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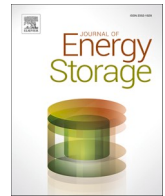
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## Research Papers

# Impact of modeling assumptions on the economic performance assessment of a storage participating in energy and reserve markets

Ahmed Mohamed<sup>a</sup>, Rémy Rigo-Mariani<sup>a,\*</sup>, Vincent Debusschere<sup>a</sup>

<sup>a</sup> Univ. Grenoble Alpes, CNRS, Grenoble INP, G2Elab, Grenoble 38000, France

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## ABSTRACT

This paper investigates the impact of key modeling assumptions for the sizing of a Battery Energy Storage Systems (BESSs) participating in energy and reserve markets. Most of the related studies in the literature assume oversimplifications of the operating conditions when computing the expected BESS revenues at the design stage. These considerations oftentimes consist of (i) constant operating efficiency of the BESS, (ii) neglected profit loss due to uncertainties in the operating phase, and (iii) degradation effects that are usually computed in a posteriori analysis. This paper then proposes to successively assess the impact of those modeling assumptions, deriving from a baseline scenario that embeds oversimplifications. At first, results are analyzed in terms of expected revenue decrease compared to the baseline for different BESS sizes, and with the participation in Day-Ahead (DA) and Frequency Containment Reserve (FCR) markets. The analysis reveals that up to 30 % overestimation (more than 60 % in the worst cases) of the profit along the project lifetime could be done in case where the key modeling assumption are simplified. Finally, a sensitivity analysis conducted with different trade-offs between BESS usage (i.e. degradation) and profits shows that the systems displaying power-to-energy ratios of 1 or 0.5 were the most profitable under the markets investigated.

## 1. Introduction

## 1.1. Stacked revenues with grid-connected BESS

The contribution of grid-connected Battery Energy Storage Systems (BESSs) to maintain grid reliability and efficiency has been widely investigated. In actual implementations, due to the high initial costs of BESS, the owners tend to provide multiple services using the same BESS to cover the investments [1]. By concurrently participating in various energy products, BESSs can maximize their economic returns while taking advantage of discrepancies between different markets – e.g. products for energy and frequency reserve [2,3]. Along the same line, the authors in [4] evaluated the maximum profits for both the Day-Ahead (DA) and Intra-Day (ID) markets. Overall, offering multiple grid services can nearly double ESS profits compared to providing a single service [5]. This paper actually builds on previous works from the same authors investigating the provision of energy, reserve and capacity products in the French context [6] (Fig. 1). Especially, results showed

that stacking the DA and FCR markets provides 57 % higher profits than the summation of the revenue uptaken when participating only in FCR or arbitraging in the DA market. This is due to the fact that the BESS can use the DA market to correct its state of charge and maximize the duration for which a given power reserve can be guaranteed (and thus be remunerated).

At this stage, it is important to note that most of the reviewed studies estimate the BESS profits based on deterministic optimization using historical data and oversimplifications of the models. This paper focuses on the sizing strategy for such BESS while assessing the expected profits with a simulation the operational phase. Especially, the objective is to propose a methodology to investigate key assumptions to simulate the operations, and their impact on the profit estimation and further sizing results. The following subsections introduce the three main modeling assumptions discussed in the paper.

*Abbreviations:* BESS, Battery Energy Storage System; DA, Day-Ahead; ID, Intra-Day; FCR, Frequency Containment Reserve; aFRR, Automatic Frequency Restoration Reserve; mFRR, Manual Frequency Restoration Reserve; RR, Replacement Reserve; TSO, Transmission System Operator; MILP, Mixed Integer Linear Programming; SoC, State of charge; OPEX, Operating Expenditure; CAPEX, Capital Expenditure; NPV, Net Present Value.

\* Corresponding author.

E-mail address: [remy.rigo-mariani@grenoble-inp.fr](mailto:remy.rigo-mariani@grenoble-inp.fr) (R. Rigo-Mariani).

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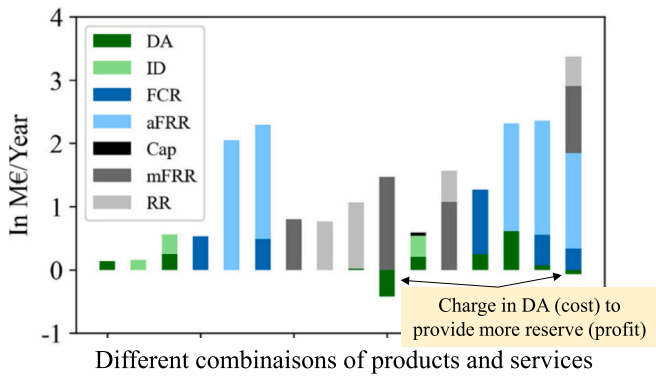


Fig. 1. Expected profits for a 10 MW / 10 MWh BESS providing multiple services [6].

### 1.2. Operation uncertainties in energy markets

In conventional energy and reserve markets, the bids for quantities are submitted before the actual prices are known – i.e. before the market is cleared. Bidding decisions and the subsequent control schedules are typically taken based on price predictions (e.g. on a day-ahead basis) [7]. In actual BESS operation in markets, discrepancies between actual prices and the prediction lead to potential loss of profit, especially in energy markets where the revenues are based on price arbitrage (i.e. charging at low rates and discharging when prices are predicted to rise). To mitigate price uncertainties, the authors in [8], used backcasting where the actual prices of the previous day are the inputs of an operational planning problem for the following day. Other studies focused on price forecasting using auto regressive models [9], neural networks [10], and dedicated statistical models [11]. The authors in [12], introduced a stochastic framework that includes price scenario generation, optimization, and schedule assessment to mitigate the uncertainties in DA. The results showed that the BESS can only reach up to 78 % of the maximum theoretical profit- i.e. estimated assuming perfect forecast.

When BESS operate in reserve markets, potential loss of profits also arises from the frequency deviations in real-time, which cannot be predicted by nature. This can degrade the expected optimal revenue due to potential penalties paid in case of unfilled commitments. This can happen if actual frequency deviations lead the BESS state of charge (SoC) to the limits, further leading to the impossibility of providing the capacity reserved. To address the issue of real-time control in the FCR operations for BESS, various state-of-charge management strategies were proposed in the literature. The authors in [13] investigated a standard drop characteristic while correcting the SoC when pre-defined limits are reached. In [14], it was proposed a bidding strategy based on historical data for batteries in the FCR market in addition to online control of the SoC level. The work in [15] evaluated different SoC management strategies while considering their effect on battery degradation in the Danish market. The authors in [16] proposed comprehensive operational planning for the BESS participating in the FCR market while considering price uncertainties, penalties, imbalance settlements, and degradation. The results showed that BESS could achieve up to 96 % of the maximum theoretical profits.

Overall, the literature has extensively investigated strategies to mitigate the aforementioned uncertainties in the operational phase. However, most of the studies relating to the investment phase systematically overlook the loss of profit incurred by those operational uncertainties.

### 1.3. BESS part-load efficiency

Another simplification always encountered in the literature relates to storage system model. In almost every case, the storage is represented

with a power-energy model assuming efficiencies considered through constant coefficients – typically charge/discharge or round-trip efficiencies around 0.8–0.95 for Li-ion batteries [17]. This is mainly due to the fact that the authors, similar to this paper, usually belong to the power and energy systems community, without specific expertise in storage technologies. Also, the time resolution of the considered problem, typically optimization on a daily/yearly basis cannot cope with accurate models such as temperature-dependent RC circuit [18], for the sake of problem trackability. In some studies related to energy system management, voltage-current models (e.g. Shepherd model in [19,20]) can be found. However, to the best knowledge of the authors, all the reviewed studies on BESS market participation consider simple power-energy models with constant efficiencies. In actual operation, this efficiency may vary with the BESS operating points (e.g. due to power converters), which incurs potential loss and hence lower profits when participating in energy and/or reserve markets.

