batteries

Review

A Review on the Degradation Implementation for the Operation of Battery Energy Storage Systems

Pedro Luis Camuñas García-Miguel [1,*], Jaime Alonso-Martínez [1], Santiago Arnaltes Gómez [1], Manuel García Plaza [2] and Andrés Peña Asensio [2]

[1] Electrical Engineering Department, Superior Polytechnique School, Faculty of Engineering, Carlos III University of Madrid, 28911 Leganes, Spain
[2] Siemens Gamesa Renewable Energy, 48170 Madrid, Spain
* Correspondence: pcamunas@pa.uc3m.es

Abstract: A naive battery operation optimization attempts to maximize short-term profits. However, it has been shown that this approach does not optimize long-term profitability, as it neglects battery degradation. Since a battery can perform a limited number of cycles during its lifetime, it may be better to operate the battery only when profits are on the high side. Researchers have dealt with this issue using various strategies to restrain battery usage, reducing short-term benefits in exchange for an increase in long-term profits. Determining this operation restraint is a topic scarcely developed in the literature. It is common to arbitrarily quantify degradation impact into short-term operation, which has proven to have an extensive impact on long-term results. This paper carries out a critical review of different methods of degradation control for short-time operation. A classification of different practices found in the literature is presented. Strengths and weaknesses of each approach are pointed out, and future possible contributions to this topic are remarked upon. The most common methodology is implemented in a simulation for demonstration purposes.

Keywords: BESS; degradation; optimization; batteries

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1. Introduction

The penetration of energy storage systems (ESS) in electrical systems is expected to grow exponentially over the next decade [1]. Conventionally, large-scale energy storage has been performed with pumped storage hydro-power. However, electrochemical batteries are becoming an alternative thanks to significant cost reductions over the last years [2].

Utility-scale battery energy storage systems (BESS) can provide a number of services thanks to reduced response times and high energy densities. The authors of [3] performed a review on which services can be provided by this technology. They demonstrated that BESS is cost-efficient even in electricity markets with low subsidies.

From the energy management system (EMS) perspective, the service provision is usually formulated as an optimization problem [4]. The decision variables are the setpoints, which are sent to the BESS, and the constraints are the system characteristics. Depending on the input type, it can be formulated as a deterministic or stochastic optimization problem. Stochastic programming has received more interest in recent years.

Degradation is one of the main issues of electrochemical batteries. Recent studies have proposed to consider battery ageing in short-term operation, since it is mainly caused by usage [5]. From the EMS perspective, this process can be integrated in an optimization model.

Degradation is caused by a series of electrochemical processes that occur on the electrodes and electrolytes. These processes may vary from one BESS technology to another; however, they tend to be similar. BESS materials become damaged by these chemical reactions, which is the cause of a loss of performance.

There are a variety of strategies to incorporate degradation into short-term BESS operation. Currently, no consensus can be found on how to consider this process. Furthermore, no literature review has been conducted yet about this topic, which is briefly discussed in most works.

This paper performs a critical study on how researchers have dealt with this issue. The different approaches found in the literature are classified and discussed. Future research streams are proposed.

This work is organised as follows. In Section 2, the BESS degradation process and implications on short-term and long-term operation are discussed. A review of the different approaches found in the literature is presented in Section 3. Section 4 shows a simulation example of the most common degradation cost implementation approach in arbitrage service. Lastly, conclusions and future works are included in Section 5.

2. Battery Energy Storage Degradation

Before associating degradation to operation, BESS ageing mechanisms must be modelled. In this section, a brief description of electrochemical battery degradation is provided. Afterwards, degradation models present in the literature are briefly reviewed.

2.1. Degradation of Electrochemical Batteries

The degradation of an electrochemical battery is a complex process caused by several factors. Degradation mainly occurs on the electrodes; for example, the formation of a layer named solid electrolyte interphase (SEI) on the negative electrode has been pointed out as one of the main causes of degradation [6]. The authors of [7] state that losses of cyclable and active materials lead to the loss of available capacity, while available power is reduced by the detriment of passive films. These ageing processes can be reduced by controlling:

- The depth of discharge (DOD), which is the depth of each cycle [8];
- The circulated current throughout the BESS [9];
- The ambient temperature of the cells [10];
- The state of charge (SOC), which is the energy stored at any given time [11].

