Optimisation and Economic Feasibility of Battery Energy Storage Systems in Electricity Markets

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ABSTRACT

This study identifies the optimal operating strategy of storage systems on the electricity markets, from the perspective of a market participant with a renewables' portfolio. The energy storage system provides a balancing service for renewable sources, while also performing energy arbitrage at the considered three short-term markets. Spot price and renewable generation predictions guide the bidding decision-making process to maximise agents' economic profit. Thus, a Long Short-Term Memory (LSTM) model was developed to forecast these variables. The designed decision support models considered market rules and the technical constraints in the operation of the storage system. The influence of storage systems in the optimal operation, regulation costs and revenues is analysed on a daily and yearly basis. The economic viability of sodium-sulphur, lithium-ion, zinc hybrid and vanadium redox flow batteries in 2018 and 2025 is studied. The results suggest that the use of forecasting techniques and battery implementation sharply reduce regulation costs. The analysis shows that acting in the balancing market can be a motivation for the storage system viability. The economic evaluation proves that only the lithium-ion battery is a profitable investment in the considered years.

Keywords: Renewables; Energy Storage Systems; Forecasting; Optimal Operation Strategy; Energy Markets.

Nomenclature

bid_h^{DA} day-ahead market bid at hour h

bid_h^{ID} intraday market bid at hour h

c_h^{DA} charge assigned to day-ahead strategy at hour h

c_h^{ID} charge assigned to intraday strategy at hour h

d_h^{DA} discharge assigned to day-ahead strategy at hour h

d_h^{ID} discharged assigned to intraday strategy at hour h

e_{ESS}^{max} energy storage system maximum capacity

g_h^{DA} predicted renewable production assigned to the day-ahead strategy at hour h

g_h^{ID} predicted renewable production assigned to the intraday strategy at hour h

imb_h^{DA} deviation from the day-ahead bid at hour h

imb_h^{ID} deviation from the intraday bid at hour h

k_h balancing market binary auxiliary variable at hour h

p_h^{for} renewable production forecast at hour h

p_h^{real} renewable production at hour h

p_{ESS}^{max} energy storage system maximum power rating

P_{PV}^{max} solar installed capacity

P_{WT}^{max} wind turbine installed capacity

RC_h^{DA} day-ahead market regulation costs at hour h

RC_h^{ID} intraday market regulation costs at hour h

r_h^d balancing market downward regulation at hour h

r_h^u balancing market upward regulation at hour h

soc_h energy storage system state of charge at hour h

sp_h^{DA} predicted day-ahead spot price at hour h

sp_h^{ID} predicted intraday spot price at hour h

sp_h^+ positive imbalance regulation costs at hour h

sp_h^- negative imbalance regulation costs at hour h

x_{c_h} percentage of the hour when the storage is charging

x_{d_h} percentage of the hour when the storage is discharging

η energy storage system roundtrip efficiency

1. Introduction

The electric sector is still evolving, with increasing market integration and more competitive wholesale markets. The deverticalization of this sector determined the emergence of a disaggregated structure in which several agents can participate. Purchase and selling bids are typically organised in a wholesale energy market which is supervised by a market operator. In the day-ahead market, participants submit their bids to sell or buy energy for each hour of the following day. After the day-ahead market has been cleared, bids are made in successive intraday market sessions. These sessions occur nearer the delivery horizon, thus allowing to minimise differences between previously contracted energy and real production. The balancing market bidding process also starts after the day-ahead market. The goal of this market is to certify that, in real-time, the system operates in secure conditions. Regulation band offers are made for every hour of the following day guaranteeing that energy can be mobilised; thus, ensuring demand and supply always meet.

All units engaging in these markets should generate their accepted bids. If there are differences between the accepted bids and the actual generated power, the agent must pay a penalty related to this difference, jeopardising the possible revenues.

Furthermore, recent years have witnessed a rising change in energy production standards. The rapid development of renewable generation and the penetration of variable energy sources can be observed in electricity markets all over the world. Renewable Energy Sources (RES) are characterised by their temporal variability, thus cannot choose when to submit their generation. Therefore, it becomes challenging to match the formerly accepted bids, increasing the possibility of extra costs.

Due to the stochastic nature of RES, forecasting methods are required. Operations like scheduling, dispatch and real-time balancing are affected by forecasting models. By deploying improved forecasting models, fewer adjustments are needed, and fewer imbalances occur. It is relevant not only when it concerns the day-ahead market, but also in the subsequent markets since these units can still make new bids based on updated forecasts. Nevertheless, since there happens to be limited accuracy of power forecasts, penalties still occur.

To lower these penalties, renewables can operate together with Energy Storage Systems (ESS), hence making them more dispatchable. The combination of RES and ESS is considered a solution to mitigate variability and difficulty to predict. When optimally allocated, ESS can provide several services and bring enormous added value to the power system. Still, it is necessary to prove the effectiveness of storage solutions from a technical and economic perspective.

Besides, predicting the price that will be settled by the day-ahead and intraday electricity markets is essential for the agents, reducing the impact of uncertainty. Electricity prices turn this into a challenging task due to its unusual characteristics. Electricity is a difficult to store good, it shows strong seasonality patterns, and a constant balance between production and consumption needs to be assured. In addition, a growing integration of RES further contributes to increasing price volatility.

Considering the described problem, this research aims to identify the optimal operating strategy of ESS on the Iberian Electricity Market (MIBEL), from the perspective of a market participant with a renewables' portfolio. To achieve this purpose, a decision support tool that allows exploring operation possibilities while ensuring BESS technical constraints, market requirements, and maximising revenues is developed. Furthermore, the economic viability of different Battery Energy Storage Systems (BESS) technologies is evaluated.

This article's key contributions with respect to previous research are the meticulous consideration of every dimension of the problem: forecasting, optimisation, and economic evaluation. In the current literature, the joint operation of a Wind Farm (WF), Photovoltaic (PV) and BESS in both energy and balancing markets has not been comprehensively explored yet. Traditionally, the view on this topic has been based on stochastic models, boiling down to a set of responses with multiple bidding and operation scenarios, instead of a unique and objective solution that this paper proposes. Furthermore, the studies which focus on the bidding and operation of these systems, do not contemplate forecasting techniques, and vice-versa. In this paper, to adequately address reality, not only the optimal operation and economic evaluation is considered, but also a suitable forecasting model (Long Short-Term Memory – LSTM) is developed to predict both spot prices and renewable production before and during the operational day while respecting MIBEL's structure and dynamics.

Following this introduction, a review of the literature sustaining this research and its contributions is provided in Section II. Then, the forecasting, optimisation and economic models are presented in Section III. Conditions and assumptions are detailed in Section IV. A realistic example is used to analyse the ESS operation and its economic viability in Section V. Finally, section VI summarises the main findings.

