 0 and $y - y^L$:

$$\Delta v(0) \leq y - y^L \tag{16a}$$
$$0 \leq \Delta v(N-2) \tag{16b}$$
$$\Delta v(n) \leq \Delta v(n-1), \text{ for } 1 \leq n \leq N-2 \tag{16c}$$

As the $\Delta v(n)$ are the relaxation of $\theta(n)\Delta y$, they also have the following McCormick relaxation constraints (found by plugging in their respective upper and lower bounds):

$$\Delta v(0) \geq (y^U - y^L)\theta(0) + y - y^U \tag{17a}$$
$$\Delta v(N-2) \leq \theta(N-2)(y^U - y^L) \tag{17b}$$
$$\Delta v(n) \geq (y^U - y^L)[\theta(n) - \theta(n-1)] + \Delta v(n-1) \tag{17c}$$
$$\text{for } 1 \leq n \leq N-3$$

Defining the global differential variable $\Delta z = \Delta x \Delta y$, the following McCormick relaxation constraints are introduced (found by plugging in their respective upper and lower bounds):

$$\Delta z \geq (y^U - y^L)\Delta x + d(y - y^U) \tag{18a}$$
$$\Delta z \leq d(y - y^L) \tag{18b}$$
$$\Delta z \leq (y^U - y^L)\Delta x \tag{18c}$$

As a result, the relaxation of each bilinear term means $2N+2$ additional variables and $4N+6$ additional constraints. It can be noted that the number of sub-intervals N controls the complexity of the problem, but also the tightness of the relaxation.

III. Case Study

We consider a case study where a stationary battery is connected to the grid and performs arbitrage on energy prices [13]–[15]. The battery will be used to buy electricity on the spot-market when the price is low and sell it back when the price is higher. However, arbitrage involves high cycling of the battery, which can cause rapid degradation. A faster degradation implies the need to replace earlier the battery, which is detrimental for the environment and for the financial results. Consequently, there is an interest to make sure that the economical gain of doing arbitrage is not overcome by the resulting cost of battery degradation. This can typically be done by the optimizer if accurate degradation equations are given. As a result, it is an interesting case study of the proposed battery degradation model.

The day-ahead European EPEX Spot prices of the year 2022 are used for this study and they are assumed to be known over the optimization horizon [16].

The objective function is to maximize the arbitrage revenue from energy exchanges with the grid, minus an equivalent battery degradation cost calculated as follows:

$$cost_{degrad}(N) = cost_{battery} \cdot \frac{SoH_0 - SoH(N)}{100 - SoH_{EoL}} \tag{19}$$

where $cost_{battery}$ is the cost of a new battery pack, SoH_0 is the initial SoH and $SoH(N)$ the SoH at the end of the horizon. The SoH_{EoL} is assumed to be 80%.

A. Optimization Problem

The battery used for this case study has a 90% round-trip efficiency and a cost of 200 EUR/kWh. An optimization horizon of 24h has been chosen with a time-step of 1 hour: it is sufficient for this application as we use hourly prices. The simulation is run assuming perfect predictions in terms of SoC for simplicity, but the predicted degradation (from the simplified models) is validated by comparing it to the original empirical SoXery degradation model.

Three simulation scenarios were performed with different levels of precision in the degradation model in the optimization:

- A0: ignoring the degradation in the optimization, and limiting the battery operating range: maximum 0.5C for charging and SoC between 10% and 90%.
- A1: simple SoH model, including exact calendar ageing from (4) and only C-rate dependent cycle ageing from (5).
- A2: complex SoH model, including (4) and adding SoC and DoD in the cycle ageing calculations in (6).

B. Results

For each scenario, 1-year simulations were performed and the output is analyzed in the following.

The histogram of C-rates is presented in Fig. 2. Most of the time, the battery is left resting at 0C (92% of the time for A1 and 74% for A2). Introducing SoH models in the optimization allows the optimizer to choose the optimal C-rate (instead of fixing hard constraints arbitrarily like in A0). With the simple SoH model in A1, the battery still operates mainly at specific C-rates, almost with an on/off behavior. On the other hand, the complex SoH model A2 exploits the entire range of C-rates because it exploits the tradeoffs between optimal SoC, DoD and C-rates values for cycle ageing. This allows to better mitigate degradation.

