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Using Energy Storage Systems in Electricity Markets

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Declaration

I declare that this document is an original work of my own authorship and that it fulfills all the requirements of the Code of Conduct and Good Practices of the Universidade de Lisboa.

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This dissertation would not have been possible without the invaluable help of some special people.

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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-sulfur, 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

Resumo

Este estudo identifica a estratégia de operação ótima de sistemas de armazenamento nos mercados de eletricidade, na perspectiva de um participante com um portefólio de energias renováveis. O sistema de armazenamento de energia fornece um serviço de balanço para as fontes renováveis, ao mesmo tempo que realiza arbitragem de energia nos três mercados de curto prazo.

As previsões de preços e produção renovável orientam o processo de tomada de decisão da licitação para maximizar o lucro económico dos agentes. Assim, um modelo Long Short-Term Memory (LSTM) foi desenvolvido para prever essas variáveis. Os modelos de apoio à decisão concebidos consideraram as regras de mercado e as restrições técnicas na operação do sistema de armazenamento. A influência dos sistemas de armazenamento na operação ideal, nos custos de regulação e nos lucros é analisada diária e anualmente. A viabilidade económica de baterias de enxofre de sódio, ião lítio, híbrido de zinco e fluxo redox de vanádio, em 2018 e 2025, é estudada.

Os resultados sugerem que o uso de técnicas de previsão e a implementação da bateria reduzem drasticamente os custos de regulação. A análise mostra que atuar no mercado de reserva pode ser uma motivação para a viabilização do sistema de armazenamento. A avaliação económica comprova que apenas a bateria de ião lítio é um investimento lucrativo nos anos considerados.

Palavras Chave

Renováveis, Sistemas de Armazenamento de Energia, Previsão, Estratégia de Operação Ótima, Mercados de Energia

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List of Acronyms

ANN	artificial neural network
BESS	battery energy storage system
BM	balancing market
CAES	compressed-air energy storage
DA	day-ahead
ESS	energy storage system
ID	intraday
IRR	internal rate of return
LSTM	long short-term memory
MIBEL	Iberian electricity market
MILP	mixed-integer linear program
MINLP	mixed-integer non-linear program
NPV	net present value
PHS	pumped hydro storage
PP	payback period
PV	photovoltaic
RES	renewable energy system
RMSE	root-mean-square error
RNN	recurrent neural network
RT	real-time
SVR	support vector regression
VRB	vanadium redox battery
WF	wind farm

WT wind turbine

List of Symbols

bid_h^{DA}	day-ahead market bid at hour h
bid_h^{ID}	intraday market bid at hour h
c_h^{DA}	storage system charge assigned to day-ahead strategy at hour h
c_h^{ID}	storage system charge assigned to intraday strategy at hour h
d_h^{DA}	storage system discharge assigned to day-ahead strategy at hour h
d_h^{ID}	storage system discharge assigned to intraday strategy at hour h
e_{ESS}^{max}	storage system maximum capacity
g_h^{DA}	predicted renewable production assigned to day-ahead strategy at hour h
g_h^{ID}	predicted renewable production assigned to 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}	storage system maximum power rating
P_{PV}^{max}	solar installed capacity
P_{wind}^{max}	wind 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	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 system is charging
x_{d_h}	percentage of the hour when the storage system is discharging
η	energy storage system roundtrip efficiency

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Introduction

Contents

1.1 Problem description

Electricity markets are still evolving, with increasing market integration and more competitive wholesale markets. The electric sector restructuring implied significant changes to the traditional vertically integrated model. The deverticalization of this sector determined the emergence of a disaggregated structure in which several agents can participate. Thus, purchase and selling bids are typically organised in a wholesale energy market which is supervised by a market operator.

Most of the total volume of energy transactions happen in the day-ahead (DA) market, in which participants submit their bids to sell or buy energy for each hour of the following day. The intraday (ID) market, structured in successive market sessions, takes place after the DA market has been cleared. At the ID market, bids are made nearer the delivery horizon thus minimising differences between previously contracted energy and real production. The balancing market (BM) bidding process also starts after the DA market. The goal of this market is to certify that, in real-time (RT), the system will continue to function smoothly regardless of any unexpected event. 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, thus jeopardising the possible revenues. Penalty payments are charged according to a regulatory system. Charges can follow a dual pricing regulation in which the price for a negative imbalance is not equal to the price for positive imbalance in sign and, or size, or a single pricing regulation.

Furthermore, the growing awareness and concernment over environmental impact and sustainability, together with economic interests, has led to a rising change in energy production standards. Recent decades have witnessed the rapid development of renewable generation, and the penetration of intermittent energy sources can be observed in power systems all over the world. There are important advantages related to the promotion of renewable energy sources. Monetary and environmental benefits come from the avoided CO_2 emissions and fuel costs savings. Nevertheless, renewables differ from conventional power sources.

Renewable energy sources are characterised by their temporal variability and weather dependence, thus cannot choose when to submit their generation. It becomes challenging to match the previously accepted bids, thus increasing the possibility of extra charges. Therefore, since the amount of power generation is subject to the instantaneous meteorological conditions, a shift in paradigm on scheduling and operating power plants is required.

Due to the stochastic nature of renewable dependent variables, forecasting methods are required to plan unit commitment properly. Operations like scheduling, dispatch and real-time balancing are affected by forecasting models. It is relevant when it concerns the DA market, since these units can still make new bids based on updated forecasts in the subsequent existent markets. Therefore, forecasting plays a crucial role. By deploying improved forecasting models, fewer adjustments are needed, and fewer imbalances occur. The ID and RT markets provide a valuable platform for transactions on renewable energy generation, enabling several opportunities to establish the final energy schedule. There is also the possibility of increasing incomes by participating in the BM, where power and energy reserves can be negotiated. In this RT market, the agent can achieve additional compensations, since this service is remunerated with two different payments: one related to the regulation band and another one to the mobilised energy.

Nevertheless, since the power generation of wind and solar resources is uncertain, and yet there happens to be limited accuracy of power forecasts, there is still revenue loss for renewable producers. To lower these penalties, storage systems can operate together with renewables, thus making them more dispatchable. The combination between a renewable energy source and a storage system is considered a solution to mitigate variability and difficulty to predict. Storage systems provide reliability and flexibility benefits while also helping to achieve clean energy goals. However, since different applications cannot simply be added together, co-optimisation between them is needed. The value of storage is compelling since storage systems can provide several services and bring enormous added value to a system, when optimally allocated.

Furthermore, predicting the price that will be settled by the DA and ID electricity markets is essential for the agents, reducing the impact of uncertainty. Still, electricity prices intrinsic properties turn this into a challenging task. Electricity is a difficult to store good, it shows strong seasonality patterns, and a constant balance between production and consumption needs to be assured at any time. Moreover, supply and demand depend on other variables like weather conditions, day of the week, the season, and so on. Due to these unusual characteristics when compared to other commodities, its dynamics are complex. Also, the increasing integration of renewable sources further contributes to this increase in volatility of prices due to its natural variability. In the electricity market, price spikes and negative prices can unexpectedly arise. Price forecasts guide the bidding decision-making process to maximise agents' economic profit. Therefore, predicting the spot prices, as accurately as possible, is of foremost importance to develop bidding strategies or adjust bids.

From a producer's point of view, the goal is to maximise the expected profit that can be achieved by its generation system. Since imbalances incur penalty payments, they must be minimised. For this purpose, a bidding and an operation strategy need to be proposed. Furthermore, the investment in a storage system needs to be studied. Estimating the expected return is a difficult task. Nevertheless, storage does not fit into traditional definitions of generation, hence the market conditions in which the storage system is planned to be participating need to be analysed. The decision support models must consider in which markets to participate and the impact of the technical constraints in the operation of the storage. As storage technologies are maturing, prices have become more competitive. Also, as the power system modernises and wind and solar penetration increases, incorporating an energy storage system will likely be the most profitable option for further renewable integration. Still, it is necessary to prove the effectiveness of energy storage solutions from a technical and economic perspective.

1.2 Objectives

Considering the previous section, this dissertation aims to identify the optimal operating strategy of storage systems on the electricity market, from the perspective of a market participant with a renewables' portfolio. To do so, the main objectives behind the elaboration of this research are:

- Design an optimal bidding model for an agent with a portfolio of renewable power sources and energy storage systems within the Iberian market framework.
- Implement an integration and operation strategy of the controllable energy storage technologies.
- Provide a reliable decision support tool to an agent with a portfolio of renewables and storage systems, allowing them to explore operation possibilities while ensuring requirements and maximising revenues.
- Evaluate the economic viability of different energy storage systems operating in a market regime.

In this thesis, literature is extended by investigating the optimal bidding strategy for an energy storage system when operating jointly with both wind and solar generation. The energy storage system provides a balancing service for renewable sources, while also performing energy arbitrage at the short-term markets (DA, ID, RT).

Operation strategies are highly dependent on both price forecasts and renewable generation. Consequently, the meteorological variables in which renewable generation relies on must be predicted and converted with adequate wind turbine (WT) and photovoltaic (PV) models. Also, the forecast of DA and ID market spot prices is attentively considered. In order to predict these variables, a recurrent neural network (RNN), namely long short-term memory (LSTM) network is the chosen method. This method can capture long-term temporal dependencies, thus being suitable for time series prediction.

Furthermore, the influence of storage systems in the revenues and optimal operation is analysed in a case study. Even though the benefits of storage are well known, its viability is still controversial. Thus, the economic viability of multiple battery storage technologies with different characteristics is examined.

1.3 Structure

This thesis is constituted by six chapters and seven annexes. In the present chapter, the problem description and objectives behind the development of the dissertation, as well as the structure overview is presented.

Chapter 2 discloses the state-of-the-art regarding the dimensions to be considered in this thesis. It presents a literature review on energy storage systems opportunities and economic viability in electricity markets, as well as on its different optimisation strategies when operating alone and integrated with renewables. Furthermore, a literature review on forecasting techniques to predict power generation and spot prices is also analysed. An insight into the identified research gaps to be fulfilled by this dissertation is also given.

Chapter 3 focuses on the proposed models used in this thesis. The chosen forecasting algorithm is meticulously explained. Moreover, the considered WT and PV models are described. The optimisation problem regarding owner's renewable and storage systems portfolio operation is also addressed. The optimisation framework introduces the proposed models for the DA, ID and RT markets. The selected economic models are also contemplated.

Chapter 4 describes the employed simulation conditions throughout this work. In this chapter, the simulation scenarios are described. The main parameters and criteria concerning the market framework and the considered systems are detailed. Considerations regarding chosen data, storage system specifications and other assumptions in the performed simulations are exposed. Besides, the results of the conceived forecasting models used as input data for the optimisation models are presented.

Chapter 5 provides the results performed with the implemented models in a case-study. The most relevant aspects regarding the system integration and operation are highlighted along with its respective analysis, and the economic evaluation of the analysed storage technologies is performed.

In chapter 6 the main conclusions drawn from this research and some recommendations for possible future work are described.

Annex A presents the forecasted meteorological variables used to obtain power forecasts for the considered simulations. Annex B and Annex C focus on the battery storage system technologies. The first one reviews the technologies' characteristics and the second points out the costs and specifications of the tested batteries. Annex D and E break down the bidding and operation strategy for a specific day after intraday and real-time optimisation, respectively. Annex F details the market transactions for each simulated day. Lastly, Annex G displays the extended results on the economic assessments.

2

State of the Art

Contents

This chapter provides a global review of the dimensions to be considered in this thesis. Various research work regarding the independent and joint operation of storage systems and renewable power plants are investigated. Furthermore, the forecasting techniques presented in the literature regarding price and power production are exposed. A review in the literature regarding energy storage systems economic viability is also presented.

Regarding optimisation, storage system operation can be divided into independent operation and coordinated operation along with renewables.

2.1 Energy storage systems opportunities and optimal strategy in electricity markets

Regarding storage system independent operation, electricity storage has been applied for arbitrage in multiple market locations. In Zafirakis *et al.* [1], 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, aiming to evaluate trading strategies and distinct energy storage roles associated with those market characteristics. Presence of significant hydropower capacity is proven to be a disincentive for energy storage while less integrated markets encourage it. Nonetheless, it was determined that arbitrage itself could not support investments in the energy storage sector.

McConnell *et al.* [2] studies the use of storage technologies in the Australian market. The Australian market is known as highly volatile, presenting one of the highest price caps in the world, hence an excellent example to explore arbitrage. A linear program for a storage facility arbitrating only in the day-ahead market is suggested. At first, storage operation is optimised, assuming perfect foresight of electricity prices. Then, price forecasts from the system operator were used to capture real-world uncertainty. Also, the similarities of emerging and traditional technologies have been compared: a case study comparing storage technology (PHS) with an open cycle gas turbine generator is presented, demonstrating that storage can be expected to compete and provide similar value to peak generation.

When independent storage operation is concerned, not only mature energy storage systems like PHS are addressed in the studies. Hu *et al.* [3] compares the operation strategy of two kinds of battery energy storage system (BESS), based on polysulfide bromide and vanadium redox, in the Danish market, which has the largest share of wind in the world. A non-linear program for battery arbitrage in the day-ahead market is proposed assuming prices to be available one day ahead. An economic analysis is established as well as the study of the storage system's optimal sizing concluding that the polysulfide bromide battery is the best investment and that the payback period can be significantly reduced if power and energy capacities are chosen appropriately.

However, the previously mentioned studies are limited because they consider only arbitrage and consequently do not reflect the real value of energy storage. In Moghaddam & Saeidian [4], the optimal scheduling of a vanadium redox battery (VRB) in multiple markets is addressed. The optimisation problem is formulated as a mixed-integer non-linear program (MINLP). The VRB plant is considered, not only for arbitrage purposes in the day-ahead market, but also with involvement in the spinning reserve and regulation markets in which the energy storage system (ESS) is paid, by both reserve and energy service. Probabilities for regulation calls are assumed to represent the uncertainty of being called to reserve and regulation markets by the transmission system operator. Nevertheless, it is concluded that the VRB has no economic merit and should be financially supported.

Even though different programming methods have been used to model this problem, mixed-integer linear program (MILP) is seen as very powerful and has been applied extensively with success. This method is considered the most appropriate from the viewpoint of accuracy and runtime [5].

In Drury *et al.* [6], a MILP simulates the optimal dispatch of conventional and adiabatic CAES providing arbitrage and reserve in several US regions (consequently, in different markets) assuming a perfect foresight of electricity prices. The relationship between net revenues and design is characterised. Main conclusions are that larger expanders are more valuable to co-optimised systems because reserves are primarily a capacity resource and that the impact of perfect foresight is not critical since reserve prices are relatively constant over most days. It is once again found that, for this technology, arbitrage-only revenues are unlikely to support the investment. Although conventional CAES could be profitable in some markets if revenues from the operating reserve are considered, the novel adiabatic CAES would likely still need additional revenue streams.

In Berrada *et al.* [7], 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. A fixed dispatch to contract ratio is used, which probably overstates the revenue of participating in the regulation market. The revenue opportunity is developed, considering the cost of using energy storage. The contemplated storage technologies are gravity storage, PHS and CAES. Furthermore, only gravity storage is appraised as not economically profitable, thus PHS and CAES still being the most cost-efficient options.

2.2 Optimal bidding and operating strategies for energy storage systems integrated with renewable power plants

As it was immensely examined in the formerly studies, ESS can act independently exploring arbitrage and reserve markets. Nevertheless, energy storage is many times looked at as one of the best options to integrate more renewable energy system (RES) and to provide flexibility of the energy system. On the one hand, arbitrage can increase the overall profit of a joint operation of a renewable power plant and an energy storage system compared with the situation where they are considered separately. On the other hand, ESS can help flatten the variations of RES output in real-time operation.

Several studies regarding the joint operation of pumped-hydro and wind farms have been performed confirming the effectiveness of the joint operation in increasing the expected profit and decreasing imbalances.

Parastegari *et al.* [8] models a MILP to determine the optimal bidding strategy of a wind farm (WF) and PHS joint operation to reduce the imbalance costs of the WF. The investigated units submit bids to day-ahead and ancillary service markets. The uncertainties of the submitted wind power production, energy price and reserve price forecasts are considered. A stochastic scenario tree is used to model the uncertainties both in wind generation and market prices. Scenario reduction is made by successive backwards method until the desired number of scenarios is obtained. Lastly, the profit for the 330 reduced scenarios is obtained and it can be concluded that a joint operation generates better results than an uncoordinated operation for all scenarios.

Likewise, in González *et al.* [9], a short-term scenario-based stochastic approach to represent the uncertainty about market prices and wind power generation is also implemented. A MILP 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 a WF and pumped storage facility can decrease imbalance penalties up to 50%. Once more, the joint optimisation of ESSs and WFs generates additional value. WF, and, or PV power plants, are participants that benefit from a balancing service due to the significant difficulty in prediction.

In some studies, a deterministic approach is followed. Bathurst & Strbac [10] present a combined optimal dispatch MILP algorithm that determines the operation of the ESS and WF. In this research, a simple persistence forecasting model predicts wind power. The joint operation's added value is analysed. If greater than zero, then all participants gain from the joint operation. Since, as the value of arbitrage increases, the value of balancing wind decreases, the focus of this work is the trade-off between the two. Therefore, the sensitivity of added value to imbalance price spread, wind contracting error and market closure time are investigated. For lower average contracting errors, it happens to be a negative added value.

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 as one can see from the previous references. However, there are substantial geographical and environmental impacts related to these plants. Even though most energy storage forms have been considered historically uneconomic, several factors have led to increasing interest in other ESS. The recent developments in some technologies and the gradually decreasing costs together with their potential uses in the electricity markets are making them look like a viable and attractive solution.

In Ding *et al.* [11], the cooperative day-ahead bidding strategy and real-time operation of a WF and a BESS is investigated. An MINLP formulation with a reserve-based operating strategy is proposed. This strategy is developed for a market with a two-price balancing system. The storage system 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.

In Pandžić *et al.* [12], the coordination of a WF, a PV power plant, PHS and a gas turbine is proposed. Therefore, three sources of uncertainty are considered: WF output, PV output and spot prices. The optimal dispatch is formulated as a MILP that maximises the weekly profit while considering the long-term bilateral contracts, which must be fulfilled. Also, to address the mentioned uncertainties, a stochastic scenario-based framework is used. Each scenario provides a certain amount of surplus electricity; thus the solution in each hour must satisfy all the constraints for the worst-case scenario.

2.3 Forecasting models to predict renewable power generation and spot prices

With the current integration of wind and solar power tendency, a new paradigm is needed. The idea of operational flexibility takes on increasing importance to ensure that supply and demand meet even though both are variable and uncertain. A significant number of techniques have been discussed for accurate forecast in recent decades, thus forecasting being a crucial tool which serves to reduce the uncertainty associated with wind and solar power output.

Research studies use statistical, computational intelligence or even combined forecasting methods. Within the scope of statistical models, GARCH, ARIMA and the respective time series with exogenous variables are among the most notable approaches. In the context of computational intelligence, neural networks, fuzzy systems and support vector machines are among the primary classes.

Preliminary studies about forecasting considered persistence and traditional statistical methods and, even until recently, forecasting was highly influenced by statistical models. However, when literature is analysed, statistical methods should not be preferred since these cannot adapt to nonlinear data and cannot handle large amounts of data quickly. Computational intelligence methods use historical data to learn stochastic dependency between the past and the future. These models are flexible, can handle complexity and non-linearity, making them promising for short-term predictions.

Concerning wind generation, the amount of power that might be generated by a wind turbine is linked to the wind speed by a power curve. Therefore, accurate forecasting wind speed plays a crucial role.

In Erdem & Shi [13], four ARMA based approaches are employed to forecast wind speed and direction. Mean absolute error is used for assessing the quality of the forecasts in two different locations. For the first site, 164 days are used to construct the models, and ten days are forecasted. Wind speed and direction are evaluated to be slightly correlated. To generalise the findings, a second site with fewer available observations (31 days) and a higher correlation coefficient between attributes is analysed. In both sites, the traditional ARMA model achieves lower mean absolute error in forecasting wind speed. However, when it comes to wind direction, the results vary depending on the correlation level between wind speed and direction. If a higher correlation is noticed, a vector autoregression model performs better since it can capture relationships between attributes.

Demolli *et al.* [14] focuses on forecasting wind power generation concerning daily wind speed data using multiple machine learning methods, namely LASSO, kNN, xGBoost, random forest and support vector regression (SVR). The best parameters for each method are selected using a trial-and-error approach, and the dataset for the studies is constituted by five years of hourly wind speed observations in which four years are used as a training set. In a case study, forecasting is carried out in 4 locations with different wind characteristics; thus 4 test sets are selected to test the algorithms. Among the methods, SVR produces the best results. Nevertheless, it is shown that all the tested algorithms are powerful in forecasting in other locations than the ones in which the model was trained.

In Qing & Niu [15], 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. Three different experiments are performed with three years of data, a random split of the dataset and 11 years of data. Even though a random split is not an actual prediction task, it allows evaluating generalisation capability. Experimental results show that the proposed algorithm is more accurate, shows less overfitting and better generalisation capability when compared to a multilayer perceptron model.

As formerly mentioned, combining forecasting methods are also studied. Dewangan *et al.* [16] aims to create a hybrid forecasting model for day-ahead solar power. By combining machine learning methods, accuracy can be improved, and the computational burden can be reduced. Linear regression, SVR with different kernel functions, tree-based regression, feed-forward neural network and LSTM are among the eight tested methods. Hourly and for all hours models are prepared. The performance for all hours model was found better and less computationally expensive. The best performing basic models during cross-validation were SVR, tree-based regression and LSTM, therefore, being the ones considered to the formulation of the final combined method.

Apart from renewable generation, spot prices are another source of uncertainty that must be considered. Day-ahead and intraday spot prices are not known beforehand. Therefore, an accurate price forecast has a definitive impact on the bidding strategy. Predicting the prices of electricity for the coming days is of foremost importance for producers to develop bidding strategies or adjust their bids.

In Kahni & Zadeh [17] a CAES unit is used as the ESS to explore arbitrage opportunities. The price forecasting is considered and an algorithm to forecast the future prices is proposed. Initially, the actual prices of the last 24h are considered future prices. However, the algorithm continuously calibrates the price forecast based on the amount of price under/over-forecasted in the past several hours through scaling and offset calibration coefficients. The proposed algorithm collects 83% of ideal revenue (perfect forecasting), outperforming the conventional method (62%) and the back-casting approach (72%).

In Contreras *et al.* [18], ARIMA models are developed to predict day-ahead spot prices in the electricity markets of Spain and California. As a result of the Spanish market's higher volatility, its ARIMA model needs data from the previous 5 hours while the Californian one needs only 2 hours. The demand is introduced as an explanatory variable in both markets, while available hydro production is also introduced in the Spanish model. Without explanatory variables, average errors are 10% in the Spanish market and 11% in the Californian. With explanatory variables, errors are 10% and 5%, respectively. In Spain, explanatory variables are only needed in months with high correlation between available hydro production and price, since in any other month the effect is cancelled out.