Temperature has been neglected in control applications with the assumption that the battery operates in a controlled environment that maintains it at 25 °C. The battery performance generally degrades in terms of available capacity and power [12]. This degradation occurs during usage (cycling ageing) and over time (calendar ageing) [7]. These mechanisms may differ from one technology from the other, but the degradation process is in any case linked to usage and storage characteristics.

State of health (SOH) is the most used indicator for battery performance. It can be defined as the proportion of available capacity over its nominal value [13]. The most common formulation is (in per unit):

$$SOH = \frac{Cap_{Av}}{Cap_{Nom}}, \tag{1}$$

where

- SOH represents the state of health;
- Cap_{Av} represents the currently available capacity *(MWh)*;
- Cap_{Nom} represents the nominal capacity *(MWh)*.

The SOH metric is universal for any storage system, not only electrochemical batteries. Therefore, the analysis conducted in this paper can be extended to any ESS.

2.2. Degradation Modelling

The degradation process is usually simulated within a degradation model. Such models receive as input usage characteristics during a time period, such as circulated current or cycle depth. As output, they yield how much SOH has been lost. These models are used to evaluate how the BESS is going to age depending on how it is operated.

There are a wide variety of degradation models available in the literature. They differ mainly in their complexity and accuracy. More complex models allow to emulate the degradation process in more detail; however, they have a computational burden which may cause trouble during long simulations [14].

The simplest model is the ampere counter. It is based on the assumption that the battery can cycle a limited amount of energy during its lifetime. As input, it receives the energy cycled during a time period [9–15].

Other models use the relationship between cycle DOD and lifetime cycles, which is usually provided by the manufacturer [8–16]. Since that relationship is usually non-linear, these curves are often linearized as piecewise functions, as in [17]. Another strategy consists of using fitting techniques, as in [18].

Equivalent circuits models are also common in the literature; depending on the degree of complexity, they have more or less elements. A voltage source emulating open-source voltage in series with a resistor emulating internal resistance are the most basic elements. This resistor can be employed to model the available power loss over time [19].

Finally, the less used models are those that are electrochemical-based. In this category, the physics-based single particle (SP) model is the most common [20]. The authors of [14] prove that these models can be very precise; however, their complexity is a hindrance for long-term simulations.

3. Degradation Impact Models on Literature

In this section, a critical literature review of the economical impact of degradation into short-term operation is performed. A classification of the different approaches is depicted in Figure 1. The different categories are presented and discussed separately.

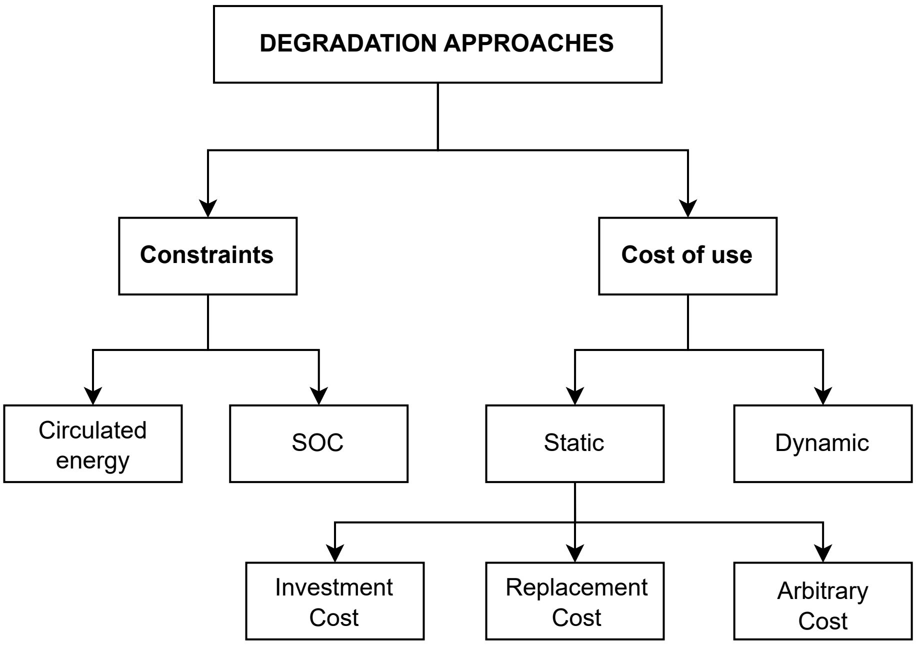

Figure 1. Classification of degradation incorporation.

