

Business model evaluation of a hybrid wind-battery virtual power plant dynamically updating the remaining battery capacity.

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Abstract

This work examines the impact of the loss of battery capacity on the business model evaluation of a hybrid wind-battery virtual power plant that participates in the day-ahead energy and reserve markets of the Spanish power system. The operation of the hybrid power plant is simulated with an optimisation model that considers the cost of the battery's cycle ageing as a function of the depth of discharge and a look-ahead period to consider the opportunity cost of stored energy in the battery at the end of the market scheduling horizon. The battery service life is calculated from the results of the simulations using different approaches, and the battery's revenues and economic feasibility are considered accordingly with such approaches. The results obtained show that neglecting the loss of battery capacity when simulating the operation of a hybrid power plant results in significant deviations in the income estimation. Although *Rainflow Counting Method* is commonly used in the literature to evaluate cycle ageing and its associated battery capacity loss, the results obtained in this paper question its reliability under certain circumstances.

1 Introduction

The transition from thermal-based power systems to decarbonised power systems is one of the main pillars to achieve the targets of reduction in greenhouse gas emissions [1].

In this context, energy storage systems have become, among other solutions, a major driver for facilitating and achieving the energy transition to decarbonised electricity systems based on renewable generation. Energy storage applications in power systems can help increase their flexibility by providing frequency control ancillary services with a different response speed depending on the technology, e.g., a battery can deploy a full response within 500 milliseconds and energy arbitrage [2, 3].

Today, pumped-storage constitutes over 90% of the total worldwide energy storage, but in recent years, the capacity of grid-scale battery energy storage systems has increased approximately to 28 GW at the end of 2022, of which 26.2 GW have been installed after 2016. The growth of grid-scale batteries has been mainly led by China and the United States with a share of 32% and 34%, respectively [4]. Various factors motivate the emphasis on investing in grid-scale battery energy storage systems instead of pumped-storage: a lower capital expenditure cost, lower overall duration of project and construction, and better ability to provide fast regulation reserve services, among others. Some authors quantify the expected growth of the global market size of battery-based energy storage systems from 4.4 billion US dollars in 2022 to 15.1 in 2027, which

means an annual growth exceeding 25% [5]. Lithium-ion battery is the most widely used technology when considering grid-scale battery energy storage systems and the cost has been reducing in recent years mainly due to the scale-up of production for deployment in various applications such as electric vehicles and electronic devices [6].

When considering grid-scale battery energy storage systems, two configurations are identified: standalone and co-located with existing variable renewable generation such as wind power or solar photovoltaic generation [7], run-of-the-river hydroelectric power plants [8], or even combinations of them [9]. The coordinated operation of an existing power plant together with a grid-scale battery energy storage system (hereinafter referred to as *hybrid power plant*) improves the availability to participate in reserve markets and enhances the opportunities in the day-ahead energy market, helping to shift variable renewable energy generation and, therefore, increasing the flexibility of the hybrid power plant [3].

One of the main concerns when considering investments in grid-scale battery energy storage systems is the uncertainty related to battery service life and the impact that the provision of balancing services will have on the battery. The degradation of battery cells, known as ageing, is associated with the chemical and mechanical processes that lead to a reduction in performance and battery service life [6], and can be categorised into two types: calendar ageing, which occurs even when the battery is not operating, and cycle ageing, which is more common and occurs during charging or discharging processes [10].

Nomenclature

Indexes and sets

Ω_t Set of decision variables of the model
 m, M linear segments of the cost curve of a charge-discharge cycle as a function of the depth of discharge

t, T hourly periods of the planning period

Parameters

η total round-trip battery efficiency [p.u.]
 μ_t^{dw} percentage of the secondary regulation downward reserve that will be required in real-time in period t
 μ_t^{up} percentage of the secondary regulation upward reserve that will be required in real-time in period t
 \bar{p}^b battery output/input power capacity [MW]
 \bar{p}^w wind farm capacity [MW]
 π_t^D day-ahead electricity market price in period t [€/MWh]
 $\pi_t^{S,dw}$ upward secondary regulation energy market price in period t [€/MWh]
 $\pi_t^{S,up}$ downward secondary regulation energy market price in period t [€/MWh]
 π_t^S secondary regulation reserve market price in period t [€/MWh]
 ρ_t ratio between the upward and the total secondary regulation reserve in period t , set by the TSO in advance
 $C_{b,m}^d$ variable cost of the m th segment of the cost curve of a charge/discharge cycle [€/p.u.]
 L_m length of the m th segment of the cost curve of a charge/discharge cycle [p.u.]