A hybrid model for day-ahead electricity price is proposed in Yang *et al.* [19]. Since real price data are non-linear and non-stationary, both non-linear and linear predictions must be considered. This hybrid method is based on the wavelet transform, ARMA and a feed-forward neural network using particle swarm optimisation during the training process. Wavelet transform decomposes the price series in stationary and non-stationary series whilst ARMA predicts the stationary series and the non-stationary ones are forecasted by the neural network. This novelty is applied to the Pennsylvania - New Jersey - Maryland interconnection, Australian and Spanish markets where the hybrid model outperforms the individual models and even other hybrid models.

As can be seen from previous studies, forecasting and energy storage are often studied independently. In Hodge *et al.* [20] the impact of renewable forecasting and electricity storage is examined. Their use, independently and cooperatively, in power system operations is studied in markets with different generation mixes and multiple levels of renewable integration. Two day-ahead forecasting improvement scenarios and two different storage penetration scenarios modelling a generic BESS are implemented. Even though electricity storage creates relatively more considerable savings, this does not imply that storage investments are more beneficial. The storage scenarios examined would likely have more significant capital investment costs than the forecasting ones. Overall, it is concluded that the value of both flexibility options is neither reduced nor increased when both are utilised. However, for instance, storage use is restricted to provide only energy and not ancillary services. In this case, more accurate forecasts could produce better estimates and allow more optimal usage of storage.

2.4 Economic analysis of energy storage systems operating in competitive electricity markets

Energy storage is portrayed as the ideal solution to ensure the integration of renewable energy. However, current storage systems still face many limitations, especially regarding technology costs. Even though these costs are decreasing because of these technologies' improvement, it is still a controversial topic.

The commercial viability of PHS, CAES or thermal storage in conjunction with a wind farm is determined in Hessami & Bowly [21]. To reliably compare such different storage systems, the best possible revenue for each needs to be found. Therefore, simulations over three years are undertaken for a wide range of storage sizes and output ratings to find the rate of return for each. Since for each considered time step, there are three possible actions: charge, discharge and bypass, there are 3n possible decisions. Dynamic programming is then used to reduce the number of outcomes. If two paths achieve the same revenue, the one with lower storage level must be discarded since it is a suboptimal solution. 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 to optimise power exchange with the grid is presented in Barsali *et al.* [22]. An optimisation technique based on dynamic programming is implemented and tested with different storage sizes considering losses. Based on revenues, net present value (NPV), internal rate of return (IRR) and payback period (PP) for the most promising storage solution is performed. Then, the NPV is evaluated imposing different depth of discharge limits. The investment only becomes viable with a depth of discharge of 50%. Taking into account current investment costs in storage technology, profitability is still strictly dependent on price patterns and power profiles.

Loudiyi & Berrada [23] aims to present an economic analysis on a hybrid renewable system consisted of storage and solar PV. An operation algorithm to maximise the profit by optimally scheduling the dispatch of the storage is presented. The cost per kWh of stored electricity is the methodology used to compare ten different technologies (from Li-ion to Zinc Air batteries). The investment, operation, maintenance and replacement costs are considered, and the annual interest rate is assumed to be 5%. 4 case studies considering a different number of annual operating days on both generation, transmission and distribution storage systems are studied. As expected, PHS has the lowest cost. However, CAES follows it closely, thus being a reasonable alternative in the near future.

Also, in Cai *et al.* [24], the viability of a BESS to balance forecast errors and operate as balancing energy for a wind farm in the German day-ahead market is studied. The profit associated with balancing the forecast errors is simulated in 2011 and 2050. The reference price associated with the BESS operating strategy is assumed as the average price of balancing energy. The economic benefit of BESS in the future (2050) using lead-acid, sodium-sulfur and lithium-ion batteries is assessed as advantageous.

It is estimated that by coupling the WF and the BESS, the gain per MW could increase by approximately 33% with the three contemplated technologies.

2.5 Research gaps and challenges

In the studies mentioned above, the joint operation of both WFs and PV resources and storage systems in energy (day-ahead and intraday) and balancing markets is not considered. None of them has simultaneously determined the bid strategy for participation in energy and ancillary service markets by considering price uncertainty. In a large share of storage-related literature, the information on renewable generation is used without proper forecasting, and the perfect foresight of future prices is assumed.

Also, the view on this topic has traditionally been based on stochastic models and boils down to a set of responses or possibilities and not an absolute operating solution, as is the purpose of this work. In this work, the problem is addressed from a producer's perspective; thus, the goal is to obtain an effective operation of the renewables and storage system in the existent Iberian electricity market (MIBEL). The structure, timeline and market closure times are methodically respected.

Additionally, the prevailing energy storage system considered in joint operation for the above-mentioned purposes is PHS, showing a lack of optimisation models that consider the short-term operation of renewables with other technologies.

In this thesis, literature is extended by considering every dimension of the problem: forecasting, optimisation, and economic evaluation. The value of energy storage when operating cooperatively with both wind and solar generation (balancing service) and performing energy arbitrage at all three short-term markets (DA,ID and RT) is investigated. Emphasis is given to the fact that a battery is chosen as the storage system, notwithstanding most of the literature.

The operation strategies are very sensible and dependent on power generation and price forecasts; thus, the choice of the forecast tool is of utmost importance. Therefore, the forecasting of renewable power production and market spot prices are carefully considered in this thesis, using deep learning-based techniques, specifically LSTM networks. This method is considered well-suited to make predictions based on time series data.

Furthermore, a case study is used to analyse the influence in the revenues and optimal operation of the chosen storage system. Even though the benefits of storage are well known, the viability and cost-effectiveness of these technologies remains debatable. For this reason, the economic viability of the BESS is also studied.

3

Proposed Models

Contents

This chapter provides a global review of the proposed models used throughout this work in the considered dimensions. From power generation to economic models, forecasting and optimisation, the used models as well as the main reasons behind those choices and formulations are explained.

In the first section, the considered representations of the WT and solar panel are presented. In section 3.2, the forecasting model theoretical background and implementation are specified. Section 3.3 addresses in detail the objective functions and system constraints of the designed optimisation strategies. The last section points out the considered economic models.

3.1 Renewable Generation

The considered agent's portfolio is constituted by renewable power plants. Therefore, the solar PV and WT models that comprise the power plants must be contemplated in this thesis.

3.1.1 Wind Turbine

Wind speed is the primary factor influencing power output originated from a WT. The WT output can be calculated via wind speed data and power curves which are prepared by wind turbine companies. Power curves express the approximate cubic relationship between wind speed and power considering the specific range of wind speeds in which the turbine is designed to operate.

In this study, Enercon E-70 E4 is the chosen turbine and its power curve, cut-in, rated, and cut-out speeds are provided in a WT database [25]. To obtain the corresponding power curve graph, an algebraic equation of degree *n* can be formulated according to the given WT specifications, as contemplated in [14]. The equation variables are approximated using the *Curve Fitting Toolbox* [26]. The obtained equation is used to model the WT behaviour, enabling to determine the generated power by each installed turbine, based on the hourly wind speed.

The resulting power curve is described by equation 3.1 and can be observed in Figure 3.1. It is possible to recognise different regions in the power curve: below cut-in speed, and above cut-out speed, no power is generated, between cut-in and nominal speed the WT generates a sub-rated power and between the nominal speed and cut-out speed, the WT generates the rated power.

$$P_w(v) = \begin{cases} 0, & v < 2.5 \\ 0.02 \cdot v^5 - 1.17 \cdot v^4 + 21.51 \cdot v^3 - 144.7 \cdot v^2 + 432.3 \cdot v - 449.5, & 2.5 \leqslant v < 14 \\ 2.3, & 14 \leqslant v < 34 \\ 0, & v \geqslant 34 \end{cases} \text{[MW]} \quad (3.1)$$

where P_w is is the output power of the WT and v is the wind speed.

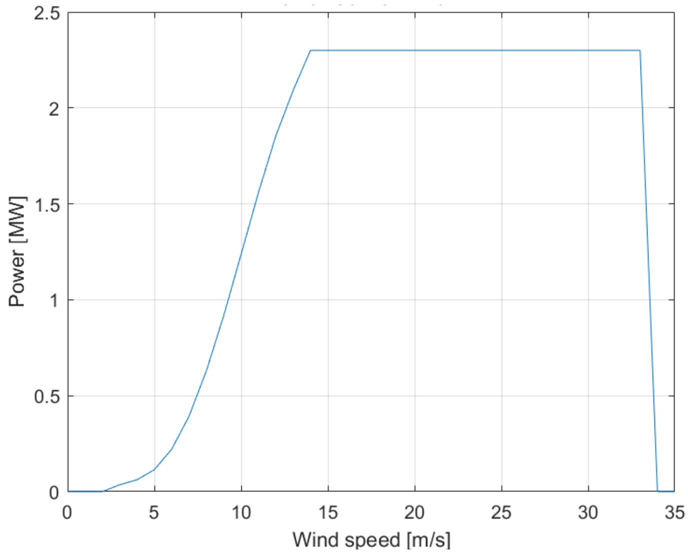


Figure 3.1: Power curve for Enercon E-70 E4 (2.3 MW)

3.1.2 Solar Panel

The power generated by a solar panel depends on several factors. Accurate solar generation computations need to display the dependence of efficiency on module operating temperatures and irradiance levels, among other factors. These characteristics cannot be disregarded since this sensibility causes the actual efficiency to be different from the rated one, consequently generating less power than in optimal conditions. The selected solar panel specifications can be found at [27].

The formulation used to model the relation between the variables mentioned above and the power generated hourly by each panel are described by equations 3.2-3.3.

$$T_{PV} = T_{amb} + G \cdot \frac{T_{NOCT} - 20}{800} \text{ [°C]} \tag{3.2}$$

$$P_S = P_{max} \cdot \frac{G}{1000} \cdot (1 + k_t \cdot (T_{PV} - 25)) \text{ [W]} \tag{3.3}$$

where T_{PV} is the cell temperature,T_{amb} is the ambient temperature, G is the irradiance, T_{NOCT} is the nominal operating cell temperature, P_s is the output power of the solar panel, P_{max} is the nominal output power at standard test conditions, and k_t is the temperature coefficient of P_{max}.

3.2 Long-Short Term Memory

In this thesis, a LSTM network [28] is the chosen model to forecast the unknown variables. LSTMs have shown remarkable results in numerous time-series learning tasks, being considered one of the most advanced RNN.

3.2.1 Theoretical Background

RNNs are a family of artificial neural networks (ANNs) that have recurrent connections, as shown in Figure 3.2, and thereby, allow to exhibit temporal behaviour. Unlike ANNs, the hidden layers of the front and back time steps are connected, keeping track of previous output and allowing information to persist.

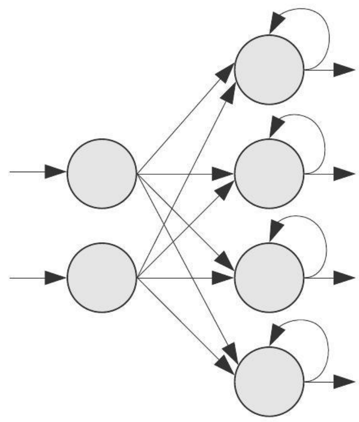


Figure 3.2: Recurrent neural network architecture

Computations consider historical information and weights are shared across time. Thus, this class of neural networks is naturally suited to process time-series data and other sequential data [29]. RNNs have a hidden state (h_t), an external input (x_t) and output (y_t). At time step *t*, the model updates its memory using equation 3.4. As it is characterised in Figure 3.3, the circles represent the network layers, and the lines represent the weighted connections.

$$h_t = \sigma(W_x \cdot x_t + W_h \cdot h_{t-1} + b_t) \tag{3.4}$$

$$y_t = \sigma(W_y \cdot h_t + c_t) \tag{3.5}$$

where σ is a nonlinear function, W_x,W_h and W_y are weight matrices, and b_t and c_t are bias terms.

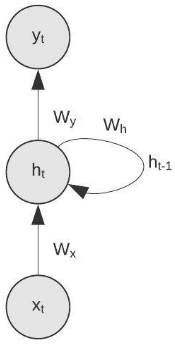


Figure 3.3: Recurrent neural network operations

RNNs can be divided into different types, depending on the relationships within the graph. Thus, the architecture must be chosen based on the problem to be solved. These architectures are one to one (as it is depicted in Figure 3.3), one to many, many to one and many to many. As the name suggests, one to one is the case in which a single input is required to give a single output (for instance, image classification). In contrast, one to many (i.e. one input to various outputs) can be an application in image recognition (for example, a case of an image described by words).

However, 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 [30]. Thus, RNNs have difficulties in learning long-term dependencies and cannot bridge if time lags are greater than 5-10 time steps [31].

To overcome this problem, RNNs were improved, leading to the emergence of LSTM networks, whose key idea is the use of memory cells. The architecture of an LSTM cell is shown in Figure 3.4.

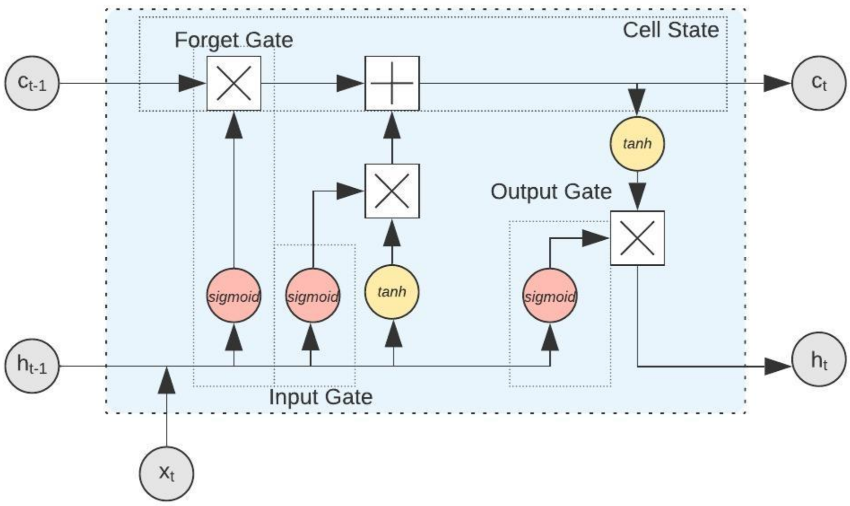


Figure 3.4: Long short-term memory cell

To avoid the multiplicative effect, information is flowed 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 forget gate decides to preserve or to remove the information by using a *sigmoid* function. The output of this gate (f_t) is a value between 0 and 1, where 0 indicates to remove the value, and 1 means preserving the value. Whenever previous information becomes irrelevant for some cells, the cell state can be reset [32]. The output is computed as described in equation 3.6.

$$f_t = \sigma(W_{f_h}[h_{t-1}], W_{f_x}[x_t], b_f) \tag{3.6}$$

The input gate decides storing new information in the LSTM memory. Thus, preventing irrelevant information from entering the memory block. A first *sigmoid* layer (i_t) decides which values to updated and the second *tanh* layer (c_t) creates a vector of new possible values that will be added into the memory. The cell state will be updated considering the input gate, and the output of the previously stated forget gate (equations 3.7-3.9).

$$i_t = \sigma(W_{i_h}[h_{t-1}], W_{i_x}[x_t], b_i) \tag{3.7}$$

$$c_t = \tanh(W_{c_h}[h_{t-1}], W_{c_x}[x_t], b_c) \tag{3.8}$$

$$c_t = f_t * c_{t-1} + i_t * c_t \tag{3.9}$$

Finally, the output gate (o_t) uses a *sigmoid* layer to decide what part of the memory contributes to the output and a *tanh* function to scale the values between -1 and 1, as explained in equations 3.10-3.11.

$$o_t = \sigma(W_{o_h}[h_{t-1}], W_{o_x}[x_t], b_o) \tag{3.10}$$

$$o_t = o_t * \tanh(c_t) \tag{3.11}$$

Even though the described methodology has outputs at each time step, this may not happen depending on the task, since only the final output might be necessary. Similarly, inputs at each time step might not be needed.

3.2.2 Implementation

Day-ahead and intraday prices are some of the mentioned variables which must be predicted. Its respective datasets used to train and test the LSTM network were collected on REN's website [33]. Likewise, the irradiance, temperature and wind speed datasets, used to train and test the developed network, were collected in Solcast [34].

Data is split into two subsets: a training set and a test set. The training set is used to train the models; it establishes weights between the nodes of the network. The test set performs a final evaluation of the generated output. In order to evaluate the model's performance, the root-mean-square error (RMSE) (equation 3.12) was the chosen metric to measure the prediction accuracy.

$$\text{RMSE} = \sqrt{\sum_{i=1}^{n} \frac{(\hat{y}_i - y_i)^2}{n}} \tag{3.12}$$

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

When evaluating the performance, the persistence model was used as a reference, which is a standard approach in the literature. The persistence model (equation 3.13) does not consider the effects of change in the inputs. It merely assumes that the present conditions will repeat for the specified time horizon.

$$\hat{y}(t) = y(t - T) \tag{3.13}$$

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

Before applying data to an algorithm, it is necessary to pre-process it. In this case, since there are no missing values in the dataset, there is no need to evaluate replacing techniques. Data is standardised based on the training set values. This procedure is the process of rescaling data to have a zero mean and unit variance.

The *Deep Learning Toolbox* [35] was used to develop the forecasting framework. The considered architecture for the implemented LSTM has four layers, namely a sequence input layer (which size corresponds to the number of features of the input data), an LSTM layer with a chosen number of hidden units, a fully connected layer (which size matches the number of responses) and a regression output layer.

The fully connected layer contains memory cells and corresponding gate units. All units in all layers have direct connections to all units in the layer above. The number of hidden units corresponds to the amount of information remembered between time steps. The hidden state can contain information from all previous time steps. Consequently, it is essential to consider the number of hidden units carefully. If the number of hidden units is too large, then the layer might overfit to the training data.

To forecast values of future time steps of a sequence, the LSTM needs to be trained with sequences shifted by one-time step. Each time step of the input sequence, the network learns how to predict the value of the next one. Furthermore, for a time series problem, it is vital to maintain temporality in the data so the LSTM network can learn patterns from the correct sequence of events.

Achieving good performance with LSTM networks requires optimisation of many hyperparameters.

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 [36]. 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. It is empirically and theoretically proven that trials are more efficient than the computationally expensive exhaustive grid search [37]. The hyperparameters are not equally essential, and grid search ends up allocating excessive resources on specific ranges and on hyperparameters that might be of minor relevance [38]. Thus, for each forecasting problem, namely for the weather variables and spot prices, the hyperparameters are set using a trial-and-error approach.

The optimisation solver is responsible for the minimisation of the objective function of the neural network. Three optimisation solvers were evaluated within the recommended settings, namely *sgdm* [39], *rmsprop* [40] and *adam* [41]. The learning rate is often the most important hyperparameter [42]. However, choosing an appropriate value can be a difficult task: if the learning rate is small, although it guarantees a local minimum is not missed, it also means that the network takes a long time to reach convergence; if it is large, there is an extensive loss fluctuation during training, and it is difficult to converge [43]. The *sgdm* uses a single learning rate for all parameters. On the contrary, *rmsprop* and *adam* use learning rates that differ by parameter and can adapt to the loss function being optimised [44].

The number of units, as long as it is not too large or too small, has only a slight effect on the results. A value of about 100 units for each LSTM is seen as a good rule of thumb [38]. Naturally, a small neural network is preferred since it will take less time than a bigger network. Also, it will incur drastically less economic costs as large-memory machines are not required [36].

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.

3.3 Optimisation Framework

The optimisation framework presented in this dissertation proposes three algorithms to maximise the revenues and minimise the imbalances deriving from the difference between contracted and real renewable production. All algorithms are deterministic and require two types of data inputs: forecasted spot prices and forecasted renewable power production. This input data comprises periods of 1-hour values. By using predictions instead of past values, a realistic simulation can be solved, returning optimal hourly bids and system operation to be followed by the agent. All algorithms described in this section are divided into hourly periods considering one day. However, the algorithm can easily be modified to execute the operation throughout a whole year.

The first algorithm to be executed defines the purchasing and selling bids that will be submitted to the day-ahead electricity market based on the input information of forecasted day-ahead spot prices and forecasted wind and solar power production. The second uses updated renewable production forecasts and intraday spot price forecasts to improve its strategy. Explicitly, the algorithm determines the bids which must be submitted to the ID market, which is a daily adjustment market nearer the energy delivery time. Finally, the third algorithm considers actual real-time production allowing imbalance minimisation, as well as the participation in the existing balancing RT markets.

Regarding the computational implementation of the strategies mentioned above, the formulated problems are all MILPs which are modelled in GAMS and solved using the CPLEX solver. This combination allows users to combine high-level modelling capabilities of GAMS with the power of CPLEX optimisers. CPLEX uses a branch and cut algorithm which solves a series of linear programming and subproblems [45]. Additionally, for better model development and more accessible result analysis, MATLAB was used as an interface for GAMS [46].

Figure 3.5 describes the overall operation of the three developed strategies.

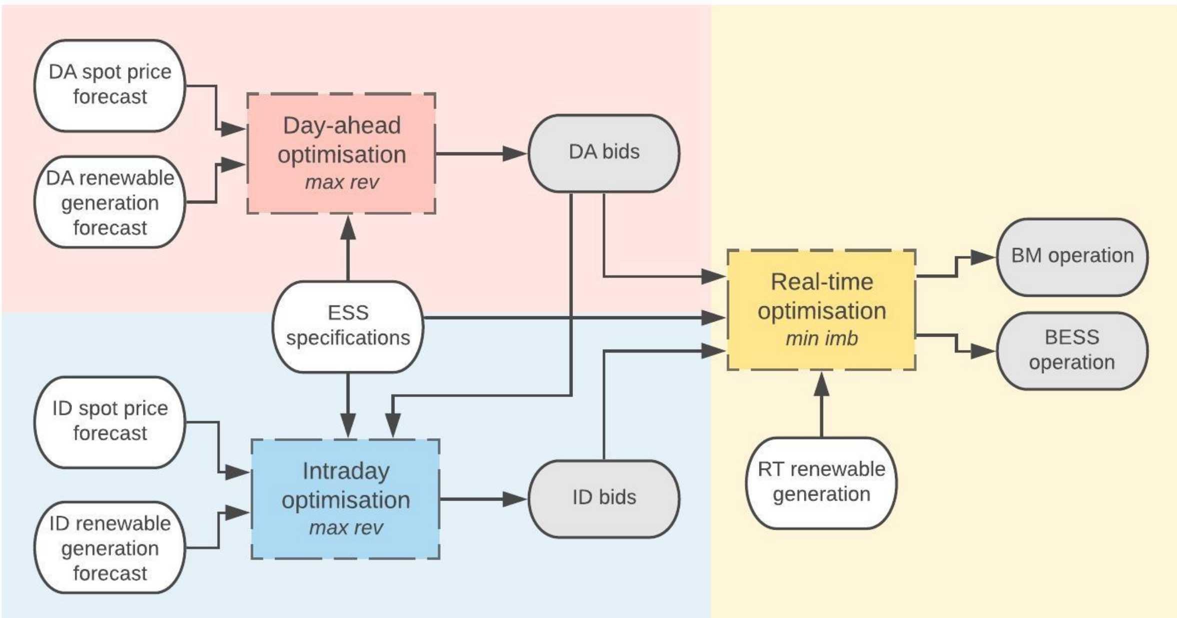


Figure 3.5: Diagram of the overall operation

As it is shown in Figure 3.5, the DA model uses as input short-term power generation and spot prices, as well as the storage system parameters. The algorithm performs an optimisation that defines the bids to be offered in the DA market. The accepted bids are then used as inputs in the ID model which, using intraday spot price forecast and updated renewable power forecasts, performs a new optimisation problem which is updated the hour before the closure of the next intraday session. The accepted bids of both previous markets are used as inputs in the RT model, which is run every hour, using actual RES production. This final algorithm defines the storage operation points and the reserve market bids with the main purpose of minimising imbalances. The detailed operation of each algorithm is clarified in the succeeding subsections.