As can be seen, the main distinction is between the use of constraints and the use of a cost of use. The former utilize the constraints of the optimization problem to consider degradation processes, while the latter implement the effect of degradation into the objective function. A summary of the literature review is presented in Table 1.

Table 1. Literature review summary.

Reference	Observations	Approach
[19]	Equivalent circuit model. Battery replacement during project is considered.	Dynamic cost
[21]	DOD-based model. Use of Rainflow algorithm for cycle counting.	Capital cost
[22]	Different applications such as peak shaving and frequency regulation. Quadratic model.	Capital cost
[5]	A sweep of different degradation costs is used to obtain the optimal value.	Arbitrary cost
[23]	Linearized DOD-based model.	Capital cost
[24]	Ampere counter. A daily cycle is considered for lifetime operation	Constraint model
[25]	SOC and voltage-based degradation model, which is nonlinear.	Capital cost
[9]	Equivalent circuit model. Degradation is applied as a reward, not a reinforcement learning algorithm.	Capital cost
[26]	Calendar and cycling degradation as wearing factors, translated into cost with an arbitrary value.	Arbitrary cost
[27]	DOD-based model. Use of capital recovery factor (CRF) to obtain the cost.	Capital cost
[28]	DOD-based mode and CRF. Empirical study of cost evolution.	Capital cost
[29]	Ampere counter model. Use of CRF.	Dynamic cost
[30]	DOD-based model with ambient temperature.	Replacement cost
[31]	Degradation model is applied cell-to-cell for an EV.	Capital cost
[32]	Both cycling and calendar degradation considered.	Capital cost
[29]	Degradation divided in three mechanisms, each with an impact factor.	Arbitrary cost
[33]	Degradation cost per kWh and degradation cost per cycle.	Capital cost
[34]	DOD-based model. Hybrid ESS with batteries and super capacitors	Replacement cost
[35]	DOD-based model with lineal calendar degradation. Allows choosing lifetime length.	Replacement cost
[16]	DOD-based model. Frequency response services.	Capital cost
[36]	Data-driven DOD-based degradation model.	Capital cost
[37]	Ampere counter model. Inflation rate considered for long-term operation cost calculation.	Capital cost
[38]	Different degradation models compared. Battery value considered to decrease during lifetime.	Capital cost
[18]	DOD-model linearized into an equation.	Capital cost
[39]	DOD-based model. Iterative algorithm using weary costs.	Capital cost
[40]	DOD-based model with complex Rainflow counting method.	Replacement cost
[8]	Linearized DOD degradation model. Degradation costs are scaled.	Arbitrary cost
[17]	DOD-based model with a piecewise function. Degradation is used only to calculate capacity loss.	Constraint model
[11]	Degradation is reduced by controlling SOC.	Constraint model
[41]	Circulated energy is restricted to control degradation.	Constraint model

3.1. Constrained Approaches

From the EMS perspective, the BESS control process is carried out by means of a constrained optimization model [4]. Constraints in the form of equalities or inequalities, which enclose the solution space, often represent the physical boundaries of the system. As mentioned in the previous section, DOD and circulated current are some of the main causes of cycling degradation [42]. In the constrained strategies, these two magnitudes are restricted in the optimization model constraints, resulting in a reduced degradation. However, they are less reliable since the link between the imposed limits and the resulting profits is weaker than in other alternatives. They are less common than the cost of use approaches presented in the following section.

3.1.1. Circulated Energy Restriction

These strategies restrain the circulated energy or current during the optimization period. The premise is to divide the circulated energy by the battery capacity to obtain the number of equivalent cycles. An inequality constraint limits the maximum amount of circulated energy; Equation (2) shows the typical expression:

$$EC \leq EC_{max} \tag{2}$$

where:

- EC represents the equivalent cycles during the optimization period;
- EC_{max} represents the maximum equivalent cycles allowed during optimization period.

The authors of [41] present an empirical study of circulated current reduction effect in a BESS performing arbitrage during 14 years. By iterating the circulated current restriction, they obtain the amount of cycles a day the BESS should perform for maximum benefits. This approach fails to consider how cycle profitability changes from one day to another.

In [24], cycle and calendar losses are considered. The degradation process is controlled by both oversizing the battery capacity and using a constraint. Afterwards, the constraint is added to the proposed optimization problem, limiting daily cycles, which is similar to the approach found in [41].