2. State of the Art Review

Different programming methods have been used to model storage operation problems. However, Mixed Integer Linear Programming (MILP) is seen as very powerful and has been applied extensively with success [1]–[6]. This method is considered the most appropriate from the viewpoint of accuracy and runtime [7]. The storage system operation can be divided into independent [1],[2],[8]–[10] and coordinated operation along with renewables [3]–[6],[11].

Regarding storage system independent operation, electricity storage has been applied for arbitrage in multiple market locations. The value of Pumped Hydro Storage (PHS) and Compressed-Air Energy Storage (CAES) on multiple European electricity markets with different characteristics such as fuel mix, competition level and cross-border transmission capacity is considered in [8], aiming to evaluate trading strategies and distinct energy storage roles associated with those market characteristics. The use of storage technologies in the Australian market is studied in [9]. This market is known as highly volatile (one of the highest price caps in the world), hence an excellent example to explore arbitrage. Similarities of emerging and traditional technologies have been compared, demonstrating that storage can be expected to compete and provide similar value to peak generation. However, to reflect the real value of energy storage, ESS needs to be considered not only for arbitrage purposes in the day-ahead market but also with involvement in the spinning reserve and regulation markets. The optimal scheduling of a Vanadium Redox Battery (VRB) energy storage system in all these markets is addressed in [10]. Also, in [2], a MILP model arbitrages in the day ahead and real-time markets while also participating in regulation markets. Perfect information about energy prices is assumed. The highest potential revenues come from the regulation market due to the two payments provided, underlying the additional benefits that can be captured by taking part in ancillary services. Furthermore, only gravity storage is appraised as not economically profitable, thus PHS and CAES are still the most cost-efficient options.

As exposed in the mentioned studies, ESS can act independently exploring arbitrage and balancing markets. Nevertheless, energy storage is many times looked at as one of the best options to integrate more renewables and to provide flexibility of the energy system. A MILP is modelled to determine the optimal bidding strategy of a wind farm and PHS joint operation to reduce the imbalance costs of the WF [3]. The investigated units submit bids to day-ahead and ancillary service markets. The uncertainties of the submitted wind power production, energy price and balancing price forecasts are considered. A stochastic scenario tree is used to model the uncertainties both in wind generation and market prices. Likewise, a stochastic approach is also implemented in [4]. A model is developed to minimise the regulation costs which are the difference between the real generation and contracted quantities, affected by imbalance prices. It is concluded that the joint operation of the wind farm and pumped storage facility can decrease imbalance penalties up to 50%.

A deterministic approach is followed in [5]. A combined optimal dispatch algorithm that determines the operation of the EES and WF is presented. The joint operation's added value is analysed:

as the value of arbitrage increases, the value of balancing wind decreases, focusing on the trade-off between the two. To investigate the day-ahead bidding strategy and real-time operation of a wind farm and a battery storage system, a deterministic approach is also followed in [11]. The battery is only used to compensate for deviations between day-ahead offers and real-time output. However, the BESS status in each interval is optimised in advance and it only intervenes if the real-time imbalance sign of the wind farm output goes with the predetermined working status.

Electricity storage can be used together with forecasting techniques. In [12], their use, independently and cooperatively, in power system operations is studied in markets with different generation mixes and multiple levels of renewable integration. It is concluded that the value of both flexibility options is neither reduced nor increased when both are utilised. However, when storage use is restricted to provide only energy and not ancillary services, more accurate forecasts could produce better estimates and allow more optimal usage of storage. Many different approaches regarding power forecasting, can be found in the literature. Spot prices are another source of uncertainty that must be considered due to its decisive impact on the bidding strategy.

Some studies simply assume perfect information [2] or persistence models [5]. A great number of techniques have been discussed for accurate forecast in recent decades thus forecasting being a crucial tool which serves to reduce the uncertainty. Research studies use statistical [13],[14], computational intelligence [15],[16], or even combined forecasting methods [17],[18].

Four ARMA based approaches are employed to forecast wind speed and direction in [13] while in [14], ARIMA models are developed to predict day-ahead spot prices in the electricity markets of Spain and California.

Multiple machine learning methods, namely LASSO, kNN, xGBoost, random forest and support vector regression (SVR) are the main focus in [15] in order to forecast wind power. The best parameters for each method are selected using a trial-and-error approach. It is shown that all the tested algorithms are powerful in forecasting in locations that differ from the ones in which the model was trained. In [16], LSTMs are the chosen model to predict hourly day-ahead solar irradiance in Cape Verde. Firstly, a statistical analysis is carried out to verify the correlation of 13 weather variables with irradiance, inferring temperature and humidity as coefficients with the highest correlation. Experimental results show that the proposed algorithm is more accurate, shows less overfitting and better generalisation capability when compared to a Multilayer Perceptron (MLP).

As formerly mentioned, combining forecasting methods are also studied. A hybrid forecasting model for day-ahead solar power is created in [17]. By combining machine learning methods, accuracy can be improved, and the computational burden can be reduced. A hybrid model for day-ahead electricity price is proposed based on the wavelet transform to decompose price series in stationary and non-stationary, ARMA to predict stationary series and a feed-forward neural network to forecast non-stationary series [18].

In the literature, among the storage systems, PHS is the most conventional energy storage system since it is the most mature and cheapest technology currently available [2],[3],[8],[9]. Other energy storage forms have been considered historically uneconomic [19], but several factors have led to increasing interest in other ESS.

The commercial viability of PHS, CAES or thermal storage in conjunction with a wind farm is determined [20]. The availability of natural underground caves in the considered location influences the CAES system to be the most profitable.

The economic benefit of a BESS coupled with a PV plant is presented in [19],[21]. The NPV is evaluated imposing different depth of discharge (DoD) limits in [21]. Taking into account current investment costs in storage technology, profitability is still strictly dependent on price patterns and power profiles. The cost per kWh of 10 different technologies (from li-ion to zinc air batteries) is compared in [19]. PHS is concluded to have the lowest cost, followed by CAES.

The viability of a BESS to balance forecast errors and operate as balancing energy in 2011 and 2050 is studied in [22]. The economic benefit of BESS in the future using lead-acid, sodium-sulphur and lithium-ion batteries is assessed as advantageous. It is estimated that by coupling a wind farm and a BESS, the gain per MW could increase by approximately 33% with the three contemplated technologies.

3. Proposed Models

3.1. Forecasting Model

Renewable generation and spot prices guide the optimisation strategy. Thus, these variables should be considered as close to reality as possible. The considered agent's portfolio is composed by a WF and PV. Wind speed is the key factor influencing WF output while irradiance and temperature are the main variables influencing PV output. To forecast weather variables and market spot prices (DA and ID), an LSTM network [23] is the chosen model.

Recurrent neural networks (RNN) are a family of artificial neural networks (ANN) that have recurrent connections, and thereby, allow to exhibit temporal behaviour. Unlike an ANN, the hidden layers of the front and back time steps are connected, keeping track of previous output, and allowing information to persist. Computations consider historical information and weights are shared across time. Thus, this class of neural networks is naturally suited to process time-series data.

