

Faculdade de Engenharia da Universidade do Porto



**A Bid Strategy Evaluation of a Battery Energy
Storage System in the day-ahead energy market
considering future opportunities costs**

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Recognitions

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Resumo

Durante os últimos anos, tem havido um aumento significativo na penetração de fontes de energia renovável nas redes elétricas em todo o mundo, não apenas devido ao seu custo de operação reduzido, mas principalmente devido as mudanças climáticas que se têm registado nas últimas décadas. Muitos países pretendem alcançar a neutralidade carbónica, o que, pelo menos por enquanto, implica o aumento da penetração de fontes de energia renovável no sistema elétrico.

No entanto, devido à sua natureza intermitente e à sua dependência em fatores externos (como a irradiação solar ou incidência do vento), que geralmente são difíceis de prever antecipadamente, o equilíbrio entre oferta e a procura pelos operadores do sistema está se tornar um desafio cada vez maior. Para enfrentar isso, houve um aumento da procura de flexibilidade no sistema, pois estes recursos flexíveis são capazes de mitigar as variações em tempo real das fontes de energia intermitentes, devido à sua capacidade de injetar assim como de absorver energia da rede.

Os recursos flexíveis que recentemente têm despertado maior interesse em termos de pesquisa e desenvolvimento, são os sistemas de armazenamento de energia em baterias (BESS - Battery Energy Storage Systems), que têm exibido uma tendência crescente na sua prevalência na rede, e espera-se que esta apenas aumente durante os próximos anos. No entanto, atualmente, os principais projetos de BESS são controlados pelo operador do sistema e são usados principalmente para reduzir os custos operacionais do sistema e evitar o corte de fontes de energia renovável mitigando os desvios registados em tempo real entre a carga e produção do sistema; uma das formas de fazer isso é realizando arbitragem de energia, ou seja, carregar energia durante períodos de baixos preços de eletricidade e descarregar essa energia durante períodos caracterizados por preços de mercado altos. Isto é benéfico em termos de fornecimento de flexibilidade à rede, porém também pode ser usado para gerar lucro devido às diferenças de preço registadas entre a compra (carregamento) e venda (descarregamento) de energia.

No entanto algumas pesquisas mostram que, atualmente, a simples realização de arbitragem de energia pelas BESS ainda não é lucrativa para proprietários privados; porém,

espera-se que isso mude num futuro próximo, principalmente devido à descida dos custos de fabrico e manutenção das baterias.

Antecipando que em breve as baterias de investidores privados (desde indivíduos a comunidades de energia) possam lucrar com a arbitragem de energia no mercado diário, é necessário um modelo para auxiliar no processo de tomada de decisão associado ao processo de submissão de ofertas pela BESS.

Com isso em mente, esta dissertação tem como objetivo desenvolver um modelo capaz de correlacionar as informações disponíveis ao operador da BESS (antes da submissão das ofertas no mercado) com a operação e lucros futuros desta de forma a prever qual será a melhor estratégia a ser utilizada, considerando algumas opções predefinidas. Com isto pretende-se melhorar o processo de decisão de um operador de uma BESS relativamente à sua participação no mercado diário.

Isto foi feito simulando a operação da bateria, instalada numa rede de distribuição de 37 barramentos usada como referência, e considerando alguns cenários de sistema com diferentes valores de carga e produção renovável, assim como três estratégias de oferta diferentes. Após a simulação da operação de mercado, os lucros resultantes de cada estratégia predefinida são usados para determinar qual a mais lucrativa para um determinado dia. Por sua vez esses resultados são utilizados para desenvolver uma ferramenta capaz de correlacionar certos parâmetros do sistema com a operação futura da BESS e indicar qual a melhor estratégia a usar no dia seguinte.

Esta ferramenta preditiva é baseada numa rede neuronal treinada com os parâmetros de carga, produção eólica e solar e os preços de mercado registados no dia anterior, de forma a prever em quais períodos a bateria deverá carregar, descarregar ou conservar a sua carga, para as 24h do dia seguinte. Desta forma a ferramenta é capaz de indicar qual a estratégia a usar durante a submissão de ofertas para o próximo mercado diário de forma a maximizar o lucro do operador da BESS.

Após ser testada para vários cenários com diferentes valores de carga e produção renovável, de forma a avaliar a sua assertividade em prever a melhor estratégia a usar e o lucro gerado pelo seu uso, constatou-se que a ferramenta é capaz de detetar variações sazonais e alterar sua estratégia de oferta de acordo. Para todos os anos testados, a ferramenta foi capaz de alcançar lucros de pelo menos 86% face ao lucro máximo possível de ser gerado (100% de assertividade) Para um ano considerado típico, a ferramenta alcançou uma assertividade de 82,2% e um lucro de 91,4% face ao lucro máximo para esse ano. Considerando um horizonte temporal sazonal, a ferramenta foi capaz de melhorar o processo de decisão de um operador de uma BESS quanto ao processo de submissão de ofertas no mercado diário para a maioria das estações dos casos de teste estudados. Apenas no verão a ferramenta revela uma tendência para piorar a sua assertividade e lucro, devido ao maior número de variações de qual estratégia é a mais lucrativa durante dias desta estação. Por

fim, foi realizada uma análise de sensibilidades de forma a determinar qual dos parâmetros de entrada da ferramenta tem maior impacto na eficiência desta, a qual revelou ser a carga.

