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Optimal Dispatch of Battery Energy Storage Considering Cycling and Calendar Ageing

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Abstract. The growing share of renewable energy sources in the energy mix and the liberalization of electricity markets drastically affected the operation of electricity generators. This transition from fossil fuel-based energy systems to renewable ones will significantly change the energy market, giving important opportunities for energy storage systems. In the next years, a large amount of storage capacity is foreseen to be integrated into the electricity grids to shave the demand peaks, mitigate price volatility, and provide services to the grid. In such a situation, to properly manage these crucial technologies, and thus guarantee the economic viability of the operation, it is essential to properly optimize the dispatch and define the best scheduling. This paper considers Battery Energy Storage (BES) to study the problem of dispatch optimization of storage technologies. The complete model of BES is developed, considering especially the effect of DoD (Deep of Discharge) on the total number of cycles, that influence significantly the degradation, and the influence of the current-rate on the total efficiency, due to the effects of losses for the Joule effect. The implemented optimization is based on a Mixed Integer Linear Programming (MILP) approach, the discretization of the state of charge (SoC), and the continuous update of rated capacity until the maximum admissible fade is reached. Different scenarios are compared showing how the effectiveness of the proposed approach at maximizing the net operational profits or minimizing the loss depending on the profitability of markets.

1 Introduction

The transition from a carbon-based energy system to Renewable Energy Sources (RES) can be seen as the most potential solution to counteract global warming and, for many countries, decrease foreign dependence on supply pursuing security and affordability of supply. Despite the share of energy from renewable sources has continuously increased in the last years, global greenhouse gas emissions have also risen, as IEA reported [1]. Therefore, pledges for the transition have been set to be more and more challenging, the EU in “Fit for 55” [2] has fixed different targets to reach carbon neutrality two key parameters are energy efficiency and renewable sources, the most ambitious target is to reach energy production from RES up to 40% of the total demand by 2030.

However, most renewable sources are strongly stochastic and not programmable, posing a serious issue in meeting instantaneously electricity generation, demand, and grid security requirements. In this scenario, the grid is required to be more flexible, and large storage systems are considered essential to mitigate the variability of RES temporarily shifting the load [3,4], and provide services such as fast frequency regulation traditionally guaranteed by large rotational inertia of spinning generators. According to the Net Zero Emission by 2050 scenario of IEA, by 2030 680 GW of grid-scale storage systems must be installed globally, while 16 GW were already installed in 2021 [5].

Battery Energy Storage Systems (BESS) show great potential for such applications, particularly lithium-ion battery are appreciated for their high efficiency and reduced cost. They represent 92% of installed grid-scale BES in the US [6] Besides lithium-ion batteries, flow batteries could emerge as a breakthrough technology for stationary storage as they do not show performance degradation for 25-30 years and are capable of being sized according to energy storage needs with limited investment [5]

Today, most countries adopt a liberalized electricity market design in which is worth for storage shifting the load if arbitrage opportunities subsist, the driving factor for arbitrage is the electricity price variability, thus the viability of storage strongly depends on the market scenario [7] Moreover for some storage, including BESS, degradation is an important issue and it must be considered to determine the optimal dispatch, such to maximize net operational profits and guarantee the return on the investment.

This paper focuses on the optimal dispatch of lithium-ion BES considering arbitrage opportunities on the electricity day-ahead market. A MILP algorithm is implemented, because of the advantages demonstrated in previous studies [8] The optimization is described in detail in the methodology section and considers the degradation of the cell due to both cycling and calendar ageing, the impact of the state of charge and depth of discharge, and the dependency of efficiency on the actual current rate, and the progressive fade in capacity. Finally, the presented optimizer is applied to different market scenarios.

2 Methodology

2.1 Capacity fade model

The BES performance shows a decay of the nominal parameters over time, the capacity fade due to the ageing mechanisms has a major impact on the BES operation condition, while power fade can be neglected [9]. The rated capacity continuously decreases because of two major contributions, first the impact of each cycle, cycling ageing, and second, even in idle conditions, a degradation, defined as calendar, occurs. The State of Health (SoH), eq. (1), is defined as the ratio of rated capacity on the nominal value, i.e., the complementary of fade. Typically, is fixed for most lithium-ion BESS the End-of-Life (EoL) at 20% of fade, SoH=80%. Under this threshold value, performance is too poor to keep BESS operating.

$$SoH = \frac{C_{rated}}{C_{nom}} \cdot 100\% = \frac{C_{nom} - C_{faded}}{C_{nom}} \cdot 100\% \tag{1}$$