3.1.2. State of Charge Restriction

In this case, the restriction is applied to the stored energy on the BESS, which is limited to a certain level. An example can be found in [11]. This restriction can be formulated as in (3):

$$SOC_{min} \leq SOC(t) \leq SOC_{max}, \tag{3}$$

where:

- SOC_{min} represents the minimum SOC;
- $SOC(t)$ represents the SOC energy during time period t;
- SOC_{max} represents the maximum SOC.

Controlling degradation by setting SOC boundaries during operation presents the same disadvantages as restricting circulated energy. It modifies the operation without considering the service profitability during the optimization period. Nevertheless, the implementations are simple and straightforward.

3.2. Cost of Use Approaches

An alternative to restricting operation in the model constraints is to use the objective function. These strategies have the main advantage that optimization problem inputs, which determine service profitability, are taken into account. The term *cost of use* refers to the way degradation is reflected into the optimization function. For example, in the case of arbitrage of a standalone BESS on the day-ahead market, the objective function can be depicted as [5]:

$$Max\left\{\sum_{t=1}^{24} \Pi_{DM}(t) \cdot \Big(E_{dis}(t) - E_{ch}(t)\Big)\right\}, \tag{4}$$

where:

- $\Pi_{DM}(t)$ represents the energy price during hour t *(€/MWh)*;
- $E_{dis}(t)$ represents the discharged energy during hour t *(MWh)*;
- $E_{ch}(t)$ represents the charged energy during hour t *(MWh)*.

The objective function expressed in (4) aims to maximize benefits by purchasing energy at lower prices and selling it at higher prices. By implementing a cost related to cycling degradation, the following expression is obtained:

$$Max\left\{ \sum_{t=1}^{24} \Pi_{DM}(t) \cdot \left(E_{dis}(t) - E_{ch}(t) \right) - C \right\}, \tag{5}$$

where:

- C represents cost of use *(€)*.

Using this strategy, BESS operation is restricted to those times where the expected profit surpasses the estimated cost of degradation. When price spread is low, the operation will be restrained until the cost of use is lower than benefits. This approach allows to adapt the impact of degradation depending on the profitability. A similar approach is to implement degradation effect as a reward to a reinforcement learning algorithm, such as in [9].

As can be seen in (5), the objective function is expressed in economical units. Expression (1) shows how degradation is expressed in a different way. Therefore, a conversion must be made in order to implement it into the objective function. Researchers propose different ways for expressing degradation as an economical value. All procedures follow the expression (6):

$$C = \Delta SOH \cdot SOH_{cost} \tag{6}$$

where:

- ΔSOH represents the state of health loss;
- SOH_{cost} represents the cost of SOH loss *(€)*.

Cost of use approaches can be divided into different categories depending on how SOH_{cost} is defined.

3.2.1. Static Approaches

Static approaches are by far the most commonly used in the literature. In this category, the factor SOH_{cost} is constant throughout the BESS lifetime. This assumes that degradation has the same cost at the start and at the end of the life of the system.

Methodologies of this category can be distinguished by attending to how the constant factor is obtained. The most common is to consider that it depends on the capital cost. This perspective considers that degrading the battery causes a cost proportional to the investment. Such approach is used, for example, by the authors of [32,33].

The idea behind using the capital cost is to amortize the investment. However, since current battery prices make arbitrage not profitable [5], considering SOH_{cost} equal to the investment cost may lead into an excessive degradation cost. When costs of ageing surpass any possible possible profitability, the BESS will never operate, which is clearly not optimal. This is the main disadvantage of implementing this degradation cost. It is common in the literature to consider only an arbitrary fraction of the investment cost to solve this issue, as in [18], which is something difficult to justify. Besides this, capital costs are sunk costs, and, therefore, they should not affect operation.

Another approach consists of using the costs of battery replacement. The idea behind this is that since the investment is already made, the operation should seek to amortize the replacement of the next battery. Unlike using capital cost, this method considers that future payments can affect operation. The method for setting the replacement cost varies between authors.

In [35], the impact of diverse replacement costs in profitability is studied. The authors of [40] propose a method to discount the replacement cost to their present value. This perspective has the disadvantage that future replacement costs are unpredictable. Technical reports such as [43] may give a perspective of how these costs will evolve, but a long-term prediction is always uncertain.