r_t^w available wind generation in period t [MWh]

\overline{soc} maximum state of charge [MWh]

\underline{soc} minimum state of charge [MWh]

Variables

c_t^b battery degradation cost in period t [€]

dcr_t battery discharge rate in period t [0,1]

$dod_{m,t}$ depth of discharge in period t and slope m

$e_t^{D,c}$ battery energy charge in the day-ahead energy market in period t [MWh]

$e_t^{D,d}$ battery energy discharge in the day-ahead energy market in period t [MWh]

$e_t^{S,dw}$ downward secondary regulation energy requested in real-time by the TSO in period t [MWh]

$e_t^{S,up}$ upward secondary regulation energy requested in real-time by the TSO in period t [MWh]

$g_t^{S,dw}$ downward secondary regulation reserve in period t [MW]

$g_t^{S,up}$ upward secondary regulation reserve in period t [MW]

p_t^b battery output (or input) power in the day-ahead electricity market in the period t [MWh]

$p_{b,t}^w$ wind energy generation in period t used to charge the battery [MWh]

p_t^w wind energy generation in period t [MWh]

soc_t battery state of charge in period t [MWh]

Integer variables

y_t^a 1 if $e_t^{D,d} > 0$; 0 otherwise

y_t^b 1 if $e_t^{S,up} > 0$; 0 otherwise

There are a number of variables that affect the battery service life, such as current, temperature, voltage, state of charge, discharge rate, depth of discharge, among others. Battery service life generally refers to the period of time in which the battery storage capacity remains higher than a specific fraction of the initial capacity (typically 80%) [11]. Even though some publications consider the battery service life as a predetermined period, e.g., ranging from 5 to 15 years [12], it should be quantified as a function of the charge-discharge cycles (hereinafter referred to as *cycles*) realised during the operation of the battery [13–15].

Several papers consider the cycle and/or calendar aging of grid-scale battery energy storage systems in the context of the day-ahead energy scheduling [16–18]. However, very few papers have done so in the context of the day-ahead energy and reserve scheduling [7, 13]. Most papers dealing with the day-ahead energy and reserve scheduling of grid-scale battery energy storage systems ignore impact of operating decisions on battery ageing [19, 20].

The cycles realised by a grid-scale battery energy storage system participating in the energy and balancing markets

strongly depend on the real-time requirements of the balancing service.

When it comes to the business model evaluation of grid-scale battery energy storage systems, one finds several papers dealing with the matter [3, 12, 21–24]. However, none of these papers consider in a detailed manner the loss of capacity of the grid-scale battery energy storage system as a function of its operational decisions.

In this work, we examine the impact of the loss of battery capacity on the business model evaluation of a hybrid wind-battery virtual power plant that participates in the day-ahead energy and automatic frequency restoration reserve market (hereinafter simply referred to as *reserve market*) of the Spanish power system.

The operation of the hybrid wind-battery virtual power plant is simulated using on a rolling horizon basis a detailed optimisation model based on the one presented in [7]. The model considers the cost of the battery's cycle aging and a look-ahead period to consider the opportunity cost of stored energy in the battery at the end of the market scheduling horizon. The battery's service life is calculated from the results of the

Table 1 Parameters of the hybrid wind-battery virtual power plant considered in the case study.

Parameter	Adopted value
Wind farm power capacity [MW]	33
Battery power input/output capacity [MW]	1
Battery storage capacity [h]	1/2/4
Battery round-trip efficiency (η)	86%
Battery maximum state of charge allowed	$90\% \times \overline{SOC}$
Battery minimum state of charge allowed	$10\% \times \overline{SOC}$
Investment cost of the battery project	386.4 €/kWh

simulations using different approaches. The battery's revenues and economic feasibility are considered accordingly with such approaches.

The paper is organised as follows: Section 2 describes the hybrid wind-battery virtual power plant used as a case study. Section 3 presents the optimisation model and methodology used to evaluate the business model. In Section 4 the results obtained are discussed, and finally, Section 5 summarises the main conclusions and further work.

2 Case study

The coordinated operation of a Lithium-ion grid-scale battery energy storage systems co-located with an existing wind farm located in the Spanish power system is considered. The existing wind farm is the same as the one used in [25] and different battery storage capacities have been considered. The parameters of the hybrid wind-battery virtual power plant used are shown in Table 1.

A set of historical data is used as input for the optimisation model that simulates the operation of the hybrid wind-battery virtual power plant, and has been taken from the web of the Spanish transmission system operator (TSO), Red Eléctrica de España [26]. The historical data used are listed below:

- day-ahead electricity market price,
- secondary regulation reserve market price,
- secondary regulation upward/downward energy market price,
- percentage of the committed secondary regulation reserves that are required in real-time (upward and downward),
- upward and downward secondary regulation reserves set by the TSO in advance.