As a battery undergoes charging and discharging cycles, its electrodes slowly degrade and become less effective at holding and releasing energy, causing cycling ageing. Many authors analyzed factors influencing cycling aging [9–13]. All of them agree that the depth of discharge is of primary importance, some [10,14,15] describe the impact of working temperature, nevertheless, this dependence is neglected by this paper since a temperature control system is assumed to be integrated with the BESS and its impact is considered on the charging and discharging efficiency model (subsection 2.2). Finally, Stroe et al. [15] and Xu et al. [10] claim an impact of the State of Charge (SoC). However, the former affirms that high SoC is less impactful, the latter the opposite. Since a gap of knowledge currently subsists on the real impact of SoC on cycling degradation, or it is strongly dependent on the specific BESS type, it is not considered in this paper.

On the other hand, calendar ageing is due to the occurrence of collateral reactions generated by the thermodynamic instability of constituent materials [15]. Then, the thermodynamic stability of the negative electrode is pivotal since graphite is not electrochemically stable when used with most electrolyte types. Calendar aging is generally less investigated than cycling in the open literature [9–11,14], nevertheless a proper model may be essential if the BESS is forced to long idling periods, e.g., because the market is not profitable enough to perform arbitrage. All authors point out that SoC is the key parameter and agree on the detrimental effect of high SoC, another factor is the temperature [10,14,15], however, as for cycling ageing, it is neglected in this paper. Finally, the proposed models differ by the kind of dependency on time, if [10,11,14] propose a linear relationship the formula indicated by Stroe reports an exponential factor of 0.8 affirming that the degradation rate progressively decreases over time.

For the purpose of this paper, the authors selected a model to refer to that consistently describes the calendar and cycling ageing, because the impact of SoC on the cycling agreeing is not certain and in any case of secondary importance, the model proposed by Sayfutdinov [12] is considered. Equations (2) and (3) describe the capacity fade, in percentage points, attributed to each cycle and idling hour respectively. Where SoC is the ratio between dischargeable energy and the nominal capacity, and the Depth of Discharge (DoD) is the SoC decrement associated with the discharge. Both of them are used as percentage values in the following equations.

$$C_{fade_{cycling}} = \left(a_{cycle} \cdot DoD^2 + b_{cycle} \cdot DoD\right) \left[\frac{p.p.}{cycle}\right] \tag{2}$$

$$C_{fade_{idling}} = \left(a_{idle} \cdot SoC^2 + b_{idle} \cdot SoC + c_{idle}\right) \left[\frac{p.p.}{h}\right] \tag{3}$$

Consequently, equations (4,5) indicate the theoretical limits of cycles and idling time independently, considering an EoL criterion of 20% of fade. These two limits are quantified in 4109 cycles with DoD=80% and $2.3 \cdot 10^4$ h (approximately 25 years) of idling at SoC=20%. Table 1 reports the coefficients of the equations (2,3).

$$n_{cycle_{max}}(DoD) = \frac{EoL}{a_{cycle} \cdot DoD^2 + b_{cycle} \cdot DoD} \tag{4}$$

$$t_{max}(SoC) = \frac{EoL}{\left(a_{idle} \cdot SoC^2 + b_{idle} \cdot SoC + c_{idle}\right)} \; [h] \tag{5}$$

Table 1. The fitting coefficient for the Calendar and Cycling ageing model [12].

Calendar			Cycling	
a_{idle}	b_{idle}	c_{idle}	a_{cycle}	b_{cycle}
2.5083e-7	5.6250e-7	7.7083e-7	-4.72e-5	9.62e-5

2.2 Efficiency model

When considering a BESS operating on the electricity grid is important to consider the global efficiency, from alternate current to alternate current (AC-AC) which is lower than the value provided by some manufacturers concerning the battery itself (DC-DC). Rancilio et al. [16] identify the C-rate and the SoC as the factors with the highest impact on AC-AC efficiency. However, the reported results show that the influence of SoC is negligible if compared to the C-rate contribution.

The dependence of efficiency on the C-rate is then considered interpolating the reported experimental data [16]. Consistently with the reference, discharge and charge efficiencies are assumed to be equal.

The associated trend reports a maximum approximatively for C-rate=0.4, moving toward higher current cause a slight decrease because of the parasitic current losses and greater effort required to maintain the cell design temperature. Decreasing C-rate below 0.2 forces the energy conversion auxiliary systems to operate in strong off-design conditions, consequently a significant drop in charging and discharging overall efficiency occurs at reduced C-rates.