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Abstract

In recent years there has been an increase in the penetration of renewable energy sources in power grids worldwide, not only due to their reduced cost of operation but also to address the environmental changes that have been prevalent in the past decades. Many countries are trying to achieve carbon neutrality which, at least for now, implies an increase in the penetration of renewable energy sources.

However, due to their intermittent nature and dependence on external factors (such as solar irradiance or wind incidence) which are usually hard to forecast in advance, the balancing of supply and demand by the system operators is becoming increasingly challenging. To face this, there has been an increase in the research and development of flexible assets, capable of mitigating the real-time deviations of intermittent energy sources due to their capabilities to both inject and absorb energy from the grid. The most well-known and researched of these assets are BESS (Battery Energy Storage Systems) which have become increasingly prevalent in the grid, and this trend is only expected to grow.

Despite this, nowadays the major BESS projects are owned by the system operator and used mainly to reduce the operational costs for the system and to avoid curtailment of renewable energy sources; a way to do this is by performing energy arbitrage, that is., charging energy during periods with low electricity prices and discharging it during peak periods. This is very beneficial in terms of the provision of flexibility to the grid, however, it can also be used to generate profit due to the price arbitrage associated with this operation.

Despite this, research shows that nowadays the sole performance of energy arbitrage by the BESS is still overall unprofitable for private owners. This, however, is expected to change soon with the decline in manufacturing costs of batteries.

Anticipating that in the near future private BESSs will be able to profit from energy arbitrage in the day-ahead market, a model is needed to support the decision-making process associated with the bidding of these BESS.

Within this scope, this dissertation pretends to develop a model that can correlate information available to the BESS operator prior to the submission of bids to the day-ahead

market that can predict which will be the best strategy to use, among some predetermined options.

This was done by simulating the operation of the battery installed in a 37-bus distribution grid for some established system scenarios, considering three different bidding strategy approaches. The resulting profits obtained by each predetermined strategy are used to determine the most profitable for a certain day; then, these results are used to develop a predictive model that can correlate some forecasted system parameters to the operating schedule of the BESS, and then predict which strategy would be the most profitable during the following day in the market operation.

The predictive model relies on a neural network trained with inputs regarding the system's load, wind energy production, solar energy production, and the previous day's market prices. It predicts the periods during the next 24 hours when the BESS should charge, discharge, or conserve its state of charge (SoC), thereby assisting in determining the bidding approach that is expected to maximize profit for the BESS operator.

This tool was then tested for several cases with different demand and RES generation scenarios, in order to evaluate its accuracy and profitability. The major findings were that the tool can detect seasonal variations and change its bidding strategy accordingly, reaching annual profits of at least 86% (when compared with the maximum profit obtained by 100% assertiveness in predicting the best bidding strategy to adopt). For a year considered as typical, the tool demonstrated an assertiveness of 82,2% and a profitability of 91,4% when compared to the max. When considering a seasonal timeframe, the tool is able to improve the decision making of a BESS operator regarding its bidding process during most seasons of the studied test cases. Only the summer season shows a general decrease in the assertiveness and profitability for the tool when compared with a static approach to the bidding process, due to the increased variability in the rank of the most profitable strategy across days belonging to this season. Furthermore, a sensitivity analysis was conducted whose results pointed towards the demand being the most influential input parameter in the efficacy of the tool.

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Abbreviations

ANN	Artificial neural network
ARIMA	Autoregressive Integrated Moving Average
BESS	Battery Energy Storage System
CAISO	California ISO
CET	Central European Time
CHP	Combined Heat and Power
CPLEX	IBM ILOG CPLEX Optimization Studio (optimization software package)
DAM	Day-ahead market
DC	Dynamic Containment
DoD	Depth of Discharge
DSO	Distribution System Operator
EES	Electrochemical Energy Storage
EIA	Energy Information Administration
ESO	Electricity System Operator
E.U.	European Union
FERC	Federal Energy Regulatory Commission
FFR	Firm Frequency Response
FN	False Negative
FP	False Positive
FZ	False Zero
GAMS	General Algebraic Modeling System
Gen.	Generation
ISO	Independent System Operator
LMP	Locational Marginal Price
m.u.	Monetary Units
MIBEL	Iberian Electricity Market
MINLP	Mixed-Integer Nonlinear Programming
MSE	Mean Square Error
PJM	Pennsylvania-New Jersey-Maryland Interconnection
p.u.	per unit value
PV	Photovoltaic
RES	Renewable energy sources SDAC

ROC	Receiver Operating Characteristic
SDAC	Single Day-Ahead Coupling market
SoC	State of Charge
T&D	Transmission and Distribution
TN	True Negative
TNR	True Negative Rate
TP	True Positive
TPR	True Positive Rate
TSO	Transmission System Operator
TZ	True Zero
TZR	True Zero Rate
U.K.	United Kingdom
U.S.	United States
WET	Western European Time