Since an RNN model is trained using the backpropagation algorithm, the gradients accumulate from the output layer and pass it back throughout the entire network. Consequently, the gradients either explode or vanish, originating the vanishing gradient problem [24]. Thus, RNNs have difficulties in learning long-term dependencies and cannot bridge if time lags are greater than 5-10-time steps [25]. To overcome this problem, RNNs were improved, leading to the emergence of LSTM networks, in which the key idea is the use of memory cells.

In an LSTM, the multiplicative effect is avoided by flowing the information additively through input, forget and output gates. These gates are used to control the update since they can decide what information to preserve and what to forget, based on the weight values assigned to the information during the training process. The cell state (1) will be updated considering the input gate, and the output of the forget gate.

$$c_t = f_t * c_{t-1} + i_t * c_t \tag{1}$$

where t is time step, c_t is the cell state, f_t is the forget gate and i_t is the input gate.

In this work, the implemented architecture has four layers, namely a sequence input layer, an LSTM layer with a chosen number of hidden units, a fully connected layer, and a regression output layer.

The hyperparameters optimised in the developed LSTM model are the learning rate, the optimisation solver, the number of hidden units and the number of epochs. Hyperparameter tuning is often a "black art" which requires experience and unwritten rules of thumb [26]. Since the optimal values depend on the type of data and datasets, little is known about how to evaluate or select the correct hyperparameter values. Also, it is empirically and theoretically proven that trials are more efficient than the computationally expensive exhaustive grid search [27]. Thus, for each forecasting problem, namely for the weather variables and spot prices, the hyperparameters are set using a trial-and-error approach. The algorithms are run with different settings and the best-observed results are chosen. Besides having a considerable influence on the obtained results, the hyperparameter values affect the performance and the time/memory cost of running the algorithm.

To evaluate the model's performance, RMSE (2) was the chosen metric to measure the prediction accuracy.

$$\mathrm{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{2}$$

where y_i is the actual value, $\hat{y}_i$ is the forecast value and n is the number of values.

The persistence model (3) was used as a reference, which is a standard approach in the literature.

$$\hat{y}(t) = y(t - T) \tag{3}$$

where $\hat{y}(t)$ is the forecast and $y(t - T)$ is the previously recorded value of the time series.

3.2. Optimisation Models

In this paper, we have developed three deterministic models to maximise the revenues and minimise the imbalances deriving from the difference between contracted and real renewable production.

3.2.1. Day-Ahead Model

Regarding day-ahead optimisation, all agents operating in MIBEL must present sell or buy bids that cover all 24h of the next day. Therefore, agents rely on day-ahead forecasting to schedule the offers. This strategy's inputs are short-term power generation and spot prices, as well as the storage system parameters.

Since all units are coordinated (WF, PV and BESS) the day-ahead strategy consists in storing renewable energy that is generated during the periods with an anticipated lower market spot price, to then sell it at times when foreseen prices are higher. However, forecasts and real values diverge. Deviations between predicted power and real delivered power arise. The concept of imbalance costs derives from these power deviations. In MIBEL, a dual pricing regulation is applied: positive imbalances force the market to pay a regulation price, while negative imbalances force the market to put in operation reserves. Thus, the agent must pay a regulation price, related to the deviations.

Mathematically, this optimisation problem can be formulated as:

$$\max \sum_{h=1}^{24} [\, sp_h^{DA} \cdot \left(bid_h^{DA} + imb_h^{DA}\right) - \, RC_h^{DA}] \tag{4}$$

s.t.

$$g_h^{DA} + d_h^{DA} - c_h^{DA} - bid_h^{DA} = imb_h^{DA} \tag{5}$$

$$imb_h^{DA} \cdot \left(sp_h^{DA} - sp_h^{+}\right) \leq RC_h^{DA} \tag{6}$$

$$imb_h^{DA} \cdot \left(sp_h^{-} - sp_h^{DA}\right) \leq RC_h^{DA} \tag{7}$$

$$c_h^{DA} \leq p_{ESS}^{max} \cdot x_{c_h} \tag{8}$$

$$d_h^{DA} \leq p_{ESS}^{max} \cdot x_{d_h} \tag{9}$$

$$x_{c_h} + x_{d_h} \leq 1 \tag{10}$$

$$soc_h = soc_{h-1} + \eta \cdot c_h^{DA} - d_h^{DA} \tag{11}$$

$$0 \leq soc_h \leq e_{ESS}^{max} \tag{12}$$

$$soc_1 = soc_{24} = 0 \tag{13}$$

$$-p_{ESS}^{max} \leq bid_h^{DA} \leq p_{ESS}^{max} + P_{wind}^{max} + P_{PV}^{max} \tag{14}$$

The objective function (4) aims to maximise the market profit of the joint operation of renewables and an ESS. The minimum bid offer is defined by the ESS installed capacity (since it can be charged through the market) and the maximum bid offer is defined by the maximum power that can be produced by the joint system (14). The bid to be submitted is optimized according to the predicted renewable power production and the ESS operation while considering the regulation costs (5) – (7). The storage system operation is described by equations (8) – (13). Within one hour, the system can charge and discharge but not both at the same time (8) – (10). The balance of energy stored in the ESS at hour h is obtained by (11) by adding or subtracting the energy corresponding to the charge or discharge of the BESS to the previous hour stored energy, affected by the BESS roundtrip efficiency. The initially stored and the planned final energy after the day-ahead scheduling is defined by (13).

3.2.2. Intraday Model

After the day-ahead market, the intraday market takes place. This market is structured in 7 sessions throughout the day with various scheduling times, allowing flexibility in the operation and optimisation of the agents' portfolio. The high variability of the wind speed and irradiance leads to uncertainty in renewable power forecasting, increasing the possibility of imbalances. The intraday optimisation aims to maximise the profit by participating in the multiple daily sessions using both the new updated renewable production forecasts and intraday spot price forecasts. The algorithm performs a new optimisation with a sliding window approach from the first to the last hour of the day, in each market session.

The intraday optimisation model can be described by:

$$\max \sum_{h=1}^{24} [\, sp_h^{DA} \cdot \left(bid_h^{DA} + imb_h^{DA}\right) - \, RC_h^{DA} + sp_h^{ID} \cdot bid_h^{ID}] \tag{15}$$

s.t.

$$g_h^{DA} + d_h^{DA} - c_h^{DA} - bid_h^{DA} = imb_h^{DA} \tag{16}$$

$$imb_h^{DA} \cdot \left(sp_h^{DA} - sp_h^{+}\right) \le RC_h^{DA} \tag{17}$$

$$-imb_h^{DA} \cdot \left(sp_h^{-} - sp_h^{DA}\right) \le RC_h^{DA} \tag{18}$$

$$g_h^{DA} + g_h^{ID} = \, p_h^{for} \tag{19}$$

$$c_h^{DA} + c_h^{ID} \le p_{ESS}^{max} \cdot x_{c_h} \tag{20}$$

$$d_h^{DA} + d_h^{ID} \le p_{ESS}^{max} \cdot x_{d_h} \tag{21}$$

$$x_{c_h} + x_{d_h} \le 1 \tag{22}$$

$$soc_h = soc_{h-1} + \eta \cdot (c_h^{DA} + c_h^{ID}) - (d_h^{DA} + d_h^{ID}) \tag{23}$$

$$0 \le soc_h \le e_{ESS}^{max} \tag{24}$$

$$soc_1 = soc_{24} = 0 \tag{25}$$

$$bid_h^{ID} = \begin{cases} 0, & bid_h^{DA} = 0 \\ g_h^{ID} + d_h^{ID} - c_h^{ID}, & bid_h^{DA} \neq 0 \end{cases} \tag{26}$$