3.3.1 Day-Ahead Model

Regarding DA optimisation, all agents operating in the 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. Thus, since all units are coordinated (WF, PV power plant, ESS), 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 (the so-called arbitrage). The problem is solved according to the input information of forecasted day-ahead spot prices and forecasted renewable power production.

However, forecasts and real values diverge; thus deviations between predicted power to be delivered and the real delivered power arise. The concept of imbalance costs derives from this power deviations. In the 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 system's operator must pay a regulation price. The regulation costs are calculated according to equation 3.14.

$$RC_h^{DA} = \begin{cases} imb_h^{DA} \cdot (sp_h^{DA} - sp_h^{+}), & imb_h^{DA} > 0 \\ -imb_h^{DA} \cdot (sp_h^{-} - sp_h^{DA}), & imb_h^{DA} < 0 \end{cases} \tag{3.14}$$

where RC_h^{DA} are the regulation costs at hour *h*, imb_h^{DA} is the imbalance at hour *h*, sp_h^{DA} is the day-ahead spot price at hour *h*, sp_h^{+} is the positive imbalance price at hour *h*, sp_h^{-} is the negative imbalance price at hour *h*.

Mathematically, this optimisation problem can be summarised by:

$$\text{max revenues} = \text{max} \sum_{h=1}^{24} [sp_h^{DA} \cdot (bid_h^{DA} + imb_h^{DA}) - RC_h^{DA}] \tag{3.15}$$

s.t.

$$g_h^{DA} + d_h^{DA} - c_h^{DA} - bid_h^{DA} = imb_h^{DA} \tag{3.16}$$

$$imb_h^{DA} \cdot (sp_h^{DA} - sp_h^{+}) \leqslant RC_h^{DA} \tag{3.17}$$

$$- imb_h^{DA} \cdot (sp_h^{-} - sp_h^{DA}) \leqslant RC_h^{DA} \tag{3.18}$$

$$c_h^{DA} \leqslant p_{ESS}^{max} \cdot x_{c_h} \tag{3.19}$$

$$d_h^{DA} \leqslant p_{ESS}^{max} \cdot x_{d_h} \tag{3.20}$$

$$x_{c_h} + x_{d_h} \leqslant 1 \tag{3.21}$$

$$soc_h = soc_{h-1} + \eta \cdot c_h^{DA} - d_h^{DA} \tag{3.22}$$

$$0 \leqslant soc_h \leqslant e_{ESS}^{max} \tag{3.23}$$

$$soc_1 = soc_{24} = 0 \tag{3.24}$$

$$-p_{ESS}^{max} \leqslant bid_h^{DA} \leqslant p_{ESS}^{max} + P_{wind}^{max} + P_{PV}^{max} \tag{3.25}$$

where sp_h^{DA} is the predicted day-ahead spot price at hour *h*; bid_h^{DA} is the bid to submit in the day-ahead market for hour *h*; imb_h^{DA} is the power deviation at hour *h*; RC_h^{DA} are the regulation costs at hour *h*; g_h^{DA} is the predicted renewable power production at hour *h*; d_h^{DA} is the storage system discharge at hour *h*; c_h^{DA} is the storage system charge at hour *h*; sp_h^+ and sp_h^- are the additional costs for a positive and negative imbalance at hour *h*, respectively; x_{c_h} is the percentage of the hour when the ESS is charging; x_{d_h} is the percentage of the hour when the ESS is discharging; soc_h is the ESS state of charge at hour *h*; e_{ESS}^{max} and p_{ESS}^{max} are the ESS maximum energy and power specifications; P_{wind}^{max} is the wind installed capacity, and P_{PV}^{max} is the PV installed capacity.

The objective function (equation 3.15) aims to maximise the market profit of the joint operation of renewables and an ESS. Apart from the variable regarding the bid to the day-ahead market (bid_h^{DA}), all variables must have positive values; thus, its minimum limits are equal to zero. The minimum bid offer is defined by the ESS installed capacity (since it can be charged through the market) and the maximum bid offer (equation 3.25) is defined by the sum of the ESS, wind and solar installed capacities which is the maximum power the joint system can produce. The bid to be submitted is optimised according to the predicted renewable power production (g_h^{DA}) and the ESS operation while considering the regulation costs (equations 3.17-3.18), as it was previously defined in equation 3.14.

However, equation 3.14 describes a continuous piecewise linear convex function. Thus, to be computed, it needs to be transformed into an equivalent linear function, taking the form presented in equations 3.16-3.18. The hourly regulation costs (RC_h^{DA}) are defined as a positive slack variable, hence can take three different values: zero when there is no imbalance, $imb_h^{DA} \cdot (sp_h^{DA} - sp_h^+)$ when the imbalance is positive ($imb_h^{DA} > 0$) and $-imb_h^{DA} \cdot (sp_h^- - sp_h^{DA})$ when the imbalance is negative ($imb_h^{DA} < 0$).

The storage system operation is described by equations 3.19-3.24. The system restriction on charging and discharging simultaneously is represented in equations 3.19-3.21. Within one hour, the system is allowed to charge and discharge but not both at the same time. The balance of energy stored in the ESS at hour *h* is obtained by equation 3.22 by adding or subtracting the energy corresponding to the charge or discharge of the BESS to the previous hour stored energy, affected by the charging efficiency of the BESS. Also, equation 3.24 defines the initially stored energy and the planned final energy after the day-ahead scheduling.

3.3.2 Intraday Model

After the DA market, the ID market takes place. In the MIBEL, the ID market is structured in 7 sessions throughout the day with various scheduling times, allowing flexibility in the operation and optimisation of the agents' portfolio. Table 3.1 describes the intraday market configuration.

Table 3.1: Sessions of the intraday market

	Session 1	Session 2	Session 3	Session 4	Session 5	Session 6	Session 7
Opening	17h	21h	1h	4h	8h	12h	16h
Closure	18h45	21h45	1h45	4h45	8h45	12h45	18h45
Scheduling Horizon	22h-24h	1h-24h	5h-24h	8h-24h	12h-24h	16h-24h	21h-24h

The high variability of the wind speed and irradiance leads to uncertainty in renewable power forecasting, increasing the possibility of imbalances. The ID optimisation aims to maximise the profit by participating in the multiple daily sessions using the new updated renewable production forecasts and intraday spot price forecasts to update its strategy. The algorithm performs a new optimisation with a sliding window approach from the first to the last hour of the day. Concerning the sliding window approach, first, the initial conditions are specified, then optimisation is performed in the sliding window width hence obtaining the operating points and, finally, the window slides forward in time. This process is repeated until the last hour of the day is reached.

Figure 3.6 depicts a diagram illustrating the ID strategy, assuming that updated renewable power forecasts are available before the closure of the current market session; thus, allowing more accurate bids to adjust the operation of the joint system. Red represents the current hour; blue represents the already defined intraday bids; yellow represents the hours to be scheduled in the session, which is about to close.

Considering, for instance, the optimisation of the third ID session (which closes at hour 2), the algorithm receives as input the ID prices of that session, updated renewable power forecast and day-ahead bids for hours 5 to 24. The optimisation is made considering that period and the bids referring to the hours 5 to 7 are explicitly defined in hour 2 since there is no further possibility to bid in these hours in the forthcoming intraday sessions. This process is repeated until the last market session. At the end of the ID optimisation, the bid values for all hours are known.

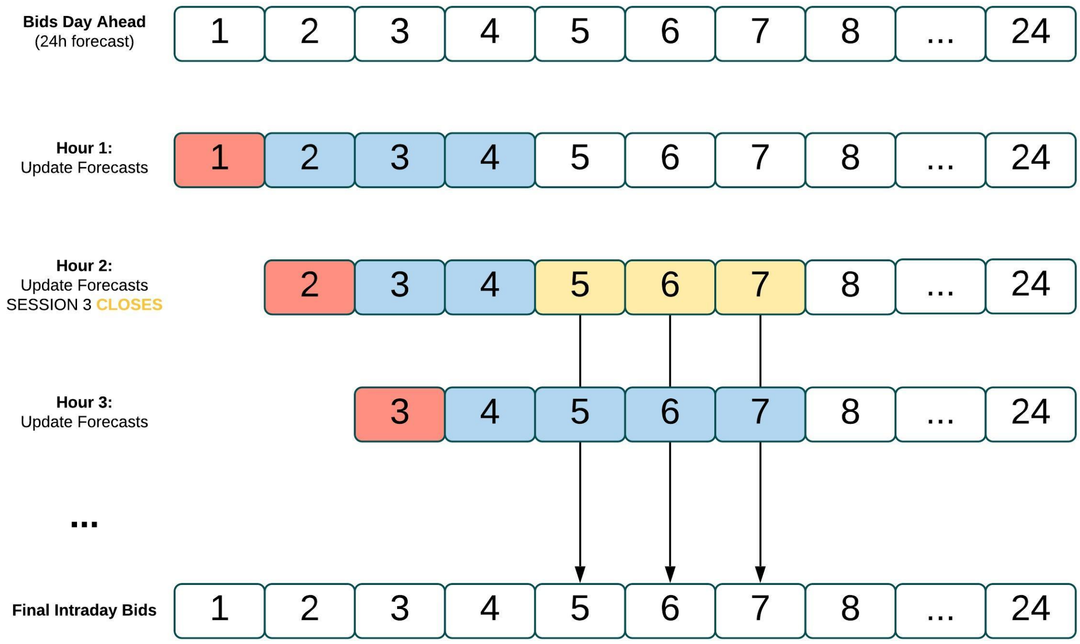


Figure 3.6: Diagram of the rolling window approach for the intraday strategy

Mathematically, this optimisation problem can be described by:

$$\text{max revenues} = \max \sum_{h=1}^{24} [sp_h^{DA} \cdot (bid_h^{DA} + imb_h^{DA}) - RC_h^{DA} + sp_h^{ID} \cdot bid_h^{ID}] \tag{3.26}$$

s.t.

$$g_h^{DA} + d_h^{DA} - c_h^{DA} - bid_h^{DA} = imb_h^{DA} \tag{3.27}$$

$$imb_h^{DA} \cdot (sp_h^{DA} - sp_h^{+}) \leqslant RC_h^{DA} \tag{3.28}$$

$$- imb_h^{DA} \cdot (sp_h^{-} - sp_h^{DA}) \leqslant RC_h^{DA} \tag{3.29}$$

$$g_h^{DA} + g_h^{ID} = p_h^{for} \tag{3.30}$$

$$c_h^{DA} + c_h^{ID} \leqslant p_{ESS}^{max} \cdot x_{c_h} \tag{3.31}$$

$$d_h^{DA} + d_h^{ID} \leqslant p_{ESS}^{max} \cdot x_{d_h} \tag{3.32}$$

$$x_{c_h} + x_{d_h} \leqslant 1 \tag{3.33}$$

$$soc_h = soc_{h-1} + \eta \cdot (c_h^{DA} + c_h^{ID}) - (d_h^{DA} + d_h^{ID}) \tag{3.34}$$

$$0 \leqslant soc_h \leqslant e_{ESS}^{max} \tag{3.35}$$

$$soc_1 = soc_{24} = 0 \tag{3.36}$$

$$bid_h^{ID} = \begin{cases} 0, & bid_h^{DA} = 0 \\ g_h^{ID} + d_h^{ID} - c_h^{ID}, & bid_h^{DA} \neq 0 \end{cases} \tag{3.37}$$

where: sp_h^{DA} is the predicted day-ahead spot price at hour *h*; bid_h^{DA} is the bid to submit in the day-ahead market for hour *h*; imb_h^{DA} is the power deviation from the day-ahead bid at hour *h*; RC_h^{DA} are the regulation costs from the day-ahead market at hour *h*; sp_h^{ID} is the predicted intraday spot price at hour *h*; bid_h^{ID} is the bid to submit in the intraday market for hour *h*; g_h^{DA} is the predicted renewable power production assigned to the day-ahead market at hour *h*; d_h^{DA} is the storage system discharge in the day-ahead market at hour *h*; c_h^{DA} is the storage system charge in the day-ahead market at hour *h*; g_h^{ID} is the predicted renewable power production assigned to the intraday market at hour *h*; d_h^{ID} is the storage system discharge in the intraday market at hour *h*; c_h^{ID} is the storage system charge in the intraday market at hour *h*; p_h^{for} is the renewable power forecast at hour *h*; sp_h^+ and sp_h^- are the additional costs for a positive and negative imbalance at hour *h*, respectively; x_{c_h} is the percentage of the hour when the ESS is charging; x_{d_h} is the percentage of the hour when the ESS is discharging; soc_h is the ESS state of charge at hour *h*; e_{ESS}^{max} and p_{ESS}^{max} are the ESS maximum energy and power specifications.

The objective function is expressed by equation 3.26 and purposes to maximise the revenues in the ID market, considering the updated forecasts regarding power production and prices. The first term refers to the DA market. The power deviation (imb_h^{DA}) is defined as the difference between the bids made by the day-ahead algorithm and the new operation points (equation 3.27). The absolute value of regulation costs is taking into account using the slack variable RC_h^{DA} (equations 3.28-3.29), which is calculated as it was previously described in equation 3.14. Equation 3.30 assures that all the forecasted renewable power is used, either in the day-ahead or intraday strategy. Equations 3.31-3.36 are similar to the ones used in the DA optimisation and define the storage system operation, now considering the existence of the two markets. The possible bid offers in the ID market are defined by equation 3.37. The intraday bid at hour *h* must be given by the renewable forecast and storage system optimal operation point if the market participant had already participated in the respective hour of the day-ahead market. Otherwise, the agent is prohibited from submitting an offer for the given hour *h*.

3.3.3 Real-Time Model

The real-time algorithm is also based on a sliding window approach. It 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.

Figure 3.7 portrays the strategy applied to this market. Every hour, the algorithm outputs the final ESS operation points along with the operation of the ESS in the secondary regulation market (balancing market). The significant difference between the formerly described algorithms and the real-time strategy is the fact that the objective is not to maximise profits but to minimise the regulation costs by optimally operating the ESS and acting in the BM.

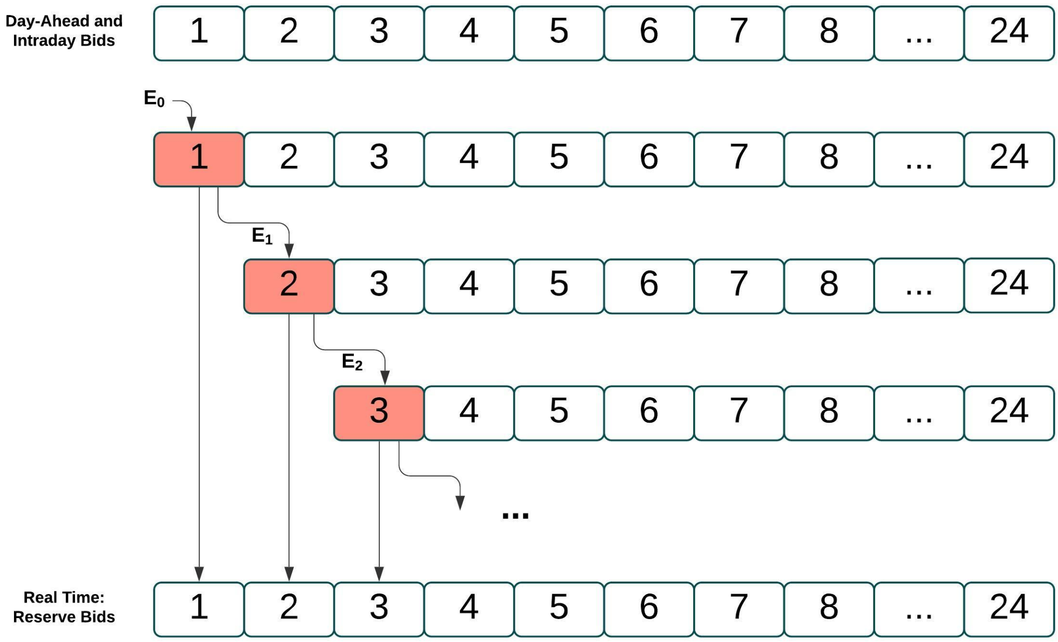


Figure 3.7: Diagram of the rolling window approach for the real-time strategy

In the MIBEL, the participation in the balancing market starts after the DA market closure, in day D-1. The agents offer its regulation bands with the corresponding prices for every hour of the following day bids. Then, these bids are drawn up in increasing price order. In RT, 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. Since it is not possible to know when a specific agent is chosen to mobilise or demobilise energy and to avoid unreasonable profit from the reserve market, in this thesis, the participation in the BM is restricted. It is assumed that the agent's participation in this market is limited to the mere minimisation of its imbalances.

Mathematically, the formulation of this optimisation problem is given by:

$$\text{min } RC = \text{min} \sum_{h=1}^{24} [RC_h^{DA} + RC_h^{ID}] \tag{3.38}$$

s.t.

$$g_h^{DA} + d_h^{DA} - c_h^{DA} - bid_h^{DA} = imb_h^{DA} \tag{3.39}$$

$$imb_h^{DA} \cdot (sp_h^{DA} - sp_h^{+}) \leqslant RC_h^{DA} \tag{3.40}$$

$$imb_h^{DA} \cdot (sp_h^{-} - sp_h^{DA}) \leqslant RC_h^{DA} \tag{3.41}$$

$$g_h^{ID} + d_h^{ID} - c_h^{ID} - bid_h^{ID} = imb_h^{ID} \tag{3.42}$$

$$imb_h^{ID} \cdot (sp_h^{ID} - sp_h^{+}) \leqslant RC_h^{ID} \tag{3.43}$$

$$imb_h^{ID} \cdot (sp_h^{-} - sp_h^{ID}) \leqslant RC_h^{ID} \tag{3.44}$$

$$g_h^{DA} + g_h^{ID} = p_h^{real} \tag{3.45}$$

$$c_h^{DA} + c_h^{ID} + r_h^{d} \leqslant p_{ESS}^{max} \cdot x_{c_h} \tag{3.46}$$

$$d_h^{DA} + d_h^{ID} + r_h^{u} \leqslant p_{ESS}^{max} \cdot x_{d_h} \tag{3.47}$$

$$x_{c_h} + x_{d_h} \leqslant 1 \tag{3.48}$$

$$soc_h = soc_{h-1} + \eta \cdot (c_h^{DA} + c_h^{ID} + r_h^{d}) - (d_h^{DA} + d_h^{ID} + r_h^{u}) \tag{3.49}$$

$$0 \leqslant soc_h \leqslant e_{ESS}^{max} \tag{3.50}$$

$$soc_1 = soc_{24} = 0 \tag{3.51}$$

$$r_h^{d} \leqslant p_{ESS}^{max} \cdot k_h \tag{3.52}$$

$$r_h^{u} \leqslant p_{ESS}^{max} \cdot (1 - k_h) \tag{3.53}$$

where: RC_h^{DA} are the regulation costs from the day-ahead market at hour *h*; RC_h^{ID} are the regulation costs from the intraday market at hour *h*; sp_h^{DA} is the predicted day-ahead spot price at hour *h*; bid_h^{DA} is the bid to submit in the day-ahead market for hour *h*; sp_h^{ID} is the predicted intraday spot price at hour *h*; bid_h^{ID} is the bid to submit in the intraday market for hour *h*; imb_h^{DA} is the power deviation from the day-ahead bid at hour *h*; g_h^{DA} is the predicted renewable power production assigned to the day-ahead market at hour *h*; d_h^{DA} is the storage system discharge in the day-ahead market at hour *h*; c_h^{DA} is the storage system charge in the day-ahead market at hour *h*; imb_h^{ID} is the power deviation from the intraday bid at hour *h*; g_h^{ID} is the predicted renewable power production assigned to the intraday market at hour *h*; d_h^{ID} is the storage system discharge in the intraday market at hour *h*; c_h^{ID} is the storage system charge in the intraday market at hour *h*; p_h^{real} is the renewable power production at hour *h*; sp_h^{+} and sp_h^{-} are the additional costs for a positive and negative imbalance at hour *h*, respectively; r_h^{d} is the balancing market downward regulation at hour *h*; r_h^{u} is the balancing market upward regulation at hour *h*; x_{c_h} is the percentage of the hour when the ESS is charging; x_{d_h} is the percentage of the hour when the ESS is discharging; soc_h is the ESS state of charge at hour *h*; e_{ESS}^{max} and p_{ESS}^{max} are the ESS maximum energy and power specifications.

Opposed to the strategies used in the DA and ID optimisation, the RT objective function (equation 3.38) aims to minimise the regulation costs related to the absolute value of the imbalances between the submitted offers in the markets mentioned above and the real energy generated. The power imbalances in both DA and ID markets and the regulation costs incurred by them are described in equations 3.39-3.41 and equations 3.42-3.44, respectively. Equation 3.45 assures that all the power generated by the renewable power plants is used. Equations 3.46-3.50 are similar to the ones presented in the DA and ID strategies. These equations define the storage system operation concerning the markets in which the storage is allowed to operate, namely the DA, ID and RT (balancing market). The ESS participation in the BM is expressed by the variables r_h^d and r_h^u. The variable r_h^d concerns the downward regulation, which means the BESS is charging from the balancing market, and the variable r_h^u regards the upward regulation, that is when the BESS is discharging to the balancing market (equations 3.46-3.49). A binary auxiliary variable (k_h) was added to assure that the BESS is not providing upward and downward regulation in the balancing market at the same time (equations 3.51-3.52).

3.4 Economic Model

In this thesis, multiple BESS based on different technologies and specifications (thus different costs, lifespans, etc) are considered. Therefore, the profitability of those projects must be analysed and compared. After obtaining the system's optimal operation from the optimisation framework, it is necessary to estimate the expected revenues. To calculate the economic benefits of integrating a BESS, it is necessary to compute both revenues of the system with and without BESS, according to equation 3.54.

$$\text{Extra Profit} = \text{Profit}_{\text{with BESS}} - \text{Profit}_{\text{without BESS}} \tag{3.54}$$

To evaluate and select the best investment, two economic models for project selection are used: NPV and IRR. Based on these approaches, the decision to accept or reject investments is made. These metrics are among the most popular discounted cash flow methods and serve a different purpose. NPV measures the change in the net worth of the firm while IRR measures the rate of return for the investment [47]. Thus, NPV is more realistic when evaluating long-term projects, where the discount rate may change over time while IRR is especially relevant to compare projects with different lifespans or amount of required capital [48, 49]. Consequently, using only one metric to analyse projects is not recommended and would oversimplify the analysis.