Symbols

Sets

N_{BESS}	Set of BESS
N_{Gen}	set of generators
N_{Load}	sets of loads

Indexes

B	index for BESS
i, j	indexes for buses
t	index for time periods
l	index for loads

Parameters

η	Efficiency
π	Price (m.u./p.u.)
B	Susceptance, imaginary part in Admittance matrix
G	Conductance, real part in Admittance matrix

Decision Variables

θ	Phase angle
C	Charge Binary variable
D	Discharge Binary variable
P	Active Power
Q	Reactive Power
V	Voltage magnitude

Subscripts and Superscripts

Ch	Charge operation
Cut	Curtailed Power
Dch	Discharge operation
Export	Export to the transmission network
Import	Import to the transmission network
Max	Upper Limit Bound
Min	Lower Limit Bound
Shed	Shed load

Chapter 1

Introduction

This chapter presents the motivation that gave way to the work presented for this dissertation, as well as the objectives and its organization. This chapter starts by providing the context in which it is inserted and the motivation to develop it. Additionally, this chapter outlines the main objectives of this dissertation, and finally, its structure is presented.

1.1 Context and Motivation

Balancing energy supply and demand in real-time has always been a challenge for power systems, and more so in recent years due to the increased prevalence of Renewable Energy Sources (RES). These sources (such as wind and solar power) are intermittent in nature and generally difficult to forecast in advance, which causes difficulties for the system operator to balance the dispatched production with the system's demand. Since the major power grids in the world are now aiming to achieve carbon-neutrality, the penetration of RES in these grids is predicted to increase rapidly (a trend that is already noticeable in recent years), implying the need for more flexibility in these grids. One resource that can answer these flexibility needs is the Energy Storage Systems (ESS), due to their ability to store energy similarly to other physical commodities, and to their fast response which can be used to mitigate the real-time deviations occurring in both the supply and the demand.

Among these storage systems, Battery Energy Storage Systems (BESS) are becoming increasingly prevalent in recent years, a trend that is predicted to continue in the future with the decline of battery production costs. By making use of this type of energy storage, the system operator can avoid the curtailment of RES during periods of low demand by storing the excess of energy generated and discharging said energy during hours characterized by a high demand. This increases the efficiency of the RES, reduces market prices (due to avoiding the operation of more expensive generators during high demand periods), and defers new investments in the generation and transmission sectors. Currently, most BESS projects serve

the purpose of increasing grid stability, aiding the integration of distributed generation and helping the system operator to manage their costs; however, private investors are seeking ways to generate profit by exploiting the requirement of flexibility by the grid.

One of the ways for privately owned BESSs to profit is by performing energy arbitrage (i.e., charging during off-peak periods and discharging during peak periods). The BESS operator can generate revenue this way by taking advantage of the difference in market prices registered during these hours. Currently, this operation does not justify the investment in privately-owned BESSs, mainly due to the costs associated with both the battery's manufacturing and its round-trip efficiency, which do not allow their operator to have a return on investment by solely performing energy arbitrage. However, with the trend of declining costs, the profitability of energy arbitrage will only increase, leading to the proliferation of company or community-owned large-scale BESSs installed in the grid. This, in turn, will shift the energy market players' focus to the strategic bidding of BESSs, as the profit generated by energy arbitrage depends on the approach adopted by the market participants in regards to the bids submitted to the energy market.

In conclusion, despite the current unprofitability associated with energy arbitrage, the rising need for flexibility and the declining in battery costs will change this paradigm in the near future, increasing the importance of decision-making models to optimize the operation of BESSs when it comes to generate profit for their owners.

In this scope, this work proposes a method to support the strategic bidding of a BESS operator interested in participating in the day-ahead energy market, by predicting which pre-established bidding strategy is the most adequate to use during the following day, based on forecasted data. This work also addresses the assessment of the established bidding strategies considering their profitability under different operating conditions.

1.2 Dissertation objectives

Despite the extensive research on this topic, there are still some gaps that need to be addressed in terms of improving decision-making for BESS participation in the energy-only market. Nowadays, the BESS participation in the electricity market while performing energy arbitrage is still unprofitable when not paired with another service, so it presents no incentives for investors to fund projects of privately owned BESSs to provide arbitrage. This is the reason why most of the applications of current grid-side BESSs are associated with renewable energy integration and frequency control due to, not only presenting higher revenues than energy arbitrage, but also because they assist in the operation of the power system. However, as will be discussed in Chapter 2, this is predicted to change in the following years, leaving room for research to be conducted on the optimization of a BESS operator's profitability while engaging in energy arbitrage in the day-ahead market. In this scope, the main research gap is: how can the BESS operator optimize its profit when

participating in the day-ahead energy-only market, that is, how can the operator make better decisions regarding its bidding based on historical or forecasted data?

To this end, the objectives that this dissertation pretends to address are:

- Designing different types of bidding approaches for the participation of a BESS in the day-ahead energy-only market;
- Developing a case study to test how the BESS operates under different conditions regarding certain system parameters;
- Find out in which conditions each of the established bidding strategies leads to better profitability for its operator;
- Development of a tool that is capable of correlating certain system parameters to predict which of the established bidding strategies is the most profitable for the following day.

