Optimizing Battery Dispatch under Consideration of Technical Constraints

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***Abstract*—This paper presents a dispatch optimization model for battery energy storage systems that considers technical constraints such as efficiency, self-discharge, cool-down times, and models the impact on battery degradation. The model aims to maximize revenues from arbitrage opportunities on the day-ahead and intraday markets while accounting for battery aging. The study demonstrates that gentle operation modes lead to up to 3% less capacity losses but also almost 30% lower revenues. The difference in revenues opens up wider in times of higher profitability. Decreasing CAPEX for batteries reduces the economic significance of gentle operation modes.**

***Index Terms*—Battery Aging, Degradation Modeling, Operational Research, Revenue Optimization, Multi-Market Optimization**

Abbreviations and Acronyms

Symbol	Description	Unit
BUY	Selling Volume	MWh
C	Costs	$kEUR$
CAP	Capacity of the BESS	MWh
CHA	Charging Volume	MWh
DIS	Discharging Volume	MWh
E	Energy Stored	MWh
P	Price	EUR/MWh
$SELL$	Buying Volume	MWh
T	Index Set of Time Steps	-
^{DA}	Day-Ahead-Market	-
^{ID}	Intraday Market	-
^{M}	Market	-
t	Time Step	-
η	Efficiency	-
λ	Liquidity Factor	-
κ	Binary Charging Variable	-
Δ_t	Length of Time Step	s

I. Introduction

A. Motivation

The advance of Renewable Energy (RE) generation is increasing the volatility of the energy mix [1]. The growing proportion of non-dispatchable or hardly dispatchable generation units is creating significant price spreads on the power exchange [1]. These price peaks during production bottlenecks and price lows during overproduction offer the opportunity for storage units to generate arbitrage revenues [2–4]. Volatile commodity prices in recent years have reinforced this trend. To make informed investment decisions on storage units such as Battery Energy Storage System (BESS), it is important to project the expected revenue streams. Little operational experience and comparably simplistic modeling in energy economics literature appears counterintuitive to the technical literature describing detailed physicochemical behavior to be relevant. Against the background of a double digit GW project pipeline in Europe alone, this paper aims to address the interface between economic and technical literature based on the German Day-Ahead (DA) and Intraday (ID) market.

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B. Literature Review and Main Contribution

Valuation of future arbitrage revenues is determined using optimization approaches [5, 6]. In the case of purely arbitrage-oriented BESS, the optimization is usually based on one or more price time series on the one hand and the properties of the storage facility on the other hand [5, 7–10]. The complexity and level of detail of the model are far-reaching. Despite the variations demonstrated in Tab. I, all models consist of four major parts, the Objective Function (OF), an energy conservation term, the physical, and the operational limitations of the BESS (see e.g. [7] for a concise mathematical description).

The generalized form of the OF for a market M is given in (1).

$$\max_{CHA_t^M, DIS_t^M} \left(\sum_{t=1}^{T} P_t^M \cdot (BUY_t^M - SELL_t^M) \right) - C \quad (1)$$

The goal of optimization is to maximize revenues over the horizon T. The revenues are made up of the price P multiplied by the amount of energy bought BUY or sold $SELL$ and the costs C incurred. BUY or $SELL$ are the non-negative

TABLE I
PUBLICATIONS ON STAND-ALONE BESS USED FOR ARBITRAGE PURPOSES

Source	Multi-Market	Short Term Technical Constraints (e.g. Efficiency)	Long term Technical Constraints (e.g. Degradation)	Duration
FlexPower [7]	yes	no	no	–
Kazemi [9]	yes	no	yes	1 day
Maheshwari [11]	no	yes	yes	7 days
Metz [10]	no	yes	no	5 years
Collath [8]	no	yes	yes	Lifetime
This contribution	**yes**	**yes**	**yes**	**10 years**

decision variables.
In case of degradation-aware optimization the financial implications of system degradation are mostly addressed through the cost term [8]. Conversely, no considerable variable costs are considered in the absence of a degradation-cost-based methodology. The integration of multiple markets or trading levels that are traded at different times and, consequently, are based on different information are regarded as two separate problems. By adding the BUY^M and $SELL^M$ volumes of each market the DA and ID are coupled to BUY and $SELL$. While the ID-volumes in the DA-stage are defined as 0, the DA-stage decisions are already determined in the ID-stage and can no longer be adjusted. Considering efficiency, the trading volumes are converted into the physically charged (CHA) and discharged (DIS) volumes. The energy conservation term ensures that the state of the battery is determined depending on its previous state and the charging processes. The physical limits constrain the energy stored in the battery to be between 0 and the battery's capacity CAP. Calculating a cost term may require additional endogenous calculations. The degradation-aware models in [8, 9, 11] calculate and minimize the aging based on empirical battery degradation models [9, 11, 12]. Battery degradation is a high-dimensional phenomenon which makes modeling complex, as it leads to a loss in both capacity and efficiency [13–19]. As shown in Fig. 1, the internal calculation and use in the OF is the most challenging approach to include the calculated degradation behavior.