### 1.4. BESS degradation

One BESS specificity that is more noticeably considered in the literature is the degradation due to calendar and cycling aging effects. The overall impact on the profits lies in the loss of storage capacity over time and the need for replacements. Similar to the operating models mentioned in the previous subsections, long-term BESS management and/or investment cannot cope with the most accurate modeling approaches such as in [21]. The simplest “energy throughput” models typically considered in power and energy systems studies consist of integrating the charge/discharge power, or the depth-of-discharge (DoD) variation [22]. Another conventional approach accounts for the loss of capacity over time with empiric models that rely on the enumeration of the number of cycles at different DoD (e.g. use of the Rainflow algorithm) as in [16,23]. It is worth mentioning that in most cases, the degradation is computed somewhat a posteriori, subsequently to the system operation along a given representative period [24,25]. This may lead to suboptimal solutions in terms of investments (i.e. battery replacements if any). Another typical approach consists in penalizing the battery usage in the objective function of an optimal long-term planning problem similar to [26]. In such formulations, the trade-off between storage degradation and profits uptaken is implicitly considered in a single optimization problem.

### 1.5. Scope and contributions

In light of the previous sections, three main modeling assumptions have been identified as sources of inaccuracy when assessing the expected profits for BESS participating in energy and/or reserve markets. In the design/investment phase, those sources include i) the prices/frequency signals uncertainties of the operating phase, ii) the part-load efficiency of the storage system, and iii) the degradation effects. Table 1 then provides a summarized literature review with a focus on BESS sizing in the context of their participation in energy and/or reserve markets, with an arbitrage between investment and operating revenues. Similar to any system design problem in the energy field, the typical sizing strategies encountered in the literature follows enumerative optimization, bi-level architectures or “all-in-one” formulation [27]. Enumerative approaches consist in successively simulating the BESS operation (e.g. through optimization) for different rated power and/or energy capacities. Bi-level architectures take the form two integrated problems with an outer loop optimizing the investment while an inner method simulates the system management. In “all-in-one” formulations, both sizing and management decisions are variables of a single optimization problem. Overall, most of the studies reviewed account for the BESS degradation, with the aging being estimated linearly with the energy throughput along the operating period. The part-load efficiency of the BESS is never considered at the design stage, and only [28] accounts for uncertainties in the operational phase while investigating the

**Table 1**  
Literature review for different modeling considerations while stacking revenues using the energy storage system.

Paper	Energy markets	BESS sizing	Optimization approach	Part-load (x/✓) Uncertainties (x/✓)	Degradation
[29]	DA + FCR Denmark	4MWh/2 MW	Bi-level Metaheuristic /MILP) on representative days	x x	Energy throughput and cycles counting
[30]	DA + real-time + FCR (PJM)	8 MWh/2 MW	All-in-one (MILP)	x x	x
[31]	DA (USA/Canada)	6 MW/19 MWh	All-in-one (LP)	x x	Linearized with DoD
[32]	DA + FCR (PJM)	10 MW/10MWh	Enumerative (LP)	x x	Linearized with DoD and energy throughput
[33]	FCR + aFRR+RR (Italy)	5.2 MW/10 MWh	Enumerative (LP)	x x	x
[34]	FCR (PJM)	100 kW /700 kWh	Enumerative (MILP)	x x	x
[35]	DA + FCR (PJM)	2 MW/0.81 MWh	Bi-level (GA + MILP)	x x	Energy throughput
[36]	DA + FCR + peak shaving	1.09 MW/0.54 Wh	Bi-level (GA + MILP)	x x	Energy throughput
[37]	DA + FCR	~2 h units	All-in-one (MILP)	x x	x
[28]	DA + aFRR	~ 1 h units	All-in-one (MISOCP)	x ✓	x
[38]	DA	100 MW/150 MWh	Enumerative (Reinforcement Learning)	x x	Energy throughput and calendar aging
This work	DA + FCR (France)	~ 0.5 h units	Enumerative MILP	✓ ✓	Linearized with energy throughput

best BESS design. This paper distinguishes itself from the methodological point of view while assessing the individual impact of each of the three modeling assumptions identified. A baseline case is provided to assess the profit of a BESS participating in the DA and FCR markets with different power/energy ratings. Then, accurate modeling assumptions are successively added to the initial simulation in order to assess their individual impact. Especially, the BESS degradation is evaluated using two approaches: i) as a posterior analysis, and ii) as a cost function integrated into the optimization problem. Finally, iterative simulations are performed to investigate the trade-off between the revenues and the BESS degradation. Finally, an enumerative approach maximizes Net Present Value (NPV) over 20 years while changing the BESS sizes in terms of energy-to-power ratio. Note that, the BESS in this study is assumed to be a price taker. The prices, frequency deviation, penalty, and imbalances are taken from actual market data for the French system in 2021. In this context, the main contributions of the paper can be summarized as:

- The consideration for part load efficiency, operation uncertainties, and degradation when assessing the profit of a BESS operating in DA and FCR markets.
- The penalization of the BESS usage in the operational objective through a linearized exponential aging model.
- The quantification of the impacts related to the different modeling proposed for BESS of different power/energy rating in terms of overall profit and net present value.

While this Section 1 introduced the context of the paper and its objectives, Section 2 presents the base model equations for a BESS participating in DA and FCR markets. Then Section 3 focuses on the formulations and methodologies proposed to account for the three modeling assumptions investigated. Section 4 evaluates the impact of the different modeling assumptions over ten years of simulations. It also provides an economic study using net present value (NPV) analysis that considers investments and replacement for different BESS sizes. Finally,

Section 5 concludes the paper and presents some perspectives.

## 2. Bess models and base equations

Before further detailing the modeling assumptions, this subsection introduces the generic equations considered all along the simulations carried out in this paper. Especially, a base model of the BESS and its participation in DA and FCR markets is introduced. Note that the methodology employed to assess the impact of the modeling assumptions will be fully described at the end of the Section 3, once all the concepts are introduced and explained.

### 2.1. BESS base model

Before considering the impact of part-load efficiency, the BESS base model adopts a typical linear formulation suitable for MILP optimization. The BESS is represented by the storage capacity ( $E_{cap}$  in kWh), the maximum power charging/discharging rate ( $p_{max}$  in kW), and its state of charge (SoC). Typical constraints (1) and (2) account for the maximum discharging/charging power flows at any time step ( $p_t^+$ ,  $p_t^-$ ), limited by the battery power capacity. Additionally, binary variables  $u_t^+$  and  $u_t^-$  and specific constraints are introduced to avoid potential simultaneous charging and discharging. The stored energy is updated at each time step ( $soc_t$ ) with charging and discharging constant efficiencies ( $\eta^-$  and  $\eta^+$ ), in (3), and shall remain between predefined maximum and minimum levels ( $soc_{min}$ ,  $soc_{max}$ ) (4).

$$0 \leq p_t^+ \leq p_{max} \times u_t^+ \quad \text{and} \quad 0 \leq p_t^- \leq p_{max} \times u_t^- \quad (1)$$

$$u_t^- + u_t^+ \leq 1 \quad (2)$$

$$soc_t = soc_{t-1} + (p_t^- \times \eta^- - p_t^+ / \eta^+) \times dt \times (100/E_{cap}) \quad (3)$$

$$soc_{min} \leq soc_t \leq soc_{max} \quad (4)$$

## 2.2. BESS participation in DA and FCR markets

In the DA market, the BESS submits energy bids for charging ( $p_{t^{da}}^{da-}$ ) or discharging ( $p_{t^{da}}^{da+}$ ) at an hourly resolution  $dt^{da}$ , as in the French market setup, and gets remunerated at the DA price ( $\pi_{t^{da}}^{da}$  in €/kWh) (not known at the time of the bidding). In the FCR market, the BESS owner gets remunerated for a reserved power ( $p_{t^a}^{res}$ ) at a price in €/MW also unknown at the time of bidding ( $\pi_{t^a}^{res}$ ). That reserved capacity is symmetric over 4-h slots with the same amount for upward and downward regulation. In actual operation, the FCR activation is proportional to frequency deviations measured around the nominal 50 Hz value. The energy is activated linearly with the frequency deviations, with 100 % activation of reserve capacity occurring at the maximum deviation ( $\Delta f_{max} = 200$  mHz). Also, there is a remuneration for the actual energy in upward regulation ( $p_{t^a}^{cr+}$ ) and a cost for the energy absorbed in case of downward regulation ( $p_{t^a}^{cr-}$ ) at a price  $\pi_{t^a}^{cr}$  in €/MWh also unknown at the time of bidding. Ultimately, the objective of the joint DA and FCR participation is to maximize the expected revenue  $R$  following (5).

