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Degradation modeling of battery energy storage system in multi-market optimization

Seminar Thesis

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List of Abbreviations

BESS .... Battery Energy Storage System
DA .... Day Ahead
DOC .... Depth of Cycle
DRL .... Deep Reinforcement Learning
FEC .... Full Equivalent Cycles
IDC .... Intraday Continuous
MILP .... Mixed-Integer Linear Program
RI .... Rolling Intrinsic algorithm
SOC .... State of Charge
SOH .... State of Health

1 Introduction

In recent years, batteries have gained increasing importance in both the transport and power sectors. This led to a decrease in average cost of approximately 90% between 2010 and 2023 (IEA, 2024). Batteries are therefore well placed to play an important role in the energy transition. In Germany, there have been more than 250 GW of grid connection requests for battery projects (Montel, 2025). The increase in renewable energy integration creates a demand for flexibility due to renewable volatility. Battery energy storage system (BESS) trading, especially close to delivery, has gained a growing importance in European energy markets. When optimizing BESS, the primary objective in most cases is to maximize the attainable revenue (Weitzel & Glock, 2018).

During BESS operation, cells are subject to various aging processes that lead to degradation. This appears as a reduction in capacity, an increase in internal resistance, and potential safety risks. Such degradation effects and especially the loss of capacity can strongly influence the profitability of a BESS (Vetter et al., 2005). Accurately modeling degradation can have a significant impact on the overall profitability of the system (Ledro, Zepter, Paludan, Idehen, & Marinelli, 2025). Consequently, it is important that a BESS trading model incorporates the effects of cell aging to ensure accurate economic assessments and optimize operational strategies. Considering degradation within the modeling framework allows for more realistic predictions of long-term performance.

This seminar paper presents an implementation of battery degradation for the maximum BESS arbitrage in a multi-market environment. This work builds upon current research that considers market-related factors, including revenue opportunities in day-ahead (DA) and intraday continuous (IDC) electricity markets. BESSBidder is an open-source multi-market bidding model proposed by (Miskiw, Ludwig, Semmelmann, & Weinhardt, 2025). It enables the evaluation of trading strategies for BESS across the DA and IDC auctions. The framework integrates three methodological components: a Mixed-Integer Linear Program (MILP) for day-ahead bidding, a Rolling Intrinsic (RI) algorithm for arbitrage in the intraday market, and a Deep Reinforcement Learning (DRL) module for coordinated bidding across markets. This seminar paper will add degradation to parts of the existing BESSBidder framework. The goal is for BESSBidder to provide a slightly more realistic description of multi-market optimization by including aging-aware operation. The research question is as follows: **How does degradation modeling of battery energy storage system (BESS) affect both the profitability and trading behaviour in multi-market optimization?**

Since *BESSBidder* is designed using a case-study approach for the German market, this framework will adopt the same perspective. Furthermore, battery ageing is typically discussed with respect to lithium-ion batteries, as they currently represent the state of the art. This work aims not to represent a specific chemistry, but rather to capture the characteristics of an average BESS. All other assumptions can be reviewed at (Miskiw et al., 2025).

First, battery ageing mechanisms and their relevant parameters are introduced. Subsequently, related work on age-aware operational modelling is reviewed. This is followed by a presentation of the implementation developed in this study. Finally, the trading behaviour of the battery with and without degradation modelling is compared.

2 Related Work

Multiple degradation modeling approaches exist ranging from data-driven empirical models up to detailed physicochemical models that represent individual aging mechanisms through sets of differential equations. Each of these approaches offers distinct advantages and disadvantages for application in BESS operation. First, the fundamental battery aging mechanisms and key parameters are introduced. Followed by an overview of different approaches for incorporating aging effects into battery operation and optimization algorithms. Lastly, the economical perspective of BESS degradation is discussed.

2.1 Age-Aware Operation

Storage and cycling conditions, as well as material parameters, have an impact on battery lifetime. Aging mechanisms can be distinguished between calendar aging, which occurs over time regardless of use, and cyclic aging, which is driven by charge and discharge cycles. Multiple stress factors impact the extent of cyclic aging. Vetter et al. give a comprehensive overview for Lithium batteries (Vetter et al., 2005). Stress factors include the Full Equivalent Cycles (FEC) and the The Depth of Cycle (DOC). Calendar aging on the other hand is mainly affected by time, temperature conditions, and the batterys state of charge (SOC) (Collath, Tepe, Englberger, Jossen, & Hesse, 2022).

Full Equivalent Cycles (FEC) is commonly used as a measure for the amount of cycles. One FEC corresponds to charging and discharging an amount of energy equal to the nominal battery capacity once. It is widely used in degradation modeling to link battery operation to cycle-related capacity fade (Collath et al., 2022).

The Depth of Cycle (DOC), also known as Depth of Discharge (DOD) or cycle depth, is aother relevant parameter influencing capacity loss. Deeper discharges cause more significant volume changes, resulting in increased mechanical stress and cracking (Collath et al., 2022).