1.3 Related Projects and publications

The work developed for this dissertation is targeted towards the objectives and results of two research projects, which are:

- DECARBONIZE - Development of strategies and policies based on energy and non-energy applications towards CARBON-neutral cities via digitalization for citizens and society (NORTE-01-0145-FEDER-000065);
- DECMERGE - Decentralized decision-making for multi-energy distribution grid management (2021.01353.CEECIND).

The work developed resulted in the publication of a scientific paper at the EEM23 conference, which should be referred to as:

- Pedro Santos, Tiago Soares, Igor Rezende, and Vladimiro Miranda, "Evaluation of different bidding strategies for a battery energy storage system performing energy arbitrage -a neural network approach", presented at EEM23.

1.4 Structure of the dissertation

The document for this dissertation is organized into six chapters, whose description is as follows:

In Chapter 1 the main context and motivation for the development of the work presented in this dissertation are described, as well as the outline of the objectives and structure for this dissertation.

In chapter 2, an extensive literature review is performed to present an overview of the main features of BESS, such as their types, characteristics, and possible applications. Then a brief overview of energy markets is also conducted to better understand how a BESS can take

advantage of their structure. Finally, the current scope of the provision of energy arbitrage by BESSs in the day-ahead market and predictive models similar to the one developed in this dissertation are presented.

In Chapter 3, the methodology applied in this work is outlined; starting by describing the problem addressed, followed by describing the concept of a bidding strategy and the general approaches adopted for their design. Then, the mathematical formulation of the economic dispatch problem for the day-ahead energy market is described in detail including the constraints applied to the BESS. Furthermore, a brief description of how the predictive model based on an artificial neural network works is provided, including which parameters will be used as inputs and outputs.

Chapter 4 presents the case study developed for this work, including the characterization of the system in which the BESS is installed (including the characteristics of each energy resource), the process that is undertaken to develop different system scenarios, and the bidding strategies established with this case study in mind. Additionally, this chapter presents the concrete methodology applied to develop the predictive tool for this case study, including its training and testing and a brief analysis of its accuracy in predicting the more profitable strategy for the next day.

In chapter 5 the results regarding the application of the developed tool in some test cases are presented, as well as an analysis of its assertiveness and profitability in an annual and seasonal basis. Additionally, a sensitivity analysis of the impact of each input parameter in the effectiveness of the tool is also conducted.

Finally, in chapter 6, the main findings pertaining to the development of this work are addressed, including possible topics to be addressed and researched in future works.

Chapter 2

State of the Art

This chapter presents the main research regarding BESS technology, particularly its characteristics and applications. Additionally, an overview of the energy markets is also portrayed, where the markets suitable for BESS participation are outlined. More important to the context of this dissertation, the current scope and existing research regarding both the participation of energy arbitrage performing BESS in the day-ahead market and predictive methods similar to the one used in the work presented are discussed.

2.1 Overview of BESSs types, characteristics, and applications

2.1.1 Types of BESS

There are many options regarding the technology of batteries used for energy storage, characterized by different manufacture and capacity costs, maturity level, round-trip efficiency, among others. The most common types of batteries are:

- **Lead acid:** These batteries are made up of cells, with a positive electrode of lead dioxide and a negative electrode of sponge lead. The electrodes are separated by a micro-porous material and are immersed in a liquid sulfuric acid electrolyte;
- **Sodium sulphur (NaS):** This battery contains two liquid electrodes where the positive is made of molten sulphur and the negative of molten sodium. These electrodes are separated by a solid beta alumina ceramic electrolyte, only allowing the positive sodium ions to go through it and combine with the sulphur to form sodium polysulfides. This battery needs to be kept at about 300 °C to ensure this process;

- **Lithium-ion (Li-ion):** This battery's electrodes are made of lithiated metal oxide (for the cathode) and graphitic carbon, with a layer structure (for the anode), with an electrolyte made up of lithium salts dissolved in organic carbonates separating the two. During the charging of the battery, the lithium atoms in the cathode turn into ions and flow through the electrolyte, combining with external electrons on the other electrode, and being deposited as lithium atoms between carbon layers. The reverse happens during the discharging process.

Lead acid batteries are the oldest and most mature technology of electrochemical energy storage, although, in recent years, Li-ion and NaS batteries have become the leading technologies, with Li-ion being the most promising in future development and optimization [1]. In the work presented in [2], the capacity costs of BESSs, particularly the lithium-ion technology, are determined to be far above the breakeven costs. This makes the performance energy arbitrage currently unprofitable, while also determining that the round-trip efficiency of batteries greatly affecting arbitrage revenue.