$$\max_{\substack{p_{t^{da}}^{da-}, p_{t^{da}}^{da+}, p_{t^a}^{res} \\ p_{t^a}^{cr+}, p_{t^a}^{cr-}}} R = \underbrace{\sum_{t^{da} \in T^{da}} \pi_{t^{da}}^{da} \times (p_{t^{da}}^{da+} - p_{t^{da}}^{da-}) \times dt^{da}}_{\text{Revenue from DA}} + \underbrace{\sum_{t^a \in T^a} \sum_{t^a \in T^a} \pi_{t^a}^{res} \times p_{t^a}^{res} + \pi_{t^a}^{cr} \times dt^a \times (p_{t^a}^{cr+} - p_{t^a}^{cr-})}_{\text{Revenue from FCR}} \quad (5)$$

At any time step, the charging or discharging power accounts for the expected power in the DA market and the upward/downward FCR activation, as described in Eqs. (6) and (7). As already mentioned, FCR activation is linearly dependent with the frequency deviations around 50 Hz, as outlined in Eq. (8). Moreover, according to specific regulations for BESS in the French context, the FCR provision is not required within a dead band range  $\Delta f_{db} = \pm 10$  mHz. Additionally, a specific rule from the Transmission System Operator (TSO) imposes a 15-min criterion – i. e. the BESS shall be able to provide the capacity reserved continuously for at least 15 min in case of emergencies. This constraint impacts the SoC limits at any point in time, as described by Eqs. (9)–(10).

$$p_t^+ = p_{t^{da}}^{da+} + p_{t^a}^{cr+} \quad (6)$$

$$p_t^- = p_{t^{da}}^{da-} + p_{t^a}^{cr-} \quad (7)$$

$$p_{t^a}^{cr+}, p_{t^a}^{cr-} = \begin{cases} p_{t^a}^{res}, & \text{if } |\Delta \hat{f}_{t^a}| \geq |\Delta f_{max}| \\ \left( \frac{|\Delta \hat{f}_{t^a}|}{\Delta f_{max}} \right) \times p_{t^a}^{res}, & \text{if } |\Delta f_{db}| \leq |\Delta \hat{f}_{t^a}| \leq |\Delta f_{max}| \\ 0, & \text{if } |\Delta \hat{f}_{t^a}| \leq |\Delta f_{db}| \end{cases} \quad (8)$$

$$soc_{max} = 1 - 0.25h \times p_{t^a}^{res} \times (1/E_{cap}) \quad (9)$$

$$soc_{min} = 0.25h \times p_{t^a}^{res} \times (1/E_{cap}) \quad (10)$$

In this study DA and FCR prices in France in 2021 will be considered. Fig. 2 displays the hourly prices distribution with the mean and median values computed along the entire year. For the DA prices, the daily trend tends to follow the national load dynamics with evening peaks and negatives occurrences during sun peak hours (Fig. 2a). The FCR charts Fig. 2b highlights the 4 h slots for which the reserve is procured.

## 3. Modeling assumptions

### 3.1. Operational markets uncertainties

The previous section presented a conventional MILP problem to estimate the revenues from the coupled participation in the DA and FCR markets under specific regulations for BESS. Solving that problem with historical price data and frequency measurements is considered in this paper as a baseline modeling assumption in the design/investment phase. As already mentioned, in actual operations, the reserve and day-ahead schedules are subject to uncertainties as the prices are not known at the time of bidding (typically one day in advance). Also, the actual frequency measurements cannot be predicted. Deviations in real-time may lead to the impossibility of delivering reserve at some point, which translates into economic penalties for the BESS owner. As an example, previous works from the same authors show that in case of bad forecasts, the profit could drop from more than 40 % compare to an ideal scenario. Especially, several forecast generation techniques and bidding strategies were investigated in order to guarantee a maximum profit. As such, for the DA market 70 % of the maximum profits could be achieved in [12] and more than 90 % in the FCR market. In this paper, the main

focus is the impact of the modeling assumptions. Predictions are kept simple with a naïve backcasting technique (i.e. measurements of day D taken as forecast for day D + 1). For the prices considered (Fig. 2), the Mean Absolute Percentage Error of backcasting forecast along 2021 is 38 % for DA and 51 % for FCR. Considering sophisticated prediction approaches is beyond the scope of the paper. However, it is worth noting that the paper builds upon previous work from the same authors, that investigated operational strategies with prediction for BESS participating in DA [12] or FCR [16] markets. For DA participation, simple “backcasting” forecasts were compared with more advanced techniques (ARIMA, Geometrical Brownian Movement). Those forecasts coupled with tailored optimizations allowed to reach better performances (up to 70 % of the optimal profit with “perfect forecast”). However, when participating in FCR, the impact of forecast quality is much less significant, with 95 % of the optimal profit reachable, even with simple predictions. Indeed, no matter the forecasted FCR price, the optimal operation always consists in reserving as much power as possible – i.e. the rated BESS capacity. Thus, when computing the actual profit with actual price values, small differences with a theoretical optimum (perfect forecast) are observed. The 5 % difference is incurred by the activation power profiles that are not optimized with bad forecast. As presented further in the results section, in this work, when participating jointly in DA and FCR, considering simple “backcasting” forecasts allows to reach 90 % of the theoretical best profit with perfect forecast. Similar to [16], the actual operations of the BESS on the DA and FCR markets are represented with a look-ahead bidding phase followed by a near-real-time controller for FCR activation and SoC correction (Fig. 3).

Ultimately, a settlement stage computes the final profits resulting from the gross revenues from the market participation minus potential penalties and payment for imbalances. Once estimated, the profits can then be compared with the theoretical optimum assessed in a case where the operational uncertainties are neglected. After the actual delivery, this revenue is computed following (5) with the actual values for the prices and reserve activations in response to the frequency deviations observed. This revenue is also reduced if the commitments are not met. At first, penalties apply whenever the expected reserve is not provided.

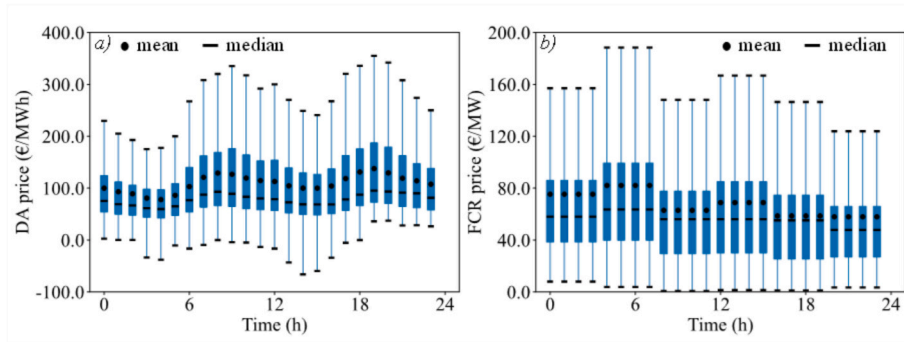


Fig. 2. Hourly distribution – a) DA prices – b) FCR reserve prices.