Finally, there are authors who consider that SOH_{cost} is an arbitrary value. In some works, the degradation cost of use is even used as a fixed penalty unrelated to expected degradation. For example, in [44], this penalty is set at 10$/MWh. An interesting study is done in [5], in which a parameter sweep for the costs of use is made to obtain the value which returns the highest net present value (NPV) for the project. In this case, it is uncertain if it will be possible to extrapolate that optimal value to a different system, a different market, or even a different time frame for the same system.

3.2.2. Dynamic Approaches

The use of a dynamic cost of use considers that the value of degradation changes during project lifetime. Literature using dynamic approaches is remarkably scarce. An example is found in [38]. In this work, a battery is coupled to a generation system, the grid and a residential customer which acts as a load. The authors of this work consider that the battery loses value during its lifetime. This value is formulated as:

$$V = \frac{\nu}{D}, \tag{7}$$

where:

- V represents the current battery value *(€)*;
- ν represents the cumulative value *(€)*;
- D represents the accumulated degradation.

The cumulative value is defined as the total value added to the system compared to the scenario in which no BESS is present. This cost of use will decrease as accumulated degradation increases, which will lead to more BESS usage. The increase in cumulative value depends on the usage conditions. The authors of [38] state that empirical results indicate a convergence of battery value in the first weeks. However, this changes with operation conditions, such as user load profiles.

4. Degradation Cost Effect on Short-Term Operation

In this section, the standard implementation of degradation cost is presented. It consists of a DOD-cycle-based degradation model, which is commonly used in the literature. It is applied to the standard optimization problem of a BESS providing arbitrage service.

SOH_{cost} in the standard form of capital costs is implemented in the degradation function. Different capital costs are tested to demonstrate the short-term effect of a such degradation cost approach in short-term operation.

4.1. DoD-Based Degradation Model

The degradation model returns the amount of SOH lost during a cycle as a function of the DOD for that cycle. The relationship between DOD and SOH loss is expressed in Figure 2. A common problem with this approach is measuring partial-cycle DOD. The authors of [21,40] use a rainflow counting algorithm for this matter.

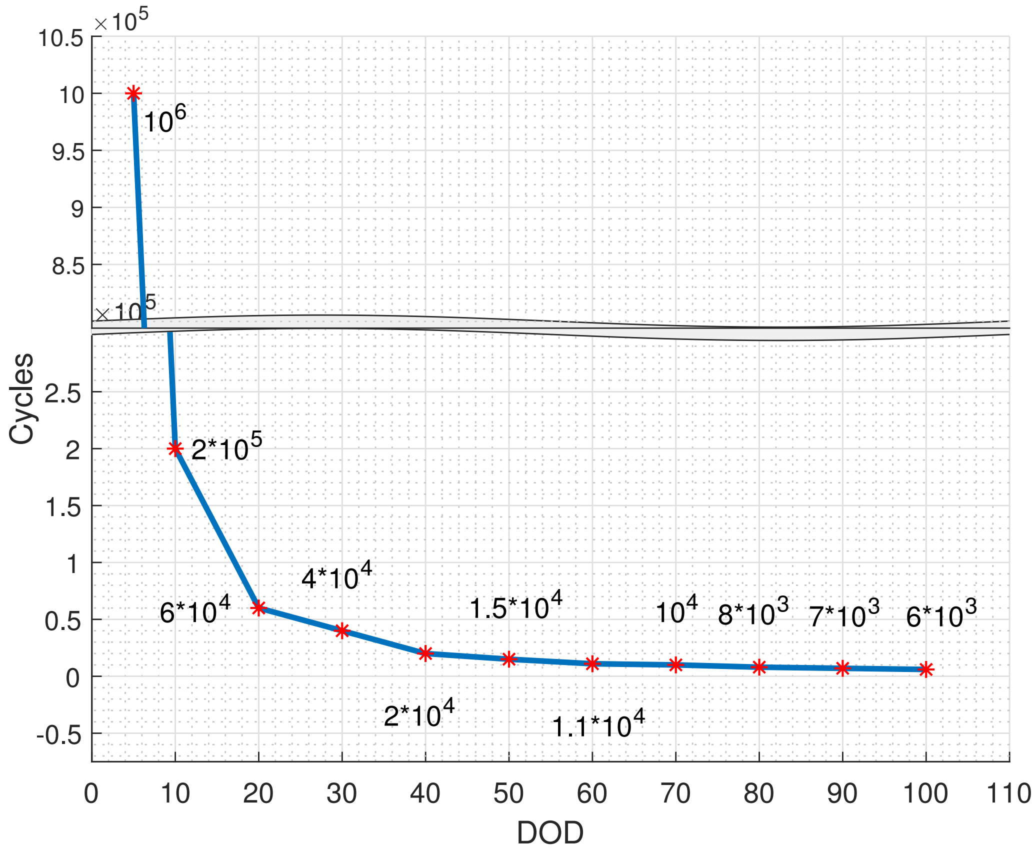

Figure 2. Relationship between DOD and useful life [45].