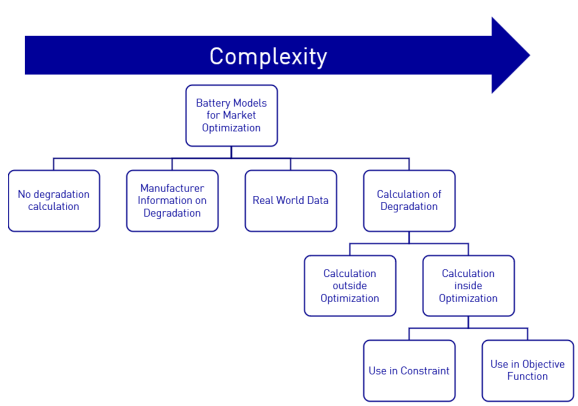

Fig. 1. Comparison of Different Approaches to Include Degradation into Optimization

In order to use degradation models endogenously for degradation aware optimization, it is important that the model can be converted into expressions that are tractable by available optimization algorithms [8, 11]. In practice, this means that problem formulations must not exceed quadratic and mixed-integer complexity [20].
Deterministic models consider the price curves in perfect foresight [8]. While this assumption may appear optimistic, in practice it is used as a conservative estimate for the ID market, as trading actions are only carried out once in the optimization. In reality, trading on the continuous ID market offers the opportunity to exploit price fluctuations several times through virtual cycling. Virtual cycling is considered as the buying and selling of energy without the physical delivery [8].
Although models with and without technical constraints are presented in the literature, there is no clear comparison between the approaches and the resulting magnitude of error. In order to investigate the impact of technical impacts and fill the gap in the literature, self-discharge, cool down time (CDT), and consideration as Mixed Integer Linear Programs (MILP) are analyzed.

C. Paper structure

II-A describes the design of the underlying optimization problem. In order to examine and evaluate further developments, a base case defining the initial situation is presented in II-B. The consumer behavior is analyzed using a MILP. Furthermore, the self-discharge of the battery and the influence of cool-down times are analyzed in detail. Applied to the replicated base case III-A demonstrates how a degradation model [12] reacts to restrictions to limit degradation, and how this affects the revenues.

II. MULTI-MARKET OPTIMIZATION

A. Optimization Model Considering Limited Intraday Liquidity

The BESS mission profiles are optimized on the DA and ID markets. Using different price series offers the opportunity to analyze different price scenarios. At the point of DA decision making, the optimizer does not have any information on the ID-price series. This leads to an internal optimization on the DA market without taking speculative positions on DA-ID-spreads.
Optimization takes place on a monthly basis. After both stages have been optimized, the battery characteristics are redefined. This update affects the capacity and efficiency. Both values decrease over the service life of the battery and correspond to the manufacturer's warranty information.

The hypothesis that the electricity price is inelastic in the German electricity market design must be critically examined. The elasticity is reinforced by low trading volumes and the associated liquidity. Especially on the ID market the liquidity is not necessarily given [21]. In order to reflect the limited liquidity of the ID market, a liquidity constraint λ^{ID} is introduced in the constraints limiting the trading volumes for buy (2) and sell (3). λ^{ID} is conservatively assumed to be 0.25 [22]. This ensures that the BESS does not affect market prices, as its traded volumes are too small to have a significant impact.

$$BUY_t^{ID} \leq \lambda^{ID} \cdot \frac{CHA_{max}}{\eta_{CHA}} \cdot \Delta_t^{ID} \quad \forall t \in T \tag{2}$$

$$SELL_t^{ID} \leq \lambda^{ID} \cdot DIS_{max} \cdot \eta_{DIS} \cdot \Delta_t^{ID} \quad \forall t \in T \tag{3}$$

The restriction of the manufacturer-specific cycle restriction is carried out according to the constraint in 4. The sum of the stored energy divided by the capacity determines the Full Cycle Equivalents (FCE) in a horizon. This value must not exceed the number of Cycles Per Day (CPD) allowed n_{cyc}^* multiplied with the number of days in a horizon D.

$$\frac{\sum_{t=1}^{T} CHA_t}{CAP} \leq n_{cyc}^* \cdot D \tag{4}$$

B. Case Study

The case study uses the historical price curves from Jan 2019 to Dec 2023. This time period enables the display of different price levels on the one hand and to describe recent trends like negative prices and high shares of RE on the other hand. The duck curve phenomenon, which is characterized by two peaks in the morning and evening in the DA prices, is readily identifiable in this period [23].