3.4.1 Net Present Value

The economic model uses the extra profit obtained in the three short-term markets each year (equation 3.54) to calculate the NPV of the system. The considered discount rate is applied to the profit by equation 3.56. To establish an economic analysis, the BESS costs must be considered. The initial investment in the BESS (equation 3.57) is done in the year 0 and takes into account the energy capacity and power conversion costs of the contemplated BESS technology. Profits are considered from year one until the year the BESS replacement would eventually occur. In this study, the operations and maintenance costs have been neglected (equation 3.55).

$$CF_t = \text{Extra Profit}_t \tag{3.55}$$

$$NPV = \sum_{t=1}^{n} \frac{CF_t}{(1+i)^t} - I_0 \tag{3.56}$$

$$I_0 = c_E \cdot E + c_P \cdot P \tag{3.57}$$

where CF_t is the annual extra profit obtained with the BESS integration, i is the discount rate, n is the BESS lifetime, I_0 is the initial investment in the BESS, c_E is the energy capacity cost in €/kWh, c_P is the power conversion cost in €/kW, E is the energy capacity of the BESS in kWh and P is the power capacity of the BESS in KW.

A positive NPV indicates a return on investment greater than the expenditures associated with the system, thus a profitable investment.

3.4.2 Internal Rate of Return

Likewise, this economic model uses the extra profit generated due to the BESS (equation 3.54) to calculate the IRR (equation 3.58). The IRR allows to rank projects by their rates of return rather than their NPVs. The investment with the highest IRR is usually preferred. The easy comparison characteristic makes this metric attractive, but there are limits to its practicality [48]. IRR does not measure the absolute size of the return, supporting investments with high rates of return, even if the monetary amount of the return is small [49]. The investment and cash flows are considered as described in equations 3.55-3.57.

$$0 = \sum_{t=1}^{n} \frac{CF_t}{(1+IRR)^t} - I_0 \tag{3.58}$$

where CF_t is the annual extra profit obtained with the BESS integration, n is the BESS lifetime, I_0 is the initial investment in the BESS.

4

Simulation Conditions

Contents

This chapter provides an overview of the conditions and assumptions taken in the electricity market, renewable portfolio and energy storage system, which end up influencing the simulations. It covers a report on the LSTM forecasting results regarding spot prices and renewable power production, both used as input of the optimisation problem. Lastly, it gives a brief clarification concerning the annual simulation.

4.1 Electricity Market

4.1.1 Market Structure

When building a model to investigate the participation of a resource in competitive electricity markets, it is mandatory to specify how the auctions of that resource affect the market outcome. Depending on its influence on the market-clearing results, a resource can be defined as a price-maker or a price-taker. A price-maker offer has an impact on the market spot price while a price-taker buying or selling offers are assumed not to influence the market-clearing outcome, thus accepting prevailing prices. If the considered facility has a negligible market share, the price-taker approach can be preferred, bringing simplicity and manipulability to the model, without compromising the outcome.

In this thesis, the system constituted of a BESS together with RES is assumed only to play a small quantity in the market. It is presumed that the system's offers will always be accepted, meaning that the submitted bids will always be lower than the marginal offer. As the system is assumed to be a price-taker in the electricity markets, the DA, ID and up or downregulation prices are independent of its bidding. However, it is crucial to recognise that the global wind and solar generation of the system might influence the marginal prices since the higher the global renewable generation, the lower the prices, as higher merit order units are taken out from the dispatch.

4.1.2 Intraday Market Sessions

Regarding the ID sessions, even though the MIBEL intraday market is structured in seven sessions (Table 3.1), the first two still take place in the day before the optimisation. As such, only the remaining five sessions are considered. As the day progresses, new information on renewable production becomes available; thus the new forecasts will eventually be more reliable than the ones made the day before. However, it is computationally expensive and time consuming to forecast the hourly production at every hour of the day, for all the following hours, to update the bids for those sessions. Hence, the new forecasts are generated only in the hour before the ongoing session closes.

Furthermore, even though each session has a different spot price curve, it is a computational burden to forecast seven different spot price sessions, mainly because generally, those do not vary significantly

(Figures 4.3-4.4). Because of that, the spot prices of these sessions are only updated twice: in the second session, which concerns the 24h of the day, since these prices are different from the day-ahead prices; and in the fifth session which refers to the last 12h of the day.

4.1.3 Spot Price Forecasting

The MIBEL day-ahead and intraday spot prices for all sessions are available in REN's website [33]. Data was collected for the DA session and for the two considered ID sessions for 3 years (1st of January 2017 to 31st of December 2019). Data was processed as described in section 3.2. The years of 2017 and 2018 were used as training set and the year of 2019 as test set.

After selecting the day in which the operation strategy will hypothetically be performed, the optimisation program input variables concerning that specific day need to be generated. The spot price is one of the inputs to be considered. Thus, the day-ahead spot price and the intraday spot prices referring to the two intraday sessions considered must be forecasted. In this section, spot price forecasting simulations for different days of the year are reviewed for illustrative purposes.

Winter Day Simulation

Firstly, a winter day was chosen to perform the spot price forecasting. Figure 4.1 depicts a comparison between the forecasted market prices obtained via the LSTM approach as well as the actual market prices in the DA market. The process must be repeated for the considered ID sessions, namely the second and the fifth sessions, regarding 24h and 12h of the day.

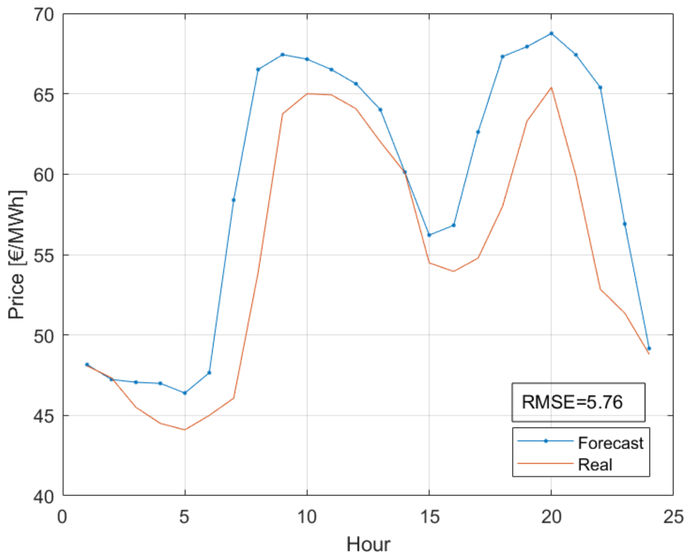
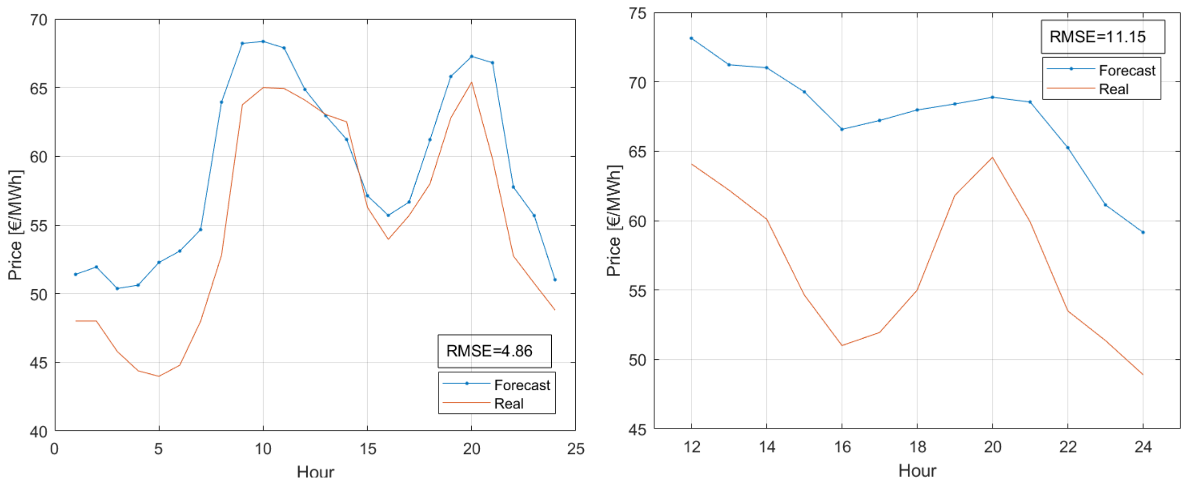


Figure 4.1: Real and LSTM forecast for the day-ahead market spot price for a winter day

In the day-ahead market, depicted in Figure 4.1, the lowest prices predicted are in hours 3,4 and 5 where the prices are below 47 €/MWh, with a minimum of 46 €/MWh reached in hour 5. Given the typical nature of the spot market prices, lower prices at the beginning of the day are expected. As for the highest prices, they are reached in the morning (hours 8, 9 and 10) and in the evening (hours 19, 20 and 21), with a maximum of about 69 €/MWh in hour 20. The day-ahead price forecast follows the real trend since the most expensive and cheapest hours match reality, as it can be seen in Figure 4.1. However, in this case, predicted prices show relatively higher values than the real ones.

The intraday spot prices for the second and fifth sessions can be seen in Figure 4.2. Again, the forecasts are depicted along with the real market values.



(a) ID session 2 **(b)** ID session 5

Figure 4.2: Real and LSTM forecast for two intraday market spot price sessions for a winter day

In the studied day, it is visible that the spot prices for both DA (Figure 4.1) and ID sessions (Figure 4.2) only vary slightly, presenting nearly the same price for every hour. By analysing the RMSE value, it can be noted that the fifth intraday session presents the worst spot price forecast results (RMSE_{DA}=11.15), when compared to the day-ahead and second intraday sessions ($\text{RMSE}_{\text{ID}_2}$=5.76 and $\text{RMSE}_{\text{ID}_5}$=4.86).

Summer Day Simulation

A second simulation is presented for a summer day. All forecasts are hypothetically conducted the day before the chosen summer day. Likewise, the input data comprising the day-ahead spot prices is obtained first and can be observed in Figure 4.3.

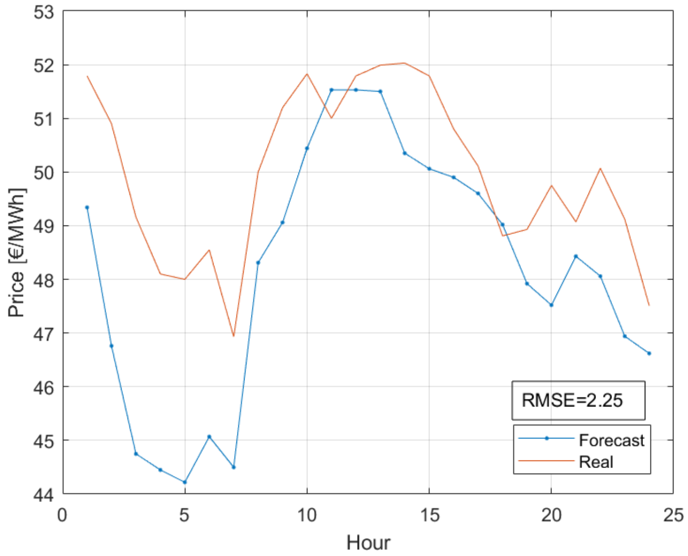
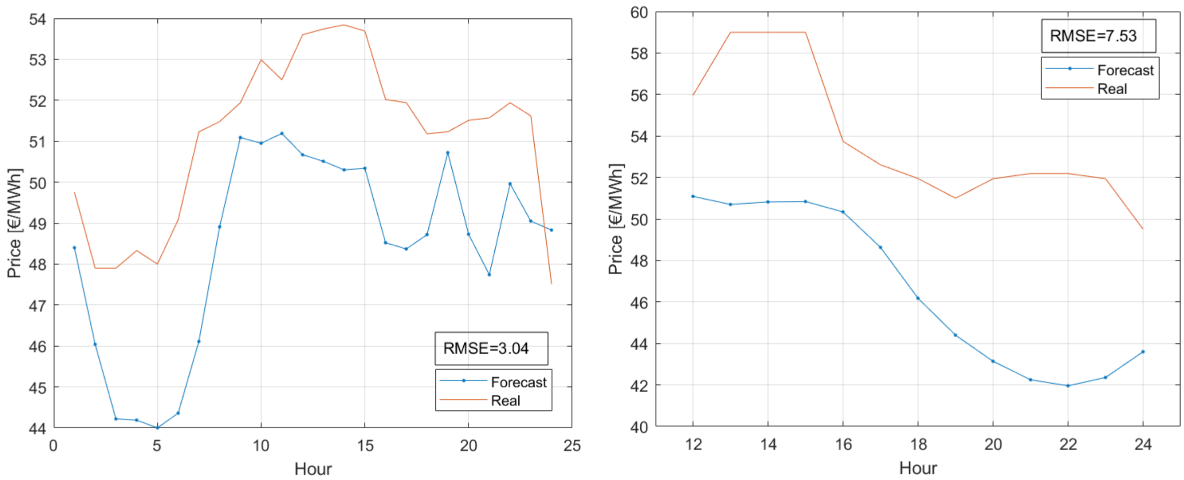


Figure 4.3: Real and LSTM forecast for the day-ahead market spot price for a summer day

The minimum price predicted is about 44.5 €/MWh, achieved in hours 5 and 7. The highest price is attained for hours 10,11 and 12 and is approximately 51.5 €/MWh. The price range is smaller in the summer day (7 €/MWh) compared to the winter day (23 €/MWh). Since an ESS can make more profits through arbitrage when the variation in electricity price is higher, it can be quickly concluded that more profits can be achieved in the winter day. Furthermore, opposed to what happens on the winter day, there is no longer a price peak in the evening.

The intraday spot prices for the second and fifth sessions can be seen in Figure 4.4.



(a) ID session 2 **(b)** ID session 5

Figure 4.4: Real and LSTM forecast for two intraday market spot price sessions for a summer day

Similarly, it can be noted that the fifth intraday session presents the worst forecast, with a RMSE of

7.53, in contrast to 3.04 concerning the second intraday session spot price forecast. These values follow the higher variability, which is shown in the last sessions of the day.

The presented DA and ID spot price forecasts are required as input for the optimisation program. Therefore, the operation of the considered system (bidding strategy in the short-term markets and decisions regarding the ESS) in the different days of the year is highly influenced by the hours in which the electricity spot price is presumed to be higher or lower.

4.1.4 Regulation Costs

As it was previously mentioned, in the MIBEL, positive and negative imbalances are charged differently. The regulation costs are related with the day-ahead spot price. The strategy taken concerning the imbalance pricing will also affect the optimisation results. In this thesis, the considered approach for the calculation of these costs was the application of a penalty factor: a factor (greater than the unit for negative imbalances and smaller than the unit for positive imbalances) by which the day-ahead spot price must be multiplied. To adopt a penalty factor which reflects the reality of the MIBEL, the imbalance costs from 2015 to 2018 were studied [50]. Various perspectives were analysed (hourly ratios, monthly average, and so on) to identify a pattern. Figure 4.5 depicts the monthly average imbalance for the investigated years. A clear pattern emerges 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, its value is about 1.2 and 0.8 for negative and positive imbalances, respectively. Therefore, those were the assumed penalty factor values.

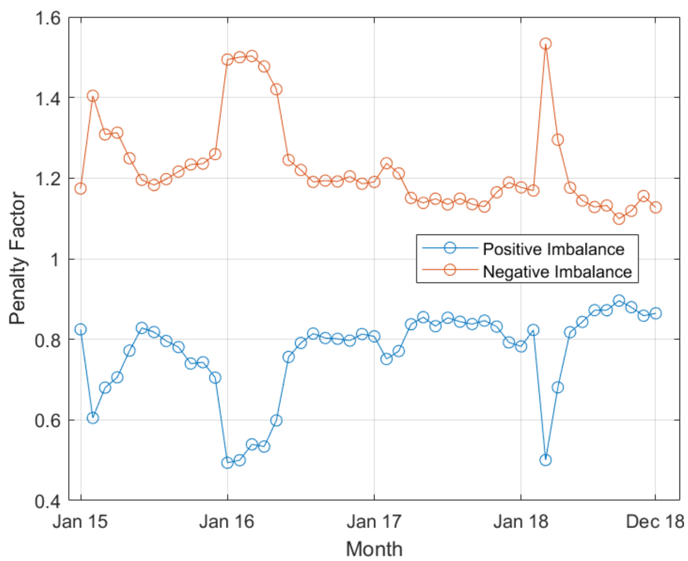


Figure 4.5: Penalty factor computed from a 4-year analysis on MIBEL's data

4.1.5 Balancing Market

In the proposed model, bids concern either upward or downward regulation. However, this does not reflect reality. In the MIBEL, there are no bids regarding each specific regulation direction. The agent submits an hourly bid concerning the reserve band and then it is obligatorily divided in two-thirds up-regulation and one-third down-regulation.

In this thesis, the reserve band, upward and downward prices considered were not forecasted. These values were obtained in REN's website [51]. In the electricity market, it can happen that it is not necessary to mobilise or demobilise energy. In this case, even though the reserve band remuneration is always specified, the mobilisation remuneration price is not determined. Consequently, there are hours without an assigned price value for upward or downward reserve. Thus, to rectify the missing prices, linear interpolation is performed.

As it was previously explained in section 3.3.3, the agent's participation in the BM is limited to the minimisation of its imbalances. Therefore, there is no monetary motivation to participate in this market other than that. However, the balancing market involves two forms of remuneration: regulation band and mobilisation/demobilisation of energy. Thus, it would be interesting to participate in this market also to maximise profits and not solely as a supporting variable that may be employed to improve the battery operation in minimising deviations. This source of income could be a real motivation for the viability of the storage system implementation. To evaluate this possibility, two different cases were considered: Case I and Case II. In this study, all results refer to Case I if not stated otherwise.

Case I

In Case I, the agent's participation is limited to the minimisation of its imbalances, as exposed in section 3.3.3. The agent is always assumed to be called to act, when that is imposed by the model, to minimise imbalances.

Case II

In Case II, the participation in the reserve market to maximise profits is considered. To legitimately assess it, it would be necessary to simulate the whole market to figure out when the agent would be called for action. Again, this matter is outside the scope of this thesis. However, by keeping the previously stated assumption that the agent would always be called to mobilise/demobilise energy, the model would always rather bid on the balancing market due to the double remuneration. This would result in a worthless operation outcome and an unrealistic profit.

To fix this, another constraint must be added to the original models. This constraint defines that only a percentage of the storage system's capacity (15%) can be 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. When the BM takes place, the agent must submit the bids concerning up and down-regulation, like in the day-ahead and intraday markets.

The remaining capacity (85%) can participate in the balancing market when required by the optimisation model, following the same guidelines of Case I.

4.2 Renewable Generation

The energy generated by the renewable power plants is required to run the optimisation algorithm depicted in Figure 3.5. In the DA and ID optimisations, forecasts are used as input while in RT optimisation, the real production is considered. Thus, the assumptions regarding this input variable play an important role.

4.2.1 Renewable Power Plants

The agent's renewables portfolio consists of a WF and a PV power plant. With the intent of simulating the portfolio realistically, the considered power plants were presumed based on real locations of the same kind of power plants existing in Portugal. Relevant information on Portuguese power generation centres using RES, such as technology, location and installed power can be found in the database e2p [52]. In this thesis, it is assumed that the WF has a total power capacity of 73.6 MW and the PV power plant has a total power capacity of 39.76 MW.

Since the power plants configurations are hypothetical and there is no energy production information available, it is necessary to consider the weather variables in which generation depends on. The values concerning meteorological variables are accessible online and can easily be converted by using the models of the WT and PV panels described in section 3.1.

All wind turbines are assumed to receive the same amount of wind, and all solar panels are assumed to receive the same irradiance and exhibit the same temperature in its surface. Thus, all WTs are assumed to generate the same amount of energy, although, in reality, the turbines are in slightly different geographical places. The same reasoning applies to the solar panels.

4.2.2 Weather Data

As previously mentioned in section 3.1, the weather variables used in the models are irradiance, temperature and wind speed. All datasets used to train and test the LSTM network, were collected in Solcast [34] for each hour of the day, comprising 3 years (from 1st of January 2017 to 31st of December 2019). The data from 1st of January 2017 to 31st of December 2018 was used as training set and the year of 2019 as test set. The considered locations for the extraction of this data were the presumed power plant sites.

According to Solcast, the wind speed data was taken at a 10 m height [34]. Thus, Prandtl Law was applied to obtain the corresponding hourly speed values at the height of the turbine, as described in equation 4.1.

$$\frac{u_{z_1}}{u_{z_2}} = \frac{\ln \frac{z_1}{z_0}}{\ln \frac{z_2}{z_0}} \tag{4.1}$$

Where u_{z_1} is the speed value at the height of the turbine, u_{z_2} is the speed value at the measurement height, z_1 is the measurement height, z_2 is the height of the turbine and z_0 is the roughness length.

As regards irradiance values, it was considered that the measurements were made at the inclination of the solar panels. Furthermore, both irradiance and temperature were only considered in daytime hours, namely from 6 to 18, since the solar panel production is restricted to the irradiance hours. Therefore, it would be irrelevant and resource-consuming to forecast variables outside that time window.

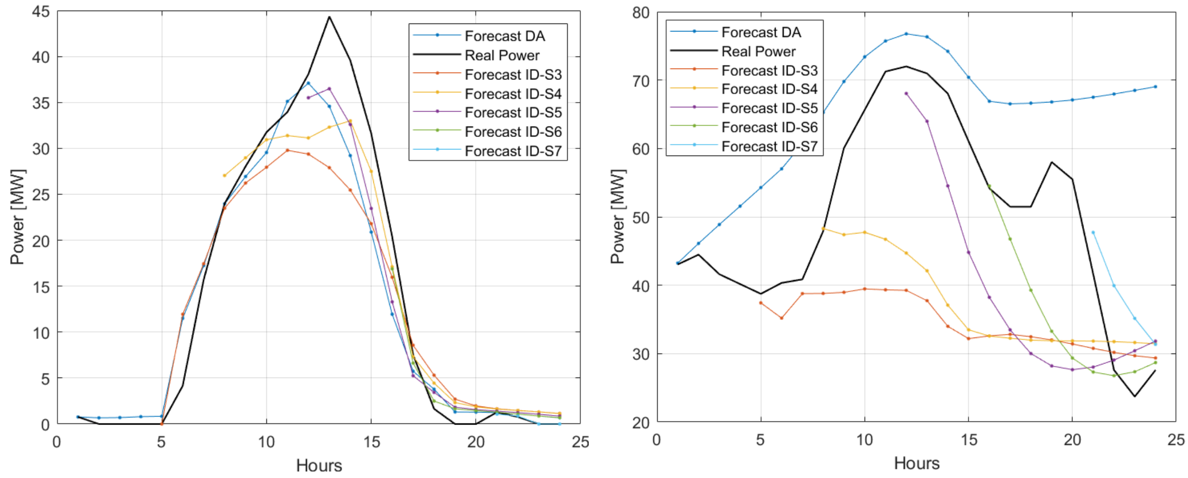
4.2.3 Power Generation Forecasting

Apart from the spot prices, renewable power production is also an input variable in the developed optimisation programs. This variable is obtained by using the models described in section 3.1, using as input the forecasted weather variables. The forecast of the considered weather variables, as well as the individual power generation of each RES, is attached to this report in Annex A.

There are some power forecasts to be generated before and during the chosen day. Before the day D, the day-ahead renewable generation needs to be predicted, taking into account 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. Forecasts are only computed the hour before the start of each one of the considered five intraday sessions (session 3 to session 7), as described in section 4.1.