2.1.2 BESS technical characteristics

The main parameters that characterize a BESS and affect its operation [3]-[5], particularly energy arbitrage, are:

- **Energy density:** the specific energy density of a battery reflects the amount of energy that can be stored by the battery per unit of its mass (Wh/kg);
- **Power density:** the specific power density of a battery reflects the power that can be outputted by the battery per unit of its mass (W/kg);
- **Energy efficiency:** The round-trip efficiency of a battery (also called cycle efficiency) is the ratio between the energy discharged by the battery and the energy charged by it when considering one full charge/discharge cycle. This parameter is correlated to the losses incurred by the battery both in the charging and discharging operations;
- **Cycle life:** The lifetime of an operating battery represented in the expected number of cycles it can complete. This parameter is dependent on the operating conditions of the battery where the most important parameter is the depth of discharge of the battery during each cycle.

2.1.3 BESS applications

Depending on the BESS's response time, its power and energy capacities, as well as its location on the grid, there are several services that this flexible asset can provide, all of them derived from the simple charging and discharging of the BESS [6].

These services can provide support to power plants, increasing their efficiency and life expectancy and reducing fuel consumption and CO₂ emissions per kW_h produced. Regarding the RES integration on the electrical grid, a BESS located near RES can also provide certain ancillary services to help ensure the stability of the grid when faced with the generation uncertainty associated with these sources. This is achieved by storing the excess of renewable production, reducing or eliminating the curtailment of renewable generation in the process.

These applications can also aim to reduce transmission line congestion, increasing system reliability and deferring new investments on new generating resources or new Transmission and Distribution (T&D) lines.

Through participation in the energy or ancillary services markets, some of these applications can be used to generate profit for the BESS operator. The potential services that a BESS can provide can be observed in Table 2.1.

Table 2.1 - Possible BESS Applications.

Energy Applications	Power Applications
Energy arbitrage / time-shift	Frequency regulation
Peak reduction	Voltage support
Load levelling	Reserves
T&D congestion relief and infrastructure investment deferral	Renewable Capacity Firming

(Adapted from [6], [7])

These potential applications of BESS can be described as:

- **Energy Time-shift/Arbitrage:** Storing low-priced energy by charging the battery during periods of low demand and then selling it during periods of high demand, where the price of energy is higher. This application of the BESS will be addressed in a more detailed manner in section 2.3;
- **Peak reduction/shaving:** To reduce the energy demand of the consumer during peak hours (with an associated high energy price), and consequently reduce the cost of the electricity bill; the BESS can charge during off-peak hours to then reduce the load

demand on the grid during high demand periods, through self-consumption (by the consumer) of the energy stored;

- **Load levelling:** Smoothing of the demand curve, thus, reducing the dependence on less-economical generators to supply the peak load. This application also defers new investments in T&D or generation systems;
- **T&D congestion relief and infrastructure investment deferral:** Time-shifting or geographical shifting of the energy supply (discharging) or demand (charging), in order to relieve line congestion in the T&D grids and to defer the need for further investments;
- **Frequency Control:** Using the fast response time of the BESS to provide the system with increased load (charging) or increased generation (discharging), in order to balance the two and therefore return the grid frequency to its base value.
- **Reserves:** To prevent loss of load, and to rebalance the system, the BESS can be used to compensate for unexpected losses in generation (e.g., generator outage and renewable production deviations) by maintaining a standby capacity, ready to be deployed when needed. These reserves are grouped depending on their response time. Reserve capacities with response times under 15 minutes are classified as spinning reserves, while the ones with slower response times are called non-spinning;
- **Voltage support:** The injection or absorption of reactive power to maintain voltage levels, in the T&D systems, within their limits and close to the nominal voltage.

Despite all these services being capable of providing support to the grid, the deployment of BESSs is slowed due to their high investment costs (although decreasing in recent years [8], [9]). So, a market strategy needs to be determined to get the highest possible profit for BESS's participation in the electricity market to reduce the risk of the investment for private investors, which, even if it does not reach break-even costs, may shorten the time until a profitable investment is guaranteed.

This market strategy was considered to be the optimal bidding performed by the BESS, that is, in which market and time period will the BESS submit its bids and offers (along with their respective values) in order to obtain the highest possible profit. In section 2.2, the overview of the electricity markets is presented to better understand how a BESS can be used to generate profit in a competitive market environment.

2.2 Electricity markets

Any energy supplier aiming to supply the demand of the power system must first offer its production capacity in a market environment. This market structure of the energy sector enables competition between consumers, but mainly between suppliers, which can lead to greater economic efficiency regarding the energy sector.

An electricity market can be succinctly resumed as a market structure, managed by a market operator, whose function is to maximize the social welfare for a given region and a given timeframe. By determining which producers can effectively provide their production capacity and which consumers are allowed to be supplied by it, the market operator can reduce the system's operational costs which ideally leads to a decrease in electricity prices. The competitive environment provided by this market structure enables the possibility for strategic bidding, that is, the effort made by each market player to increase their profits by exploiting the design of the market. Despite the strategic bidding of an energy supplier being intended to increase their profits, the way each strategy is designed must be carefully thought-out, otherwise, the risk of a non-ideal outcome (although always present in a competitive environment) may become too high to handle by a private energy supplier.