State of Health (SoH) quantifies the aging state of a battery by expressing its remaining usable capacity relative to its nominal capacity at beginning of life. It is commonly defined as the ratio between the current available capacity and the initial capacity. The parameter provides a direct representation of capacity loss induced by battery aging mechanisms. Thus, SOH estimation techniques enable the development of aging-aware trading strategies and provide an indicator of the resulting degradation over the BESS lifetime (Ledro et al., 2025).

End of Life (EOL) denotes the point at which a battery is considered no longer suitable for its intended application, typically defined by a minimum allowable SOH. Values range from 65% to 80% of initial capacity (Wankmüller, Thimmapuram, Gallagher, & Botterud, 2017)

2.1.1 Effects on Revenue

To enable age-aware operation, existing trading models are commonly extended by degradation-related constraints or penalty terms. While these additions typically reduce short-term operational revenues by limiting aggressive cycling strategies, they can lead to a substantial increase in cumulative lifetime revenue by mitigating battery degradation and extending the usable lifetime of the BESS (Ledro et al., 2025). Several studies quantify this trade-off between short-term profit reduction and long-term value creation (Collath et al., 2022; Ellis, White, & Swan, 2023). Wankmüller et al. highlight the value of degradation effects on revenues by comparing degradation-aware operation against an idealized benchmark without any battery degradation. They show that explicitly accounting for battery aging reduces the achievable net present value by approximately 12–46%, depending on the chosen degradation model and end-of-life assumptions (Wankmüller et al., 2017).

2.2 Age-Aware Implementation Approaches

Existing approaches to battery degradation modeling range from purely data-driven empirical formulations and semi-empirical models to detailed physicochemical models that explicitly represent individual aging mechanisms using systems of differential equations (Collath et al., 2022).

Physicochemical battery degradation models aim to explicitly represent cell-internal aging mechanisms by describing the underlying electrochemical and physical processes through systems of differential equations. In contrast to empirical and semi-empirical approaches, these models offer a higher level of physical interpretability but are generally considered computationally expensive and therefore challenging to integrate into operational BESS optimization frameworks (Collath et al., 2022). Representative examples include reduced-order physicochemical models that capture capacity loss mechanisms in graphite anodes of lithium-ion batteries based on physically motivated state equations (Jin et al., 2017; Reniers, Mulder, & Howey, 2019). Such approaches typically require a detailed representation of internal state variables, including cell voltage, temperature, electrochemical potentials, and gas formation processes, in order to reliably predict degradation behavior (Weitzel & Glock, 2018). To improve computability, some studies combine physicochemical degradation modeling with simplified system-level representations. For instance, Liu et al. propose a coupled battery model consisting of an electrothermal sub-model and a capacity loss sub-model (Liu, Hu, Yang, Xie, & Feng, 2019).

Empirical degradation models are widely employed in BESS operation studies due to their comparatively low computational complexity and straightforward integration into optimization frameworks. These models can be derived from experimental aging studies in which battery cells are exposed to controlled stress factors (Ellis et al., 2023; Muenzel, de Hoog, Brazil, Vishwanath, & Kalyanaraman, 2015). The observed relationships between applied stress factors and degradation are subsequently approximated using analytical expressions, typically polynomial, exponential, or power-law functions (Engels, Claessens, & Deconinck, 2019).

The simplest class of empirical models assumes that battery lifetime is limited by a fixed number of FECs. Under this assumption, each unit of cycling contributes equally to degradation, and the battery is assumed to reach its end of life once either the maximum allowable number of FECs or the specified shelf life is exceeded. Due to their simplicity, such models are computationally efficient and widely used as baseline representations of degradation (Collath et al., 2022).

A closely related formulation is the energy-throughput-based aging model, in which degradation costs are proportional to the cumulative amount of energy processed by the BESS. Each unit of charged or discharged energy contributes a fixed fraction to lifetime consumption, independent of operating conditions such as SOC, DOC, or C-rate. As a result, energy-throughput models implicitly assume uniform degradation per unit of processed energy and do not distinguish between calendar and cyclic aging mechanisms (Collath, Cornejo, Engwerth, Hesse, & Jossen, 2023).

Ledro et al. classify both FEC-based and energy-throughput-based formulations as single-factor degradation models, as they rely on a single aging proxy to represent battery wear. While these approaches enable straightforward integration into optimization-based trading models, they neglect the influence of operating conditions on degradation rates and may therefore misrepresent the true economic cost of aggressive cycling strategies (Ledro et al., 2025). To partially address this limitation, refined empirical single-factor models introduce a dependency of the allowable number of FECs on the DOC. This reflects experimental observations that a small number of deep cycles can cause disproportionately higher degradation than a larger number of shallow cycles. DOC-dependent FEC models therefore assign higher degradation costs to cycles with larger DOC and have been adopted in several BESS scheduling studies to better capture the impact of cycling intensity on battery lifetime (Collath et al., 2022).

Beyond single-stress-factor formulations, multi-factor empirical degradation models link capacity loss to multiple operational variables simultaneously. This may include the DOC, C-rate, average SOC, and temperature (Collath et al., 2022). Integrating such detailed aging models into trading strategies can improve lifetime performance, but at the cost of increased model complexity (Ledro et al., 2025).