Furthermore, the authors have used a historical time series of the hourly electricity production of the above-mentioned wind farm.

3 Methodology

The evaluation of the business model is performed using an optimisation model that simulates the self-scheduling of a hybrid wind-battery virtual power plant participating in the day-ahead energy and reserve markets of the Spanish power system. Two different approaches have been considered to simulate the self-scheduling of the hybrid wind-battery virtual power plant and then evaluate the business model: one

approach (hereinafter referred to as S1) consists in simulating the self-scheduling of the hybrid wind-battery virtual power plant for a whole year without updating the remaining battery capacity and, and another approach (hereinafter referred to as S2) consists in simulating the self-scheduling of the hybrid wind-battery virtual power plant updating the remaining battery capacity on a weekly-basis until the remaining battery capacity is lower than 80% of the initial one.

The optimisation model is the same in both approaches. The formulation of the optimisation model used is exposed in Section 3.1, and the above-mentioned approaches are detailed in Section 3.2.

3.1 Formulation of the optimisation model

A deterministic optimisation model based on the model named GRM in [7] is used to simulate the self-scheduling of the hybrid wind-battery virtual power plant. The optimisation model has an hourly resolution and considers a planning horizon of 72 hours to avoid that the battery state of charge at the end of the period $t = 24$ equals the minimum one. The model assumed perfect knowledge of the hourly prices of the day-ahead electricity market, the hourly prices of the secondary regulation reserve and the secondary regulation energy (upward and downward), the hourly percentage of the committed secondary regulation reserves that are required in real time, and finally, of the available renewable generation. The objective function of the optimisation model is given by (1).

$$\max_{\Omega_t} \sum_t \left\{ \begin{array}{l} \pi_t^D \cdot (p_t^w + p_t^b) + \pi_t^S \cdot (g_t^{S,up} + g_t^{S,dw}) \\ + \pi_t^{S,up} \cdot e_t^{S,up} - \pi_t^{S,dw} \cdot e_t^{S,dw} - c_t^b \end{array} \right\} \quad (1)$$

$$p_t^w + p_{b,t}^w \leq r_t^w \quad \forall t \quad (2)$$

$$p_t^w + p_{b,t}^w \leq \bar{p}^w \quad \forall t \quad (3)$$

$$-\bar{p}^b \leq p_t^b \leq \bar{p}^b \quad \forall t \quad (4)$$

$$e_t^{D,d} - p_{b,t}^w = p_t^b \quad \forall t \quad (5)$$

$$e_t^{D,d} \leq \bar{p}^b \cdot y_t^a \quad \forall t \quad (6)$$

$$p_{b,t}^w \leq \bar{p}^b \cdot (1 - y_t^a) \quad \forall t \quad (7)$$

$$g_t^{S,up} \leq \begin{cases} \bar{p}^b - p_t^b \\ 2 \cdot \bar{p}^b \end{cases} \quad \forall t \quad (8)$$

$$g_t^{S,dw} \leq \begin{cases} \bar{p}_t^b + p^b \\ 2 \cdot \bar{p}^b \end{cases} \quad \forall t \quad (9)$$

$$g_t^{S,up} = \rho_t \cdot (g_t^{S,up} + g_t^{S,dw}) \quad \forall t \quad (10)$$

$$e_t^{S,up} - e_t^{S,dw} = \mu_t^{up} \cdot g_t^{S,up} - \mu_t^{dw} \cdot g_t^{S,dw} \quad \forall t \quad (11)$$

$$e_t^{S,up} \leq \bar{p}^b \cdot y_t^b \quad \forall t \quad (12)$$

$$e_t^{S,dw} \leq \bar{p}^b \cdot (1 - y_t^b) \quad \forall t \quad (13)$$

$$soc_t = soc_{t-1} + \eta \cdot (e_t^{S,dw} + p_{b,t}^w) - (e_t^{D,d} + e_t^{S,up}) \quad \forall t \quad (14)$$

$$\underline{soc} \leq soc_t \leq \overline{soc} \quad \forall t \quad (15)$$

$$dod_{t,m} \leq L_m \quad \forall m, t \quad (16)$$

$$dcr_t \leq \sum_m dod_{t,m} \quad \forall t \quad (17)$$

$$dcr_t \geq \frac{soc_{t-1} - soc_t}{\overline{soc}} \quad \forall t \quad (18)$$

$$c_t^b = \sum_m dod_{t,m} \cdot C_{b,m}^d \quad \forall t \quad (19)$$

$$p_t^w + e_t^{D,d} + e_t^{S,up} - e_t^{S,dw} \geq 0 \quad \forall t \quad (20)$$