The objective function is expressed by (15) and proposes to maximise the revenues considering the updated forecasts regarding both power production and prices. Constraints (16) – (25) are similar to the ones considered in the DA model, now considering the existence of the two markets. The intraday bid at hour h (26) must be given by the renewable forecast and storage system optimal operation point. It should be pointed out that, according to MIBEL regulations, the market participant can only submit an offer if a bid has been submitted in that respective hour of the day-ahead market. Otherwise, the agent is prohibited from submitting an offer for the given hour h.

3.2.3. Real-Time Model

The real-time algorithm is also based on a sliding window approach and performs a new optimisation every hour, using as input data the real renewable power generation, the day-ahead and intraday submitted bids and the past states of the system. Every hour, the algorithm outputs the final ESS operation points along with the operation of the ESS in the balancing market.

In MIBEL, the participants offer its regulation bands with the corresponding prices for every hour of the following day bids, after the DA market closure. Then, these bids are drawn up in increasing price order. In real-time, the market is cleared considering cost minimisation for providing requirements. The system manager removes the existing deviations by selecting from the previously submitted offers, the ones which ensure a lower total cost to the system. Thus, it is not possible to know in advance when a specific agent is chosen to mobilise or demobilise energy. The option to assume that the agent under study would always be selected seems unfeasible and, if implemented, would give rise to unrealistic profits.

Therefore, in this paper, we have decided that the participation of the agent under study in the balancing market is restricted to imbalance minimisation. Opposed to the DA and ID optimisation models, the objective is not to maximise profits but to minimise the imbalances by optimally operating the ESS and acting in the balancing market.

The formulation of this optimization problem is given by:

$$\min \sum_{h=1}^{24} [RC_h^{DA} + RC_h^{ID}] \tag{27}$$

s.t.

$$g_h^{DA} + d_h^{DA} - c_h^{DA} - bid_h^{DA} = imb_h^{DA} \tag{28}$$

$$imb_h^{DA} \cdot \left(sp_h^{DA} - sp_h^{+}\right) \leq RC_h^{DA} \tag{29}$$

$$-imb_h^{DA} \cdot \left(sp_h^- - sp_h^{DA}\right) \leq RC_h^{DA} \tag{30}$$

$$g_h^{ID} + d_h^{ID} - c_h^{ID} - bid_h^{ID} = imb_h^{ID} \tag{31}$$

$$imb_h^{ID} \cdot \left(sp_h^{ID} - sp_h^+\right) \leq RC_h^{ID} \tag{32}$$

$$-imb_h^{ID} \cdot \left(sp_h^- - sp_h^{ID}\right) \leq RC_h^{ID} \tag{33}$$

$$g_h^{DA} + g_h^{ID} = \ p_h^{real} \tag{34}$$

$$c_h^{DA} + c_h^{ID} + r_h^d \leq p_{ESS}^{max} \cdot x_{c_h} \tag{35}$$

$$d_h^{DA} + d_h^{ID} + r_h^u \leq p_{ESS}^{max} \cdot x_{d_h} \tag{36}$$

$$x_{c_h} + x_{d_h} \leq 1 \tag{37}$$

$$soc_h = soc_{h-1} + \eta \cdot (c_h^{DA} + c_h^{ID} + r_h^d) - (d_h^{DA} + d_h^{ID} + r_h^u) \tag{38}$$

$$0 \leq soc_h \leq e_{ESS}^{max} \tag{39}$$

$$soc_1 = soc_{24} = 0 \tag{40}$$

$$r_h^d \leq p_{ESS}^{max} \cdot k_h \tag{41}$$

$$r_h^u \leq p_{ESS}^{max} \cdot (1 - k_h) \tag{42}$$

The RT objective function (27) aims to minimise the regulation costs related to the absolute value of the imbalances between the submitted offers in the DA and ID markets and the real energy generated. Constraints (28) – (40) are similar to the ones considered in the DA and ID models, now considering the existence of the three short-term markets and the actual renewable generation. The ESS participation in the balancing market is expressed by r_h^d and r_h^u, and it is constrained so the BESS is not providing upward and downward regulation concurrently (41) – (42).

3.3. Economic Models

In this work, multiple BESS based on different technologies and specifications (cost, lifespan, efficiency, etc) are considered. Therefore, the profitability of those projects must be analysed and compared. After obtaining the system's optimal operation from the overall optimisation model, it is necessary to estimate the revenues. To calculate the economic benefits of integrating a BESS, the annual revenues of the system with and without BESS must be computed according to (43).

$$\text{Extra Profit} = \text{Profit}_{\text{with BESS}} - \text{Profit}_{\text{without BESS}} \tag{43}$$

To evaluate and select the best investment, two economic models for the project economic assessment are used: net present value (NPV) and internal rate of return (IRR). These metrics are among the most popular discounted cash flow methods and serve different purposes. NPV measures the change in the net worth of the firm, while IRR measures the rate of return for the investment [28].

The NPV model (44) uses the yearly extra profit (43) obtained in the three short-term markets discounted at a certain discount rate i. The initial investment is considered to happen in year 0 (I_0). Profits are considered from year 1 until the year the BESS replacement would eventually occur. BESS operation and maintenance costs have been neglected. A positive NPV indicates a profitable investment.

$$\text{NPV} = \sum_{t=1}^{n} \frac{\text{Extra Profit}_t}{(1+i)^t} - I_0 \tag{44}$$

Likewise, the IRR (45) uses the extra profit generated due to the BESS implementation. The IRR is the discount rate that turns the NPV equal to zero and displays the project's real rate of return. If the IRR is greater than the discount rate, the project is profitable.

$$0 = \sum_{t=1}^{n} \frac{\text{Extra Profit}_t}{(1+\text{IRR})^t} - I_0 \tag{45}$$