Again, to examine the forecasts that will be fed as input in the optimisation problem, two simulations concerning two different days of the year (a summer and a winter day) are analysed.

A comparison between the day-ahead and the intraday power production forecasts and its real values, for both summer and winter day, can be observed in Figure 4.6. The day-ahead renewable generation is the first one to be forecasted in order to be used as input in the day-ahead optimisation program. Then, the succeeding intraday predictions for the next hours are consecutively forecasted.



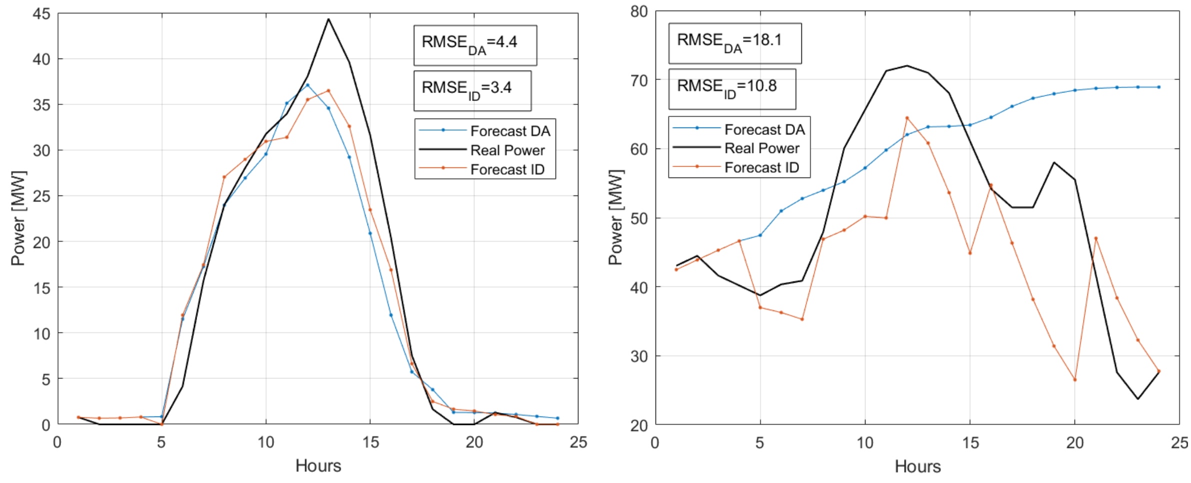
(a) Summer day **(b)** Winter day

Figure 4.6: Day-ahead and multiple intraday renewable production LSTM forecasts and real renewable production

In Figure 4.6, it is possible to clearly distinguish the profile resulting from solar production and its relevance on overall power generation. There are only two peaks regarding wind production on the chosen summer day: the first at 12h-14h and the second at 21h (Annex A). In the ID predictions, one can observe the successive forecast readjustments in each session. Figure 4.6 refers to a winter day which implies modest solar production due to low irradiance levels (Annex A). The wind park output power is considerably high, as winter is typically characterised by strong winds.

Although a new forecast is generated for all next hours before a new intraday session (as explained in section 4.1), those power values will ultimately change until the last session in which they are considered happens. As such, in Figure 4.7, the intraday forecast concerning the last predicted values for each hour is displayed along with the day-ahead prediction. The RMSE values for both DA and ID predictions are also presented, allowing a comparison between the first and last forecast for each hour.

In the summer day, only slight changes can be observed since the forecast from the previous day is already relatively close to reality ($RMSE_{DA}$=4.4 and $RMSE_{ID}$=3.4). Nonetheless, in the winter day, changes and improvements regarding the intraday forecast in comparison with the day-ahead are more prominent ($RMSE_{DA}$=18.1 and $RMSE_{ID}$=10.8). Figure 4.7 corroborates the existing high variability of wind power which, among the commercially available renewable sources, is the most difficult to predict.



(a) Summer day

(b) Winter day

Figure 4.7: Day-ahead and final intraday renewable production LSTM forecasts and real renewable production

4.3 Energy Storage System

In this thesis, the operation of a generic BESS is modelled using equations 3.19-3.24. As detailed in Figure 3.5, the specifications for each tested BESS are input variables. The BESS limitations with respect to power and energy are one of those input variables, thus being considered. Also, the roundtrip efficiency is a parameter that is specified by the manufacturer to contemplate the charging efficiency.

The initial and final state of charge at the end of the day were assumed to be zero (section 3.3), but another value could have been chosen. This statement has relevance because the algorithm performs the optimisation for several days, and this constraint forces a standard initial and final daily energy levels. If another condition were presumed, a different operation strategy would have been attained.

Several types of batteries can be used, but some properties such as high charge efficiency, low self-discharge and long life under cyclic charge-discharge are mandatory [53]. Information about commercialised battery technologies was collected in a cost report developed by the US Department of Energy [54] and in manufacturers' website [55–58]. Four technologies were considered: sodium-sulfur, lithium-ion, zinc hybrid and vanadium redox flow. A brief review on the intrinsic properties of all contemplated technologies, as well as some of the advantageous and unfavourable characteristics, can be found in Annex B.

It is not easy to have access to specifications and costs of large-scale BESS, as manufacturers only provide them after an assessment of the client's requirements. Nevertheless, the chosen manufacturers display on their websites multiple projects within a range of power and stored energy.

To establish an economic analysis (section 3.4), the BESS costs must be considered. The capital cost is a function of the storage device power and energy capacities and their specific costs depending on the chosen technology. Technical and economic characteristics of each considered BESS are based on [54]. Data published in [54] was obtained from literature, conversations and questionnaire responses from vendors. As the economic analysis is computed in euros, the conversion ratio of 1$=0.88€, (as fixed on 4th June) was used to convert the report price data from USD to EUR.

In economic simulations, BESS were tested not only with information regarding actual technology development and costs but also with the prediction of the BESS costs for the year of 2025, based on [54]. Annex C states the specification and cost data that were inserted into the BESS model regarding the year of 2018 and the predictions concerning the year of 2025. Also, the selected storage sizes of each manufacturer [55–58] are specified.

4.4 Annual Simulation

The optimisation is performed following the MIBEL market structure and its rules the closest possible to reality, as described in section 4.1. 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 (section 3.4).

Since the forecasting of the power generation and spot prices for a single day and the multiple considered sessions takes approximately 45 minutes, the decision of analysing a whole year is unbearable. It would be excruciating to predict the necessary inputs for 365 days. Therefore, the analysis of a whole year is accomplished by choosing four typical days: one for each season. This assumption allows to assess the optimal operation 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 typical days, one can extrapolate the results for the whole year. Also, revenues are calculated considering the resulting optimal bidding strategy in the three short-term markets given by the algorithm, with and without the BESS, allowing the profitability of the projects to be analysed and compared.

5

Results and Discussion

Contents

This chapter presents and elucidates the results obtained with the algorithms defined in the previous fourth chapter. The first section contains a technical analysis which comprehends the operation and bidding strategies of the considered owner's portfolio in the multiple markets. The second section concerns an economic analysis which aims to discuss the profitability of the tested energy storage systems.

5.1 Technical Analysis of the Operation and Bidding Strategy

To examine the bidding and operation strategy of the system, simulations are going to be presented concerning a day of the year. For each day, the spot market prices, renewable power production and imbalance costs are forecasted. A breakdown of the result for this simulated day for the three developed algorithms (DA, ID, and RT) is exhibited next. The considered case-study is depicted in Figure 5.1, and it is constituted by a WF, PV power plant and BESS. Conditions and specifications regarding this system were described in chapter 4, and its possible power exchanges in the three-short term markets were carefully detailed in chapter 3. In the simulations exhibited in the present section, a lithium-ion 20 MW/20 MWh battery (detailed in Annex B) was the adopted BESS.

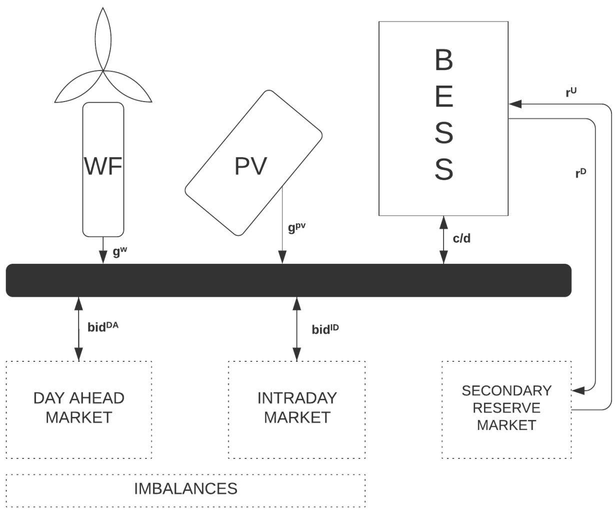
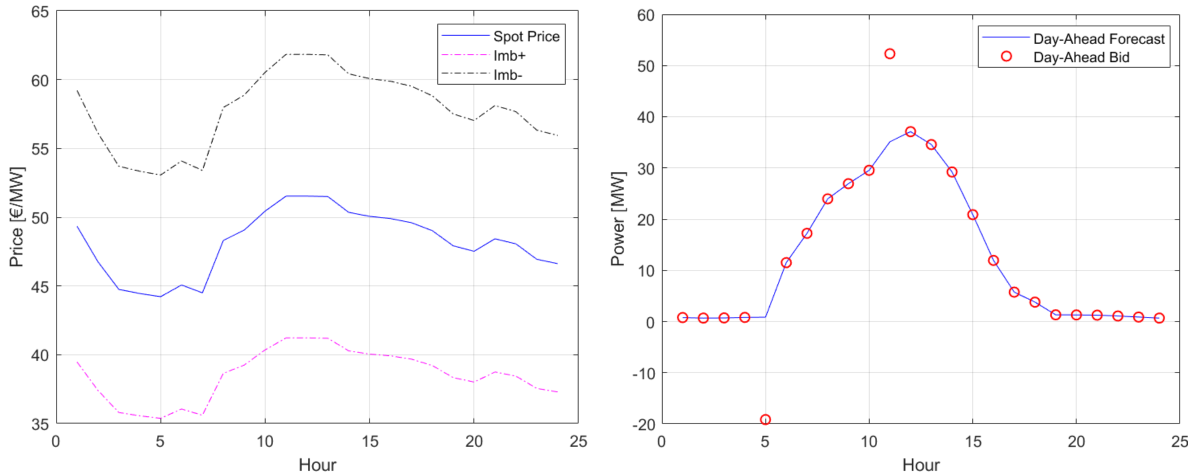


Figure 5.1: Case-study configuration and its interactions within components and markets

5.1.1 Day-Ahead Optimisation

The simulated day is the summer day detailed in chapter 4. Figure 5.2 contains the model input variables: forecasted day-ahead prices, imbalance regulation costs and forecasted production. One of the model's goal is to find the optimal bidding strategy in this market: the one which maximises revenues. Thus, the resultant day-ahead bids throughout the day are also depicted in Figure 5.2, superimposed on the forecast. Looking at Figure 5.2, one can conclude that this day is characterised by a valley of low market prices at the beginning of the day and peak spot price hours around midday, as described in section 4.1.3 The day-ahead forecasted values (one of the model's input variables) are depicted in blue, and the hourly bids submitted to this market (one of the model's output variables) are represented by red circles.



(a) Day-ahead spot price and regulation costs

(b) Day-ahead forecast and bidding strategy

Figure 5.2: Forecasted day-ahead spot prices, production and regulation costs, and bidding strategy for the summer day

In Figure 5.2, the power to be bid in the day-ahead market is equal to the renewable power forecast for 22 hours of the 24 hours of the day. The algorithm fixes the bids in the DA market as the expected renewable power production (except in hours 5 and 11). It aims to increase the system revenue by performing price arbitrage with the BESS within the DA market (hours 5 and 11). A negative bid is submitted in the market during hour 5, aiming to charge the storage. Then, at hour 11, an offer with a higher power production value than the one forecasted to be generated is programmed.

Figure 5.3 demonstrates the second model's output variable: the state of charge at every hour. It is possible to observe the filling of the BESS at hour 5 and its emptying at hour 11, explaining the bidding strategy adopted.

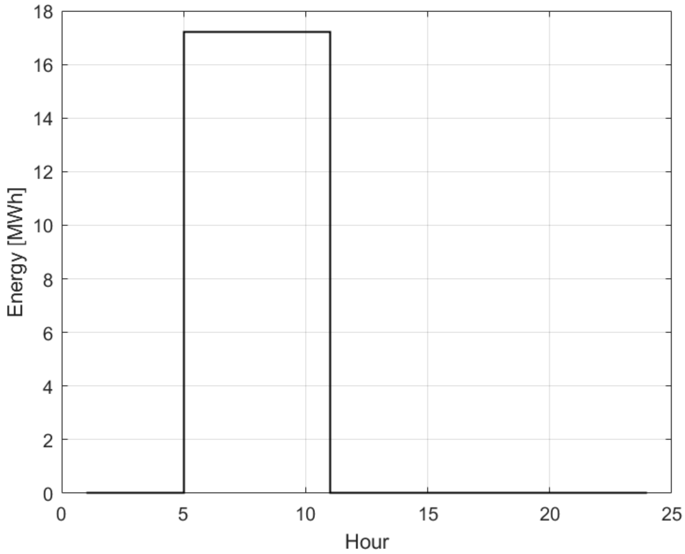


Figure 5.3: Battery scheduled state of charge for the summer day, after the day-ahead optimisation

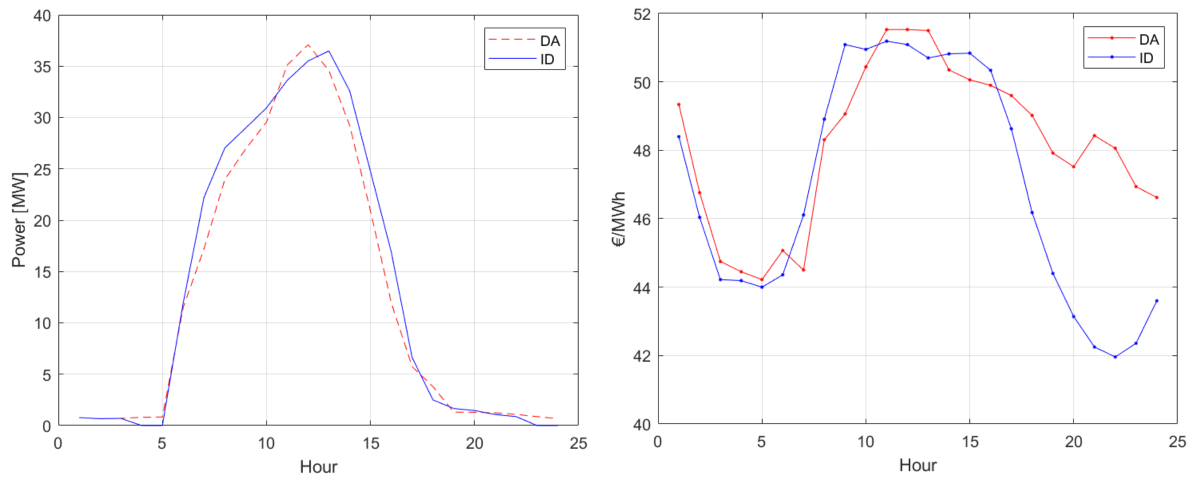
Given the nature of spot prices, it is more profitable to charge the BESS at dawn (5h) and deliver energy at peak hours (11h), when the price reaches the highest values. Since there is no foresight of power deviations throughout the DA strategy, the BESS operation is strictly correlated to the DA spot prices. Nevertheless, it is important to mention that the developed optimisation model allows the BESS to be charged both from the market (as it is happening here) and directly from the renewables.

This output is the one maximising owner's revenues. Thus, no further BESS operations are scheduled in the day-ahead. The fact that the chosen day evinces a relatively modest price difference (section 4.1.3) should be highlighted since it does not significantly stimulate BESS arbitrage within the DA market. As Figure 4.1.3 shows, the initial (hour 1) and final (hour 24) levels are the same (assumed to be 0), and the maximum energy level of the battery (20 MWh) is not planned to be used.

5.1.2 Intraday Optimisation

Following the DA strategy, the ID strategy comes into play. This 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. The ID optimisation depends not only in the updated forecasted renewables and spot prices introduced as input, but also in the formerly DA adopted strategy. Thus, not only the profit coming from the ID market must be maximised, but the regulation costs resulting from power imbalances from the DA submitted bids must be minimised. Even though ID optimisation is less evident than DA optimisation, one can still draw conclusions and tendencies in the results.

Figure 5.4 depicts the ID model input variables, which are the newly updated forecasted power production and ID spot prices. When it comes to the updated forecasts on renewable power production, there are three possible outcomes: they can match the DA forecasts or assume values below (new forecast predicts that underproduction will occur) or above those (overproduction). Regarding the ID spot prices, they may or may not show the same trend as the DA spot prices, enabling new potential BESS operations.



(a) Renewable production forecasts

(b) Day-ahead and intraday spot prices

Figure 5.4: Comparison between day-ahead and intraday forecasts (renewable production and spot prices) for the summer day

To analyse the ID model output, a set of hours was selected. This selection is displayed in Table 5.1. The rows regarding each hour of the day are coloured differently based on the relation between production predicted in the day-ahead forecasts and the intraday forecasts. Green rows refer to hours in which both day-ahead and intraday forecasts agree on the renewable generation values. Red rows refer to hours in which the intraday forecast is below the predicted values in the DA. Blue rows refer to hours in which the intraday forecast is above the day-ahead forecast. Regarding the BESS operations column, BESS discharges and charges are considered negative and positive, respectively.

Table 5.1: Intraday bidding and operation strategy for a selection of hours of the summer day

Hour [h]	ID Forecast [MWh]	Bid DA [MWh]	Bid ID [MWh]	BESS operations [MW]	SoC [MWh]
...					
3	0.70	0.70	0.00	-	0.00
4	0.00	0.80	-4.19	+ 4.19 **(ID)** - 0.80 **(DA)**	2.80
5	0.00	-19.16	-0.84	+ 19.16 **(DA)** + 0.84 **(ID)**	20.00
6	11.95	11.50	0.45	-	20.00
...					

Up until hour 4, the ID forecasted production matches the DA one, as it can be observed in Figure 5.4. Subsequently, no action is taken both in the bidding strategy and BESS decisions. However, at hour 4, the new forecast is below what was expected in the DA prediction. Looking at Table 5.1, in the previous hour (hour 3), the BESS was empty. In hour 4, no operations were programmed in the DA strategy (presented in the previous section). Thus, since the ID spot prices are predicted to be lower than the DA spot prices, the system chooses to charge the battery in the ID market and discharges it partially to avoid imbalances that would come from the bid made in the DA market.

At hour 5, the system charges again, as it was established beforehand in the DA optimisation: a negative bid was made in the DA market with this purpose. Since the BESS was anticipated not to be fully charged by that hour (Figure 5.3) and the predicted ID spot price is lower than the DA one, the system uses the rest of that hour to reach full charge from the ID market.

In the morning hours (6 to 10), the new prediction is above the DA one (Figure 5.4). Consequently, as it is seen in Table 5.1, at hour 6, the additional production is submitted in the ID market sessions, to obtain additional revenues.

An extended analysis specifying the ID bidding strategy and the BESS programmed operations during the 24h of the day can be found annexed to this report in Annex D.

5.1.3 Real-Time Optimisation: Case I

The day-ahead and intraday optimisation models schedule the bids proposed to the electricity markets. Lastly, those bids are compared with the real operation points giving the real production of the renewable power plants. Then, the operation within the BM and the BESS operations are settled correspondingly.

The energy transactions concerning the balancing market only occur when considered optimal by the developed real-time model. Since it is assumed that the producer in question is always called to act, there is no need to submit bids in advance as it happened in the DA and ID sessions. Even though the operation in the market is more straightforward, the optimisation results are more complicated because they depend on a larger number of factors than the previously described strategies, such as the DA and ID previous operation points and bids.

This analysis aims to understand and evaluate if the real-time strategy can successfully minimise the impact of the power imbalances (derived from forecasting inaccuracy) by operating the BESS and acting in the BM when it favours the model's objective.

Figure 5.5 illustrates the actual power production compared with the forecasts used in the DA and ID models. Even though the forecasts follow a close pattern, when compared to reality, one can conclude that the real power is unquestionably different from the predictions. This is where the real-time model comes in.

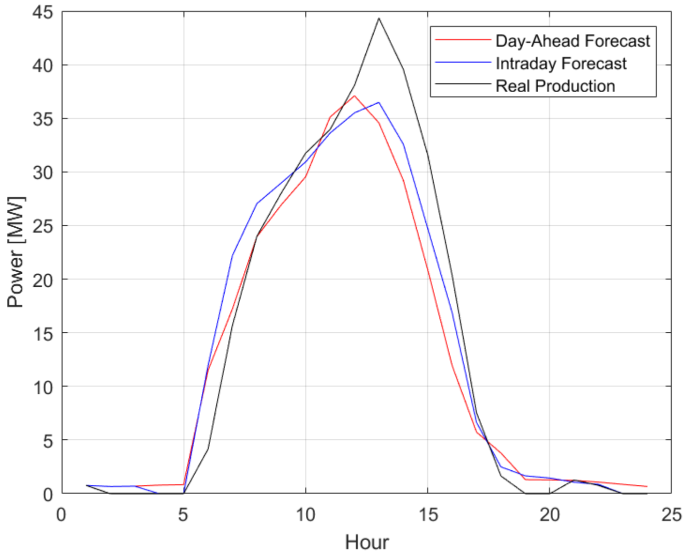


Figure 5.5: Comparison between day-ahead and intraday production forecasts and actual production for the summer day

Figure 5.6 proves the deviations between real production and both the day-ahead and intraday predictions. A mismatch is observed in most of the day, with clear renewables' underproduction from 5h to 7h and substantial overproduction between 13h and 16h. Notwithstanding the enhancements achieved due to the new forecasts used in the ID strategy (in terms of volume mismatch, there is an improvement of 20% on this day), it could be further enhanced.

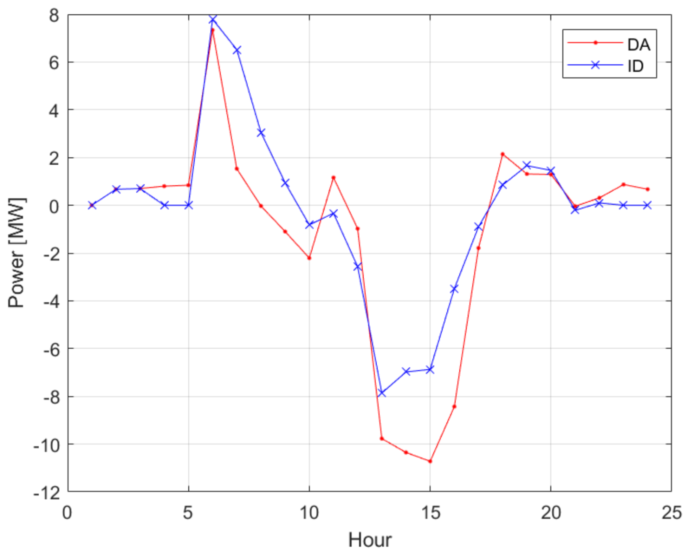


Figure 5.6: Deviations between real and forecasted day-ahead and intraday renewable production for each hour of the summer day

Again, to analyse the bidding and BESS operation results, a set of hours was selected. This selection is displayed in Table 5.2. The rows regarding each hour of the day are coloured differently based on the relation between predicted and real production. Red rows refer to hours in which the real production is below the predicted values reflected in the DA and ID bids, while blue rows refer to hours in which the real production is above the predicted values. Regarding the BESS operations column, BESS discharges and charges are considered negative and positive, respectively.