The first term of (1) represents the result obtained in the day-ahead electricity market due to the sale of wind energy and the output of the battery. The second term corresponds to the revenue in the secondary regulation reserve market, considering that the hybrid wind-battery virtual power plant exclusively offers the battery capacity in this market. The third and fourth terms correspond to the revenue and cost resulting from the upward and downward secondary regulation energy, respectively. Finally, the last term corresponds to the battery

degradation cost incurred during the operation of the hybrid wind-battery virtual power plant.

Wind energy scheduled in the day-ahead electricity market is calculated according to (2) and (3). As can be seen, the optimisation model can use part of the available wind energy for charging the battery ($p_{b,t}^w$).

The maximum power output/input of the battery in charge or discharge mode is given by (4). Equation (5) calculates the energy scheduled for the battery in the day-ahead electricity market, and equations (6)-(7) are used to force the battery to be in discharge or charge mode exclusively. It is important to note that according to the regulations in the Spanish power system when this study was done, grid-scale battery energy storage systems co-located with wind or solar PV farms that shares a grid were not allowed to withdraw energy from the grid. For this reason, the battery can only charge using power from the wind farm.

The maximum upward/downward secondary regulation reserve that can be made available in the secondary regulation reserve market is given by equations (8) and (9), respectively. Equation (10) forces the secondary regulation reserve made available in the reserve market to satisfy the ratio ρ_t between the upward and the total secondary regulation reserve set by the TSO in advance. Upward and downward secondary regulation energy is given by (11) considering the percentage of the committed reserves that will be required in real-time (μ_t^{up}/μ_t^{dw}). Equations (12) and (13) force the secondary regulation energy to be either upward or downward for each period t , since the secondary regulation energy is paid as a function of the net regulation energy. Equations (10)-(13) are a consequence of specific rules of the secondary regulation market of the Spanish power system and can be found in, e.g., [27].

The state of charge of the battery for a period t is given by equations (14) and (15).

The battery degradation cost (c_t^b) considered in the objective function (1) is calculated according to the depth of discharge of each discharge manoeuvre using the Lithium-ion battery lifetime characteristic proposed in [14]. This curve is depicted in Figure 1 and relates the number of cycles of each depth of discharge that a Lithium-ion battery can perform before losing 20% of its rated storage capacity. To consider the battery degradation cost as a function of the depth of discharge of each discharge manoeuvre, the curve of Figure 1 has been transformed into the blue curve in Figure 2, which relates the cost of a cycle to its depth of discharge: the lifetime loss associated with a charge-discharge cycle of a given depth has been calculated from Figure 1 as the inverse of the ordinate value, and multiplied by the replacement cost of the battery. The replacement cost has been assumed equal to the investment cost shown in Table 1. The blue curve in Figure 2 has been approximated by m linear segments to be used in the optimisation model, represented by the red piece-wise curve in Figure 2. Equations (16)-(19) are used to consider the battery degradation cost in the optimisation model.

Last, Equation (20) ensures that the power flow in the grid connection point is always positive, consistently with the above-mentioned Spanish regulation.

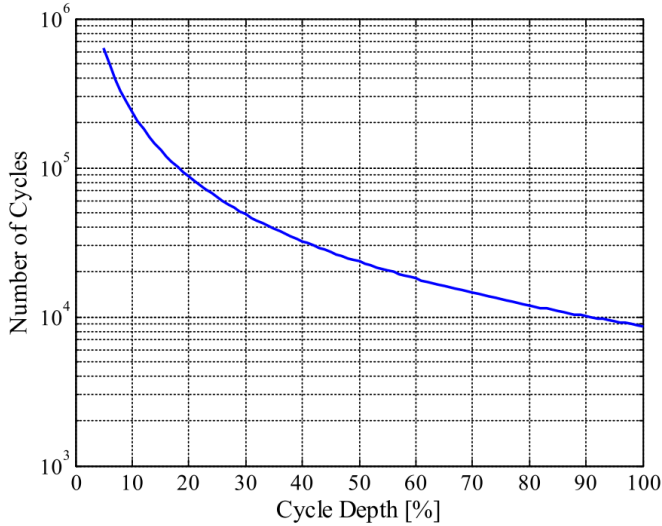


Fig. 1 Lifetime characteristic of a Lithium-ion battery. Taken from [14].