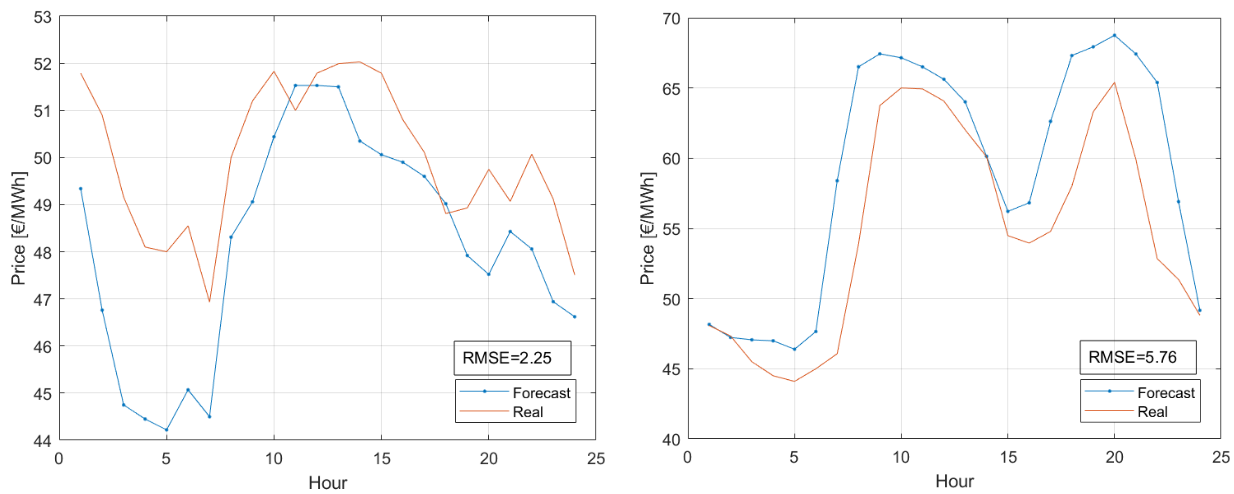
4. Simulation Conditions

In this research, assumptions regarding model's inputs were imposed, as well as conditions were presumed in the tested scenarios.

4.1. Spot Price Forecasting

As mentioned before, the DA and ID spot prices must be forecasted. The input data comprising the day-ahead spot price for two distinct typical days can be observed in Fig 1.

Given the typical nature of the spot market prices, lower prices at the beginning of the day are expected. This characteristic emphasizes the use of the storage system: it favours arbitrage and ends up increasing profit when implementing an ESS.



a) Typical summer day b) Typical winter day

Figure 1. Real and LSTM forecast for the day-ahead market spot price.

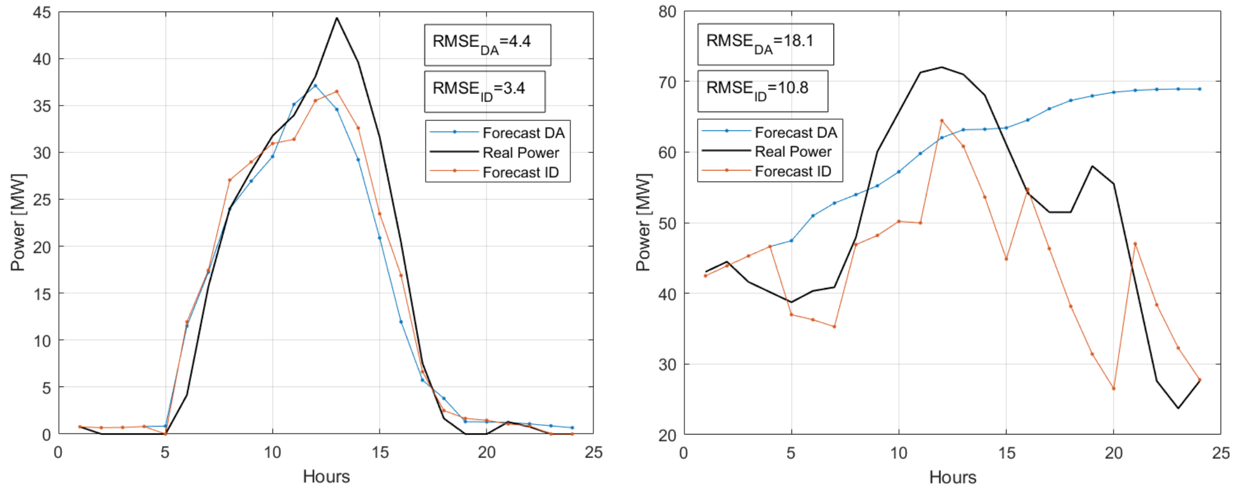
4.2. Regulation Costs

In MIBEL, positive and negative imbalances are charged differently. In this paper, the considered method for the calculation of these costs was the application of a penalty factor by which the day-ahead spot price must be multiplied. To adopt a value which reflects the reality of MIBEL, the costs from 2015 to 2018 were studied. A clear pattern emerged from the 4-year analysis: there is always a symmetry between the penalty factor applied to imbalances in both directions and, for 80% of the considered months, this value is about 1.2 and 0.8 for negative and positive imbalances, respectively. These two penalty factors were considered in this paper.

4.3. Power Forecasting

The Wind Turbine (WT) and PV were mathematically modelled, enabling to determine the generated power, from the input variables. For the WT, a generic power curve was considered and for the PV, a simple model based on the peak power temperature coefficient was used. In this study, the WF and PV power plant installed capacity are 73.6 MW and 39.76 MW, respectively.

Before day D, the renewable generation needs to be predicted considering the available data until day D-1. However, as soon as the day progresses, updated forecasts regarding the new information about past hours need to be generated to serve as input in the intraday optimisation. The day-ahead and intraday power forecasts for two typical days are displayed in Fig. 2.



a) Typical summer day b) Typical winter day

Figure 2. Real renewable production and day-ahead and intraday LSTM forecasts.

Regarding the summer day, it is possible to clearly distinguish the profile resulting from solar production and its relevance on overall power generation. The winter day implies modest solar production due to low irradiance levels, while the wind production is considerably high, as winter is typically characterised by strong winds. The comparison between both forecasts corroborates the high variability of wind power, which is the RES most difficult to predict.

4.4. Balancing Market

As mentioned in Section III, to avoid unreasonable profit from the balancing market (BM), participation is restricted to imbalance minimisation. Nevertheless, this market involves two forms of remuneration: regulation band and mobilisation/demobilisation of energy. It would be interesting to participate in this market to also maximise profits and not solely as a supporting variable that may be employed to improve the battery operation in minimising deviations. Therefore, two different cases were considered.

In Case I, the agent's participation in the balancing market is limited to the minimisation of its imbalances, as previously mentioned. The BESS full capacity is used only to minimise regulation costs. Therefore, there is no monetary motivation to participate in this market other than avoiding deviations from the submitted bids.

In Case II, only a percentage of the storage system's capacity (15%) is considered with the purpose of increasing profits. The percentage was chosen in such a way that, on the one hand, a substantial amount of storage can already be used to maximise profits but, on the other hand, it does not incur an absurd value, ending up ignoring imbalance minimisation and being too optimistic on the amount of energy needed.

4.5. Energy Storage Considerations

Twelve BESS were tested in this study: four different BESS technologies with three different storage sizes. The considered technologies are sodium-sulphur, li-ion, zinc hybrid and vanadium redox flow. BESS characteristics with respect to power, energy, roundtrip efficiency and lifetime are considered as optimisation models' input variables and stated in Table 1.