A related class of empirical approaches are weighted energy throughput models. These models scale the processed energy by weighting factors representing stress conditions such as maximum DOC, average SOC, charging voltage, or internal temperature. For example, deeper discharges reduce the total number of achievable life cycles and therefore increase the effective degradation cost per unit of energy throughput (Weitzel & Glock, 2018).

The specific implementation can follow different modeling approaches, which mainly differ in how battery degradation is represented within the scheduling problem. One common approach relies on constraint-based formulations, where operational stress factors associated with battery aging are restricted through fixed bounds in the optimization problem. Typical examples include limits on charge and discharge power, constraints on the allowable SOC range, or indirect restrictions on the resulting DOC (Collath et al., 2022).

Several studies apply such constraint-based strategies to reduce degradation. Wankmüller et al. restrict the usable SOC window to 60% of the nominal battery capacity and analyze the techno-economic implications of different SOC limits within an energy arbitrage framework (Wankmüller et al., 2017). While constraint-based approaches are straightforward to implement and computationally efficient, most scheduling strategies proposed in the literature are optimization-based and aim to balance revenue generation against degradation effects (Collath et al., 2022). Rather than relying exclusively on hard operational limits, the majority of studies incorporate degradation directly into the objective function by introducing a penalty term. This penalty can be formulated either as a technical proxy for aging, such as energy throughput or cycle count, or as an economic representation of degradation costs derived from replacement or investment costs. This objective-based formulation enables a continuous trade-off between short-term market revenues and long-term battery degradation within the optimization framework (Collath et al., 2022).

2.3 Economic Evaluation of Degradation

A common approach to account for battery degradation within optimization-based operation strategies is the introduction of a Cost of Use (COU), which represents the economic penalty associated with battery ageing. In many studies, this cost is derived directly from techno-economic assumptions, most commonly from the battery investment cost or the replacement cost at end of life. It works by distributing the assumed replacement or investment cost uniformly over the usable lifetime of the battery. The resulting COU is then interpreted as a fixed marginal cost per unit of degradation and incorporated into the objective function of the operational optimization problem (Ledro et al., 2025).

However, Ledro et al. emphasize that such a cost-based derivation implicitly treats degradation cost as a proxy for sunk or future capital expenditures and does not necessarily reflect the operationally optimal trade-off between short-term market revenues and long-term lifetime consumption. Since the battery generates revenues only during operation, while the original investment cost is independent of dispatch decisions, the COU primarily acts as a penalty parameter that shapes operational behavior. Consequently, a COU derived purely from investment or replacement cost assumptions may lead either to overly conservative operation or to excessive cycling that reduces lifetime profitability. For this reason, Ledro et al. argue that the COU should be treated as a free optimization parameter whose optimal value is determined endogenously by maximizing lifetime economic performance rather than fixed ex ante based on cost allocation rules (Ledro et al., 2025).

Ledro et al. analyse two implementations of the COU concept. The single-factor approach models degradation solely via energy throughput or full equivalent cycles (FECs) and introduces a constant COU per cycle in the objective function. This yields a uniform marginal cycling cost and leads to threshold-based operation, where the battery is dispatched only if expected arbitrage revenues exceed the cycling penalty (Ledro et al., 2025). The multi-factor approach applies the COU directly to estimated SOH loss and distinguishes between calendar and cyclic ageing. As a result, the effective degradation cost becomes state-dependent and reflects operating conditions such as SOC level, depth of cycle, and cycling intensity, allowing the optimization to avoid particularly degradation-intensive operating regimes (Ledro et al., 2025).

Using a rolling-horizon lifetime simulation, Ledro et al. determine the COU values that maximize annualized lifetime profit. While a replacement-cost-based derivation yields a COU of approximately 10 £/MWh, the economically optimal value is found to be significantly lower at 3.75 £/MWh for the single-factor formulation. The lifetime revenue increases of up to approximately 21% relative to unbounded trading (Ledro et al., 2025).

In contrast, Collath et al. determine the aging cost explicitly through a model predictive control framework combined with a digital twin of the BESS. The aging cost is treated as a free optimization parameter and systematically varied, while the full system lifetime is simulated to identify the value that maximizes annualized lifetime profit. Collath et al. show that the optimal aging cost depends strongly on the underlying degradation model: while simple energy-throughput-based formulations already improve lifetime performance compared to unbounded trading, optimization models that explicitly account for both calendar and cyclic aging achieve the highest lifetime profitability with arbitrage profits by up to 29.3% compared to simpler energy-throughput-based aging cost formulations (Collath et al., 2023).

The reviewed literature consistently shows that explicitly accounting for battery degradation fundamentally alters optimal dispatch behavior and economic outcomes. However, existing approaches differ substantially in how degradation is represented and monetized. At the same time, most degradation-aware studies focus on single-market settings or ancillary services, while interactions between day-ahead and intraday trading remain underexplored. This work builds on these insights by adopting a simple FEC-based degradation model with an COU and embedding it into a multi-market bidding framework, thereby addressing its impact on revenues and trading behavior across DA and IDC markets.