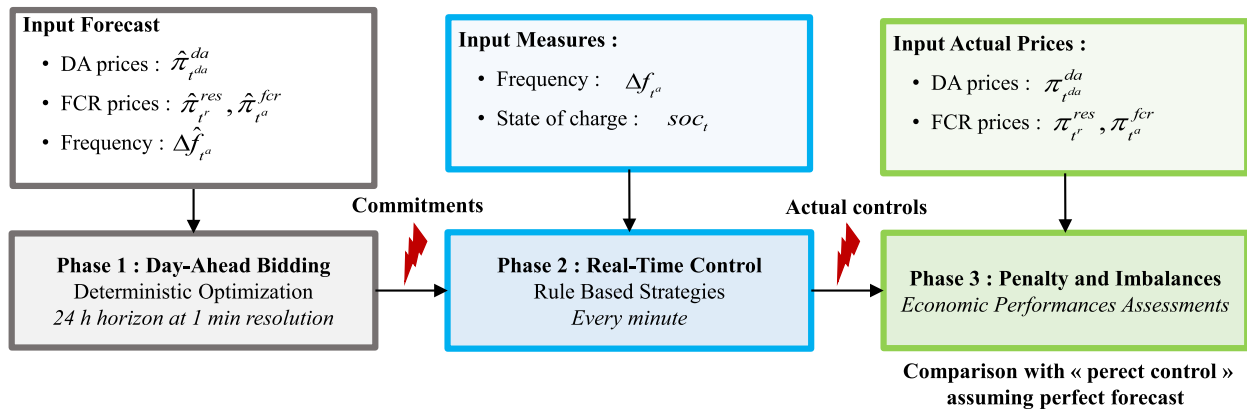


Fig. 3. BESS operations for participation in DA and FCR markets.

In practice, in the French context, the Transmission System Operator (TSO) imposes a high penalty to encourage the suppliers to ensure the availability of the scheduled reserve. The penalty is five times the regulated capacity price (PFC), set at the beginning of each year.<sup>1</sup> The penalty is calculated on a 30-min basis, with a failure ratio that represents the number of provision failures over the total number of frequency incidents. A provisions failure is counted whenever the battery SoC exceeds the limits and hence no reserve is available – i.e. the energy within the storage is outside the range  $[0.25 \times p_t^{res} \times 1h, 0.75 \times p_t^{res} \times 1h]$  that allows to fulfill at any time the reserve capacity during 15 min (specific rule in the French context<sup>1</sup>) (11).

$$\rho_t = 5 \times PFC \times \alpha_t^{fail} \times p_t^{res}$$

$$\text{with } \alpha_t^{fail} \begin{cases} = 1 & \text{if } soc_t \notin [0.25 \times p_t^{res} \times 1h, 0.75 \times p_t^{res} \times 1h] \\ = 0 & \text{otherwise} \end{cases} \quad (11)$$

Secondly, at the end of every delivery period (30 min), the actual energy delivered/absorbed by the BESS is measured  $(p_t^+ + p_t^-) \times dt$  and is compared to the commitments on the DA markets  $(p_t^{da+} + p_t^{da-}) \times dt$  and the expected reserve provision based on the frequency deviations measured  $\sum_{i^a} (p_{i^a}^{cr+} + p_{i^a}^{cr-}) \times dt^a$ . If the measured BESS energy is above the commitments then the system is considered positively imbalances ( $i_t^+$ ). If that measure is below the expectations the systems is negatively

imbalances ( $i_t^-$ ). The imbalance is then paid to the TSO which sets prices for positive/negative imbalance at 30 min resolution<sup>2</sup> ( $\pi_t^{i+}, \pi_t^{i-}$ ) (12).

$$\begin{cases} i_t^+ = \max \left( 0, (p_t^+ + p_t^-) \times dt - (p_t^{da+} + p_t^{da-}) \times dt - \sum_{i^a} (p_{i^a}^{cr+} + p_{i^a}^{cr-}) \times dt^a \right) \\ i_t^- = \max \left( 0, (p_t^{da+} + p_t^{da-}) \times dt + \sum_{i^a} (p_{i^a}^{cr+} + p_{i^a}^{cr-}) \times dt^a - (p_t^+ + p_t^-) \times dt \right) \end{cases} \quad (12)$$

The final profit can ultimately be computed following (13) as the revenue  $R$  in (5) for the participation in DA and FCR with the actual prices, and frequency activations in response to the actual frequency deviations minus the payment for potential penalties and imbalances.

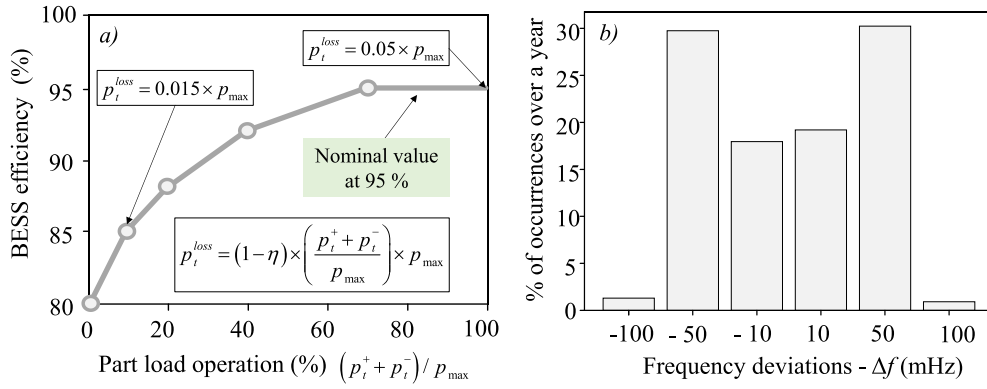
$$Profit = R - \sum_t \rho_t + i_t^+ \times \pi_t^{i+} + i_t^- \times \pi_t^{i-} \quad (13)$$

### 3.2. Part load efficiency

The second modeling assumption whose impact is studied in this paper corresponds to the part-load efficiency of the BESS. As already mentioned, most of the studies assume constant efficiencies no matter the charge/discharge operating power. However, as highlighted in Fig. 4a, due to converters, the BESS efficiency may vary a lot, especially at lower operating points. This can then have a significant impact with non-negligible losses when the targeted application corresponds to lower power levels. As illustrated in Fig. 4b, the frequency deviations

<sup>1</sup> RTE, "Providing frequency ancillary services," 2024. [Online]. Available: <https://www.services-rte.com/en/learn-more-about-our-services/providing-frequency-ancillary-services.html>.

<sup>2</sup> RTE, "Imbalance settlement price." Jul. 22, 2023. [Online]. Available: <https://www.services-rte.com/en/learn-more-about-our-services/becoming-a-balance-responsible-party/Imbalance-settlement-price.html>.



**Fig. 4.** Part load considerations for BESS. a) The BESS efficiency curve against the operation load factor. b) One-year statistics of frequency deviations in the French market in 2021.

remain 95 % of the time below 0.05 Hz (French data along 2021). Given that the maximum frequency deviation  $\Delta f_{max}$  is 200 mHz, this means that the activated reserve in the case of a BESS participating in FCR typically amounts to less than 25 % of the reserved capacity. Consequently, the BESS operates at a load factor less than 25 % for 95 % of the year, which could significantly affect the expected revenues if the part load efficiency is lower than its nominal value.