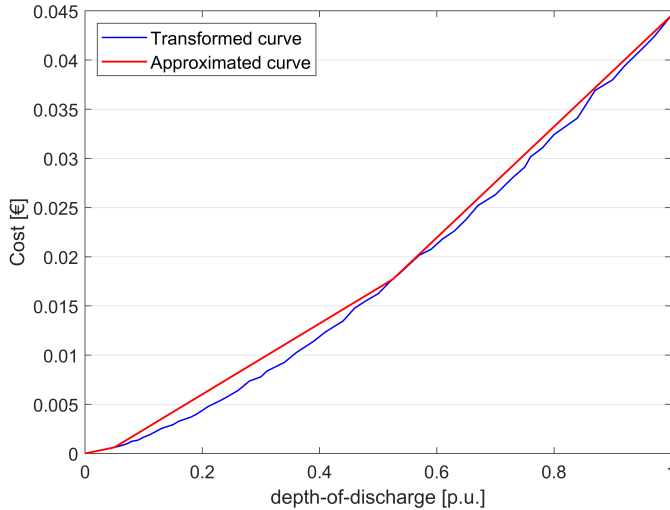


Fig. 2 Cost of a charge-discharge cycle as a function of the depth of discharge, obtained from [14] for a battery of 1kWh of capacity and the investment cost of Table 1.

In summary, the optimisation model is defined by the objective function (1) subject to the constraints (2)-(20).

3.2 Business model evaluation

As mentioned above, when following approach S1, the optimisation model described in Section 3.1 is run on a rolling horizon basis for an entire year. Then, the loss of battery capacity due to the operation of the hybrid wind-battery virtual power plant, is quantified using the well-known *Rainflow Counting Method* [28] applied over the state of charge of the battery along the year. All cycles identified by the Rainflow Counting Method are then used to compute the total loss of battery capacity along the year by applying the *Miner's Rule*. The feasibility of the business model is then evaluated assuming that the operation

of the battery obtained in the simulation is repeated every year until the remaining battery capacity is lower than 80% of the initial one, and that the annual loss of battery capacity is equal to the one obtained from the simulation.

When following the approach S2, the same optimisation model is used to simulate the self-scheduling of the hybrid wind-battery virtual power plant, but in this case, the remaining battery capacity is quantified and updated on a weekly basis. Two different methods are used to quantify the remaining battery capacity. The first method (hereinafter referred to as S2-a) computes at the end of every week the number of cycles the battery has realised from the start of the simulations by applying the *Rainflow Counting Method* to the battery's state of charge (SOC) profile. The loss of battery capacity until the end of each week is computed in the same way as in the approach S1. The second method (hereinafter referred to as S2-b) computes at the end of every week the total energy throughput that has flowed across the battery terminals from the start of the simulations, similarly to [6]. The computed throughput is divided by the maximum accumulated throughput the battery can withstand before losing 20 % of its initial storage capacity. The latter value is computed from Figure 1 as the maximum number of cycles with a 100% depth multiplied by 2 times the initial storage capacity. The ratio between the throughput computed at the end of each week and the maximum accumulated throughput of the battery is multiplied by 20% to calculate the capacity loss from the start of the simulation to the end of the relevant week.

When following the approach S2 the simulation does not last only 1 year, but rather it lasts until the remaining battery capacity is lower than 80% of the initial one. It is important to note that the annual data set used in the simulation is the same as the one used when following approach S1, repeated year after year. Our hypothesis is that the approach S2 allows a more realistic evaluation of the battery's operation and its revenue, and thus of the business model.

Regardless of the approach followed in the simulation, once the simulation is done the annual cash flows are computed from the results of the simulation, taking into account the fixed and variable operational expenditures (OPEX) shown in Table 2. In Equation (21) I_y represents the battery income for the year y , $OPEX^f$ represents the fixed operational expenditure, and $OPEX_y^v$ represents the variable operational expenditure calculated according to the throughput that has flowed through the battery terminals in year y , similarly to [29]. The values corresponding to the fixed and variable OPEX have been taken from [30].

It is important to note that the battery income considered in the business model evaluation I_y corresponds to the increase in income with respect to the case in which the wind farm sells all available wind energy in the day-ahead electricity market. Consistently, I_y is computed as the total income of the hybrid wind-battery virtual power plant obtained in the simulation minus the income corresponding to selling all the available wind energy in the day-ahead electricity market.

$$CF_y = I_y - OPEX^f - OPEX_y^v \quad (21)$$

Table 2 Parameters considered in the business model evaluation.