3 Methods

This section outlines how degradation modelling is integrated into the existing multi-market bidding framework *BESSBidder*. The methodology is structured along the original architecture of the framework and extends three bidding approaches with an empirical FEC based degradation model.

3.1 BESS Bidder

The modelling foundation of this work is the open-source multi-market bidding framework *BESSBidder* introduced by Miskiw et al.. It enables coordinated and myopic participation of a BESS in both day ahead (DA) and intraday continuous (IDC) markets (Miskiw et al., 2025). This work focuses on the myopic approach in DA and IDC markets. This framework consists of three methodological components:

1. **Mixed-Integer Linear Program (MILP):** Models day-ahead bidding on a daily basis based on a price forecast while considering technical constraints.
2. **Rolling Intrinsic (RI) Algorithm:** Models risk-free continuous intraday arbitrage by discretising the IDC market, updating its strategy bucket-by-bucket.
3. **Myopic approach:** Implements coordinated multi-market bidding by first determining optimal DA via the MILP and subsequently applying a rolling intrinsic strategy that accounts for the resulting DA positions.

We assume perfect foresight, thus the price forecast is equal to the real price. The existing framework is extended by introducing ageing-aware operation via degradation modelling, thereby enabling economic evaluation across battery lifetime. Following the approach of Ledro et al., a COU parameter is introduced, resembling the optimal economic punishment per FEC. This parameter is derived within the MILP and used for all 3 methodological components.

Applicable for all three approaches, two new parameters are introduced; Lifetime Cycles and Battery Lifetime as a time horizon. They are commonly provided by manufacturers.

3.2 MILP Integration

The implemented degradation model follows an FEC counting, energy-throughput-based approach, in which battery aging is assumed to be proportional to the cumulative charged and discharged energy. A FEC corresponds to one complete charge and discharge of the battery over its nominal energy capacity.

The key modeling assumption is that each additional FEC causes a constant marginal degradation cost, referred to as the COU. As a result, cyclic degradation is not modeled as a dynamic state variable (e.g. via SOH), but instead enters the optimization problem as an additive cost term in the objective function. This preserves the linear structure of the MILP and avoids additional state coupling across optimization horizons.

For each time step t, the Δcycles_t variable is defined as the two times the absolute energy throughput of the battery (3.1). Where P_t^{ch} and P_t^{dis} denote the charging and discharging power, respectively. C_{BESS} is the nominal energy capacity of the battery and Δt is the time-step duration.

$$\Delta\text{cycles}_t = \frac{\left(P_t^{\text{ch}} + P_t^{\text{dis}}\right)\,\Delta t}{2\,C_{\text{BESS}}} \tag{3.1}$$

The sum of this variable of all previous iterations of the MILP ($\text{cycles}_{\text{used, init}}$) is then used as an input for the next iteration. A predefined maximum cycles constraint ($\text{cycles}_{\text{max}}$) in the lifetime of the BESS is used to connect all independently solved time periods (3.2). The maximum cycles are defined based on the manufacturer data (3.4).

$$\text{cycles}_{\text{used, init}} + \Delta\text{cycles} \leq \text{cycles}_{\text{max}} \tag{3.2}$$

The total degradation cost over the iteration horizon is calculated as 3.3, with COU predefined and expressed in EUR/FEC. The objective function is extended by subtracting this linear degradation cost term C_{deg}.

$$C_{\text{deg}} = \sum_t \Delta\text{cycles}_t \cdot \text{COU}, \tag{3.3}$$

Through the COU parameter, the model explicitly trades off short-term market profits against long-term battery usage. It will never take a trade, where the arbitrage is less than the initialized COU. The optimizer is skipping all arbitrage trades that are lower then the COU, shifting revenues into the future. However, the optimizer has no foresight, that better trades will be possible in the future. All of this is based on setting the right COU value.

3.2.1 Optimal Cost of Use

Introducing the COU as an indirect optimization parameter is needed because degradation costs derived purely from investment or replacement assumptions do not necessarily reflect the economically optimal trade-off between cycling and revenue generation (Ledro et al., 2025).

The COU is calibrated using an outer-loop iterative procedure on the MILP. It can be seen as a sensitivity analysis, following the approach of (Ledro et al., 2025). There is a monotone relationship between COU and optimal cycle usage: higher COU values penalize cycling more strongly and therefore reduce total FEC throughput. The resulting COU represents a horizon-consistent marginal degradation cost that enforces the lifetime cycle constraint implicitly within the MILP.

Given a maximum lifetime cycle budget $\text{Cycles}_{\text{life}}$ over a technical lifetime of Y_{life} years, the admissible number of cycles for the optimization horizon $[T_{\text{start}}, T_{\text{end}}]$ is defined as (3.4).

$$\text{Cycles}_{\text{target}} = \text{Cycles}_{\text{life}} \cdot \frac{Y_{\text{horizon}}}{Y_{\text{life}}}, \qquad Y_{\text{horizon}} = \frac{T_{\text{end}} - T_{\text{start}}}{365.25} \tag{3.4}$$

For a given COU value, the day-ahead MILP is solved sequentially for each day $d \in \mathcal{D}$ over the optimization horizon.