Table 5.2: Final bidding and operation strategy for a selection of hours of the summer day

Hour [h]	Real Production [MWh]	Bid DA [MWh]	Bid ID [MWh]	BESS operations [MW]	SoC [MWh]
...					
8	23.99	23.96	3.08	- 3.05 (**ID**)	2.63
9	28.03	26.93	2.04	- 0.94 (**DA**) + 18.56 (**BM**)	17.65
10	31.75	29.54	1.39	+ 0.82	18.36
11	33.95	52.31	0.00	- 18.36 (**DA**)	0.00
...					
15	31.10	20.95	3.90	+ 6.25	5.37
16	20.12	12.24	4.95	+ 2.93 - 4.57 (**BM**)	3.32
...					

Looking at the first row of the table, stating hour 8, both DA and ID forecasts predicted a more considerable amount of renewable generation than the actual production. In the real-time model, to avoid deviations from those values, the system discharges the battery to cover the remaining ID bid that was not fulfilled by the actual production. In the BESS operations column, the market bid which implied the discharge (an ID bid) is identified in bold. At hour 9, there is still underproduction. Therefore, the lacking amount is deducted by discharging the BESS again to avoid regulation costs, as it would decrease the revenues. Then, the BESS uses the rest of the hour to charge from the balancing market, since there happens to be a future discharge scheduled in the DA at hour 11h. The developed model recognises it can take advantage of the balancing market to cover the unexpected.

At hour 10, overproduction is observed. Since the BESS state of charge is below full capacity, it charges from the renewable production surplus. Then, at 11, like it was scheduled in the day-ahead market bid, the battery is discharged with the intent of taking advantage of the price difference observed in that market.

Fast-forwarding to hour 16, production surpasses the predicted power values; thus the BESS charges partially. However, since the system deliberates that it is not valuable to have such level of energy (since the state of charge at 15h was 5.37 MWh, it would sum up to 7.89 MWh at 16h), it uses the rest of the hour to dispatch part of it (4.57 MWh) to the BM.

Figure 5.7 displays the final levels of energy for each hour of the summer day, corroborating all operations described above.

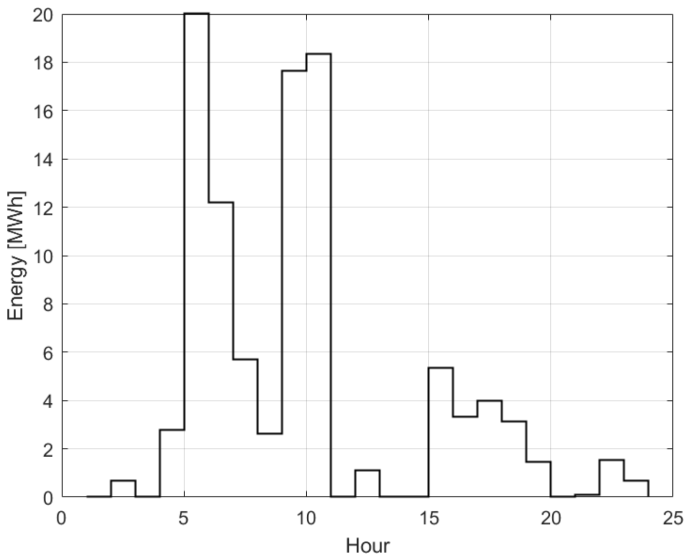


Figure 5.7: Final state of charge of the energy storage system for the summer day

The bidding, storage, and BM operation complete results regarding the typical summer day can be found in Annex E.

5.1.4 Results Comparison

In Table 5.3, the traded energy in each market is exhibited. 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 in the considered spot markets happens in the day-ahead market. For the chosen day, this value is about 81.7%. This was proved to be transversal in all simulations performed, varying between 79.4% and 82.5%. The full information comprising the traded power in the simulations for each typical day can be found in Annex F.

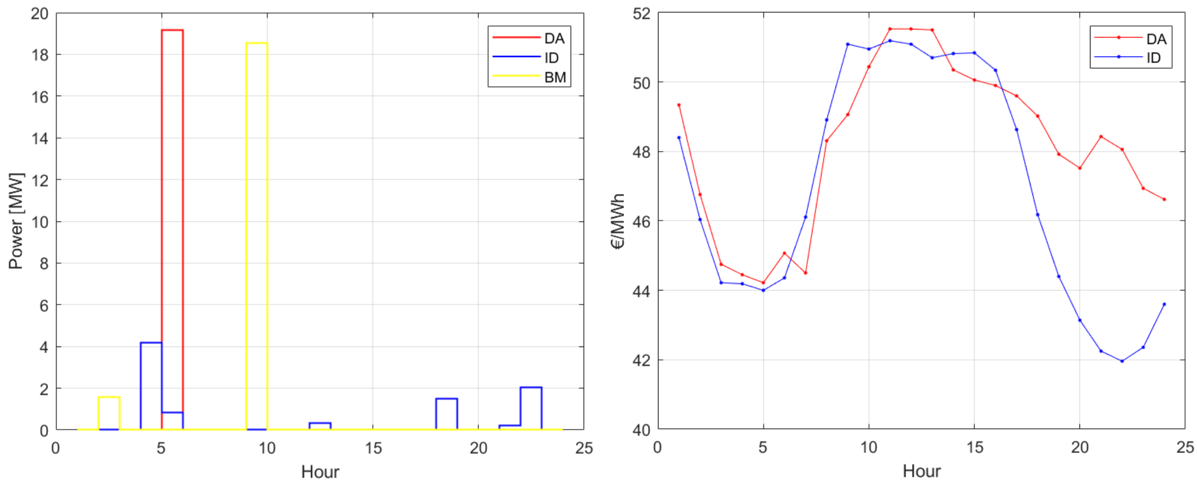
Table 5.3: Energy traded in the day-ahead, intraday, and real-time markets in the summer day

Market	Traded Energy [MWh]	Buying [MWh]	Selling [MWh]	Transactions [%]
Day-Ahead	334.2	19.2	315.0	81.7
Intraday	36.7	9.1	27.6	9.0
Balancing	38.1	20.1	18.0	9.3

Looking at Table 5.3 and concerning the buying bids in the chosen day, which are submitted with the sole purpose of charging the BESS, one can infer more significant amounts are offered in the day-ahead and balancing markets. These charging bids are for arbitrage purposes and strategic avoidance of imbalances in real-time.

Figure 5.8 focuses specifically on the buying transactions in the three-short term markets considered.

The DA and ID spot prices are also displayed in Figure 5.8. The BM prices are not represented because they are meaningless: the strategy within this market is to eliminate imbalances and, therefore, the model does not even need to have access to them.



(a) Hourly buying bids in the DA, ID, and BM market **(b)** Spot prices in the DA and ID markets

Figure 5.8: Bids submitted to buy energy in the three short-term markets and its respective spot prices

Even though there is a smaller quantity bought in the ID market (9.1 MW, compared to 19.2 MW and 20.1 MW in the other two markets), the frequency of these transactions is higher (6 times, compared to 1 bid in the DA and 2 in the RT) since the updated forecast of renewables and spot prices motivates the system to cover the deviations in this market and also, in this specific case, to exploit the lower spot prices to partially charge the system, as it can be seen in Figure 5.8.

Finally, Figure 5.9 portrays the state of charge of the BESS, which is an output variable in the three developed models (DA, ID, and RT).

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 real-time. Even though the three states of charge results were analysed in the preceding sections, by overlapping the three graphs, it is possible to verify that many of the previously taken decisions, with particular emphasis on the ones involving arbitrage and directly related to bids, are maintained. The operations added in the real-time strategy are based on that premise and with the exclusive purpose of assuring deviations are avoided.

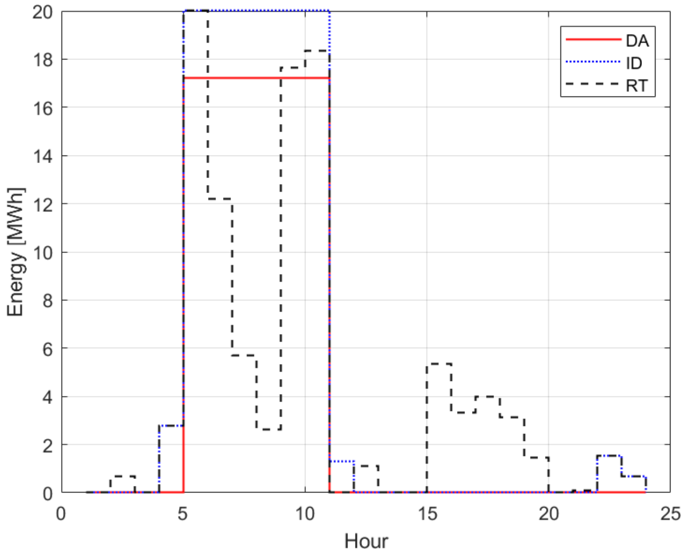


Figure 5.9: Comparison between day-ahead, intraday, and real-time battery state of charge in the summer day

5.1.5 Real-Time Optimisation: Case II

Lastly, the second approach (Case II) regarding balancing market participation was evaluated. In Case II, 15% of the storage capacity can be used to maximise profits.

In Table 5.4, the percentage of power exchanges concerning both balancing market cases in the elected summer day are exposed. The affirmation on the transactions in the BM being way more attractive in Case II is proven: 18% of the total transactions happen in this market compared to the former 9%.

Table 5.4: Percentage of transactions in each market concerning both balancing market approaches, for the summer day

Market	Transactions [%]	
	Case I	Case II
Day-Ahead	81.7	71.2
Intraday	9.0	10.7
Balancing	9.3	18.1

The spot prices of the day-ahead, intraday, and balancing market (three different values for the reserve band, down-regulation and up-regulation) are exposed simultaneously in Figure 5.10, witnessing the price discrepancy between them.

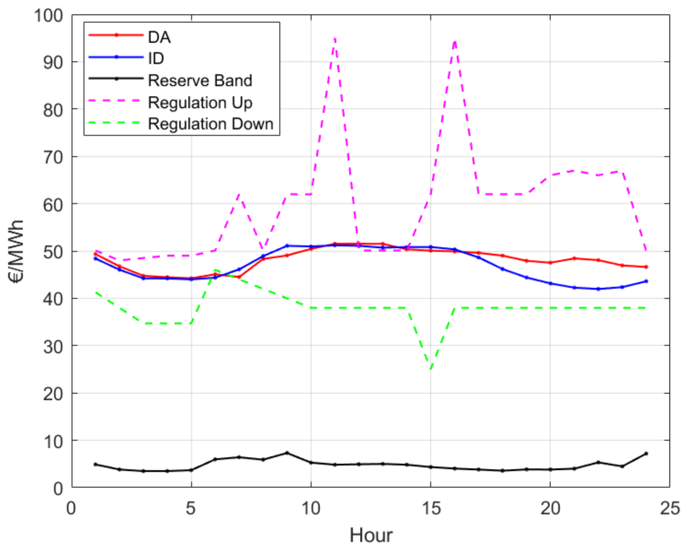


Figure 5.10: Spot prices in the day-ahead and intraday, and balancing market remunerations in the summer day

In the chosen summer day, up-regulation is highly remunerated: it presents the highest values in 21 hours of the day. Explicitly, up-regulation reaches a value of 95 €/MWh at hours 11 and 16. Down-regulation bids are a valuable resource since the BESS can charge from the balancing market and be paid for doing so. As charging is seen as a profit (something that does not happen in any of the other markets), down-regulation is strategically preferred by the model to charge the battery whenever necessary. Even though in the simulated day, the reserve band remuneration is much lower than the DA and ID spot prices, this must not be taken as an assumption because, for other simulated days, the opposite was verified.

The inclusion of the BM as a money-making opportunity changes the strategy of the algorithm entirely and, consequently, the output variables. The submission of offers to this market starts to be done in day D-1, like the day-ahead market, although it is subject to change until delivery time. Thus, the optimisation model considers this new information and must take it into account in the operation strategy since the day-ahead.

Table 5.5 displays the results for the same selection of hours previously presented in Table 5.2 regarding the output of the real-time model. The bids in the DA and ID markets, as well as the BESS operations within the three short-term markets, are analysed. The results from both Case I and Case II are exposed. The cells highlighted in green express the same submitted bids in the DA and ID markets in both cases: the fact that the BM is now seen as a profit-making opportunity did not change the bidding strategy. Cells highlighted in red mean that the bids made within the previously assumed approach (Case I) are different from the ones submitted now (Case II).

Table 5.5: Comparison of the final bidding and operation strategy on both balancing market approaches (Cases I and II) for the typical summer day

Hour [h]	Bid DA [MWh]		Bid ID [MWh]		BESS operations [MW]	
	Case I	Case II	Case I	Case II	Case I	Case II
...						
8	23.96	23.96	3.08	3.08	- 3.05 (**ID**)	+ 3.00 (**BM**) - 3.05 (**ID**)
9	26.93	26.93	2.04	2.04	- 0.94 (**DA**) + 18.56 (**BM**)	- 0.94 (**ID**)
10	29.54	29.54	1.39	1.39	+ 0.82	+ 0.82 + 3.00 (**BM**)
11	52.31	35.11	0.00	1.53	- 18.36 (**DA**)	- 1.16 (**DA**) - 1.53 (**ID**) - 0.76 (**BM**)
...						
15	20.95	20.88	3.90	3.85	+ 6.25	+ 6.87 - 3.19 (**BM**)
16	12.24	11.94	4.95	4.94	+ 2.93 - 4.57 (**BM**)	+ 3.49 - 3.00 (**BM**)
...						

Naturally, the operations in the balancing market are different since they serve diverse purposes. Notice that, up until 3 MW, the up or down-regulation correspond to maximisation purposes (15% of the BESS capacity).

Most importantly, it is shown that the bidding strategies in the DA and ID are also modified in this new simulation when compared to the ones that do not consider the BM as a profit-making opportunity (rows highlighted in red in Table 5.5). This happens because the submission of balancing offers starts to be done in day D-1, affecting all models.

The level of difficulty in analysing the solutions and strategies given by the algorithm to act is more remarkable for these new conditions. Nevertheless, the intention of this different approach is not to examine its technicalities (in operational terms, it is analogous to the simulations reviewed and analysed in sections 5.1.1 to 5.1.4) but the distinct economic outcome.

The full operation and bidding strategy during the 24 hours of the typical summer day for Case II can be found in Annex E.

5.2 Economic Analysis

To evaluate the profitability of different BESS projects, the designed algorithm is now executed over the typical year as described in section 4.4 to determine the parameters described in section 3.4 that are used to compare the different BESS. Initially, the algorithm is executed without a BESS to compute the revenues for the baseline case. Then, to test each of the BESS configurations and technologies listed in Annex C, to each BESS, its characteristics are used as input in the optimisation models, and the revenues are calculated.

5.2.1 Typical Year Simulation: Characteristics and Daily Simulations

The four chosen days which represent the typical year, try to capture each season trends, both at the renewable power production and the price level. Table 5.6 presents some important parameters substantiating reflections and conclusions which influence the simulation results exposed in Table 5.7.

Four critical parameters are included in Table 5.6: the price difference experienced in each one of the typical days (the difference between peak and bottom price within the day); the forecasting error (RMSE) regarding the renewable production predictions executed in day D-1 and day D when compared to reality; the real production (to perceive the renewable generation magnitude in each typical day); and, the percentage of energy generation that concerns each one of the renewable energy sources considered (wind and solar).

Table 5.6: Typical days characteristics regarding renewable production and spot prices

Day	Daily Price Difference [€/MWh]	Production Forecast RMS error [%]		Production [MWh]	Production [%]	
		DA	ID		Wind	Solar
Winter	22.4	18.1	10.8	1 197.3	94.7	5.3
Spring	18.1	9.8	6.3	740.7	82.9	17.1
Summer	7.3	4.4	3.4	323.5	22.6	77.4
Autumn	18.6	3.3	2.3	264.0	49.7	50.3

The winter day (characterised in section 4 and detailed in Annex A) shows high renewable power production (more than 1 000 MW produced throughout the day). This is a result of the strong winds, characteristic of winter days. Overall, wind power represents 94.7% of the total power produced by renewables that day. Since it is the most unpredictable renewable source, it is challenging to provide the optimisation model with accurate forecasts, as it can be evidenced by looking at the RMSE values. Also, these forecasting errors concern high wind production levels, thus represent larger quantities, becoming more complicated to eliminate large deviations.

Looking at the spring day, although there is already a percentage reduction in production and specifically in the quantity that comes from the WF, similar conclusions can be withdrawn.

The typical summer day (fully characterised in both section 4 and Annex A) has the opposite characteristics when compared to the winter day, as it can be discerned by looking at Table 5.6. The majority of the renewable production comes from solar, which is a RES that has a more constant and predictable pattern, especially in clear and cloudless skies, typical on summer days.

The autumn day shows a fair distribution of RES production, not pointing out to high RMSE values, like the winter and spring days. This typical day presents the lowest magnitude of production: it is characterised by lower irradiance levels than in summer and lighter winds than in winter or spring. If there is less production, there is less energy to sell: the chance of reaching significant profits is smaller. Thus, it is projected that this will be the day when the lowest profit is achieved.

Regarding spot prices, the considered days show similar patterns: lower prices at early hours and two peak-hour intervals in the morning and evening, except on the summer day, which only has the morning peak and the smallest price variation. The winter day shows significant price differences. It is followed by the autumn and spring day. This characteristic emphasises the use of the storage system: it favours arbitrage and ends up increasing the profit value when implementing an ESS.

Table 5.7 states the economic results with and without an ESS regarding both BM approaches (Case I and II). The market revenues in the three-short term markets (DA, ID and balancing), as well as the regulation costs, are exposed for the simulations on the four typical days of the year. It is crucial to evaluate these results keeping in mind the previously described inherent characteristics to each day.

Table 5.7: Monetary results for each simulated day without and with a BESS (Cases I and II)

Revenues [k€]	Without Storage				With Li-Ion 20MW/20MWh							
					Case I				Case II			
	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn	Winter	Spring	Summer	Autumn
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 day-ahead market, with small adjustments in the intraday 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. In the winter and summer days, positive deviations occur, hence the profit value greater than zero in the ID market (Table 5.7). On days with more accurate forecasts (summer and autumn days), fewer deviations (the difference between expected and actual production) materialise, thus fewer regulation costs are involved.

When the BESS is employed, the possibility to act in the ID sessions when insufficient production is expected and, in real-time (balancing market) arises. Typically, these markets are mostly used to buy energy to charge the battery; hence the negative cash-flow values publicised in Table 5.7.

It is shown that the three short-term market revenues (DA, ID and RT) and regulation costs differ when comparing Case I and II, proving different strategies are followed in each. In Case I, the only goal is to minimise the regulation costs while in Case II, there is 15% of the BESS capacity being used to maximise profits.

As estimated when looking at the parameters presented in Table 5.6, days with higher renewable generation will naturally produce higher total revenues (winter and spring typical days) since there is more energy to be sold in the markets. Then, looking at the autumn and summer days (which are the days with the least production involved), one can understand the worth of the price difference. In the summer day, which was characterised by an insignificant price difference, the BESS implementation does not show much influence in the profit increase (16.5 to 16.6 k€ - Case I or 16.5 to 16.8 k€ - Case II). However, the opposite conclusion is taken by looking at the autumn day. Even though it is the day with least production and, thus, fewer revenues, due to the high price difference, arbitrage is favoured, and the BESS is the key to increase the daily profit from 12.6 to 14 k€ Case I) or to 14.4 k€ (Case II).

The total market revenues and regulation costs obtained with and without BESS also need to be scrutinized. A further analysis on the variations of these variables due to BESS implementation in Cases I and II is detailed in 5.8.

Table 5.8: Variation on regulation costs and revenues each typical day (Cases I and II) due to li-ion 20MW/20MWh battery 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

Variations on revenue vary between 0.6% and 11.1%. Therefore, one can infer that profits are not significantly improved. This happens because, in the original approach (Case I), the only purpose of the BM is to minimise imbalances. Thus, the joint system drastically reduces the regulation costs (Tables 5.7 and 5.8) in 3 of 4 typical days, as it is the main goal of the conceived real-time model. The winter day shows the worst results with only 30% of the regulation costs reduced. It is the day with highest renewable production and wind power represents 94.7% of it (5.6), thus large deviations occur. Due to the implemented storage system constraints, and previous DA and ID strategy, operations cannot be adjusted properly.

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 (varying between 1.7% and 14.3%). Regulation costs variations are either the same (winter and summer) or inferior (spring and autumn) since now only 85% of the capacity is utilised to minimise deviation penalties.

Lastly, when extrapolating the daily results stated in Tables 5.9 and 5.8 to the annual context, the battery's effectiveness in eliminating regulation costs is proven. One can conclude that yearly regulation costs decrease by 53.2% and 49.9%, when comparing Cases I and II to the scenario without a BESS.

5.2.2 Years of 2018 and 2025

After executing the daily simulations which comprise a typical year and realising the implications of each day characteristics, the economic assessment is calculated across the whole year. As explained in chapter 4, since it would be computationally expensive to simulate the 365 days of the year, only the typical days presented above are considered. Each winter, summer, spring, and autumn day is assumed to be equal to the typical day. Then, the outputs from the simulated days are extrapolated for the whole year.

The economic assessment is performed by applying the two elected metrics exposed in section 3.4: NPV and IRR. To do that, both revenues of the system with and without BESS are computed, according to equation 3.54. The profitability analysis of the multiple studied projects is computed both in the year 2018 (based on literature and manufacturers) and in the year 2025 (predictions), collected in the US Energy Department Cost Report [54].

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. The discount rate is a representation of the level of confidence that future incomes will equal what is projected in the present: it reflects a measure of risk. Hence, 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%.

Table 5.9 states some selected simulation results for the year of 2018 and 2025, regarding the participation in the balancing market as described for Case I. The results concerning all the studied sizes of each technology type can be found in Annex F.