Table 1. Tested BESS Characteristics.

Technology	Tested BESS [MW/MWh]			Roundtrip Efficiency [%]	Lifetime [Years]
NaS	0.8/5.8	3/18	4.2/25.2	75	13.5
Li-Ion	2/2	6/10	20/20	86	10
Zinc-Hybrid	0.5/2	1/4	2/8	72	10
Vanadium	0.5/3	4/6	10/40	67.5	15

The initial and final state of charge are assumed to be zero, but another value could have been chosen. This is relevant because the algorithm performs the optimisation for several days and this constraint forces a standard initial and final daily energy levels. In economic simulations, BESS were tested not only with information regarding technology development and costs in 2018 but also with predictions for the year of 2025, based on [29]. The considered BESS investment costs for the years of 2018 and 2025 are specified in Table 2.

Table 2. BESS Energy and Power Costs in 2018 and 2025.

Technology	Energy Cost [k€/MWh]		Power Cost [k€/MW]	
	2018	2025	2018	2025
Sodium-Sulphur	580	408	307	185
Li-Ion	237	166	252	185
Zinc-Hybrid	232	168	307	185
Vanadium	487	347	307	185

4.6. Annual Simulation

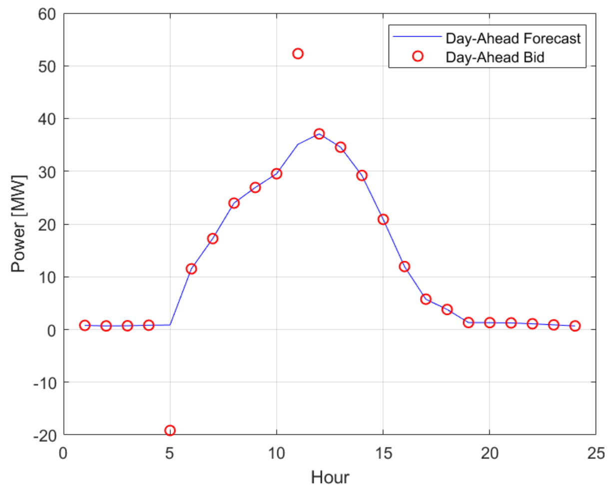
Even though the optimisation algorithms were developed considering one day, the optimisation throughout a whole year is required to evaluate the profitability of different BESS projects. Since the forecasting of the power generation and spot prices for a single day takes approximately 45 minutes, the decision of analysing a whole year is unbearable. Therefore, the analysis of a whole year is accomplished by choosing four typical days: one for each season. This assumption allows for assessing the optimal operation of the system and the expected revenues for a whole year in a reasonable time. One year consists of 90 winter days, 92 summer days, 92 spring days and 91 autumn days. Due to this supposition, it is only necessary to execute the algorithm through the four typical days. With the operation outputs from those days, results are extrapolated for the whole year. Revenues are calculated considering the optimal bidding strategy in the three short-term markets given by the model, with and without the BESS, allowing the profitability of the projects to be analysed and compared.

5. Results and Discussion

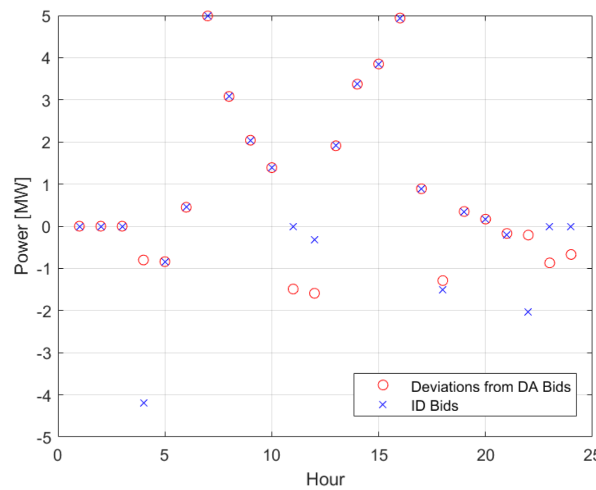
5.1. Operation and Bidding Strategy for a typical summer day

For illustration purposes, the simulated day is a typical summer day. The models' input variables were detailed in section IV and depicted in Fig. 1 and Fig. 2.

Fig. 3 shows the bids submitted in the DA market overlaid on the DA production forecast, as well as the bids proposed in the ID market alongside with the resultant deviations from the updated forecasts when compared to the submitted DA bids.



a) Day-Ahead



b) Intraday

Figure 3. Submitted bids in the DA and ID markets.

Fig. 4 portrays the final state of charge of the BESS.

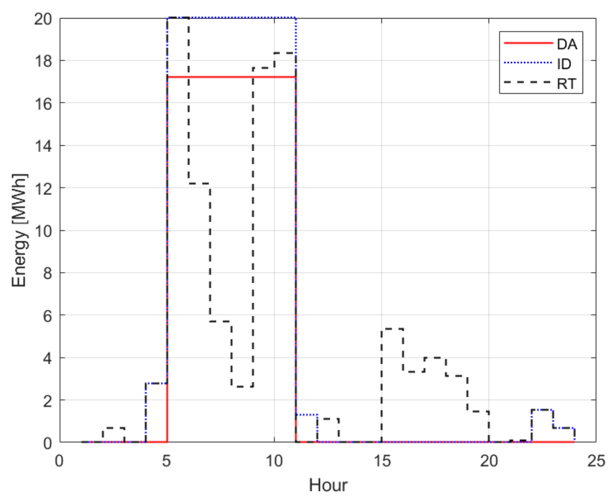


Figure 4. Comparison between DA, ID and RT battery state of charge.

Naturally, the strategy taken on the three-short term markets differs and, with the successive update on input information regarding spot prices and power generation, the BESS operation is subject to modification until RT.

5.1.1. Day-Ahead

In Fig. 3, DA bids throughout the day are superimposed on the renewable production forecast. The bidding strategy and BESS operation are strictly correlated to the predicted production and spot prices. The algorithm fixes the DA bids as the expected production (except in hours 5 and 11) and aims to increase the system revenue by performing price arbitrage with the BESS within the DA market. Given the nature of spot prices, arbitrage happens in hours 5 and 11 (Fig. 4) which present the lower and higher predicted DA spot prices (Fig. 1).

5.1.2. Intraday

Subsequently, the ID strategy attempts to maximise the profit by using new production forecasts to bid in ID market sessions accordingly and by updating the BESS operation decisions both for compensating possible imbalances and arbitrage across markets. Thus, the bids are displayed along with the expected deviations due to newly updated predictions. Also, the ID predicted spot prices shown in Fig. 1 must be considered.

If overproduction is predicted (e.g., 6h-10h), the additional production is sold in the ID market sessions, to obtain additional revenues (Fig. 3). If underproduction is predicted (e.g., 23h-24h), the BESS is discharged (Fig. 4) to cover imbalances from the DA bids (Fig. 3).