For convenience, it is assumed that the BESS does not perform more than two cycles a day, a workaround for application proposed in [46]. This is reasonable since a typical daily energy price curve has two peaks; however, this method could be extended to more cycles. Additionally, no energy is kept for the following day. Furthermore, since BESS starts and finishes its operation empty, in this case, DOD can be considered equal to SOC. The sum of the daily DOD for both cycles is computed using the circulated energy as:

$$DOD_{tot} = \Delta SOC_{tot} = \sum_{h=1}^{24} \frac{|P_{BESS}(t)|}{2 \cdot E_{nom}} \quad (8)$$

where:

- DOD_{tot} represents the total daily DOD;
- ΔSOC_{tot} represents the total daily SOC variation;
- $P_{BESS}(t)$ represents the BESS power during hour t *(MW)*;
- E_{nom} represents the BESS nominal capacity *(MWh)*.

It is assumed that the first cycle is as deep as possible considering the SOC levels during the cycle. The DOD for the second cycle is obtained considering the remaining circulated energy once that the energy for the first cycle is subtracted from the total circulated energy. This is, of course, an approximation, but it allows a simple implementation in a linear optimization problem. This is formulated as follows:

$$\begin{cases} DOD_1 = SOC_{max} - SOC_{min} \\ DOD_2 = \min(DOD_{tot} - DOD_1, DOD_1) \end{cases}$$

where:

- SOC_{max} represents the maximum daily SOC;
- SOC_{min} represents the minimum daily SOC;
- DOD_1 represents the DOD of the first cycle;
- DOD_2 represents the DOD of the second cycle.

Expression (9) is used for calculating SOH loss. The DOD-cycle relationship depicted in Figure 2 is used.

$$\Delta SOH = \sum_{c=1}^{2} \frac{1}{N_{cyc}(DOD_c)}, \tag{9}$$

where:

- ΔSOH represents the SOH lost;
- $N_{cyc}(DOD_c)$ represents the cycles at each DOD before end of life (EOL).

4.2. Degradation Cost Formulation

In this example, capital costs are used for obtaining the economical magnitude of degradation costs. This is the most common approach in the literature. It follows expression (10). As can be seen, it aims to amortize the BESS capital costs.

$$Deg_{Cost} = \Delta SOH \cdot BESS_{Cost}, \tag{10}$$

where:

- Deg_{Cost} represents the degradation cost *(€)*;
- $BESS_{Cost}$ represents the BESS capital cost *(€)*.

4.3. Optimization Problem Formulation

The arbitrage service schedule is formulated as a mixed-integer linear program (MILP), and the degradation model uses a piecewise linear version of the curve depicted in Figure 2. Some of the variables are restricted to the form of integers to avoid simultaneous charge-discharge.

The decision variables are the hourly BESS power setpoints. As input, it receives a vector of 24 hourly electricity prices. The linear objective function maximizes the benefits of arbitrage operation for a single day. The following constraints are implemented:

1. The BESS cannot charge over its nominal power:

$$P_{ch}(t) \leq P_{nom} \cdot ND(t), \tag{11}$$

   where:

   - $P_{ch}(t)$ represents the charging power during hour t *(MW)*;
   - P_{nom} represents the nominal power *(MW)*;
   - $ND(t)$ represents a Boolean variable whose value is 1 when it is not discharging at period t.

2. The BESS cannot discharge over its nominal power:

$$P_{dis}(t) \leq P_{nom} \cdot NC(t), \tag{12}$$

   where:

   - $P_{dis}(t)$ represents discharging power during hour t *(MW)*;
   - P_{nom} represents the nominal power *(MW)*;
   - $NC(t)$ represents a Boolean variable whose value is 1 when it is not charging at period t.