A BESS with the initial specification in Tab. II is selected as the reference system. This system corresponds to current utility scale standards. It is to say that the degradation which is updated every month follows the warranty conditions of the manufacturer and will change.

TABLE II
BASECASE SETTINGS

Variable	Explanation	Value
E_{max}	Initial capacity	$200MWh$
CHA_{max}	Maximum Charging power	$100MW$
CPD	Cycles per Day	2
DIS_{max}	Maximum Discharging power	$100MW$
Δ_t^{DA}	DA time step	$1h$
Δ_t^{ID}	ID time step	$15min$
λ^{ID}	Liquidity Factor	0.25
Δ_h	Length of horizon	1*month*
η	Initial Round trip efficiency	0.86

In the benchmarking period, the basecase setting generates revenues of 30.93 MioEUR. 78% of the revenue is attributable to the DA, while the ID accounts for 22% of revenue. Besides the model calibration regarding liquidity, the revenues are heavily impacted by the price levels. In times of high price spreads the revenues do increase as well.

C. Model Extension

1) Consumer Behavior: The investigation of the basecase shows inaccuracies in the modeling of the BESS. The optimized mission profile charges and discharges at the same time. This phenomenon occurs when prices are negative and the battery is full. The reason for this behavior lies in the efficiency losses. Simultaneous charging and discharging eliminates this loss in the simulation. The negative prices lead to a financial profit, which could not be realized in real life. Physically the energy can only flow in one direction.

To avoid this unrealistic behavior it is necessary to allow just one charging process at a time. By introducing a binary variable κ in (5) and (6) it's possible to avoid the simultaneous actions.

$$0 \leq \frac{CHA_t}{\Delta_t} \leq CHA_{max} \cdot \kappa_t \quad \forall t \in T \tag{5}$$

$$0 \leq \frac{DIS_t}{\Delta_t} \leq DIS_{max} \cdot (1 - \kappa_t) \quad \forall t \in T \tag{6}$$

The formulation introduces integer variables and therefore increase the complexity to a mixed-integer problem. However, the linearity of the problem is maintained, as the binary variable is multiplied exclusively by parameters. This ensures that the computational effort to be minimal. It is evident that this adaptation has a direct impact on the negative price hours, and consequently, its observable change is most evident in the recent past, where negative prices occur the most [24]. Overall the reduction in revenues adds up to 93kEUR, which is around 0.3% of the overall revenues. Even though this delta appears small it is to say that an increasing number of negative hours, which can be expected based on the increase of RE, may increase size and the economic relevance of this difference.

2) Self Discharge: Batteries do not only have an efficiency factor present in the charging process, but they do also have losses in the process of storage. Losing reversible capacity over time is called self-discharge [25]. In order to verify the relevance of self-discharge for the model the energy conservation term is adapted in (7). ζ_{Δ_t} denotes the relative loss of Energy per time step.

$$E_t = E_{t-1} \cdot (1 - \zeta_{\Delta_t}) + CHA_{t-1} - DIS_{t-1} \quad \forall t \in T \backslash \{0\} \tag{7}$$

It is important to note that the deduction is only on the amount stored for the point of time. This means that the energy charged or discharged energy is considered to be a step function. However, since the ramping up and down of the energy is of a similar order of magnitude, this simplification is permissible. Even under the pessimistic assumption of a monthly discharge rate of 3% the deviation does not exceed 0.05% in revenues. It can be asserted that this effect is negligible.