The SoC constraints in (3) can then be updated with an additional term to represent the losses at part load operations. From the efficiency curve in Fig. 4a, power losses are computed for different part-load operating points  $p_t^{loss} = f\left(\frac{p_t^+ + p_t^-}{p_{max}}\right) \times p_{max}$ . This function is then linearized with a standard least square minimization method to estimate the coefficients in (14), ( $R^2 = 0.875$ ). Note that, in case where the BESS does not operate (i.e. no charge/discharge) the loss term is nullified with charge/discharge binary variables. The updated SoC can then be calculated while adding this loss to the charge/discharge balance of the battery in (15).

$$p_t^{loss} = \left( 0.0379 \times \frac{p_t^+ + p_t^-}{p_{max}} + 0.01174 \times (u_t^- + u_t^+) \right) \times p_{max} \quad (14)$$

$$soc_t = soc_{t-1} + (p_t^- - p_t^+ - p_t^{loss}) \times dt \times (100/E_{cap}) \quad (15)$$

### 3.3. BESS degradation along project lifetime

The BESS degradation model aims at estimating the decline in performances over time due to battery usage. In the considered case study, loss of capacity directly translates into reduced expected profits and

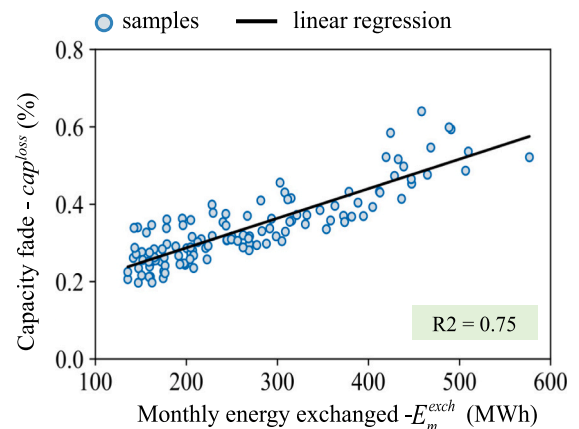
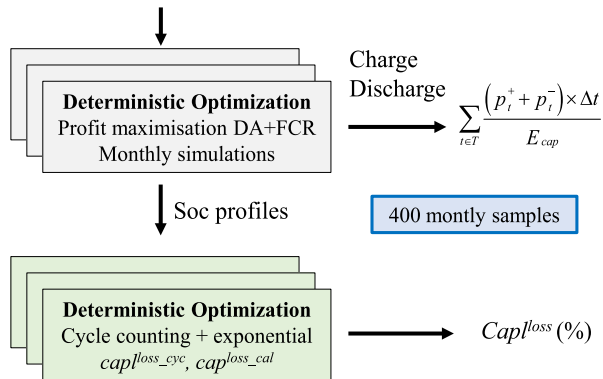
potential system replacements. Note that battery aging is not at the core of the proposed paper and is beyond the expertise of the authors. A simple degradation model, usable in power and energy system studies developed by [23] is considered here. That original model assesses the loss of storage capacity due to calendar aging ( $c^{loss, cal}$ ) as a function of the idling SoC level ( $soc^l$ ) and the time duration in months ( $m$ ), as shown in (16). Capacity loss due to cycling ( $c^{loss, cyc}$ ) is estimated in (17) as a function of the depth of discharge ( $DoD$ ), the number of cycles that occurred at a given  $DoD$  ( $n$ ), and the average SoC during these cycles ( $soc^{av}$ ).

$$cap^{loss, cal} = 0.1723 \times e^{0.0073 \times soc^l} \times m^{0.8} \quad (16)$$

$$cap^{loss, cyc} = 0.021 \times e^{-0.0194 \times soc^{av}} \times dod^{0.716} \times n^{0.5} \quad (17)$$

That reference exponential model is not usable as it is in MILP formulation due to the need to enumerate the BESS cycles at all  $DoD$  levels (typical use of a Rainflow algorithm). A linearized version is then introduced in (18) where the overall capacity loss ( $cap^{loss}$  as the sum of calendar and cycling capacity fades) is updated monthly based on the BESS energy exchanged ( $E_m^{exch}$ ). This follows the methodology introduced in [39] in which it has been demonstrated that, at the first order, the capacity fade depends on the monthly energy exchanged. In practice, several BESS operating curves along individual months are generated for different BESS power capacities (5 MW, 10 MW, and 20 MW) while running the profit maximization problem in DA and FCR markets. The corresponding SoC profiles are then given as an input to the reference degradation model (i.e. cycles counting algorithm + exponential and non-convexities). For every monthly samples with 400 simulations in

DA/FCR prices, frequency deviations



**Fig. 5.** Linear regression of the BESS degradation model.

total, the energy exchanged is computed to ultimately map it with the corresponding capacity fade before performing a standard linear regression (18) (Fig. 5).

$$E_m^{exch} = \sum_{t \in T} \frac{(p_t^+ + p_t^-) \times \Delta t}{E_{cap}} \quad (18)$$

Ultimately, the monthly energy exchanged is then being considered as a proxy to the battery degradation. As illustrated in (16), the BESS usage can then be integrated into the MILP formulation at the DA and FCR scheduling stage when optimizing along one-month and with a penalty factor  $\alpha$  that will be furtherly tuned.

$$\max_{p_{da}^{da-}, p_{da}^{da+}, p_{fc}^{fc}} R - \alpha \times E_m^{exch} \quad (19)$$

### 3.4. Simulation methodology

From the modeling assumptions and formulations discussed in the previous section, it is then possible to run simulations along the overall BESS project's lifetime. The generic methodology used is illustrated in Fig. 6 with an operational phase followed by the economic assessment after ten years. Remember that the objective of the paper is to estimate the impact of the modeling assumptions on the expected profit at the investment stage for a BESS participating in the DA and FCR markets. From the methodology proposed, different case studies are therefore simulated, while replicating the yearly prices/frequency measurements from one year to another.

- **Baseline:** a first simulation is performed with the most simplified estimation of the expected profit. This baseline does not account for any modeling specificities introduced in this paper. Typically, the operational phase consists of the optimal schedule problem run with actual values of DA/FCR prices and frequency measurements. Also, there is no real-time control in the picture (i.e. no need to correct/adapt SoC in real time due to actual frequency deviations) and there is no degradation considered (i.e. no capacity fade and potential BESS replacement).
- **Part-Load-Efficiency (PL):** a second set of simulation includes the part load efficiency. In practice, the equation corresponding to the varying efficiency (section 3.2) is included in the DA and FCR scheduling MILP problem and at the real-time stage when the SoC is updated on a minute basis. Note that a nominal round-trip efficiency of 0.9 is considered.
- **Part-Load-Efficiency and Operation Uncertainties (PL + OP):** under this configuration, the BESS operation is simulated while successively running the scheduling and real-time stages. As mentioned in section 3.1, this implies to account for prices/frequency forecasts in the MILP problem, while the real-time control adapts the SoC if needed. Unlike the previous simulations (Baseline and PL), the profits in that case can be reduced due to potential penalties in case of unfulfilled commitments.
- **Part-Load-Efficiency, Operation Uncertainties, and Degradation/Replacements (PL + OP + DR):** building upon the previous configurations, that last set of simulations accounts for all the modeling assumptions. Especially, the BESS degradation is considered through the proxy (monthly energy exchanged)