Table 5.9: Economic evaluation for the BESS smallest sizes of each technology regarding participation in the balancing market as described in Case I

Technology	Size [MW / MWh]	Annual Revenue [k€]	Annual Profit [k€]	NPV [k€] i=7.5%		NPV [k€] i=5%		NPV [k€] i=10%		IRR [%]	
				2018	2025	2018	2025	2018	2025	2018	2025
Sodium Sulfur	0.8 / 5.8	11 227.2	35.2	-3 317	-2 222	-3 270	-2 175	-3 355	-2 260	-20.4	-17.5
Li-Ion	2 / 2	11 328.1	136.1	-43	232	83	349	-142	134	6.5	14.3
Zinc Hybrid	0.5 / 2	11 211.1	19.1	-496	-298	-480	-281	-500	-311	-17.1	-12.6
Vanadium Redox Flow	0.5 / 3	11 207.8	15.8	-1 475	-988	-1 450	-963	-1 494	-1 007	-17.9	-15.2

Table 5.10: Economic evaluation for the BESS smallest sizes of each technology regarding participation in the balancing market as described in Case II

Technology	Size [MW / MWh]	Annual Revenue [k€]	Annual Profit [k€]	NPV [k€] i=7.5%		NPV [k€] i=5%		NPV [k€] i=10%		IRR [%]	
				2018	2025	2018	2025	2018	2025	2018	2025
Sodium Sulfur	0.8 / 5.8	11 237.4	45.4	-3 233	-2 137	-3 172	-2 077	-3 281	-2 186	-18.4	-15.3
Li-Ion	2 / 2	11 356.5	164.5	151	427	292	568	33	309	10.8	19.5
Zinc Hybrid	0.5 / 2	11 217.5	25.5	-443	-254	-421	-232	-461	-272	-13.5	-8.5
Vanadium Redox Flow	0.5 / 3	11 213.5	21.5	-1 425	-938	-1 392	-905	-1 451	-964	-15.6	-12.7

In the year 2018, almost all NPVs are negative values. As such, none of those projects is considered viable. However, for the lithium-ion battery, if the discount rate is assumed to be 5%, the project is feasible ($\text{NPV}_{5\%} = 83$ k€). The IRR has a value of 6.5%, which means that for this annual rate of return, the net present value is equal to zero. Consequently, this project should only be undertaken if the investor's cost of capital is smaller than 6.5%. Otherwise, it must be rejected. All other technologies exhibit negative values regarding both metrics.

In the year 2025, the lithium-ion battery is considered viable in both metrics (IRR $= 14.3\%$) and regardless of the discount rate ($\text{NPV}_{5\%} = 349$ k€, $\text{NPV}_{7.5\%} = 232$ k€ and $\text{NPV}_{10\%} = 134$ k€). Unfortunately, regarding the other three explored technologies, the annual profit achieved and its yet high investment costs (Annex D), are not enough to cover and make it realistic to invest in a BESS.

Nonetheless, in these simulations, the BM was implemented exclusively to minimise imbalances (Case I), not fully exploring the potential of this market. Then, simulations regarding balancing market conditions described in Case II were carried out. It is expected that revenues will increase. Nevertheless, it is relevant to analyse how profit is influenced by storage technology. As such, for the smallest size of each technology, profit was computed for both cases.

In Table 5.11, profit variation when comparing Case II with Case I, for each technology, can be found. The technology with the least increase in profits (20.9%) is lithium-ion since, as it is the most developed, it is the one already capturing most value.

Table 5.11: Annual profit variation when comparing balancing market participation in Case II with Case I for the smaller battery size

Technology	Annual Profit Variation [%]
Sodium Sulfur Battery	+29.0
Li-Ion Battery	+20.9
Zinc Hybrid Battery	+33.5
Vanadium Redox Flow Battery	+36.1

Simulations regarding participation in the BM while implementing Case II assumptions, aim to assess this solution to turn BESS projects viable. The economic evaluation results are stated in Table 5.10.

It is concluded that the lithium-ion BESS would already be viable in the year of 2018 for both metrics: under the three considered discount rates (($\text{NPV}_{5\%} = 292$ k€, $\text{NPV}_{7.5\%} = 151$ k€ and $\text{NPV}_{10\%} = 33$ k€)) and presenting an IRR of 10.8%. This is the only possible solution since all the other technologies show negative NPVs and IRRs. Even though that for all technologies (as it is demonstrated in Table 5.8) profits increase roughly between 20 and 36% (for the smaller size), this increase is not enough to cover the (still high) costs. Sodium-sulfur, zinc hybrid and vanadium redox flow batteries are not viable and possibly will not be in the year of 2025.

In the extended table, attached to this report in Annex F, the economic assessment of each technology evaluated sizes is displayed. Emphasis is given to the medium size of the lithium-ion battery.

This project presents two positive metrics (IRR=5.8% and $NPV_{5\%}$=114 k€). No further analysis is made since no other technologies are shown to be viable. The present (and future) costs of each technology (except lithium-ion) are still too high, compared with the possible profits that the BESS can achieve throughout the three-short term markets under the assumptions inferred in this thesis.

6

Conclusion

Contents

This chapter presents the general conclusions that can be outlined from the results. Some guidelines and recommendations to enhance the quality and extend the work of the present dissertation are also exposed.

6.1 Reflections

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. The thesis was ultimately divided into the forecasting of key input variables (power production and spot prices) throughout the relevant optimisation periods, optimisation of the system's operation within short-term markets and a study regarding the investment feasibility. Even though the analysis was performed for the context of the Portuguese market, the methodology is rather generic. It can be applied to any other electricity market with minor adjustments. All forecast and economic models were developed on MATLAB and the optimisation models on GAMS.

On the optimisation framework, 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. Especially 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.

The analysis and results presented in this dissertation reveal the particular importance of the real-time strategy. Despite natural uncertainty associated with forecasting, the developed models can reduce regulation costs to a minimum value. This is attained due to the flexibility added by the battery both in terms of its operation and its performance in the balancing market. Due to 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.

To evaluate the economic viability of battery technologies, a reference year was modelled by extrapolating the operation methodology of typical days. Three different sizes concerning four distinct BESS technologies (sodium-sulfur, lithium-ion, zinc hybrid and vanadium redox flow) were tested. 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.

NPV and IRR were chosen as economic evaluation metrics for BESS projects in the years of 2018 and 2025. Specifically, regarding the economic evaluation on 2018, only the smaller size of the lithium-ion battery disclosed a positive IRR (IRR=6.5%) and NPV for a discount rate of 5% (NPV$_{5\%}$=83 k€). However, the same investment is projected to be feasible in 2025, under both metrics (NPV and IRR) and all discount rates.

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%). Although an improvement of 21% to 36% (depending on technology) in the expected profit is obtained for the smaller size, the economic evaluation reveals that these extra revenues in the yearly operation are still not encouraging BESS implementation. The effectiveness from an economic perspective was proved with the calculation of NPV and IRR. These metrics revealed negative values for all tested technologies except for the smaller size of lithium-ion in both 2018 (NPV$_{7.5\%}$=151 k€, IRR=10.8%) and 2025 (NPV$_{7.5\%}$=427 k€, IRR=19.5%). Additionaly, in the year of 2025, the lithium-ion medium size BESS will likely be a viable project, presenting two positive metrics (IRR=5.8% and NPV$_{5\%}$=114 k€). Thus, presenting technical and development advantages over sodium-sulfur, zinc hybrid and vanadium redox flow BESSs.

Neverthless, one must keep in mind that storage technologies are maturing, and prices are gradually becoming more competitive. The rapid growth in renewable energy drives the urge for flexibility resources and the government support and energy transition policies are underlying factors for BESS projects. The overall ESS market is expanding and is expected to increase dramatically in the coming decade. Thus, battery technologies are on the way to become an attractive solution.

6.2 Future Work

Considering the major research topics addressed in this thesis, the elaborated work has possibilities to be expanded upon and improved.

Concerning the deep-learning approach on renewables and spot prices predictions, two main points to be enhanced were identified: the computational time of the forecasts and its accuracy. For each simulated day, the forecasting program takes about 45 minutes to define the results, making it impossible to develop an extensive and wide-ranging analysis. A proposal for future work is either to improve the existing LSTM model or to develop an optimisation tool to decrease the computational time. Additionally, forecasting accuracy could be further improved by using external variables. For instance, concerning solar power forecasting, a study on the importance of supplementary variables like cloud opacity could be done. Also, on the WT and PV modelling, more complex and accurate models, taking into account other climate variables could be implemented.

The results presented in this work should be considered with some caution as they are the output of a model that does not entirely depict the reality. The most significant approximation concerns the balancing market. In this thesis, the agent is assumed to be always called to mobilise or demobilise energy. In reality, the combination of agents that makes the total system less costly is the one chosen. Although another procedure is explored by assuming a percentage of capacity to maximise profit, it only allows a small energy quantity to be traded. Therefore, another method allowing a fairer comparison with reality on the BM can be studied in the future. It could be based on a similar producer's real data (supplied by the operator) concerning mobilisation calls. This would help to find out more accurately if the extra profits of applying the battery to the ancillary services would cover investment costs.

Other enhancements can be made within the simulation conditions. Notice that, simulations were performed for a single day, ignoring the previous and following days BESS operation. A monthly optimisation, for instance, would make the setting of initial and final stored energy values a decisive characteristic in the optimisation process. It would result in a more accurate understanding of the renewables and storage combined operation. Also, a different approach for the typical year simulation which considers, for instance, more typical days with diverse characteristics could be taken, resulting in a fairer comparison with reality.

Since this study is centred on the use of energy storage systems, some considerations regarding the BESS model could be added. Two major examples are the BESS degradation and depth of discharge throughout its operational years. These characteristics end up influencing the BESS operation and lifetime. Another upgrading of the current optimisation models would be to consider the optimal battery size as an optimisation variable instead of an established input value. Finally, other perspectives for future work could compare the investment in BESS with other storage alternatives.

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A

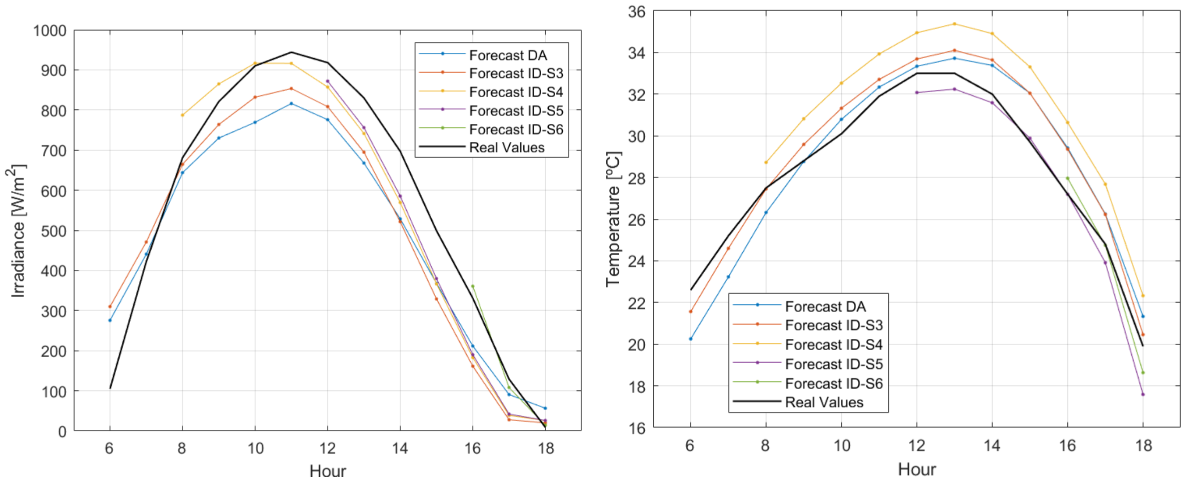
Weather Variables Forecast

To obtain the power generation forecasts for the day-ahead and intraday optimization programs, the weather variables forecast is required. Then, by using the models described in section 3.1, power forecasts are obtained. The meteorological variables referring to the winter and summer simulations exposed in section 4.2 are presented in this annex.

A.1 Summer Day

The forecasted irradiance and temperature can be observed in Figure A.1. The last session (seventh session) is not represented since it refers to the hours from 21 to 24 and, for solar forecasting, only daytime hours are considered. In Figure A.2, the typical solar production profile of the PV plant can be observed.

The power output of the wind park is shown in Figure A.3 resulting from the application of the respective power curve to the forecasted wind speed. Power forecast until 10h is irrelevant as wind speed



(a) Irradiance

(b) Temperature

Figure A.1: Forecast and real values of the solar panel model input variables (irradiance and temperature) for a summer day

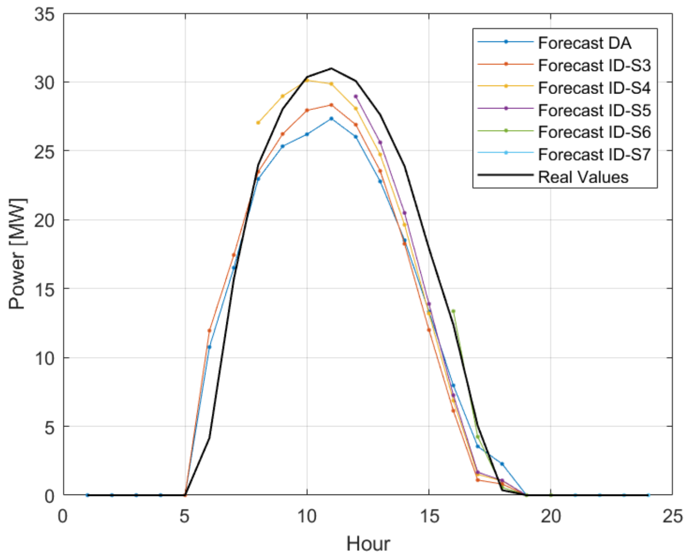
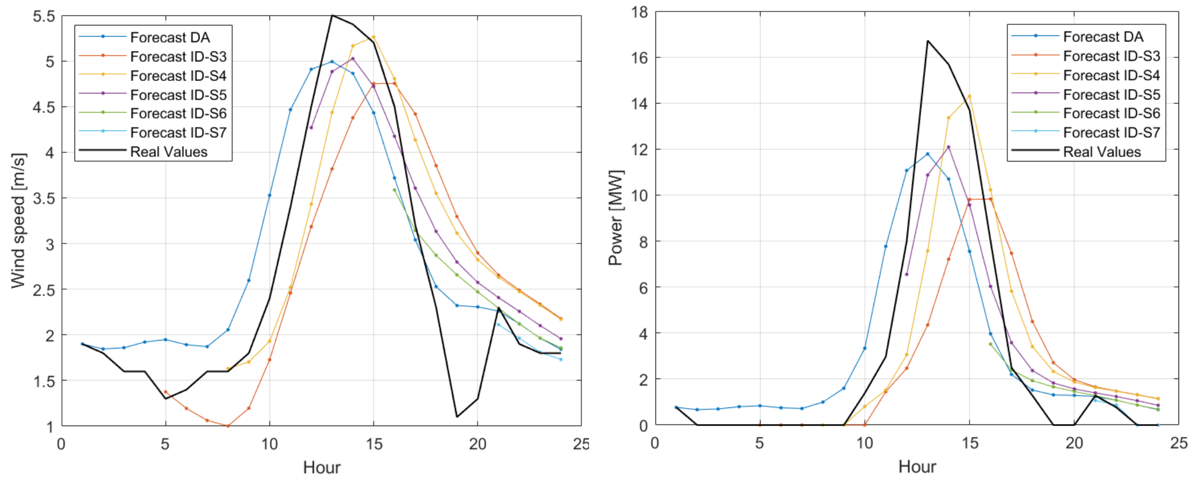


Figure A.2: Solar power forecast and real values for a summer day is predicted to be below cut-in speed. As mentioned in section 4.2, there are only two wind production peaks in the chosen day. As expected for a summer day, solar production is more significant.



(a) Input: wind speed

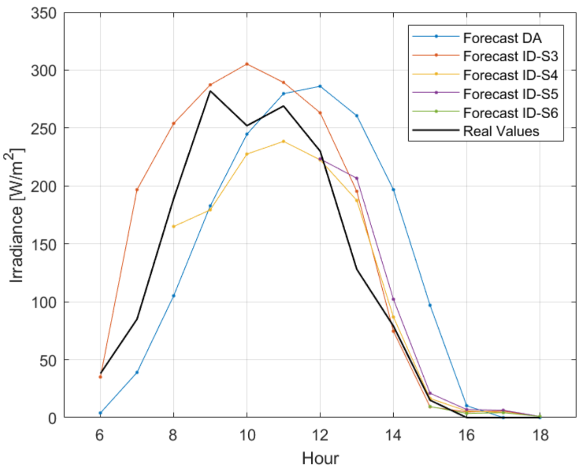
(b) Output: power

Figure A.3: Forecast and real values of the input (wind speed) and output (power) of the wind turbine model for a summer day

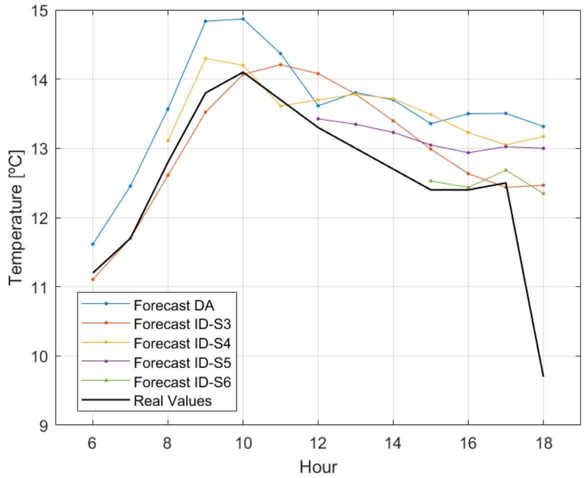
A.2 Winter Day

The irradiance and temperature forecasted for the winter day in all sessions considered can be observed in Figure A.4. In Figure A.5, the real and forecasted solar power production can be observed. As mentioned in section 4.2, in the winter day, one can observe low irradiance levels (about 250 W/m2 opposed to 950 W/m2 observed in the summer day) hence solar power is significantly less.

The predicted wind speed in the winter day, as well as the resulting power produced by the WF, can be seen in the Figure A.6.



(a) Irradiance



(b) Temperature

Figure A.4: Forecast and real values of the solar panel model input variables (irradiance and temperature) for a winter day

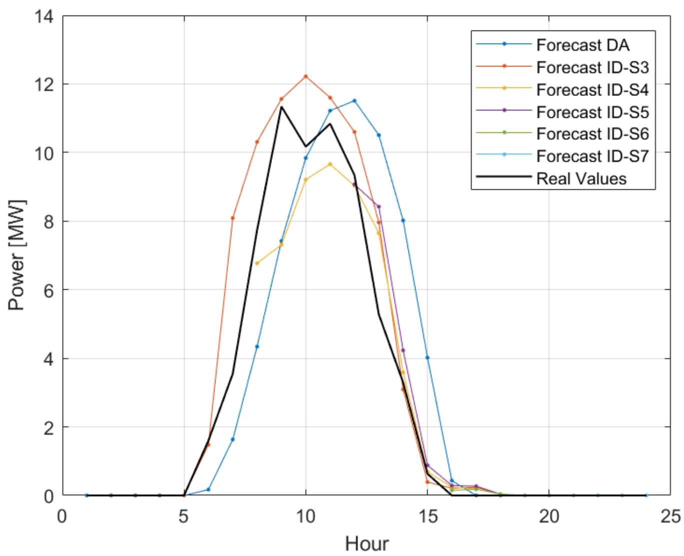
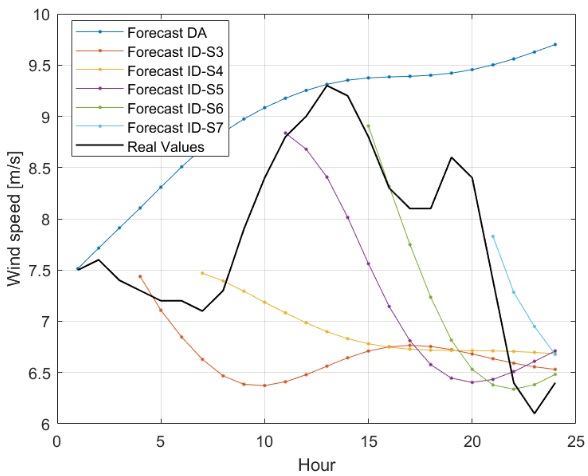
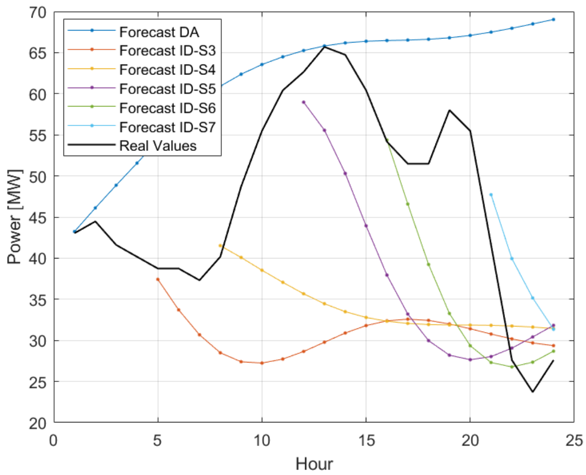


Figure A.5: Solar power forecast and real values for a winter day



(a) Input: wind speed



(b) Output: power

Figure A.6: Forecast and real values of the input (wind speed) and output (power) of the wind turbine model for a winter day

B

BESS Technologies

Sodium-sulfur, lithium-ion, zinc hybrid and vanadium redox flow were chosen to be an object of study in this thesis due to their suitability regarding renewable integration services and its technology and manufacturing readiness, at present times. A comparison on its relevant properties within the content and application of this thesis and its technical, economic and environmental features are briefly reviewed.

B.1 Sodium-Sulfur

Sodium-sulfur are mature rechargeable batteries in which the active materials are in molten states. Any degradation of these electrodes is automatically repaired every time the electrodes are liquified [59]. They are separated by alumina which plays the role of electrolyte [53]. One of the major drawbacks of this technology is that it operates under high temperature to maintain the molten state. Thus, there is a need for an external heat source for its efficient operation and, in case of a short circuit, it can lead to severe fire accidents [60], raising safety concerns. Alongside with li-ion, sodium-sulfur presents higher efficiency, power and energy densities, when compared to the other outlined technologies. However, it still has high production costs. At large power level, this is the leading market technology [61].

B.2 Lithium-Ion

Lithium-ion batteries operate on the transfer of lithium ions from the positive electrode to the negative electrode (charge) and vice versa (discharge). These batteries need temperature control for a safe operation [53] since they experience temperature increases when over-charged or with internal short circuits [60]. Even though lithium-ion technology is considered the most mature of battery storage technologies, they are mostly used for small-scale. However, this technology has opportunities in grid storage as well, especially for power applications. The high energy and power density together with rapid cost decreases driven by policies and incentives to promote and implement this technology led to increased deployment [59].

B.3 Zinc Hybrid Cathode

Zinc-based hybrid batteries belong to the other category of flow batteries. They are called hybrid flow which means only one electrolyte is stored in a tank. Likewise, hybrid flow batteries can be used without significant performance degradation [59]. Furthermore, this high energy density electrochemical storage technology uses inexpensive and widely available materials. Explicitly, some zinc-based batteries, like zinc-air, are 100% recyclable [59]. Consequently, this technology offers great promise in terms of cost [62]. Alongside vanadium, these batteries are one of the few flow batteries to be commercialized. Thus far, it has only been installed in a few sites. Therefore, limited information is available, and its technology and manufacturing readiness are both low [54].