The bidding process that each energy producer and consumer take part in is based on submitting bids to the electricity market, which will be accepted or rejected by the market operator to reduce the system's operating cost. This market bidding process consists of the submission of bids by each supplier, defined by the quantity of energy that it is willing to supply and a price that represents the minimum amount of monetary units that it is willing to accept to supply that energy. On the other side, this process is also defined by the submission of the consumer's bids, with the amount of energy needed to supply their demand and the maximum price they're willing to pay for that energy. The market operator will collect every bid submitted and, by maximizing social welfare, will determine which bids are accepted, relaying that information to the producers and consumers so that they know how to proceed with the actual operation.

Regarding BESSs (which will be the focus of this work), due to the capacity of the battery to both buy (by charging) and sell (by discharging) energy, they can behave as both a producer and a consumer. This implies that a BESS operator can submit both types of bids to the electricity market, paying or receiving compensation according to the service provided.

2.2.1 Classification as a Market Player

Regardless of the market in which they participate, any market player including the BESS can be classified as one of two types of players. price-makers and price-takers:

- **Price-maker:** A price-maker is a market player whose market power is significant enough that their bids influence the final price cleared by the market. A BESS can assume a price-maker role if its capacity is large enough (or if there are multiple BESS aggregated to the same operator). This does not generally happen as the capacity of a single BESS (or even multiple aggregated BESSs) is much lower than that of the other players such as conventional generators. However, perhaps in the future, the large prevalence of BESSs in the grid and the consequential deferral of

conventional generation may lead to these systems being characterized as price-makers at some or all hours of the operating day.

- **Price-taker:** This is usually the predisposed classification of the BESS as a market participant. A price-taker can not influence in a significative way the setting of the market clearing price, because it does not have enough market power. The strategy for profit generation for a BESS considered as a price-taker is solely the maximization of its profit based on the forecasted market prices set during market clearing, not considering how its bidding may affect those prices.

2.2.2 Types of electricity markets

The electricity markets can be divided into two different types of markets depending on the service that their market players provide and their operating timeframe (as seen in Figure 2.1). The energy and ancillary services markets are the two types of markets.

2.2.2.1 Energy markets

The energy markets are often split into three main stages, as detailed below:

- **Day ahead market:** In this market, the wholesale of energy takes place between producers and consumers following a symmetric pool model. The consumers place buying bids, declaring the amount of energy needed for every hour of the next day, and how much they're willing to pay for it, while the producers place selling bids disclaiming the amount of energy offered and its price. These hourly bids, when ordered to maximize social welfare (taking grid constraints into account), allow for the calculation of the marginal market price of the system, which corresponds to the price of the last bid that was accepted. The market price sets the cost of every unit of energy sold for that respective hour (considering a pay-as-clear system) [10]-[13].
- **Intraday market:** This is a Spot market that helps the balancing of energy supply and demand. Due to uncertainty in the load and generation forecast, market players may need to adjust the volumes traded in the day-ahead market to avoid surpluses or shortfalls of energy. These markets' opening and closing hours vary from country to country (usually opening at the closing of the day-ahead market, and closing 1 hour before delivery), and energy can be traded for intervals of 15, 30 or 60 minutes [10], [13], [14]. Some Intraday markets follow an auction system instead of being continuous, such as the case of the Iberian electricity market [11].
- **Balancing market:** Even after the intraday market clearing, there may still be some last-minute adjustments to be made, particularly caused by RES, whose generation output can only be accurately forecasted very close to the dispatch hour. For this reason, a balancing market exists, where producers and consumers can adjust their trade volumes on a real-time continuous market [15].

2.2.2.2 Ancillary services market

Some unforeseen fluctuations in generation or demand, which must be matched continuously by the Independent System Operator (ISO), may happen in the real-time system operation. Because of this and the consequential need to preserve the stability and reliability of the grid, the system operators provide an ancillary services market that usually comprises a regulation market (to control the system frequency) and a reserve/capacity market (to help in the recovery of the system balance in the event of a loss of a generator).

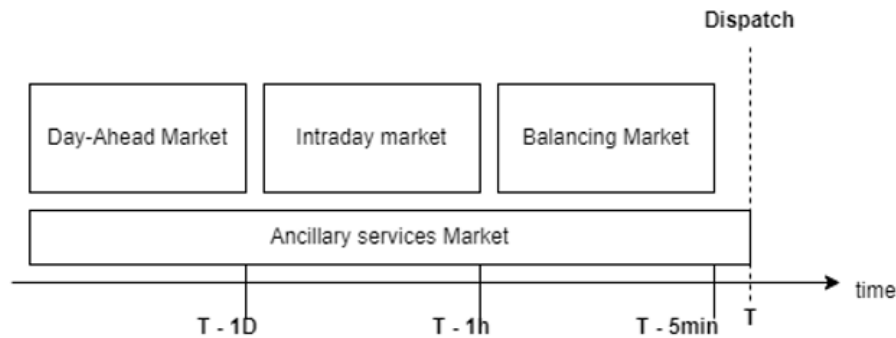


Figure 2.1 - Operating timeframe of the electricity markets.

2.2.3 Regional Markets

The aforementioned market structures are implemented in all major power grids. Thus, some of the regional markets will be briefly analysed regarding their overall design.

2.2.3.1 CAISO

This system operator is one of the largest in both the U.S. and the world, providing 3 different market operations: the day-ahead market, the real-time market and the ancillary services market (as can be seen in Figure 2.2).