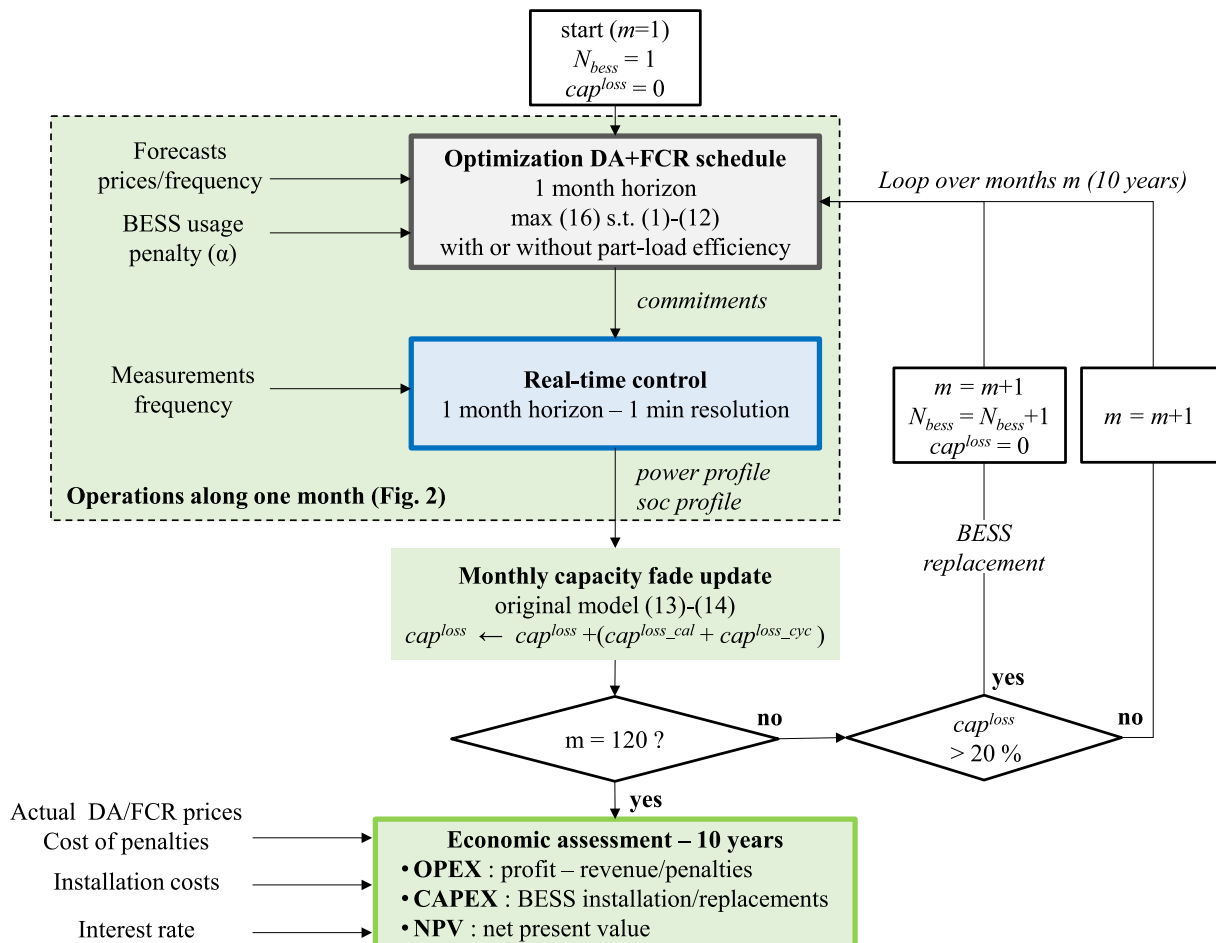


Fig. 6. Flowchart of the simulation methodology along 10 years.

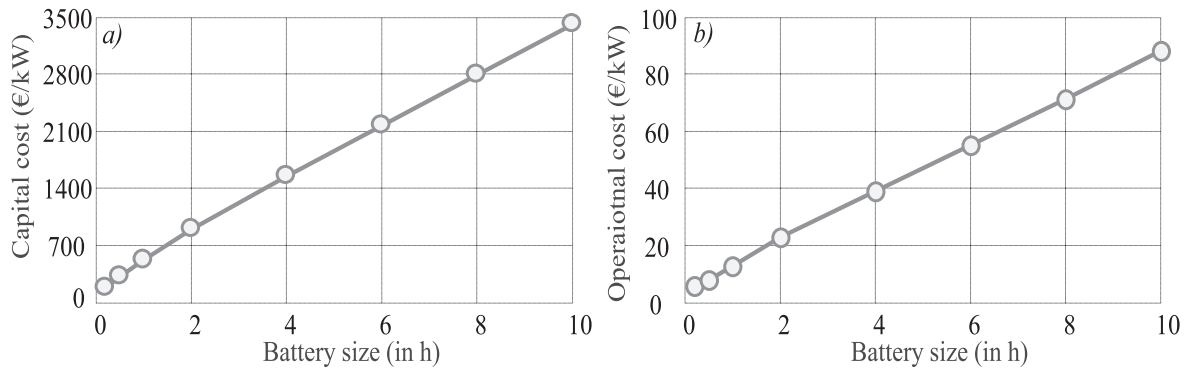


Fig. 7. Commercial BESS costs based on NREL guidelines 2023]. a) CAPEX, b) annual OPEX (<https://www.nrel.gov/docs/fy23osti/85332.pdf>).

penalized in the scheduling MILP problem (run on a monthly basis). Then, at the end of every month, the capacity fade is updated using the original degradation model (i.e. Rainflow algorithm for cycles enumeration and empirical equations). The BESS is considered unusable whenever the capacity fade reaches 20 %, and a new system is installed (i.e. replacement costs and capacity fade initialized to 0 %). In case where  $\alpha = 0$ , the degradation is only considered a posteriori, at the end of every month. With non-null values there is a trade-off between degradation and utilization (i.e. profit).

In every case, once the BESS operation is simulated for the different scenarios, it is possible to complete the economic assessment at the end of the project lifetime. Installation costs from Fig. 7 from NREL are considered with different BESS sizes expressed in hours. Those capacities are expressed in hours relatively to the rated power – e.g. a 2-H BESS in case of 1 MW related power referring to 2 MWh system. The net Present Value (NPV) at the end of the project lifetime is ultimately considered to identify the best investment plan, in terms of BESS size, and depending on the profits and potential replacements.

#### 4. Simulation results

##### 4.1. Profits in DA and FCR

As preliminary results, Fig. 8 details the profits when participating individually or simultaneously in DA and FCR markets – those correspond to baseline simulations over 10 years for a 1 MW / 1 MWh BESS. One main results is that, in case of coupled participation in DA and FCR, most of the profit (> 85 %) is generated through the reserve provision - i.e. remuneration for the power capacity reserved in FCR. Remind that the BESS pays for downward activation. However, the overall revenue in the

FCR market for the energy activation is almost null. This is due to the frequency upward/downward deviations that are almost equals on the long run. More importantly, when stacking the DA and FCR provision, the overall profit is greater than the sum of individual revenues when participating individually in those markets. This is due to the possibility to use the DA market to maintain the SoC while correcting potential drifts in over-charge/over-discharge. This ultimately allows to guarantee the reserve provision along longer periods of times (more 4-h slots) and generate greater revenues from the FCR.

##### 4.2. Profits over ten years

At first, the simulation methodology presented previously is applied to estimate the expected BESS profit in M€ over 10 years. In particular, two rated power values, 1 MW and 10 MW, are investigated with different storage energy capacities. The overall results are displayed in Fig. 9. As already mentioned, most of the revenues comes from the capacity reserved in the FCR markets. Thus, the profit strongly depends on the rated power, which explains the difference of magnitude in the Y-axis between Fig. 9a and Fig. 9b. Also, the results indicates that there is no point increasing the BESS energy capacity beyond 6-H for a constant rated power. Indeed, the capacity reserved is limited by the rated power and the 15-min provision rule (i.e. being able to provide the reserved capacity for at least 15 min). Increasing the usable energy beyond 6-H would lead to the risk of over investing in energy capacity, while most of the revenue is uptaken from the reserved power.

Moving from the baseline scenario and considering the part-load efficiency (PL) significantly decreases the expected revenues. This is especially true for smaller battery sizes as in those configurations, less power capacity can be reserve to respect the 15-min rule (i.e. less than 1 or 10 MW rated). Thus, the systems operate lower power levels with regards to the rated values with more losses. Considering the impact of operational uncertainties (PL + OP) tends to shift down the profit by roughly 10 % for the investigated combinations which is in line with previous works when assessing the loss of profit compared to an ideal scenarios when participating in FCR [16]. Similar to the PL scenario, the impact slightly reduces with the BESS sizes as larger energy capacity makes the BESS more resilient to frequency deviation uncertainties. A wider valid SoC operation range reduces the need to restore SoC levels (i.e. fewer penalties/extra costs). Lastly, PL + OP+DR considers the BESS degradation a posteriori every month to update the capacity fade. Results indicate that there is no impact on the profit. The main reason here is that the degradation is not considered through its proxy in the scheduling problem (i.e. penalty factor  $\alpha = 0$ ). Also, most of the profit comes from the FCR market with a power reserved that is never fully activated (i.e. overall, frequency deviations remain small as displayed on Fig. 4). Thus, except for small BESS (i.e. 0.5H) SoC limits are never reached, and the energy “volume” does not limit the profits. Thus, capacity fade lower than 20 % has no impact on the long run on the

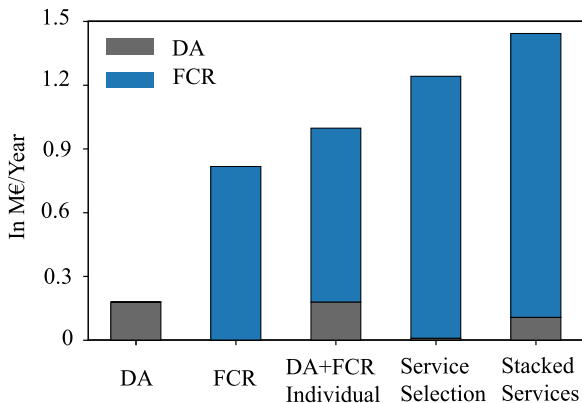


Fig. 8. Profits in DA and FCR.