Starting from a high initial COU value (discouraging cycling), COU is iteratively reduced to increase encouragement of cycling. The calibration objective is to achieve (3.5).

$$\text{Cycles}_{\text{used}} = \text{Cycles}_{\text{target}} \tag{3.5}$$

The iteration terminates once the cycle mismatch falls within the admissible tolerance or a maximum number of iterations is reached. The derived optimal COU c_{deg^*} is then saved and used as the input for all 3 approaches.

3.3 Rolling Intrinsic Integration

The Rolling Intrinsic (RI) algorithm models continuous intraday arbitrage by solving a sequence of deterministic optimization problems on a rolling time grid ("buckets"). In each bucket, the strategy is updated using the most recent intraday price information, while all previously executed trades remain binding (Semmelmann, Dresselhaus, Miskiw, Ludwig, & Weinhardt, 2025).

Consistent with the MILP approach, cycle usage is approximated by energy throughput FECs. The incremental cycles in bucket b are:

$$\Delta\text{cycles}_b = \sum_{t \in T} \frac{(P^{\text{ch}}_{b,t} + P^{\text{dis}}_{b,t})\Delta t}{2\, C_{\text{BESS}}}. \tag{3.6}$$

On the IDC, the RI algorithm may execute virtual trades, i.e., buying and selling products for a given execution time without inducing any physical charging or discharging of the battery. Since battery degradation is only caused by real cycling of the BESS, such virtual trades should not be penalized in the same way as physical operation. To account for this, a time-dependent weighting factor is introduced. Trades that are temporally close to the execution time are penalized more strongly, as they are more likely to result in actual battery operation, whereas trades further away in time receive a lower weight, reflecting their reduced likelihood of affecting the BESS. This weight is defined as $w_t^{\text{COU}} \in [0, 1]$.

Thus, trades executed close to the execution time are fully penalized with respect to cycle usage, while trades far away in time receive a reduced or zero penalty. The weighted cycle degradation cost entering the objective function is then given by (3.7)

$$C_{\text{deg}} \;=\; \text{COU} \cdot \Delta\text{cycles}_t \cdot w_t^{\text{COU}} \tag{3.7}$$

For each bucket b, the optimization maximizes intraday trading profit minus the degradation cost factor C_{deg}.

4 Results

The results presented in the following section are based on three new parameter definitions that extend beyond Miskiw et al. In particular, a BESS lifetime of 20 years and a total lifetime cycle limit of 10.000 cycles are assumed. All optimization results are evaluated over an analyzed timeframe of approximately one year, spanning from 2019-04-01 to 2020-03-27.

Assuming a total lifetime of 20 years and a limit of 10,000 FECs, the analyzed time horizon corresponds to 494.18 allowable cycles. Applying the iterative procedure for determining the optimal COU, described in Chapter 3 results in an optimal value of 5.39 EUR/FEC.

Figure 4.1 illustrates the DA MILP revenues and associated FECs for varying COU values. The cycle limit of 494.18 cycles as well as the optimal COU are highlighted.

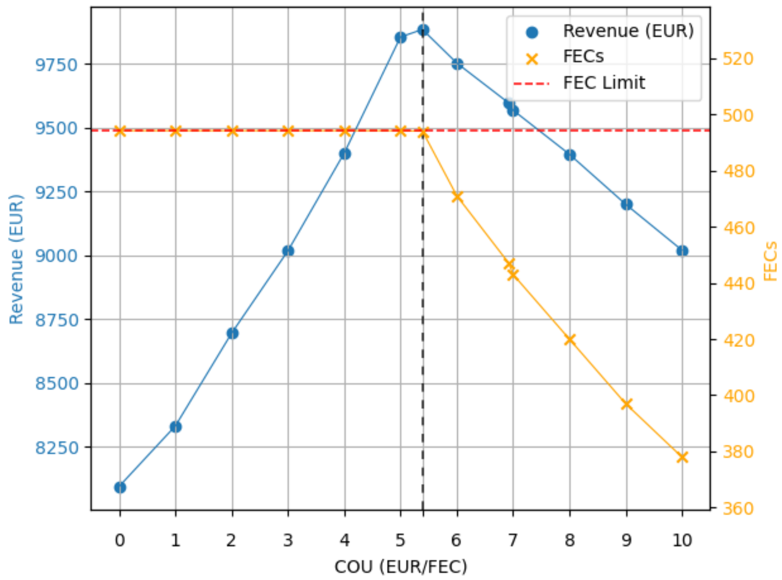


Figure 4.1: Revenues and FECs of Day Ahead (MILP) over different COUs

Considering the cycling behavior first, the results show that the maximum cycle constraint is binding for low COU values. At COU = 0, the model would optimally perform substantially more cycling. However, this is restricted by the imposed maximum of 494.18 FECs through the max cycles constraint. At the optimal COU, this situation changes: the cycle constraint is no longer binding, and the model selects a lower cycling level than the allowed maximum.