3) Cool Down Time: Manufacturers often undersize the cooling systems in order to reduce costs. These cooling systems cannot achieve thermal equilibrium at full power, charging or discharging. Instead, manufacturers require CDT after full cycles. Assuming the heat generation to be equal at charging and discharging gives the opportunity to include the CDT through (8) and (9). The charging and discharging volume in the period of a full cycle and CDT defined cool down horizon (CDH) is restricted to not exceed twice the capacity.

$$\sum_{k=t-CDH}^{t} (CHA_t + DIS_t) \leq 2 \cdot CAP \quad \forall t > CDH \in T \quad (8)$$

$$\sum_{k=0}^{t} (CHA_t + DIS_t) \leq 2 \cdot CAP \quad \forall t \leq CDH \in T \quad (9)$$

Fig. 2 demonstrates, that the impact of this constraint is minor. Only when the CDT constraint comes into conflict with the CPD condition can an influence be recognized. A conflict results from high CPD values. A 2-hour battery with 4 hours CDT results in a maximum of 3 CPD itself. This restriction is stricter than CPD since this approach specifies where cycles must occur. The comparable small impact can be explained by the dominance of the DA market. The DA market and its spreads are dominated by the duck curve [23, 26]. This pattern results in a mean number of 2.13 CPDs, even in the presence of 3 available CPDs. The typical intervals between the charging and discharging are about 6 hours apart. As a result, the CDT at DA is naturally observed at the moment. It needs to be observed whether an increase in flexible assets in the market flattens out the curve and might eliminate this effect [23, 26]. The ID market is characterized by greater volatility, thus presenting significant arbitrage opportunities outside the duck curve related spreads. However, the impact of this market is significantly restricted by the liquidity constraint, which limits the utilization of its volatility. If the parameter of interest was set to the value of one, the revenue would increase by 56%.

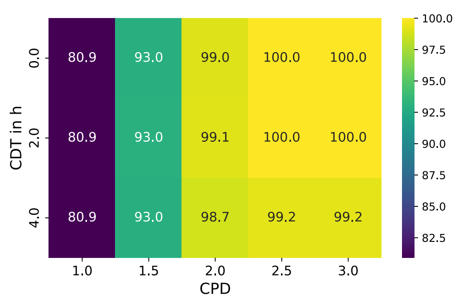

Fig. 2. Normalized Revenues Comparing of CDT and CPD

III. Degradation-Aware Operation

So far, degradation has been considered as a function of time. In order to represent the interaction between degradation and past mission profiles, it is important to use a degradation model. For the calculations a model in the spirit of Naumann [12] is developed. The model differentiates between cyclic and calendric aging. For the cyclic aging the model includes Depth Of Discharge (DOD), C-Rate and throughput in form of FCE as impact factors. The calendric component includes the State Of Charge (SOC), temperature and time. The differentiation enables to include the degradation effects before commissioning as batteries are usually overdimensioned to meet the conditions when commissioned. The approach to include the degradation costs into the OF is the optimum when it comes to maximizing the revenues at low degradation. As shown in Fig. 1, this calculation is rather complex. For instance, the integration of a cycle-counting algorithm into the MILP leads to a substantial number of auxiliary variables yielding a considerable number of combinatorial solutions that are interconnected and, consequently, cannot be disaggregated into smaller problems. These combinatorial solutions are also further linked to the cubic aging function that must be calculated or approximated. The approach is impractical because the computation time per horizon is extended to several days, while the basecase takes only seconds for the two stages on a typical PC setup. In order to still investigate the interaction of operation mode and degradation the impact factors are limited and the results, including value loss of the BESS are compared. The aim of the study is to examine long-term revenues, taking into account various trading and dispatching strategies.

A. Direct Impact

Varying the direct impact factors C-rate and CPD, Fig. 3 demonstrates that a gentle operation mode (low C-Rate, low throughput) leads to lower degradation and lower revenues. As mentioned before, it is clear that the effect of throughput above 2.2 CPD appears to be largely negligible in the DA-focused problem formulation and the 2-hour BESS. Given the negligible use of the additional throughput available from 2.5 to 3 CPD, it is reasonable to expect that degradation will increase only slightly.

The relevance of different C-rates is demonstrated, with a clear positive correlation to the calculated revenues. It is also noteworthy that the impact of C-rate is more significant when CPD is higher, and vice versa. This can be explained by the multiplicative linking of the factors within the degradation model [12].

In order to assign a financial value to the battery and the loss in battery value the Financial Value (FV) is introduced in (10). The FV describes the value in dependence of its State Of Health (SOH) under consideration of a SOH_{min} of 70% of the initial capacity as the end of life.

$$FV(SOH) = (SOH - SOH_{min}) \cdot \frac{FV(SOH = 1)}{1 - SOH_{min}} \quad (10)$$

Assuming a purchasing price of 110 kEUR/MWh leads to a cost of 366.7 kEUR per lost MWh on the reference system. Following this approach, the Running Asset Value (RAV) can be determined. This value adds up from the BESS FV and the discounted revenues of the market. A discount rate of $7\frac{\%}{a}$ is applied. The final RAV can be seen as the Net Present Value (NPV) for a ten year horizon. Applying those curves to the looped basecase Fig. 4 demonstrates the bigger FV through gentle operation has only a minor effect on the RAV. Comparing a gentle operation mode **a)** to the initial basecase