Parameter	Adopted value
Rate of return considered	3%
Capital expenditure (CAPEX)	386.4 €/kWh
Fixed operational expenditure (OPEX)	9 €/kW/year
Variable operational expenditure (OPEX)	0.03€/kWh

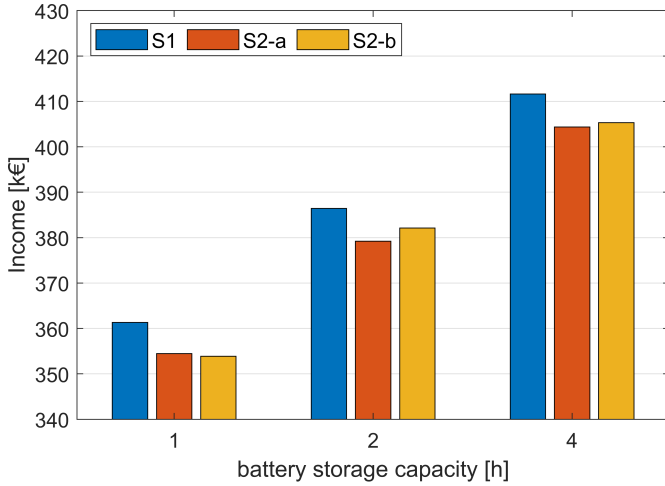


Fig. 3 Average annual income of the battery for the different storage capacities analysed.

The computed cash flow are used to calculate the net present value (NPV) applying the general formula (22) [31], where i is the rate of return and t the battery service life in years. The CAPEX considered in Equation (22) is shown in Table 1.

$$NPV = \sum_t \frac{CF_t}{(1+i)^t} - CAPEX \quad (22)$$

4 Discussion of results

Figure 3 depicts the average annual income of the battery obtained when using both S1 and S2 approaches. As expected, neglecting the loss of the battery capacity in the simulation of the hybrid wind-battery virtual power plant, yields a higher battery income, 1.9/1.9/1.8% when considering a storage capacity of 1/2/4 hours, respectively, in the case of S2a and of 2.1/1.1/1.5% in the case of S2b.

Neglecting the loss of battery capacity in the simulation yields not only an optimistic income estimation but also an infeasible battery operation pattern. This is illustrated in Figure 4, where the red line depicts the annual duration curve of the SOC for a 1 hour battery storage capacity when following the approach S1, and the grey lines represent the annual duration curves of the SOC of the battery when following the approach S2-a. There are 21 grey curves, each corresponding to 1 of the years of the battery service life according to the results of the simulation. As can be seen in Figure 4 the range of the SOC decreases as the remaining capacity of the battery decreases. The annual decrease of the battery capacity when

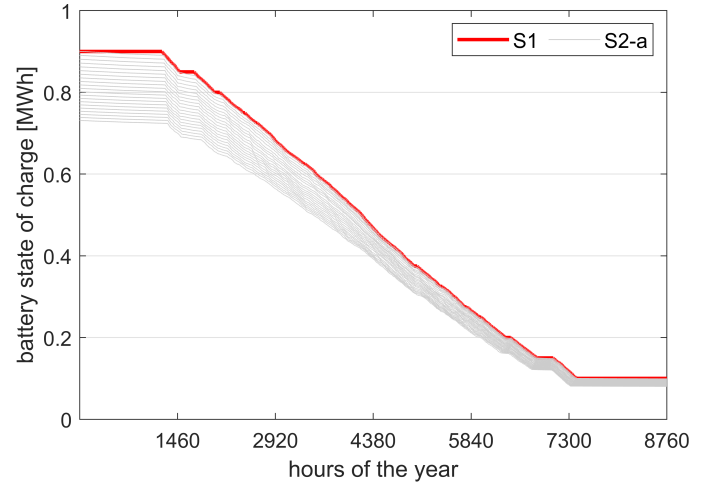


Fig. 4 Annual duration curves of the battery state of charge for a storage capacity of 1 hour when considering S1 and S2a.

using S2-a is 0.8/1.2/1.5% for an initial storage capacity of 1/2/4 hours, respectively, and 1.2/1.8/2.3% when considering S2-b. When following the approach S1 no loss of battery capacity is considered in the simulation, and therefore the battery SOC ranges from 0.1 to 0.9 MWh, consistently with the limits set in Table 1.

It is worth mentioning that the shapes of all duration curves are very similar since, as previously exposed, the data set used in the simulation is the same on an annual basis with the two approaches.

An important parameter when conducting the business model evaluation of a grid-scale battery energy storage system is the number of years the battery will be in operation. The battery service life obtained with the considered approaches is shown in Figure 5. As can be seen, there is a significant deviation between the different approaches, being the battery service particularly high when following the approach S1.