Turning to revenues, the optimal COU coincides with the maximum of the revenue curve. While lower COU values would incentivize more cycling and, in the absence of constraints, higher revenues, the binding cycle limit prevents this outcome, resulting in lower achievable revenues. Conversely, higher COU values penalize cycling more strongly, leading to fewer FECs and consequently lower revenues. The optimal COU therefore represents a balance point where revenues are maximized while remaining within the allowable cycle budget over the analyzed time horizon.

Similarly, figure 4.2 presents the revenues and FECs of the IDC market for different COU values. The FECs shown correspond exclusively to real BESS cycling. Due to the structure of the IDC market, where products are traded for different execution times, the algorithm can also perform virtual trades that do not result in physical battery cycling. These virtual trades are therefore excluded from the FECs shown in the figure. However virtual trades have a substantial impact on revenues and thus strongly influence the revenue curve.

In contrast to DA, RI does not impose an explicit cycle limit. The only degradation-aware mechanism is the COU. As a result, both cycling and revenues increase sharply for low COU values, where degradation is weakly penalized. At the optimal COU level obtained from the DA MILP, the RI strategy results in only 165 FECs over the analyzed period, well below the allowable cycle budget. Thus, inherit through the COU, the BESS did not cycle over the allowed limit. However it also indicates that, from a purely RI perspective, a lower COU would be better, as additional cycling would still be feasible and economically beneficial. Consequently, the DA-optimal COU is conservative when applied to RI and does not fully exploit the remaining degradation budget.

In Figure 4.3, the multi-market (Myopic) approach is illustrated in the same way. The FECs exceed the cycle limit across the entire range of COU values considered, including COUs above 10 EUR/FEC. The MILP optimal COU would lead to a total of 860 FECs for the Myopic approach.

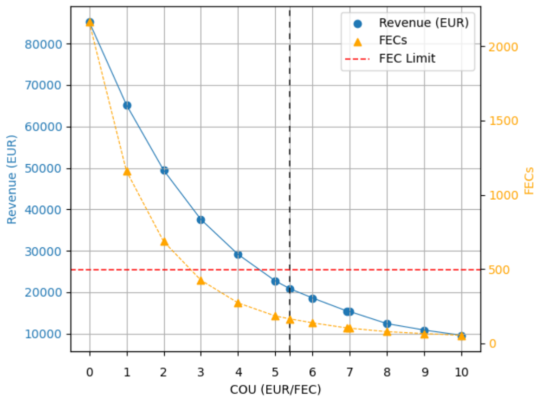


Figure 4.2: Intraday Conntinuous (RI)

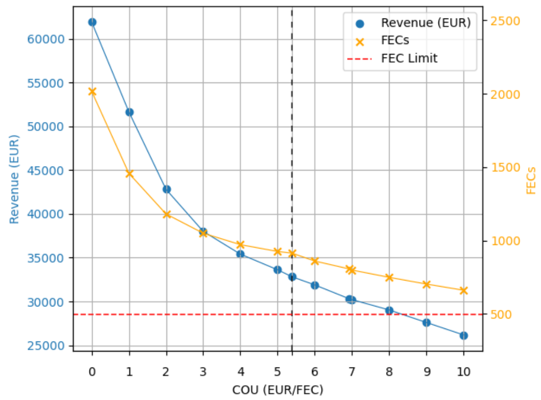


Figure 4.3: Myopic (MILP + RI)

Revenues and FECs over different COUs

Figure 4.4 shows revenues as a function of COU for DA, RI, and the multi-market Myopic approach. RI revenues are highest at low COU values and decrease monotonically with increasing COU. The Myopic approach yields higher revenues than DA across the entire COU range, while also exhibiting a declining revenue trend as COU increases. DA revenues remain comparatively low and, in comparison, vary less with COU.

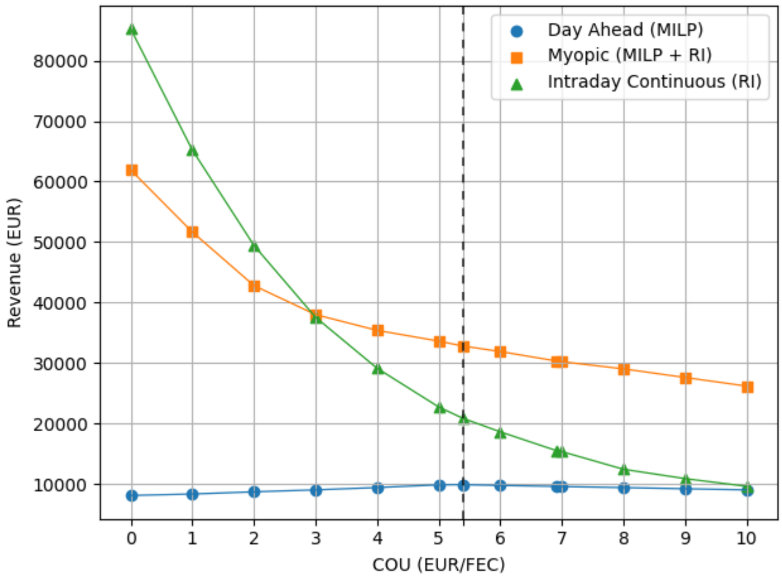
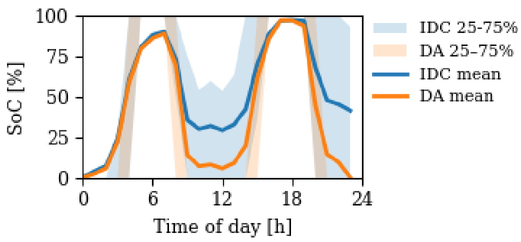