2.3 BES MILP model developing

The present section focuses on the optimization algorithm, which is independent of the degradation and efficiency models selected in subsections 2.1 and 2.2 respectively. Here is explained how these factors are accounted for at the optimization stage. The optimizer implementation can be generalized regardless of the models to quantify the aforementioned factors. The selection previously carried out is used in Section 3, reporting results of two case studies as a practical application of the algorithm here presented.

A MILP Algorithm is used since it is demonstrated to handle the complexity of the problem without losing efficiency in finding the optimal solution [8]. The objective function is presented in eq (6). Two terms can be distinguished, the first concerns the operating profits (OP) that are exclusively related to the charging and discharging phases, and the second quantifies the degradation cost ($Cost_{degr}$), determined as the sum of the contributions of both cycling and idling ageing.

$$OP_{Net} = \sum \left(\left(Revenue - Cost_{Charging} \right) - \left(Cost_{cycle} + Cost_{idle} \right) \right) = \sum \left(OP - Cost_{degr} \right) \tag{6}$$

Indeed, the capacity fade represents a cost since, once the EoL criterion is reached, the battery must be replaced. While OP represents the actual cash flow for the operator, what is worth maximizing is the OP_{net} to avoid performing cycles characterized by too low OP to justify the lifetime consumption of the cell. Such a strategy guarantees maximizing earnings, net of CAPEX, over a long period. On yearly basis, the summation of $Cost_{degr}$ can be considered as a provision for new investment at the end of BES life or amortization of already paid CAPEX. Consequently, the costs associated with cycling or idling are determined by equations (6,7) as the ratio between CAPEX and the maximum number of cycles or the maximum idling time respectively (eq(4-5)).

$$Cost_{cycle}(DoD) = \frac{CAPEX}{n_{cycle_{max}}(DoD)} \tag{7}$$

$$Cost_{idle}(SoC) = \frac{CAPEX}{t_{max}(SoC)} \tag{8}$$

Since the optimization is carried out considering the day ahead market, the time discretization is set to one hour in accordance with the time interval. Optimization of dispatch is performed subsequently day by day, considering a forecasting horizon of 36 hours as the best trade-off between computational time and global optimum identification [8].

The general problem formulation for the MILP is presented in equation eq. (9). And optimization variable x is a binary variable that can be visualized by the matrix approach of Figure 1. For each time step, a matrix is defined, columns indicate the initial SoC while rows determine the final. At each time step t, one and only one element must be set to 1 selecting an operational mode. Is then imposed the consistency between the final SoC at time t and the initial SoC at time t+1.

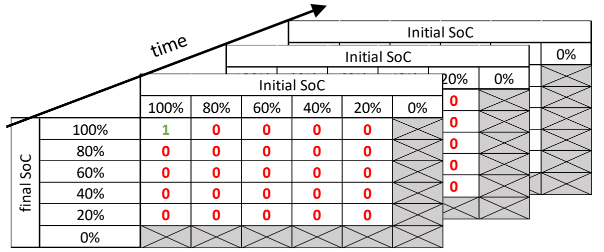

Fig. 1. Matrix visualization of optimization variable x.

Analogously, the f array can be defined with the same 3D matrix shape. For each position in the matrix, $Cost_{degr}$ is determined by the SoC and ΔSoC associated and OP is computed by the ΔSoC of each operational mode, the electricity zonal price (ZP), which depends on the time, and the charging or discharging efficiency, depending on C-rate and so on ΔSoC. Equation (10) reports in detail how each element of f is computed according to the objective function, eq.(6). f is then reshaped as a 1-D array before running the MILP algorithm.

$$\min_{x} f^T x \;\; s.t. \begin{cases} A \cdot \mathrm{x} \leq \mathrm{b} \\ lb \leq \mathrm{x} \leq \mathrm{u}b \end{cases} \tag{9}$$

$$f_{i,j,t}(\Delta SOC_{i,j}) = \begin{cases} \frac{\Delta SoC_{i,j}}{100} \cdot C_{nom} \cdot \eta_{discharge}(\Delta SoC_{i,j}) \cdot \mathrm{ZP}_t - Cost_{cycle}(DoD_{i,j}) & \Delta SOC_i i > j \\ -Cost_{idle}(SoC_{i,j}) & \Delta SOC_i i = j \\ \left(\frac{\Delta SoC_{i,j}}{100 \cdot \eta_{chage}(\Delta SOC_{i,j})} \cdot C_{nom} \cdot \mathrm{ZP}_t - Cost_{idle}(SoC_{mean_{i,j}})\right) & \Delta SOC_i i < j \end{cases} \tag{10}$$

The previously mentioned constraints of consistency between t and t+1 and the requirement to select one, and only one, operational mode at the same time are imposed by the inequality constraints expressed by the matrix A and the array b. Analogously, is imposed that the initial SoC at the first hour of the day_n is equal to the final SoC at the 24^{th} hour of the day_{n-1}. The upper and lower bounds (ub and lb) impose x to be binary.