In order to understand the differences in the battery service life obtained with the 3 approaches, we have first inspected the SOC of the battery along the first year of the simulation. Figure 6 shows the duration curves of the depth of charge and discharge manoeuvres according to the SOC obtained with the 3 approaches. As can be seen in Figure 6, the differences between the 3 approaches are barely appreciable. This result is consistent with the computed capacity loss with the approaches S2-a and S2-b at the end of the first year of the simulation, 0.94 and 1.28 %, respectively.

Then, we have analysed the results provided by the *Rainflow Counting Method* for the SOC of the battery along the first year of the simulation. Figure 7 shows the duration curves of the depth of the full cycles provided by the *Rainflow Counting Method* available in MATLAB®. As can be seen in Figure 7, the depth of the full cycles obtained with approach S1 is considerably lower than the one obtained with the approaches S2-a and S2-b. Figure 8 shows in turn the duration curves of the depth of the half cycles provided by the *Rainflow Counting Method* available in MATLAB®. By contrast to Figure 7, the depth of

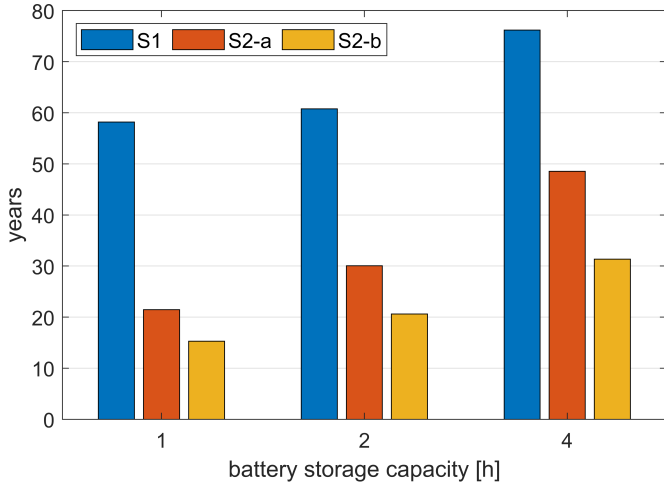


Fig. 5 Battery service life obtained with the considered approaches.

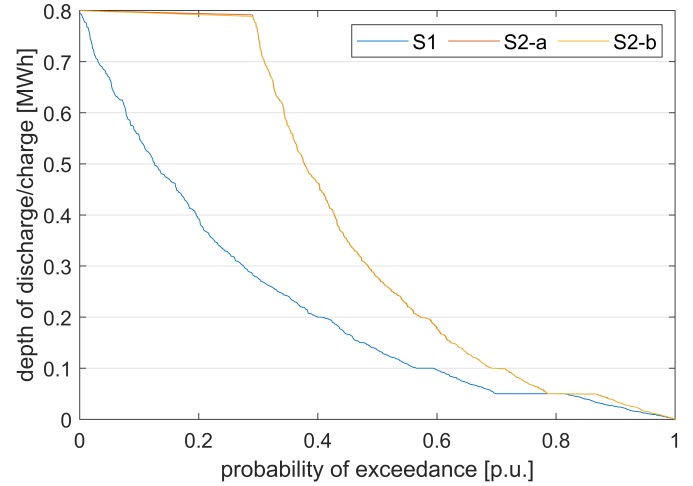


Fig. 7 Duration curve of the depth of full cycles with the considered approaches.

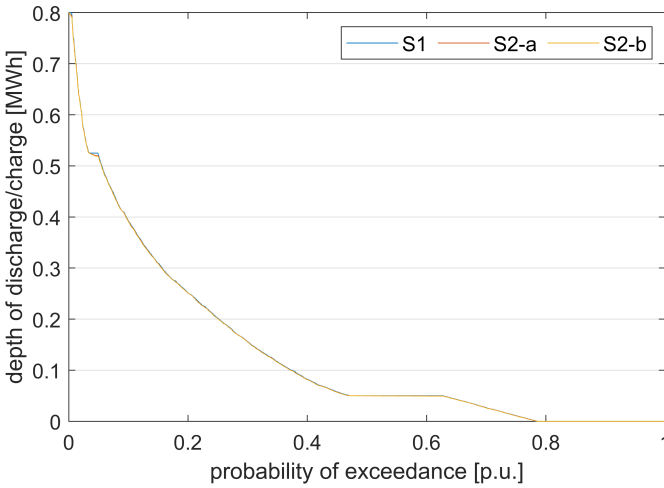


Fig. 6 Duration curve of the depth of charge and discharge manoeuvres with the considered approaches.