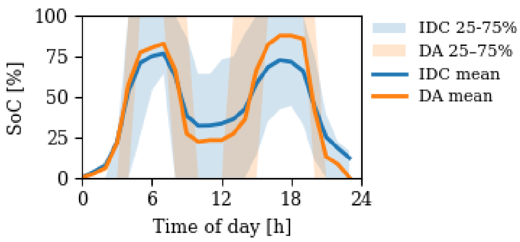
Figure 4.4: Revenues over different COUs

Figure 4.5 shows the average SOC profile of the battery in the IDC and DA markets for two different COU values. For each case, the mean SOC is plotted together with the 25–75% and 25–95% quantile bands, illustrating the statistical spread of SOC trajectories over all considered days. Panel (a) corresponds to COU = 0, while panel (b) shows the results for COU = 5.39. The horizontal axis denotes the hour of the day, and the vertical axis represents the SOC in percent. The shaded areas indicate the interquartile range and the wider percentile range, respectively, around the mean SoC profile.

For the case without degradation (COU = 0), the mean SOC profiles of both DA and IDC exhibit lower minima around midday and higher maxima during peak periods, resulting in a larger SOC range. The quantile bands are wider for the optimal COU case, indicating a larger spread of SOC values across days.



(a) COU = 0



(b) COU = 5.39 (optimal)

Figure 4.5: Mean SOC profiles of myopic approach over hours of the day

5 Discussion

This discussion contextualizes the presented results with respect to the underlying research question and the existing literature. First, the implications of degradation-aware operation on trading behavior and profitability are interpreted. Subsequently, key limitations of the analysis are addressed. The following section uses the COU value as a proxy for the extent of degradation modeling applied. A COU of zero corresponds to a setting without any degradation modeling.

The results show a clear impact of degradation modeling on achievable revenues in multi-market BESS operation. When degradation is neglected, the optimization exploits high-frequency and deep cycling opportunities, particularly in the IDC market, leading to high short-term revenues. Once degradation costs are introduced, revenues decline and trading behavior becomes more selective. This indicates that the COU acts as a threshold, forcing the optimization to evaluate each potential trade against its marginal degradation cost. Across all three configurations, degradation-aware strategies reduce total energy throughput and suppress marginal trades with low price spreads. This behavior is consistent with the findings of Ledro et al., who show that a COU effectively introduces a dispatch threshold: trades are only executed if expected revenues exceed the associated degradation cost (Ledro et al., 2025).

The COU = 0 scenario represents an operation without degradation awareness, while increasing COU values correspond to a progressively stronger consideration of aging effects. Revenues of both the Myopic and IDC strategies peak at small or zero COU values. However, these scenarios are also characterized by a very high number of cycles, indicating an operational regime with excessive and potentially unhealthy cycling.

At higher COU values, different sensitivities of cycling behavior with respect to the COU can be observed. This difference is primarily driven by the structure of the Myopic approach. Since the Myopic strategy operates across both the DA and IDC markets, cycles from both markets accumulate. As shown in Figure 4.3, the resulting FECs remain too high at low COU values, implying that a higher COU is required to sufficiently limit total cycling. Even so, for COU = 5.39, the smoother mean SOC profile and the avoidance of extreme SOC levels in Figure 4.5 correspond to the sharp decline in cycling shown in Figure 4.3 At the same time, the wider quantile bands indicate that the battery no longer follows a rigid daily arbitrage pattern, but instead adapts its operation to fewer, higher-value trading opportunities.

For the IDC only, at a COU of 5.39, the results indicate that this value is too high for the single market setting. The FECs are below the allowed limit and thus trading behaviour is too conservative and the revenue is not maximized. Overall, a steep decline in FECs is observed up to a COU of approximately 2–3 EUR/FEC. This range therefore represents the effective optimal COU for the intraday market, as it is the lowest value at which the cycle constraint of 494 FECs is no longer violated.

A critical question arising from these results is whether a COU value can be transferred across markets or operational settings. The findings suggest that such a transferability is limited. The COU is not a technical battery parameter, but an operational penalty that emerges from the interaction between market design, trading frequency, and the optimization framework. As demonstrated, a COU that is even too low for a multi-market Myopic strategy leads to overly conservative behavior in an intraday-only setting.

Overall, intraday revenues dominate at low levels of degradation modeling. As the COU increases, intraday revenues decline more sharply due to reduced cycling, while the Myopic approach increasingly benefits from its access to both markets. At higher COU values, the Myopic strategy therefore surpasses the intraday-only approach in terms of achievable revenues.

Taken together, Figures 4.2–4.5 demonstrate that the COU affects revenues not only by limiting the number of executed trades, but by fundamentally reshaping trading behavior. Lower COU values favor systematic, high-frequency arbitrage with excessive cycling, while higher COUs induce selective dispatch, reduced cycling intensity, and a stronger reliance on structurally higher-value trades. The observed SOC profiles therefore provide a behavioral explanation for the revenue–degradation trade-offs discussed in the previous sections.