B.4 Vanadium Redox Flow

Redox (reduction-oxidation) batteries are a category of flow batteries. Specifically, in a redox flow battery, both solutions are kept in different external tanks. The conversion between electric and chemical energy is achieved by exploiting the existence of four different vanadium oxidation states to transfer the electrons during battery operation [60]. The power of this technology depends on its size and design whereas the stored energy is increased by using larger thanks [53]. Thus, it is easy to store extensive amounts of power and energy in simple designs. Also, the arrangement and design are very flexible, as a result of scheming power and energy capacities separately. Due to excellent electrochemical reversibility [53] and lack of sensitivity to temperatures [54], long cycle life is achieved. However, they are complex in comparison with standard batteries, incur high production costs [60] and have low energy densities [61].

C

Energy Storage Specifications

The specifications of each tested BESS are demonstrated in this annex. Values stated on Table C.1 refer to the development of the nominated technologies in the year of 2018 and the predictions concerning the year of 2025, based on [54].

Table C.1: Costs and information of the tested BESS

Technology	Energy Cost [€/kWh]		Power Cost [€/kW]		Roundtrip Efficiency [%]	Life [Years]
	2018	2025	2018	2025		
Sodium-Sulfur	580	408	307	185	75	13.5
Lithium-Ion	237	166	252	185	86	10
Zinc Hybrid	232	168	307	185	72	10
Vanadium	487	345	307	185	67.5	15

Lithium-ion batteries are prevalent across industries and its technology is already deployed worldwide by multiple manufacturers. The chosen manufacturer was Samsung SDI [55]. On the contrary, utility-scale sodium-sulfur batteries are manufactured by only one company, NGK Insulators [56]. Regarding zinc hybrid cathode batteries, Eos [58] was the chosen manufacturer since it provided more information about the technology. Vanadium redox flow batteries are commercialized by a few companies and the chosen specifications refer to the batteries commercialised by Vionx Energy [57]. The tested battery sizes are organised in Table C.2.

Table C.2: Size of the tested BESS

Technology	Manufacturer	Small	Medium	Large
Sodium-Sulfur	NGK Insulators	0.8 MW/5.8 MWh	3 MW/18 MWh	4.2 MW/25.2 MWh
Lithium-Ion	Samsung SDI	2 MW/2 MWh	6 MW/10 MWh	20 MW/20 MWh
Zinc Hybrid	Eos	0.5 MW/2 MWh	1 MW/4 MWh	2 MW/8 MWh
Vanadium	Vionx Energy	0.5 MW/3 MWh	4 MW/6 MWh	10 MW/40 MWh

D

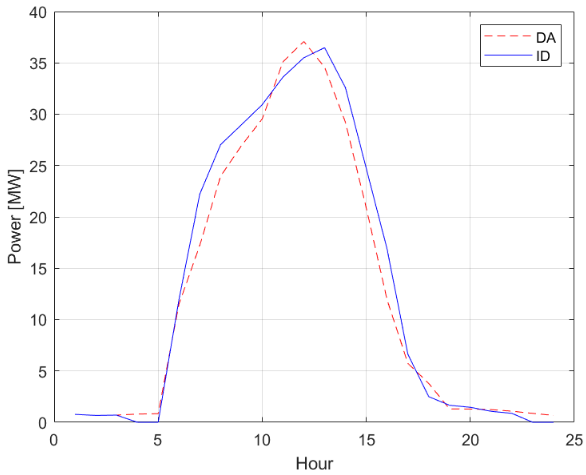
Intraday Bidding and Operation Strategy for a typical summer day

In the present Annex, an analysis of the intraday optimisation results concerning the typical summer day is described in detail. All operations and decisions at each hour of the day in question are scrutinised. To properly examine the day, inputs and outputs are presented first.

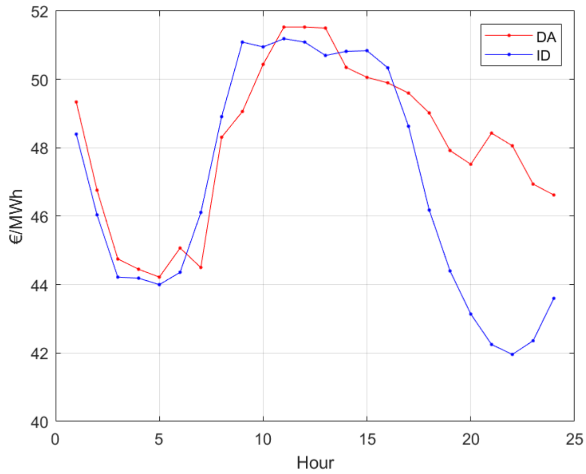
Figure D.1 depicts the ID model input variables together with the DA input variables, which are the spot prices and the newly updated forecasted power production. The overlap of the same input variables for each strategy (DA and ID) allows to observe and conclude on the model's operating decisions.

Figure D.2 shows the model output results: the bids submitted in the ID market sessions and the state of charge of the BESS. The ID bids are represented together with the deviations resulting from the difference between DA forecast and new ID forecast.

In Figure D.1, up until hour 4, the ID forecasted production matches the DA one: no deviations are predicted (Figure D.2). Subsequently, no action is taken both in the bidding strategy and BESS decisions (Figure D.2).

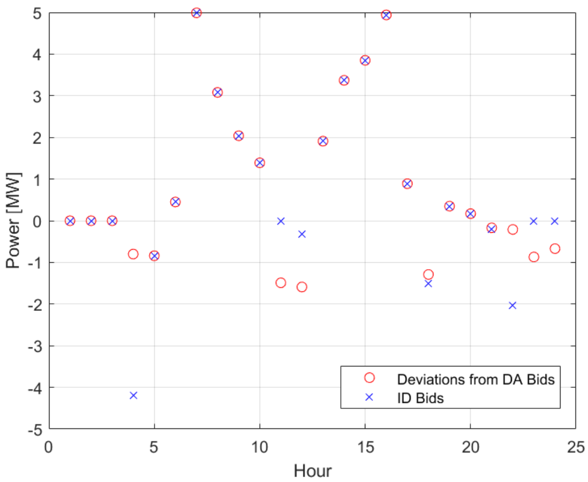


(a) Renewable production forecasts

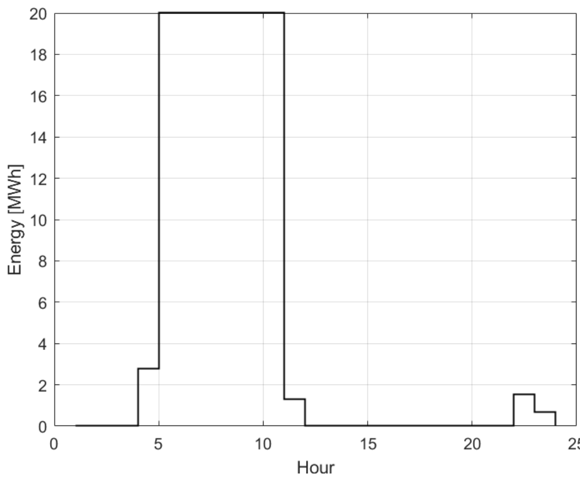


(b) Day-ahead and intraday spot prices

Figure D.1: Comparison between day-ahead and intraday forecasts (production and spot prices) for the summer day



(a) Bidding strategy in the intraday market



(b) State of charge of the battery

Figure D.2: Submitted bids in the intraday market sessions and battery state of charge after the intraday optimization

However, at hour 4, the new production forecast is below what was expected in the DA prediction. At that time, the BESS is programmed to be empty (exposed in the day-ahead strategy), thus, since the ID spot prices are predicted to be lower than the DA ones (Figure D.1), the system chooses to charge the battery in the ID market and discharges it partially to avoid imbalances that would come from the bid made in the DA market.

At hour 5, the system charges again, as it was established beforehand in the DA optimisation. Since the BESS was anticipated not to be fully charged by that hour (Figure D.2) and the predicted ID spot price is lower than the DA one, the system uses the rest of that hour to reach full charge from the ID market.

In the morning hours (6 to 10), the new prediction is above the DA one. Consequently, as it is depicted in Figure D.2, all the additional production is submitted in the following ID market sessions, to obtain additional revenues.

At hour 11h, the system discharges the storage as scheduled in the DA optimisation with a further minor discharge due to the new ID forecast.

From 13h to 17h, values above the ones considered before (overproduction) are foreseen, thus being bid in the respective ID sessions (Figure D.2).

At hour 18, the new production value is expected to be below the day D-1 forecast. A deviation will eventually occur, as shown in Figure D.2. However, the optimisation concludes the optimal operation is to charge and discharge the BESS within that hour across markets. This is possible because the prospected deviation is small and can be covered by charging some minutes from the ID market and, afterwards, discharging during some minutes to ensure that that the DA bid is covered.

Finally, in the last two hours of the day (23h to 24h), due to the new intraday forecasts, it is perceived that the renewables will not be producing energy, contradicting what was anticipated in the previously obtained day-ahead forecasts (Figure D.1). Hence, the ID strategy decides on charging the BESS during the lower ID spot price hour (at 22h, as one can observe in Figure D.2) with the amount of energy needed to guarantee there will not be any deviations (depicted in Figure D.2) from the initial bid in the following hours.

E

Final Bidding and Operation Strategy for a typical summer day

E.1 Participating in the Balancing Market: Case I

In this annex, Table E.1 reveals the extended results on the bidding and operation strategy for a summer day. The rows regarding each hour of the day are coloured differently based on the relation between predicted and real production. Red rows refer to hours in which the real production is below the predicted values (reflected in the DA and ID bids). Blue rows refer to hours in which the real production is above the predicted values. Also, if the production and last forecast match, the row is coloured in green. Regarding the BESS operations column, BESS discharges and charges are considered negative and positive, respectively, and the market/model in which they happen is specified.

Table E.1: Final bidding and operation strategy in the DA, ID and RT for the summer day: Case I

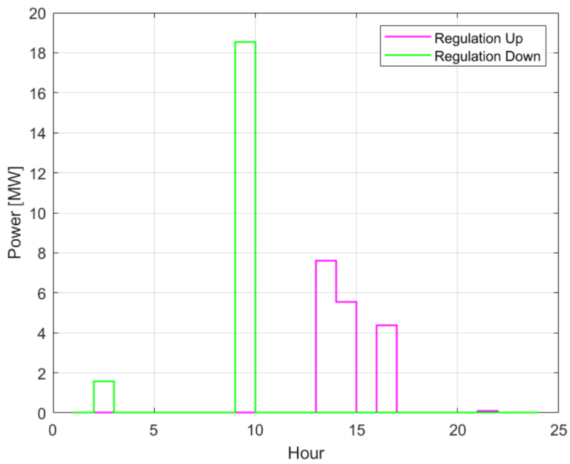
Hour [h]	Real Production [MWh]	Bid DA [MWh]	Bid ID [MWh]	BESS operations [MW]	SoC [MWh]
1	0.77	0.77	0.00	-	0.00
2	0.00	0.67	0.00	+ 1.59 (**BM**) - 0.67 (**DA**)	0.70
3	0.00	0.70	0.00	- 0.70 (**DA**)	0.00
4	0.00	0.80	-4.19	+ 4.19 (**ID**) - 0.8 (**DA**)	2.80
5	0.00	-19.16	-0.84	+ 19.16 (**DA**) + 0.84 (**ID**)	20.00
6	4.16	11.50	0.45	- 7.79 (**DA**)	12.21
7	15.70	17.23	4.99	- 1.53 (**DA**) - 4.99 (**ID**)	5.69
8	23.99	23.96	3.08	- 3.05 (**ID**)	2.63
9	28.03	26.93	2.04	- 0.94 (**DA**) + 18.56 (**BM**)	17.65
10	31.75	29.54	1.39	+ 0.82	18.36
11	33.95	52.31	0.00	- 18.36 (**DA**)	0.00
12	38.07	37.09	-0.33	+ 0.98 + 0.33 (**ID**)	1.12
13	44.3	34.77	1.97	+ 7.56 7.62 (**BM**)	0.00
14	39.44	29.42	3.34	+ 6.59 - 5.66 (**BM**)	0.00
15	31.10	20.95	3.90	+ 6.25	5.37
16	20.12	12.24	4.95	+ 2.93 - 4.57 (**BM**)	3.32
17	7.53	5.84	0.9	+ 0.79	4.00
18	1.65	3.82	-1.50	+ 1.50 (**ID**) - 2.17 (**DA**)	3.12
19	0.00	1.31	0.35	- 1.31 (**DA**) - 0.35 (**ID**)	1.46
20	0.00	1.29	0.17	- 1.29 (**DA**) - 0.17 (**ID**)	0.00
21	1.28	1.24	-0.20	+ 0.04 + 0.20 (**ID**) - 0.10 (**BM**)	0.10
22	0.77	1.08	-2.04	- 0.31 (**DA**) + 2.04 (**ID**)	1.54
23	0.00	0.87	0.00	- 0.87 (**DA**)	0.67
24	0.00	0.67	0.00	- 0.67 (**DA**)	0.00

E.2 Participating in the Balancing Market: Case II

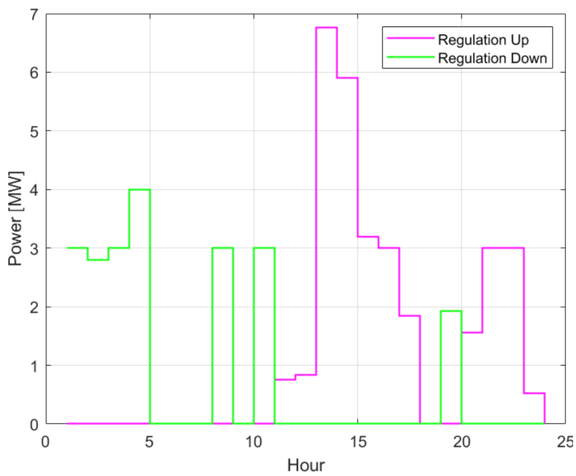
In this annex, Table E.2 reveals the extended results on the bidding and operation strategy for a summer day when participating in the balancing market as described in Case II. Cells highlighted in green express the same submitted bids in the DA and/or ID markets in both approaches: the fact that the balancing market is now seen as a profit-making opportunity did not change the bidding strategy. Cells highlighted in red mean that the DA and/or ID bids made within the previously assumed balancing market approach are different from the ones submitted now.

E.3 Comparison of the Balancing Market Operations

Figure E.1 illustrates the BESS operations on the balancing market during the 24h of the day for both approaches. When introducing the possibility of participating to maximise profits, the engagement in this market is higher (38 MW to 51 MW traded). Also, better imbalance management is achieved. Although the market was called on less often, when it happened, it was to heavily charge/discharge the battery: biggest transactions are 18.56 MW and 6.76 MW, respectively. Note that, in the second case, there are still 17 MW (85% capacity) always available to imbalance minimisation purposes. Although the operations and decisions presented in Tables E.1 and E.2 are different, the regulation costs are zero in both.



(a) Case I (Table E.1)



(b) Case II (Table E.2)

Figure E.1: Comparison between the battery operations in the balancing market regarding Case I and Case II

Table E.2: Final bidding and operation strategy in the DA, ID and RT for the summer day: Case II

Hour [h]	Real Production [MWh]	Bid DA [MWh]	Bid ID [MWh]	BESS operations [MW]	SoC [MWh]
1	0.77	3.35	0.00	+ 3.00 (**BM**) - 2.58 (**DA**)	0.00
2	0.00	0.67	0.00	+ 2.80 (**BM**) - 0.67 (**DA**)	1.74
3	0.00	0.70	0.00	+ 3.00 (**BM**) - 0.70 (**DA**)	3.62
4	0.00	0.80	0.00	+ 3.00 (**BM**) - 0.80 (**DA**)	5.40
5	0.00	-10.42	-1.77	+ 10.42 (**DA**) + 1.77 (**ID**)	15.88
6	4.16	11.50	0.45	- 7.34 (**DA**) - 0.45 (**ID**)	8.09
7	15.70	16.63	5.59	- 0.93 (**DA**) - 5.59 (**ID**)	1.57
8	23.99	23.96	3.08	+ 3.00 (**BM**) - 3.05 (**ID**)	1.10
9	28.03	26.93	2.04	- 0.94 (**DA**)	0.16
10	31.75	29.54	1.39	+ 0.82 + 3.00 (**BM**)	3.45
11	33.95	35.11	1.53	- 1.16 (**DA**) - 1.53 (**ID**) - 0.76 (**BM**)	0.00
12	38.07	37.09	0.00	+ 0.98 - 0.84 (**BM**)	0.00
13	44.3	34.57	1.91	+ 7.86 - 6.76 (**BM**)	0.00
14	39.44	29.21	3.37	+ 6.86 - 5.90 (**BM**)	0.00
15	31.10	20.88	3.85	+ 6.87 - 3.19 (**BM**)	2.71
16	20.12	11.94	4.94	+ 3.49 - 3.00 (**BM**)	3.20
17	7.53	5.74	0.89	+ 0.90 - 1.84 (**BM**)	2.14
18	1.65	3.79	0.00	- 2.14 (**DA**)	0.00
19	0.00	1.31	0.35	+ 1.93 (**BM**) - 1.31 (**DA**) - 0.35 (**ID**)	0.00
20	0.00	1.29	-3.32	+ 3.32 (**ID**) - 1.29 (**DA**) - 1.56 (**BM**)	0.00
21	1.28	1.24	-3.69	+ 3.69 (**ID**) + 0.04 - 3.00 (**BM**)	0.20
22	0.77	1.08	-9.01	+ 9.01 (**ID**) - 0.31 (**DA**) - 3.00 (**BM**)	4.64
23	0.00	0.87	0.00	- 0.87 (**DA**) - 0.52 (**BM**)	3.25
24	0.00	3.25	0.00	- 3.25 (**DA**)	0.00

F

Transactions in each market for the simulated days

Table F.1 details the direction of the submitted bids in each market for the four simulated days. Naturally, most of the transactions occur in the day-ahead market in all the simulations. In the intraday market, it is possible to minimise the deviations thus the buying and selling offers mostly to compensate for the over or underproduction predictions. In the winter and spring day, which are the simulated days with higher power production, no energy is bought in the day-ahead market to charge the battery to perform arbitrage since the models find it optimal to charge directly from the renewable production and not from the market.

Table F.1: Traded energy for each simulated day in all three short-term markets

Day	Market	Traded Energy [MWh]	Buying [MWh]	Selling [MWh]	Transactions [%]
Winter	Day-Ahead	1 410.5	0.0	1 410.5	**82.5**
	Intraday	222.3	112.8	109.5	13.0
	Balancing	76.3	44.3	32.0	4.5
Spring	Day-Ahead	921.3	0.0	921.3	**79.4**
	Intraday	108.5	91.8	16.7	18.9
	Balancing	130.1	130.1	0.0	1.6
Summer	Day-Ahead	334.2	19.2	315.0	**81.7**
	Intraday	36.7	9.1	27.6	9.0
	Balancing	38.1	20.1	18.0	9.3
Autumn	Day-Ahead	327.1	13.6	313.5	**82.5**
	Intraday	29.5	19.8	9.7	7.4
	Balancing	40.1	37.9	2.2	10.1

G

Economic Assessment

The extended results on the two economic assessment metrics used in this thesis are presented in the present annex. The output regarding Case I is comprised in Table G.1 while the results regarding Case II are presented in Table G.2.

G.1 Balancing Market: Case I

Table G.1: Economic evaluation for the tested BESS of each technology: Case I

Technology	Size [MW / MWh]	Annual Revenue [k€]	Annual Profit [k€]	NPV [k€] i=7.5%		NPV [k€] i=5%		NPV [k€] i=10%		IRR [%]	
				2018	2025	2018	2025	2018	2025	2018	2025
Without Storage		11 192.0									
Sodium-Sulfur *NGK*	0.8 / 5.8	11 227.2	35.2	-3 317	-2 222	-3 270	-2 175	-3 355	-2 260	-20.4	-17.5
	3 / 18	11 304.8	112.8	-10 423	-6 962	-10 272	-6 811	-10 544	-7 083	-20.3	-17.3
	4.2 / 25.2	11 334.6	142.6	-14 720	-9 873	-14 529	-9 682	-14 873	-10 026	-21-0	-18.2
Li-Ion *Samsung SDI*	2 / 2	11 328.1	136.1	-43	232	83	349	-142	134	6.5	14.3
	6 / 10	11 501.3	309.3	-1 759	-652	-1 432	-381	-1 981	-869	-3.9	2.0
	20 / 20	11 649.3	457.3	-6 641	-3 881	-6 149	-3 489	-6 970	-4 210	-11.9	-7.2
Zinc Hybrid *EoS*	0.5 / 2	11 211.1	19.1	-496	-298	-480	-281	-500	-311	-17.1	-12.6
	1 / 4	11 229.1	37.1	-1 000	-602	-968	-570	-1 007	-629	-17.5	-12.9
	2 / 8	11 266.0	74.0	-1 962	-1 206	-1 939	-1 142	-2 015	-1 259	-17.5	-12.9
Vanadium Redox Flow *Vionx Energy*	0.5 / 3	11 207.8	15.8	-1 475	-988	-1 450	-963	-1 494	-1 007	-17.9	-15.2
	4 / 6	11 311.3	119.3	-3 097	-1 757	-2 912	-1 572	-3 243	-1 903	-9.1	-5.2
	10 / 40	11 339.9	147.9	-21 244	-14 344	-21 014	-14 115	-21 425	-14 525	-20.7	-18.2

G.2 Balancing Market: Case II

Table G.2: Economic evaluation for the tested BESS of each technology: Case II

Technology	Size [MW / MWh]	Annual Revenue [k€]	Annual Profit [k€]	NPV [k€] i=7.5%		NPV [k€] i=5%		NPV [k€] i=10%		IRR [%]	
				2018	2025	2018	2025	2018	2025	2018	2025
Without Storage		11 192.0									
Sodium-Sulfur *NGK*	0.8 / 5.8	11 237.4	45.4	-3 233	-2 137	-3 172	-2 077	-3 281	-2 186	-18.4	-15.3
	3 / 18	11 336.2	144.2	-10 162	-6 700	-9 969	-6 507	-10 317	-6 855	-18.3	-15.2
	4.2 / 25.2	11 372.1	180.1	-14 409	-9 562	-14 168	-9 321	-14 602	-9 755	-19.2	-16.2
Li-Ion *Samsung SDI*	2 / 2	11 356.5	164.5	151	427	292	568	33	309	10.8	19.5
	6 / 10	11 565.6	373.6	-1 318	-206	-998	114	-1 587	-475	-0.7	5.8
	20 / 20	11 910.0	718.0	-4 851	-2 092	-4 236	-1 476	-5 368	-2 608	-5.3	-0.4
Zinc Hybrid *EoS*	0.5 / 2	11 217.5	25.5	-443	-254	-421	-232	-461	-272	-13.5	-8.5
	1 / 4	11 241.8	49.8	-893	-515	-851	-473	-929	-551	-13.8	-8.8
	2 / 8	11 291.9	99.9	-1 784	-1 028	-1 698	-942	-1 856	-1 100	-13.8	-8.8
Vanadium Redox Flow *Vionx Energy*	0.5 / 3	11 213.5	21.5	-1 425	-938	-1 392	-905	-1 451	-964	-15.6	-12.7
	4 / 6	11 370.0	178.0	-2 578	-1 239	-2 302	-962	-2 796	-1 456	-5.1	-0.6
	10 / 40	11 461.7	269.7	-20 170	-13 270	-19 751	-12 851	-20 499	-13 599	-16.4	-13.5