The day ahead market opens 7 days before the trading day, and closes the day before, with the market clearing results being published at 1:00 PM. The ISO can get these results by running the integrated forward market, and obtaining the Locational Marginal Price (LMP) for the day-ahead market.

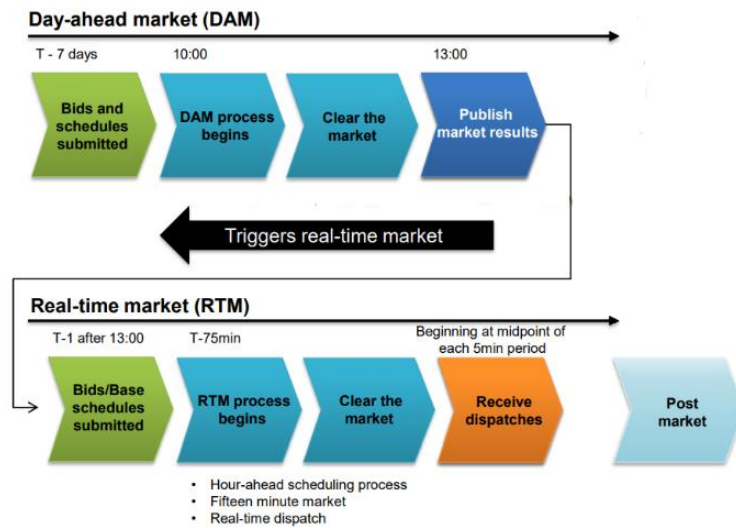


Figure 2.2 - Operating timeframe for CAISO's energy markets [10].

2.2.3.2 MIBEL

The Iberian electricity markets can be divided into the day-ahead market and the intraday market. Since 2014, the day-ahead market works as part of a pan-European Single Day-Ahead Coupling market (SDAC), setting prices for every European electricity market. The bids for selling and buying energy in this market are accepted based on their merit order, until this spot market closes at 11:00 (WET), publishing the price of energy and its scheduled quantities for every hour of the next day, or until the interconnection between Spain and Portugal becomes saturated (after which, each zone gets its own energy price, i.e., market splitting) [16].

2.2.3.3 Nord Pool

This market (Figure 2.3) is divided into a day-ahead market (ElSpot) and an intraday market (Elbas), each operating in both the Nordic and Baltic regions. These regions are divided into different bidding zones which allow different prices according to the market clearing of each zone. The day-ahead market can accept single-hour, block and flexible bids, with each market player being able to submit one or more types of these bids. The Elspot closes, and publishes its energy prices and scheduled quantities, at 12:00 CET.

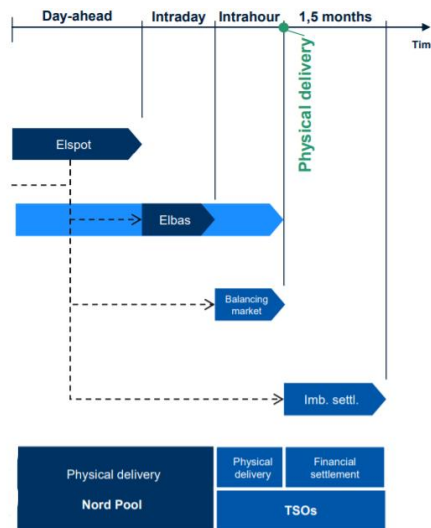


Figure 2.3 - Operating timeframe for Nord Pool's markets [14].

2.2.4 Flexibility

The flexibility of a power system can be defined as “the possibility of modifying generation and/or consumption patterns in reaction to an external signal to contribute to the power system stability in a cost-effective manner” [19]. The rise in the need for flexibility can be attributed to the increasing prevalence of intermittent RES (i.e., Wind and Solar) in today's power systems, due to the uncertainty, and high variability associated with their generation. Considering the concept of net load (defined by the difference between the system load and renewable generation), it is easy to understand that higher penetration of RES in the grid leads to steeper ramps in the net load. If conventional reserves do not have the ramping capabilities necessary to respond to these steep ramp events, there will be temporary price spikes in the real-time energy markets [18], and frequent curtailment of renewable generation [19].

This lack of flexibility can be mitigated through the deployment of energy storage devices/assets due to their capabilities of renewable capacity firming (when the BESS is directly connected to the RES), load levelling (by time-shifting demand or generation to stabilize the load curve) and fast ramping. The deployment of BESSs is a tailor-fit solution to provide adequate flexibility to the system, because of their fast-ramping capabilities and capacity to both absorb or inject energy into the grid. The falling prices of batteries are a major driver for the rising trends of BESS installations. In the future, following this trend, regional markets must accommodate the prevalence of BESSs providing on-grid applications (mainly energy arbitrage and frequency control), in order to take advantage of this flexibility resource more efficiently [20], which some are already doing.