5.1 Limitations

Firstly, this analysis is limited to the IDC and DA Markets. However, degradation effects vary across market types. Shi et al. show that in pay-for-performance ancillary service markets such as frequency regulation, degradation-aware control significantly alters optimal dispatch by limiting high-frequency cycling. This can reduce short-term tracking performance and, depending on the penalty structure, achievable revenues, as regulation-induced micro-cycling contributes disproportionately to lifetime degradation (Shi, Xu, Tan, Kirschen, & Zhang, 2019). Similarly, Ellis et al. show that simultaneous provision of energy arbitrage and frequency regulation leads to higher degradation rates than single-service operation. Their experimental results indicate that energy-intensive arbitrage cycles dominate lifetime degradation, even when frequency regulation contributes substantially to overall revenues (Ellis et al., 2023). By restricting the present analysis to the DA and IDC markets, these cross-market degradation interactions are excluded.

Furthermore, a key limitation of the presented analysis is its strong dependence on the chosen time period. Market volatility, price spreads, and intraday liquidity vary substantially across years and directly determine both achievable revenues and cycling behavior. The analyzed period is characterized by comparatively low volatility, while more recent years exhibit significantly higher short-term price fluctuations. As a result, optimal COU values and trading behavior calibrated for one year cannot be assumed to remain valid under different market conditions. When running the algorithm to determine the optimal COU within the MILP over a longer time horizon of three years, spanning from the beginning of 2019 to the end of 2021, an optimal COU value of 6.9 is obtained. This indicates that, over a longer time span, the algorithm can identify more high-value trading opportunities. These findings highlight that conclusions based on a small number of years should be interpreted cautiously, as long-term market evolution plays a decisive role in determining both optimal operation and economic viability.

As outlined in Chapter 2, battery degradation can be modeled with a substantially higher level of physical detail than applied in this work. The selected FEC throughput model therefore represents a deliberately simplified approximation of lithium-ion battery aging. More advanced approaches, such as the non-linear degradation formulation proposed by Maheshwari et al., further emphasize that neglecting C-rate and SOC-dependent effects can distort both operational decisions and lifetime assessments (Maheshwari, Paterakis, Santarelli, & Gibescu, 2020).

Wankmüller et al. highlight that simplified throughput-based models tend to underestimate degradation costs, particularly under aggressive cycling, leading to overly optimistic profitability estimates. This behavior is also observed in the present analysis. The IDC performs a total throughput of up to 13362 traded FECs over the analyzed period of a year (Wankmüller et al., 2017).

In addition, the SOH of the battery is not explicitly modeled as a dynamic state variable in the chosen formulation. In reality, progressive aging leads to a gradual reduction in usable capacity, which directly constrains future trading opportunities and reduces achievable revenues over time. This feedback mechanism is neglected. The implemented aging framework also does not account for discounted revenues. Introducing consistent discounting could work for instance by adjusting the optimal COU value dynamically and allowing it to increase over time in line with a discount rate.

Despite these limitations, the chosen degradation model offers important advantages. Its lower computational complexity suited for long time series and repeated optimization runs, such as those required in the BESSBidder framework. The model serves as a transparent baseline representation of degradation. More detailed, state-dependent aging models would likely improve physical realism, but at the cost of increased model complexity.

6 Conclusion

This seminar paper investigated how degradation modeling affects the profitability and trading behavior of battery energy storage systems in a multi-market setting. By extending the BESSBidder framework with an ageing-aware formulation based on energy throughput based FECs and a Cost of Use parameter, the analysis demonstrates that explicitly accounting for degradation fundamentally alters optimal dispatch decisions in both day-ahead and intraday continuous electricity markets.

The results show that neglecting degradation leads to aggressive, high-frequency cycling, particularly in the intraday market, yielding high short-term revenues but excessive battery usage. Introducing a COU shifts operation toward more selective trading, suppresses low-margin arbitrage opportunities, and significantly reduces cycle throughput. For the day-ahead market, an optimal COU was identified that maximizes revenues while respecting the allocated lifetime cycle budget. In contrast, the intraday-only strategy exhibits a lower economically optimal COU, indicating that degradation penalties are not directly transferable across markets. In the multi-market myopic setting, degradation-aware operation smooths SOC trajectories and avoids extreme SOC levels.

Overall, the findings highlight that degradation is not merely a technical constraint but a key economic driver that reshapes trading behavior and revenue composition. The COU should therefore be interpreted as an operational tuning parameter emerging from the interaction between market design, price volatility, trading frequency, and optimization structure. While the applied FEC-based degradation model is simple, it provides a transparent and computationally efficient baseline that captures essential trade-offs between short-term profits and long-term battery usage. Future work should extend the analysis to additional markets, as well as implement the 2025 regulatory changes to the day ahead market regarding the product size. Longer and more uncertain time horizons, as well as a more complex degradation model would further improve the realism of multi-market BESS optimization.

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