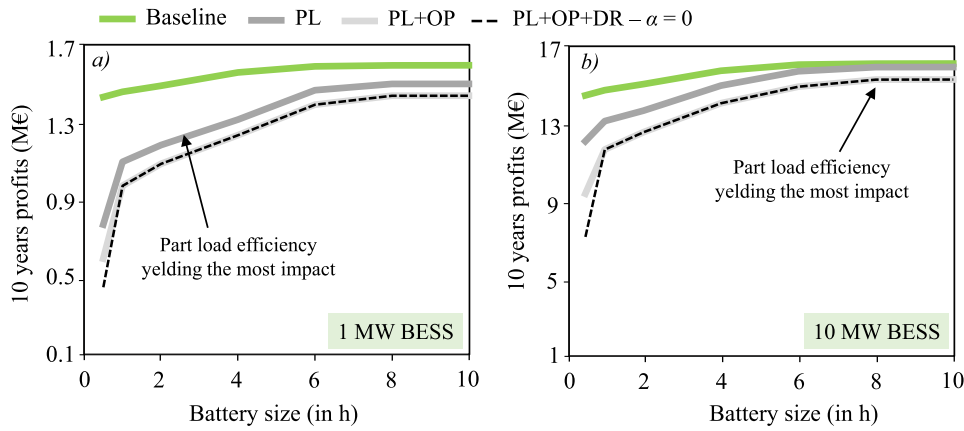


Fig. 9. Ten years stacked revenues in DA + FCR. - a) 1 MW BESS - b) 10 MW BESS.

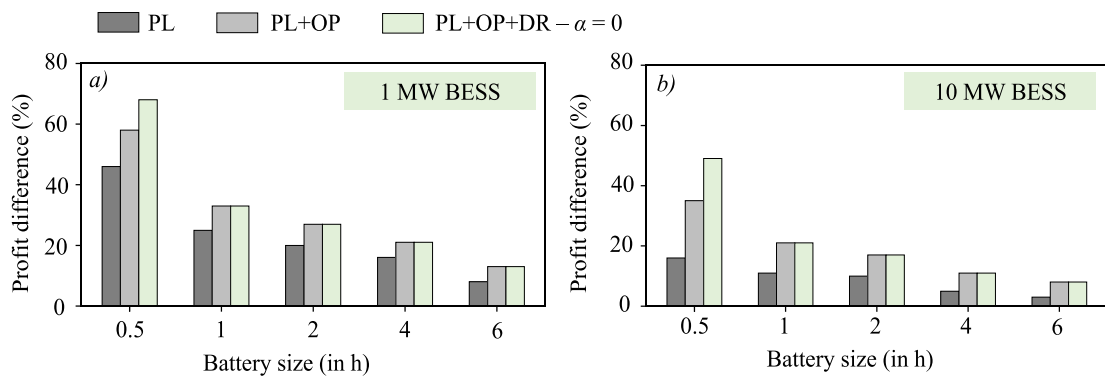


Fig. 10. Profit difference, decrease in % of the baseline for different BESS sizes and modeling assumption - a) 1 MW BESS - b) 10 MW BESS.

operating value. It does however impact the investment in cases where replacements are necessary. For 0.5H BESS, once the capacity fades, it is impossible to reserve the greater power levels for FCR purposes, and hence, profits can be drastically reduced.

Fig. 10 summarizes the previous results for BESS below 6-H sizes, in terms of cumulated profit decrease compared to the baseline scenario. In other words, the figure displays the cumulative impact of the modeling assumptions considered on the 10-years profits. As previously discussed,

the impact is greater for smaller BESS – a 67 % decrease from an ideal theoretical scenario for 0.5H BESS. The part load efficiency incurs the greatest differences. Overall, non-considering the modeling assumptions discussed in this paper leads to 20–30 % profit overestimation, and the greater the power-to-energy ratio the greater the impact.

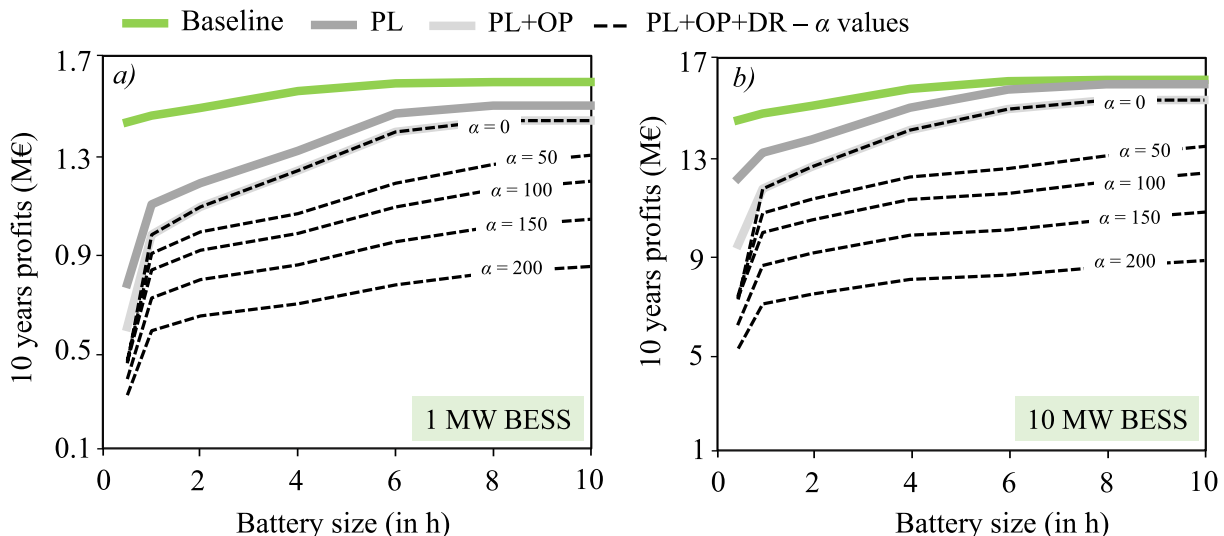


Fig. 11. 10 years stacked revenues in DA + FCR considering degradation by different penalty factors ( $\alpha$ ) - a) 1 MW BESS - b) 10 MW BESS.

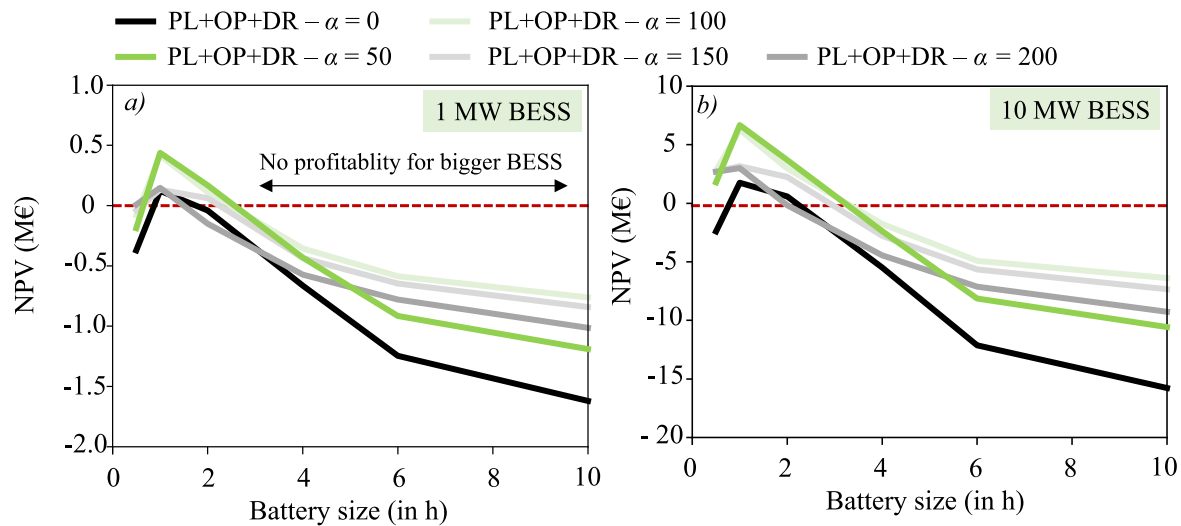


Fig. 12. NPV analysis over 20 years for different penalty factors. a) 1 MW BESS. b) 10 MW BESS.