Degradation results are presented in Table I. The real SoH loss is calculated *a posteriori* based on the optimized SoC and C-rate profiles with the original SoXery model. This is assumed to be the ground truth in terms of degradation. The battery end-of-Life (EoL) is assumed when the battery reaches a SoH of 80%. Finally, the computing time reflects the complexity of using each degradation model in the optimization.

TABLE I
DEGRADATION RESULTS WITH ACCURACY AND COMPLEXITY

Arbitrage 1 year	**Real SoH loss [%/year]**	**Battery life-time [years]**	**Relative difference for SoH**	**Time per run [s]**
A0: No degradation	4.2	5	-	0.1
A1: Simple SoH	1.7	12	1.2 %	0.2
A2: Complex SoH	1.7	12	<0.1 %	5

The economical results, reported in Table II and given in EUR per MWh of battery installed per year, are broken down in two parts. First, the arbitrage gain is calculated as the gain

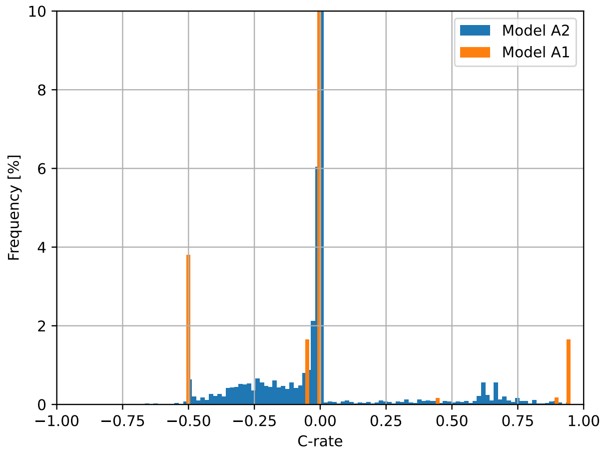

Fig. 2. Histogram of the C-rates over 1 year for degradation models A1, A2

from selling energy from the battery to the grid, minus the cost of the energy bought from the grid. Also, an equivalent cost of degradation is computed by assuming that the batteries need to be replaced at EoL, and attributing a fraction of the replacement cost proportional to SoH loss over that year (this is consistent with the cost of degradation incorporated in the optimization). Finally, the total real benefit is the difference between the arbitrage gain and the equivalent degradation cost.

TABLE II
ECONOMICAL RESULTS

Arbitrage results [EUR/MWh/year]	Arbitrage gain	Real cost of degradation	Total real benefit
A0: No degradation	27,750	28,950	-1,200
A1: Simplest SoH	18,250	12,000	6,250
A2: Complex SoH	20,300	10,300	10,000

The total real benefit is negative in option A0 (if degradation is only limited with hard constraints) meaning that the degradation cost exceeds the benefit from using a battery for arbitrage. The simple SoH model of option A1 is quite accurate (1.2% difference with exact degradation equations) and allows to significantly reduce the SoH loss per year and extends the battery life to 12 years. As a result, the benefit has a positive value of 6,250 EUR/MWh/year, making arbitrage beneficial over the battery lifetime. The complex SoH proposed in A2 allows to reduce further the degradation cost and yields a higher benefit, allowing up to 10,000 EUR/MWh/year, while exhibiting a manageable computing time per run of 5 seconds. Overall, we conclude that both A1 and A2 options are viable and which one is to be used depends on the desired trade-off between performance and computational load in a given application.

IV. CONCLUSION

We show in this work that including degradation in a predictive energy management strategy allows to account accurately for the hidden cost of degradation, therefore boosting the economic viability and lifetime of batteries in an arbitrage scenario. It has also been demonstrated that it is possible to manage a tradeoff between accuracy, computational load and optimality with different levels of degradation model accuracy, leading up to savings of up to 10,000 EUR/MWh/year.

Future work can include further investigation of the McCormick relaxation with multivariate partitioning, or will consider more realistic case studies with other grid services.

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