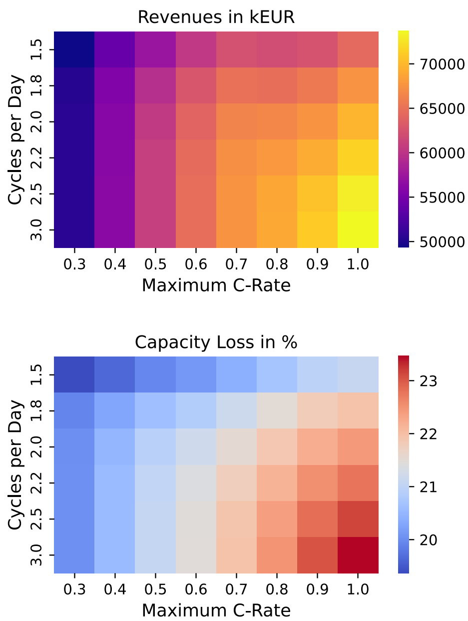

Fig. 3. Comparison of Operation Modes based on C-Rate and CPD

settings **b)** the delta in NPV is at 2.70 MioEUR even though the capacity differs by 860 kWh. The capacity difference is valuated to a FV of 315.58 kEUR in our example, which refers to approximately 10% of the revenue gap. In addition it's noteworthy that even at 860 kWh more capacity **a)** cannot outperform the advantageous high C-Rate of **b)**. Even in the last month **b)** generates more revenues than **a)**.

IV. Conclusion & Future Work

The study demonstrates that the self-discharging effect of BESS is negligible. In instances where there are only a few negative hours and primarily daily spreads are utilized, consumption behavior and CDT are also insignificant. In case the number of negative hours increases or the market is further dominated by short-term volatility, these findings should be re-examined. Gentle operation modes face a trade-off between lower degradation and lower profitability. The financial benefit for the battery, assessed based on its state of health, shows that the impact of degradation is relatively minor compared to the revenue generated.

Future work should focus on further developing degradation models and optimization-friendly cycle counting algorithms. Furthermore the integration of additional technical constraints such as load dependent efficiency and economic factors like virtual cycling, the liquidity constraint should be considered.

The expansion to different markets like frequency control offers additional revenue streams. Considering degradation it can be said that the frequency control market reduces the aging as the power merely needs to be available with no requirement for it to be called up. This further supports the approach of not explicitly optimizing under degradation constraints.

Additionally, real-world validation of the proposed models through pilot projects and utility scale assets are crucial to ensure the practical applicability and effectiveness.

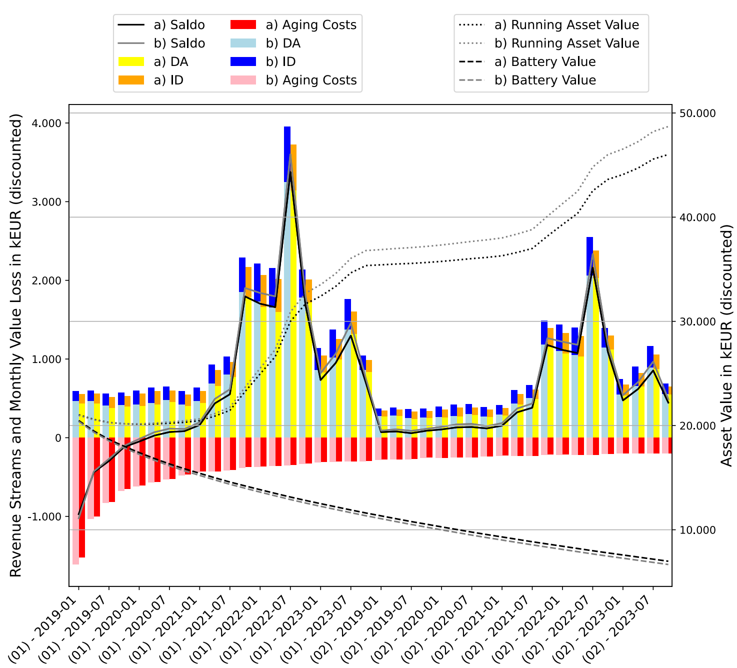

Fig. 4. Comparison of Revenues against Degradation Costs **a)** CPD=1.8; C-rate=0.4 **b)** CPD=2; C-rate=0.5

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