**Table 2**  
Economic analysis for optimal BESS duration (1 MW).

BESS size (H)	Penalty factor ( $\alpha$ )	CAPEX	Annual OPEX	Number of replacements	NPV	Payback period
1H	0	539 k€	13 k€	2	124 k€	11
1H	50	539 k€	13 k€	1	438 k€	5
1H	100	539 k€	13 k€	1	416 k€	6

### 4.3. Impact of BESS usage penalty

This section evaluates the impact of the penalty terms for the BESS usage in the DA and FCR scheduling problem – i.e. proxy of degradation with the energy exchanged. Especially, different values for the penalty factor  $\alpha$  are considered and results are presented in Fig. 11. Obviously, increasing that penalty factor reduces the BESS energy throughput and hence the participation in both DA and FCR markets. This results in a 28 % - 35 % reduction in profits compared to the scenarios PL + OP+DR previously investigated depending the values of  $\alpha$  investigated.

### 4.4. Net present value

Following the results from the previous section, an additional analysis is necessary in order to identify the most relevant  $\alpha$  values in terms of profitability. The NPV is then computed for the different sizes investigated and different  $\alpha$  values (assuming 20 years project lifetime and an interest rate of 4 %). From the results presented in Fig. 12, it can be seen that in cases where the BESS usage is not limited in the scheduling problem (i.e.  $\alpha = 0$ ) the profitability is only ensured for 1-H BESS. Without penalization of the BESS usage, the NPV is then impacted by over degradation of the storages leading to replacements and thus increasing the CAPEX. No matter the  $\alpha$  value investigated, BESS displaying an energy capacity greater than 4-H is never profitable. Indeed, the majority of the revenue arising from the FCR reserved power, there is no interest in oversizing the BESS in energy capacity beyond a certain point. This would be equivalent to purchasing energy quantity that cannot be valorized enough in the targeted market.

Overall, for 1 MW rated power, the 1-H and 2-H BESS sizes are

profitable at penalty factors of  $\alpha = 50$  and  $100$ . The highest NPV was found at  $\alpha = 50$ , yielding 438,116 € and a 5-year payback period as presented in Table 2. It can also be shown that increasing the penalty up to 100 increases the payback by only one year and yet adds two more years to the BESS lifetime.

For the 10 MW BESS, the NPV observed follows the same tendency but displays greater values as the expected profits are more significant due to the valorization of the reserved power: The results show that a BESS size of 0.5H can be profitable when considering any value of degradation penalty. Table 3 displays that the highest NPV was found at  $\alpha = 50$  for 1H BESS size achieving 6,672,663 € and 4 years of payback period. This emphasizes that while increasing power capacity can improve profitability, it does not affect the degradation rate of the battery. Thus, no need for higher penalization on the energy exchange.

## 5. Conclusions

The study carried out in this paper highlights the profitability of BESS participating simultaneously in the energy and reserve markets, which has already been demonstrated in the literature. However, in the investment phase, most of the reviewed articles consider simplistic assumptions regarding the operation of BESS, leading to an overestimation of the expected benefits. The analysis focused on three key modeling assumptions regarding BESS part load efficiency, operational uncertainties and degradation effects. Over ten years of simulations, the results showed that the revenue overestimation reached an average of 20–30 % (more than 60 % in the worst cases) considering the usually simplified assumptions. When considering a proxy for battery degradation in operational planning, the analysis shows that penalizing the

**Table 3**  
Economic analysis for optimal BESS duration (10 MW).

BESS size (H)	Penalty factor ( $\alpha$ )	CAPEX	Annual OPEX	Number of replacements	NPV	Payback period
1H	0	5,390 k€	130 k€	2	1,752 k€	10
1H	50	5,390 k€	130 k€	1	6,673 k€	4
1H	100	5,390 k€	130 k€	1	6,293 k€	5

use of BESS reduces profits but extends battery life, which in turn reduces replacement costs and increases the overall NPV. This finding highlights the importance of considering both operational efficiency and long-term sustainability when optimizing BESS. Finally, the NPV analysis showed that with an appropriate choice of BESS usage penalty (factor  $\alpha$  in the paper, which could refer to a replacement cost per MWh), the 1H and 2H sizes of BESS yielded the highest profitability. These values are consistent with previous findings in the literature on BESS sizing (Table 1). With the market data considered, the payback period for a 1 MW/1MWh system is estimated to be 5 years, while for a 10 MW/10MWh system it is reduced to 4 years, demonstrating the influence of scale on financial performance. In fact, higher power BESS tends to be more profitable compared to higher energy capacity, as more revenue is taken from the power capacity reserve for FCR.

The study carried out in this paper highlights the profitability of BESS participating simultaneously in energy and reserve markets which has already been demonstrated in the literature. However, in the investment phase, most of the reviewed articles consider simplistic assumptions regarding the BESS operation, which leads to overestimation of the expected profits. The analysis focused on three key modeling assumptions with the BESS part-load efficiency, the operational uncertainties, and the degradation effect. Over ten years of simulations, results indicated that the revenue overestimation reached an average of 20% - 30% when considering the usually simplified assumptions (more than 60% in the worst cases). When investigating a proxy to the battery degradation in the operational scheduling, the analysis reveals that penalizing the BESS usage reduces profits but extends battery lifetime, which in turn reduces replacement costs and increases the total NPV. This finding underscores the importance of considering both operational efficiency and long-term sustainability in optimizing BESS. Ultimately, a NPV analysis demonstrated that 1-H and 2-H sizes BESS yield the most profitability with an appropriate choice of BESS usage penalty (factor  $\alpha$  in the paper that could relate to a cost of exchange MWh). Those values are in line with previous findings in the literature related to BESS sizing (Table 1). With the market data considered, the payback period for a 1 MW/1MWh system is estimated at 5 years, whereas a 10 MW/10MWh system reduces this to 4 years, demonstrating the influence of scale on financial performance. Indeed, with more revenue being uptaken from the power capacity reserve for FCR, higher power-rated BESS tends to be more profitable in comparison to greater capacities in energy. Finally, it is worth mentioning two limitations of the proposed approach, which are also systematically found in the literature. First, the calculation of profits neglects network tariffs, i.e. network taxes for connection and feeding/consumption to/from medium or high voltage networks. These taxes are country and system specific (i.e. difficult to generalize) and allow system operators to manage and maintain the networks. More importantly, the evolution of DA and FCR prices over the project lifetime has been overlooked, as the main purpose of the paper was to investigate the BESS modeling assumptions. Long-term scenario-based approaches will then be implemented to propose a more robust/relevant design while anticipating potential price drift. Finally, and as already mentioned, one limitation of the study carried out lies in the use of simple forecasts that incur around 10% losses compared to an ideal case with perfect previsions. Further works shall investigate better forecast, especially while estimating the improvements with regard to the added complexity or the need for data and expertise.

#### CRedit authorship contribution statement

**Ahmed Mohamed:** Visualization, Validation, Software, Methodology, Investigation, Conceptualization. **Rémy Rigo-Mariani:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Conceptualization. **Vincent Debusschere:** Writing – review & editing, Supervision, Funding acquisition.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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#### Data availability

Data will be made available on request.

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