In the ID strategy, the profit coming from the respective market must be maximised, like in the DA. Additionally, the regulation costs resulting from power imbalances from the DA submitted bids must be minimised.

5.1.3. Real-Time

Lastly, DA and ID bids are compared with the real operation points giving the real production of the renewable power plants. Then, the operation within the balancing market and BESS operations are settled correspondingly. The results stated in this section refer to Case I.

Fig. 5 reveals the deviations between real production and both predictions. Even though forecasts follow a close pattern when compared to reality (Fig. 2), one can conclude that real production is unquestionably different from the predictions.

A mismatch is observed in most of the day, with clear renewables' underproduction (more generation was predicted than in fact produced) from 5h to 7h and considerable overproduction between 13h and 16h. Although a substantial deviation regarding ID forecasts still occurs, an improvement of 20% is observed on this day due to its adoption. Regarding other typical days with poorer DA forecasts, enhancements up to 42% were observed.

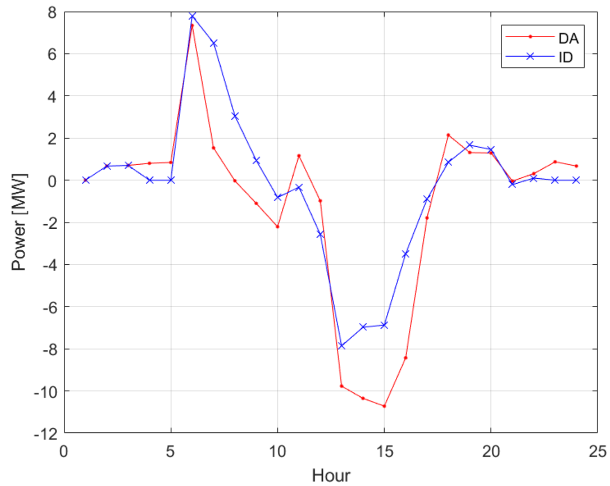


Figure 5. Mismatch between real and forecasted DA and ID renewable generation.

This is where the real-time model comes in. The effectiveness of the BESS, plus the possibility to act in the balancing market are proven by eliminating these deviations. Notwithstanding, enhancements of 20% just due to the new forecasts (from the DA to the ID predictions) are achieved in the considered day.

In Table 3, the traded energy in each market (DA, ID and BM, case I) is exhibited. The direction of the transactions is specified, as well as the percentage of energy exchanged in each short-term market. The amount of traded energy decreases substantially as the delivery horizon becomes nearer. This behaviour is a result of the implemented strategy and reflects reality. Most of the total traded volume happens in the day-ahead market. Concerning the buying bids, which are submitted with the sole purpose of charging the BESS, one can infer more significant amounts are offered in the DA and BM. Transactions in the ID and BM occur for arbitrage purposes and strategic avoidance of imbalances.

Table 3. Energy traded in the DA, ID, and BM markets in the chosen day.

Market	Traded Energy [MWh]	Buying [MWh]	Selling [MWh]	Transactions [%]
DA	334.2	19.2	315.0	81.7
ID	36.7	9.1	27.6	9.0
BM (Case I)	38.1	20.1	18.0	9.3

However, the balancing market participation as an additional money-making opportunity (Case II) changes the strategy. If Case II is contemplated, the transactions in the DA, ID and BM markets become 71.2%, 10.7% and 18.1%, respectively.

5.2. Economic Analysis

To analyse the application and to evaluate the profitability of different BESS projects, the developed model is executed over the typical days and typical year.

5.2.1. Daily Simulations

The four chosen days aim to represent the typical year. Thus, each season trends are captured both at the renewable production and price level. Table 4 states the economic results with and without an ESS regarding both balancing market approaches (Case I and II). The market revenues in the three short term markets, as well as the regulation costs are exposed for the simulations on the four typical days of the year.

Table 4. Monetary Results for each simulated day with and without a BESS.

Wi = winter, Sp = spring, Su = summer, Au = autumn

Revenues [k€]	Without Storage				With Li-Ion 20 MW/20MWh							
					Case I				Case II			
	Wi	Sp	Su	Au	Wi	Sp	Su	Au	Wi	Sp	Su	Au
DA	78.6	36.6	15.2	15.2	79.0	36.4	15.1	15.3	79.1	38.5	14.9	14.2
ID	5.4	0.0	1.5	0.0	-0.2	-3.1	1.0	-0.5	2.5	-2.8	0.7	-0.6
BM	not applicable				1.8	-1.5	0.5	-0.8	-0.7	-1.9	1.2	0.9
RC	-20.0	-8.3	-0.1	-2.6	-14.0	-0.6	0.0	0.0	-14.0	-1.5	0.0	-0.1
Total	64.0	28.3	16.5	12.6	66.6	31.2	16.6	14.0	66.9	32.3	16.8	14.4

Without using any storage system, the owner is restricted to operate in the DA and ID markets. The amount of renewable energy likely to be generated is all submitted in the DA market. Then, small adjustments are made in the ID market when the newly updated forecasts declare greater quantities will occur, adding minor profits. In case of insufficient production predictions, the agent can eventually buy the excess energy formerly offered in the DA market.

It is crucial to evaluate the results without BESS keeping in mind the inherent characteristics of each day. In the winter and summer days, positive deviations occur (overproduction), hence the profit value bigger than zero in the ID market. On days with more accurate forecasts like summer

(Fig.2, $RMSE_{Su}$=4.4%) and autumn ($RMSE_{Au}$=3.3%), fewer deviations materialise, thus fewer regulation costs are involved.

Regarding BESS implementation results, some conclusions can be withdrawn for both Case I and II. If underproduction is expected (spring and autumn), the possibility to act in the ID sessions and in real-time (balancing market) arises. Typically, these markets are mostly used to buy energy to charge the battery; hence the negative revenues values publicised in Table 4. Looking at the typical days' regulation costs and revenues, one can conclude that the BESS implementation is less significant in the summer day, for both cases. In this day, the daily price difference (Fig. 1) is negligible (7 €/MWh) when compared to other days (e.g. 23 €/MWh in winter), not leaving room for the ESS to be relevant.

In Table 4 it is shown that the three short-term market revenues and regulation costs differ when comparing Case I and II, proving different strategies are followed in each case. A further analysis on the variation of these variables due to BESS implementation in Case I and II is detailed in Table 5.

Table 5. Variation on Regulation Costs and Revenues each day due to Li-Ion 20MW/20MWh BESS implementation.

Day	Regulation Costs [%]		Revenues [%]	
	Case I	Case II	Case I	Case II
Winter	-30.0	-30.0	+4.0	+4.5
Spring	-92.8	-81.9	+10.2	+14.1
Summer	-100.0	-100.0	+0.6	+1.8
Autumn	-100.0	-96.2	+11.1	+14.3

Regarding Case I, the only purpose of balancing market participation is to minimise imbalances. Regulation costs are drastically reduced in 3 of 4 typical days, as it is the main goal of the real-time model. The winter day shows the worst results with only 30% of the regulation costs reduced. Despite high changes in the regulated costs, variations on revenue just vary between 0.6% and 11.1%. Therefore, one can infer that profits are not significantly improved, for the chosen typical days.