3 Results

The present section applies the optimizer described in Subsection 2.3, the ageing model proposed by Sayfutdinov [12], and the efficiency formulation presented in Subsection 2.2 to a 1MWh/1MW BESS in some real market scenarios. The Italy NORD zone is assumed as a case study and different scenarios are created considering electricity prices from different years repeated several times.

Dispatch of BES is optimized daily and the rated capacity is continuously updated consistently with the adopted ageing model, once the EoL (20%) is reached the process stops. The discretization parameter n is imposed to 9, limiting the minimum SoC to 20%.

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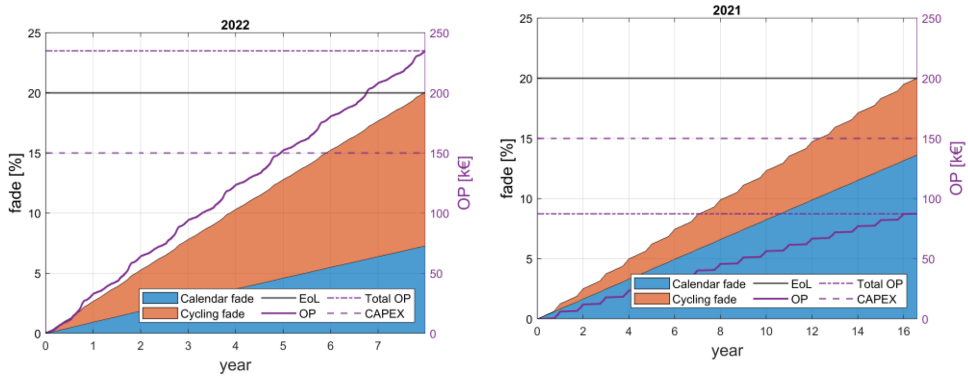

(a) (b)

Fig. 2. Cycling and Calendar contribution to capacity fade (left y-axis) and cumulative OP for 2022 (a) and 2021 (b) scenarios. Dashed horizontal lines indicate the CAPEX (150 k€) and the cumulative OP at the EoL highlighting the net profits or loss.

Figures 2(a) and (b) report the results for the scenarios 2022 and 2021 respectively. 2022 was characterized by high prices, which are commonly associated with increased variability, i.e., the main driving factor for energy arbitrage. In 2022 the average daily variability of electricity price, i.e., the difference between the maximum and minimum daily prices, scored 161.52 €/MWh, while in 2021 it was limited to 59.40 €/MWh. Consequently, BESS operates much more in the 2022 scenario performing 0.84 equivalent cycles per day against 0.20 if 2021 prices are adopted.

This is immediately reflected in the ageing process, in the first case the lifespan is estimated at 8.0 years with a relevant impact of cycling (63.8%) on the overall fade. In the second scenario BESS lasts more (16.6) and calendar ageing is by far more relevant than cycling, which contributes only by 31.9% to the overall fade. However, what is important is to look at the cumulative sum of OP at the end of life. 234.9 k€ and 87.4 k€ for the two scenarios respectively. Considering that the CAPEX for a 1MWh BESS is assumed to be 150 k€, its possible to conclude that the optimization of operation, considering energy arbitrage opportunities on the day-ahead market of electricity, guarantees 10.63k€/year of net profits in the 2022 scenario. Conversely, considering prices of 2021, it minimizes the losses to 3.77€/year, but the arbitrage itself is not enough to pay back the investment in such conditions.

4 Conclusions

In this paper, a dispatching model for the BES system was developed accounting, during the optimization stage, for the impact of charge and discharge cycles on the battery capacity fade, as well as the contribution of idling. Moreover, the dependency of charging and discharging efficiencies on the C-rate, thus on the power, is considered.

The percentage of fade caused by cycling during profitable (i.e., characterized by high price variability on daily basis) market periods is significantly high, up to 60-65%. For the market conditions as of 2022, the profits opportunities for the batteries are sufficient to operate almost one full cycle per day, while for 2021 conditions, the battery on average performs one cycle every five days.

Even if such continuous operations have a great impact on the lifespan, which in the 2022 scenario is less than half of 2021, the most important economic indicator, i.e. the annual net profit is positive and significantly higher.

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