3. Charging power is always positive:

$$P_{ch}(t) \geq 0, \tag{13}$$

4. Discharging power is also always positive. This sign criteria is kept for simplicity on the optimization algorithm:

$$P_{dis}(t) \geq 0, \tag{14}$$

5. The BESS cannot be charged and discharged simultaneously:

$$NC(t) + ND(t) \leq 1. \tag{15}$$

6. The resulting BESS power at period t is computed for convenience as follows:

$$P_{Bat}(t) = P_{Dis}(t) - P_{Ch}(t), \tag{16}$$

7. The energy stored at the end of the period equals the amount stored at the end of the previous hour and the charged/discharged energy considering efficiencies:

$$E(t) = E(t-1) + \left(P_{ch}(t) \cdot \xi_{Ch} - \frac{P_{dis}(t)}{\xi_{Dis}}\right), \tag{17}$$

where:

- $E(t)$ represents the stored energy at the end of hour t *(MWh)*;
- ξ_{Ch} represents the charging efficiency *(%)*;
- ξ_{Dis} represents the discharging efficiency *(%)*.

8. The SOC at $t = 0$ is the initial SOC SOC_{init} set by the user (by default 0)

$$SOC(0) = SOC_{init}, \tag{18}$$

The objective function follows expression (5), adjusted for this optimization problem implementation. A vector of 24 charge-discharge operations is returned as output.

$$Max\left\{\sum_{t=1}^{24} \Pi(t) \cdot P_{Bat}(t) - Deg_{Cost}\right\}, \tag{19}$$

where:

- $\Pi(t)$ represents the electricity price during hour *t €/MWh)*;
- $P_{Bat}(t)$ represents the BESS power during hour *t (MW)*.

4.4. Simulation Results

The optimization problem and degradation cost approach presented above were used in a simulation of a single-day arbitrage operation. BESS parameters are depicted in Table 2. Different costs of use based on different capital costs were implemented for the same day to show their effect on short-term operation. These costs, in terms of €/kWh of nominal capacity, were applied following expression (10). The base case of a non-existent capital costs, which removes costs of use, was also considered.

Table 2. BESS parameters.

Parameter	Value
Capacity	10 MWh
Nominal power	5 MW
Efficiency	95%

As input, real Iberian day-ahead market electricity prices were implemented. In this case, the prices of April the 4th 2018 were used. The problem was formulated using the Python package *Pyomo* and the *cbc* or *coin-or branch-and-cut* solver. This solver was chosen because it is open-source and suitable for MILP models. Daily energy prices and BESS SOC on different simulations are shown in Figure 3.

It can be seen that market prices show two peaks. In the case in which no degradation are costs considered, the BESS performs two full cycles taking advantage of these peaks. As capital costs increase, battery degradation becomes more "expensive", and therefore, the optimization algorithm reduces cycle depth due to two reasons: first, to increase price spread so that the profit is higher than the degradation cost, and second, to reduce degradation as per Figure 2.

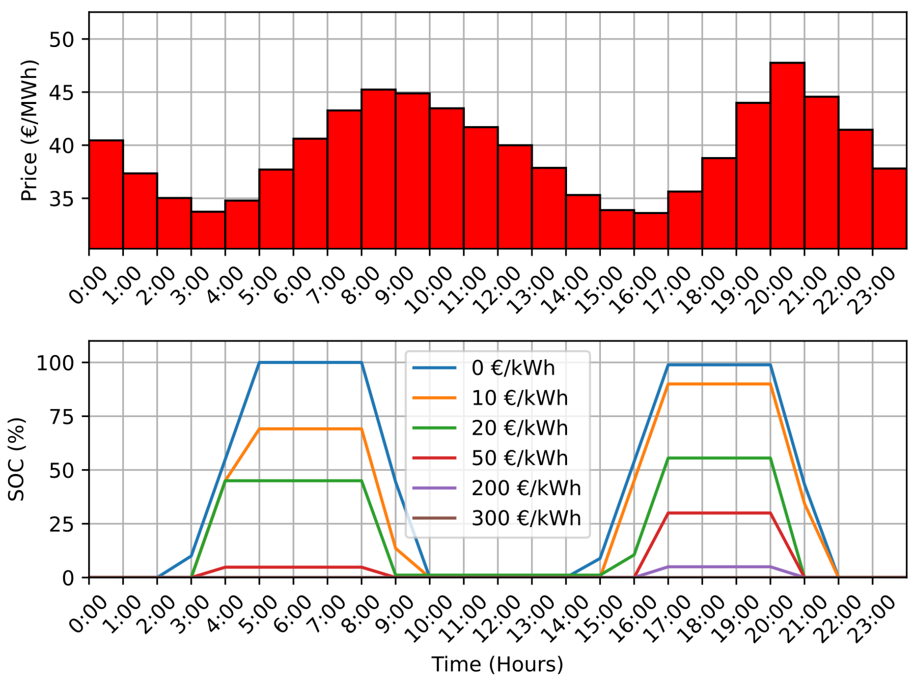

Figure 3. Daily operation results for different capital costs.