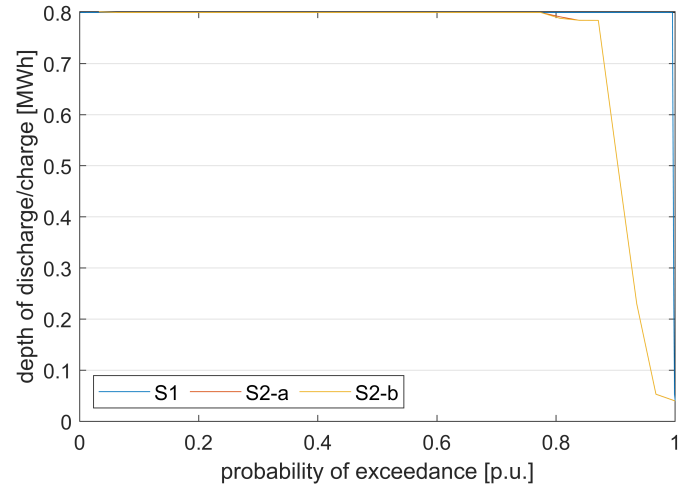


Fig. 8 Duration curve of the depth of half cycles with the considered approaches.

half cycles obtained with approach S1 is rather higher than the one obtained with the approaches S2-a and S2-b.

Last, we have calculated the energy content of the full and half cycles provided by the *Rainflow Counting Method* available in MATLAB® along the first year of the simulation with the 3 approaches, as well as the throughput, for the 3 values of storage capacity considered in this work. Table 3 summarises these data. As can be seen in Table 3, the energy content of the full cycles is higher/lower than the one of the half cycles with the approach S1/S2. This result is inconsistent with the similarities observed in the battery SOC obtained with the 3 approaches, and in the throughput. For a given storage capacity the latter is almost the same with the 3 approaches.

This analysis questions the reliability of the *Rainflow Counting Method* available in MATLAB®. Notwithstanding, further work is required to verify its reliability.

Last, Table 4 shows the net present value obtained with the 3 approaches for the considered storage capacities. Consistently with previous results, the net present value obtained with approach S1 is significantly higher than the one obtained with approaches S2-a and S2-b.

The results in Table 4 are expressed in relative terms with respect to the ones corresponding to approach S1 for the reason explained next. The simulations have been performed by the use of an optimisation model that considers perfect knowledge of all the parameters related to wind farm generation and the markets in which the hybrid wind-battery virtual power plant participates. This is not consistent with the conditions under which the hybrid wind-battery virtual power plant would operate in real life. The operator of the hybrid wind-battery virtual power plant would use the optimisation model to schedule the energy and reserve of the hybrid wind-battery virtual power plant based on imperfect knowledge of the above-mentioned variables. The income obtained from the simulation is therefore

Table 3 Energy content of full and half-cycles given by the *Rainflow Counting Method* and throughput, along the first year of the simulation.

Storage [h]	S1			S2-a			S2-b		
	full-cycle	half-cycle	throughput	full-cycle	half-cycle	throughput	full-cycle	half-cycle	throughput
1	396.3	1258.3	1258.3	1793.8	1752.3	1253.0	1787.7	1753.2	1250.9
2	1174.3	3499.1	1837.9	4151.5	3492.2	1832.7	4117.6	3493.5	1831.5
4	3084.9	6994.1	2358.4	8847.2	6963.7	2356.5	8846.2	6965.6	2355.6

too optimistic. The difference between the income obtained with perfect and imperfect knowledge has been referred to as in the literature as value of perfect information (VPI) [27, 32]. To the author's knowledge, there is no previous work in the literature suggesting a VPI for a grid-scale battery energy storage systems participating in day-ahead energy and reserve markets. The authors have already started to work on the matter, and will soon provide some (hopefully) useful results for the evaluation of the business model of grid-scale battery energy storage systems.

Table 4 Relative values of the net present value with respect the one obtained for methodology S1.

Storage [h]	S1	S2-a	S2-b
1	100.00	54.94	41.48
2	100.00	67.23	50.60
4	100.00	82.23	62.20

5 Conclusions

The results obtained in this work show that neglecting the loss of battery capacity when simulating the operation of a hybrid power plant results in significant deviations in the income estimation.

Although the *Rainflow Counting Method* is commonly used in the literature to evaluate cycle aging and its associated battery capacity loss, the results obtained in this paper question its reliability under certain circumstances.

Further work to estimate the value of perfect information when considering the self-scheduling of a hybrid wind-battery virtual power plant participating in the day-ahead energy and reserve markets is key for a solid evaluation of its business model.

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