Although in Case II only 15% of the BESS capacity is assigned to maximise profits, variations on revenue are already higher in all typical days. Regulation costs variations are either the same or inferior since now only 85% of the capacity is utilised to minimise imbalances.

Extrapolating the daily results stated on Tables 4 and 5 to the annual context, it is determined that, yearly regulation costs decrease by 53.2% and 49.9%, and yearly revenues increase by 5.7% and 7.4%, when comparing Cases I and II to the scenario without a BESS.

5.2.2. Yearly Simulations

The economic assessment is calculated across the whole year. The two elected economic metrics (NPV and IRR) are applied. Revenues of the system with and without BESS are computed. The profitability analysis of the multiple studied projects is computed both in the year 2018 and in the year 2025 based on [29]. At this point, considering the IRR, all variables needed to compute it (revenues, costs, lifetimes) are well-known. Regarding the NPV, only the discount rate is not an acknowledged value. Higher discount rates imply more risk associated with the investment opportunity. Since BESS are not a mature technology, NPVs are calculated with a discount rate of 7.5%. Also, a sensitivity analysis is conducted with two more discount rate options: 5% and 10%.

Tables 6 and 7 state some selected simulation results regarding the smaller battery size tested of each considered technology for the year 2018 and 2025, for both considered cases of participation in the balancing market (Cases I and II). Table 6 refers to Case I while Case II results are assigned to Table 7.

Table 6. Economic Evaluation for the smaller size tested BESS of each technology (Case I).

Technology [MW/MWh]	NPV [k€] i=7.5%		NPV [k€] i=5%		NPV [k€] i=10%		IRR [%]	
	2018	2025	2018	2025	2018	2025	2018	2025
Sodium-Sulphur [0.8/5.8]	-3317	-2222	-3270	-21755	-3355	-2260	-20.4	-17.5
Li-Ion [2/2]	-43	**232**	**83**	**349**	-142	**134**	**6.5**	**14.3**
Zinc-Hybrid [0.5/2]	-496	-298	-480	-281	-500	-311	-17.1	-12.6
Vanadium [0.5/3]	-1475	-988	-1450	-963	-1494	-1007	-17.9	-15.2

Table 7. Economic Evaluation for the smaller size tested BESS of each technology (Case II).

Technology [MW/MWh]	NPV [k€] i=7.5%		NPV [k€] i=5%		NPV [k€] i=10%		IRR [%]	
	2018	2025	2018	2025	2018	2025	2018	2025
Sodium-Sulphur [0.8/5.8]	-3233	-2137	-3172	-2077	-3281	-2186	-18.4	-15.3
Li-Ion [2/2]	**151**	**427**	**292**	**568**	**33**	**309**	**10.8**	**19.5**
Zinc-Hybrid [0.5/2]	-443	-254	-421	-232	-461	-272	-13.5	-8.5
Vanadium [0.5/3]	-1425	-938	-1392	-905	-1451	-964	-15.6	-12.7

Regarding Case I (Table 6), in year 2018, the lithium-ion battery is considered viable by both IRR (6.5%) and NPV if the discount rate is assumed to be 5% (NPV5%=83 k€). All other technologies exhibit negative values regarding both metrics. Similarly, in the year 2025, the lithium-ion battery is viable by both metrics (IRR=14.3%) and regardless of the discount rate (NPV5%, 7.5%, 10%=349 k€, 232 k€, 134 k€). About the other three explored technologies, the annual profit achieved and its yet high investment costs (Table 2), are not enough to cover and make it realistic to invest in a BESS both in the years of 2018 and 2025.

Regarding Case II (Table 7), in which a percentage of the BESS capacity is used to maximise profits, it is concluded that the lithium-ion BESS would already be viable in the year of 2018 for both metrics and all considered discount rates (NPV5%,7.5%, 10%=292 k€, 151 k€, 33 k€ and IRR=10.8%). Even though for all considered technologies, profits increase roughly between 20 and 36% (for the BESS sizes presented in Table 4), this is not enough to cover the (still high) costs. All other technologies still present negative NPVs and IRRs. Sodium-sulphur, zinc-hybrid and vanadium redox-flow batteries are not viable and possibly will not be in the year of 2025.

Results about the other tested sizes of each technology are not specified in Tables 6 and 7 since negative values were obtained for both metrics (NPV and IRR) for Case I and II.

6. Conclusions

In this work, the role of energy storage systems acting jointly with renewables in the Iberian electricity market from a producer's point of view was studied. Even though the analysis was performed for the context of the Portuguese power system, the methodology is rather generic and can be applied to any other market with minor adjustments.

On the optimisation modelling, the day-ahead strategy followed a procedure in which energy would be saved in the BESS during low spot market prices to increase the energy bids during high spot market prices. This is especially true on days in which the price difference is significant, thus compelling arbitrage. Afterwards, by exploiting more accurate forecasts, the intraday strategy focused on maximising revenues bidding in the intraday market sessions and minimising the imbalances resultant from forecast inaccuracy. Finally, the real-time strategy focused on avoiding deviations by acting in the balancing market and operating the storage system.

The forecasting techniques are shown as of great importance since the quality of the input variables (renewable power and spot prices) shapes the optimisation decisions across all developed models. Due to the application of the newly updated forecasts in the ID strategy, it is possible to observe for the typical simulated days, that there is an improvement within the range of 20%-42% concerning the energy volume mismatch.

Regarding BESS implementation, regulation costs decreased between 30% and 100% on the simulated days, allowing a yearly decrease of 53% (Case I) on costs, when compared to the scenario without a BESS. Even though under the stated formulations and conditions, regulation costs were reduced up to 100% (eliminating regulation costs) in some typical days, it was concluded that the amount of regulation costs avoided does not justify the great investment in other storage technology than lithium-ion yet.

The economic models (NPV and IRR) revealed negative values for all tested technologies except for lithium-ion BESS in both 2018 and 2025. These results expose the technical and economic advantages of lithium-ion over sodium-sulphur, zinc hybrid and vanadium.

A more realistic (and optimistic) perspective was taken in Case II, where 15% of the BESS capacity is considered to maximise profits and the remaining 85% is still used to minimise deviations. This modification on the model conditions doubled the percentage of transactions happening in the balancing market (9% to 18%). An improvement of 21% to 36% (depending on technology) in the expected profit is obtained for the smaller BESS size, in Case II. Still, only lithium-ion batteries are a feasible investment. The economic evaluation reveals that these extra revenues in the yearly operation are still not encouraging the implementation of other BESS technologies. Nevertheless, one must keep in mind that storage technologies are more and more mature, and prices are gradually becoming more competitive. The overall BESS market is expanding and is expected to increase dramatically in the coming decade.

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