When capital costs reach 50 €/kWh, the BESS prioritises cycling using the second price peak, which has a higher price spread. At 300 €/kWh, degradation costs are too high to have any profits; therefore, the BESS does not operate. This illustrates how overestimating degradation costs may have no sense in control applications. Figure 4 depicts short-time degradation against gross benefits attained with each capital cost. It can be seen how degradation increases exponentially as capital costs decreases, just as gross benefits.

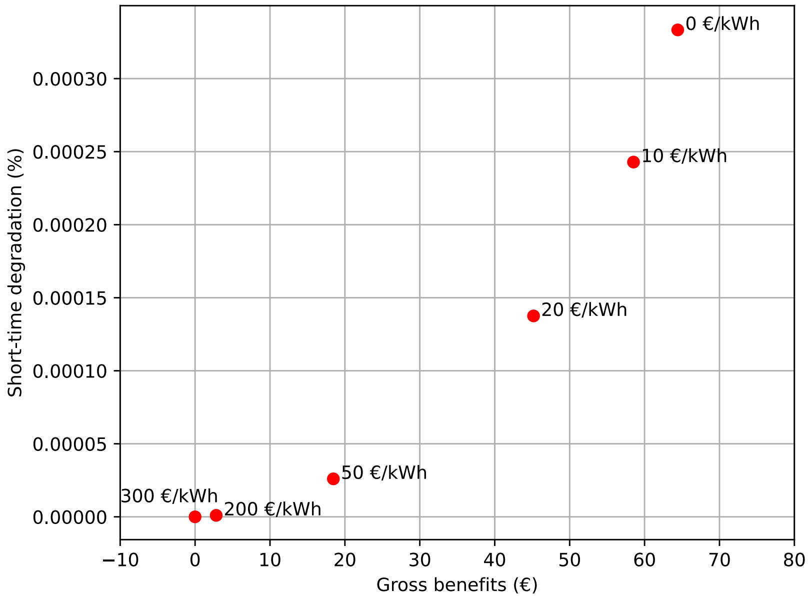

Figure 4. Degradation vs. gross benefits.

5. Conclusions and Future Works

The implementation of degradation costs reduces short-term benefits in favour of increasing long-term profitability by extending the BESS useful life. From the two main categories of degradation implementation approaches, it is found that the methods based on costs of use yield better results than the methods based on constraints. This strategy allows to better modulate degradation depending on the scenario in which the BESS operates.

The most common methods are based on static costs of use, especially for those who consider a fraction of BESS capital costs. Independently of how it is determined, all static costs of use strategies end up being arbitrary. There is a lack of theoretical support in the literature when determining such static cost. This can cause trouble since it does not allow one to know which is the best value at the beginning of the project.

The literature misses a comparison between using replacement or investment costs for quantifying degradation cost. Furthermore, the importance of battery ageing can change during its lifetime, and this is not considered in most works. This has special relevance when planning the project and considering a discount rate.

An example of degradation cost implementation has been shown. Different costs have been implemented in a 24-h arbitrage operation schedule. Results demonstrate that the excessive impact of degradation can even prevent BESS operation.

Future works should aim to find a way of formulating a degradation cost that considers the project's lifetime. The dynamic approach found in the literature takes into account the opportunity cost of reserving BESS along with the degradation impact. Additionally, the effect of the rate of return should be studied with these dynamic formulations.

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Abbreviations

The following abbreviations are used in this manuscript:

ESS	Energy Storage System
BESS	Battery Energy Storage System
EMS	Energy Management System
SEI	Solid Electrolyte Interphase
DOD	Depth of Discharge
SOC	State of Charge
SOH	State of Health
SP	Single Particle
CRF	Capital Recovery Factor
NPV	Net Present Value
EOL	End of Life
MILP	Mixed-Integer Linear Program

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