2.2.4.1 Europe

In Europe, there are many interconnected regional markets such as Central Western Europe (which includes Germany, France and the Netherlands), Northern Europe (Nordic and Baltic countries), the British Isles (UK and Ireland), the Iberian Peninsula (Spain and Portugal) and the Apennine peninsula (Italy and Malta). These zones have different wholesale energy markets, and different countries have different regulations and financial risks [21], [22], which means that the profit resulting from the operation of the BESS in a competitive market environment, depends on the country it is located.

Despite being capable of providing numerous services, the main applications for a BESS are energy arbitrage and frequency control. However, recent studies show that energy arbitrage is currently not profitable in European markets, due to the slim gap between peak and valley prices [22].

The UK is currently the European country with the largest BESS capacity installed (and the largest capacity for unbuilt authorized projects), followed by Germany and, with significantly less capacity, Italy and Netherlands. The UK government, ISO/ESO and regulation agency, facing these developments, made it easier for flexibility providers (such as BESS) to participate in capacity and balancing markets by implementing several measures. More precisely, it reduced the minimum capacity threshold for participating in these markets to 1MW, implemented a new faster frequency response product, and implemented new local flexibility markets [20].

This new product called Dynamic Containment (DC), which aims to correct post-fault frequency deviations (i.e. after the deviation crosses either the upper or lower imposed limits), was introduced in October 2020, and will eventually phase out the monthly tenders of the standard Firm Frequency Response (FFR). Compared to the FFR requisites, a market player willing to provide dynamic frequency containment needs to be able to act much faster (full delivery in 1s vs 10s). At the same time, the frequency band for which no response, or little response, is needed, is much larger for the DC than for the FFR, which means that the energy actually delivered to the grid is much higher for the FFR than for the DC. These two factors show that batteries are the perfect asset to provide dynamic frequency response to the grid, which explains why only BESS participate in the DC market. Since its launch, the DC market has yet to reach saturation, meaning that the market clearing is not yet truly competitive, which explains the high prices registered compared to the ones cleared in the FFR market.

In November 2021, high DC was introduced to complement the low DC. These two services are procured separately and respond to low and high frequency deviation, respectively. The compensation system was also changed from pay-as-bid to pay-as-clear, while the contract length was shortened from 24h to 4h blocks, allowing the National Grid ESO to adjust its DC

requirements along the day, instead of always procuring its maximum requirement for the 24h period.

In Germany, the primary containment reserve market has undergone some changes in the last decade, evolving from an oligopolistic market with only 5 providers to a more competitive one with more than 20 providers in 2016 [23]. The minimum bid size for frequency regulation reserves is currently 1MW and they are procured in a coupled market area that includes neighbouring countries (e.g., France, Austria and Netherlands) through daily tenders. The submitted bids must also be symmetrical. Recent changes to this market introduced some measures to allow for the better exploitation of BESS. These include the possibility of over and under regulation and the possibility of activation within the frequency deadband. The compensation for providing this service is based solely on the capacity provided, with the payments being determined by a marginal price system [24].

2.2.4.2 United States

In the United States, the Federal Energy Regulatory Commission (FERC) along with the American ISO's, are taking action to facilitate the participation of energy storage in the energy markets. FERC order 755, issued in 2011, requires the ISOs to provide compensation to resources that can provide fast-ramping frequency control. Following this order, PJM interconnection split its frequency regulation market into fast-ramping and slow-ramping services which resulted in the installation of more than 180MW of BESS capacity, located within PJM territory in 2015. But, due to the overdependence of this fast-ramping service (relative to the slow-ramping one), some technical issues arose that led to the changing of PJM regulation signals, which in turn led to a heavy decline in new battery installations. Another FERC order (841) required ISOs to remove barriers to the participation of BESSs in the energy and ancillary services market (by lowering minimum size requirements, allowing aggregation and defining duration requirements, for example) [25].

Besides FERC orders, other state-level policies have been passed (with California being the state most active in this regard), mainly about setting mandates for utilities to procure energy storage capacity.

PJM Interconnection currently has the highest BESS capacity installed in its territory. A BESS willing to participate in this ISO's Energy market can submit both charging and discharging bids/offers (which was not possible before FERC order 841, when BESS could only submit 0\$ discharging bids). For participation in PJM's regulation market, the BESS must submit two-part bids, containing its traditional capacity offer, as well as a performance offer that was introduced by the FERC order 755 to reflect the regulation resource's performance in the market clearing and payment (with performance being evaluated through a Performance score, mileage ratio and benefit factor, all introduced by the same FERC order) [26].

The inclusion of these new products and the relaxation of market restrictions for BESSs in the energy markets leads to an increase in BESS units installed in power grids due to their potential for being good economic investments. However, these are focused on providing an increasingly better market environment for BESSs designed to provide frequency regulation to the grid, which is of great importance to the system operator (DSO or TSO), but does not impact the economic value of BESSs that provide energy arbitrage.

Even new investments in batteries with large energy capacities (adequate for energy arbitrage) are mainly targeted to aid the integration of renewable production in regions with a large penetration of RES and not to engage in arbitrage, which shows the current lack of interest in the economic potential of this operation. In section 2.3, it is presented an overview of energy arbitrage as a potential BESS application in the day-ahead energy market, considering its current scope and potential future developments.

2.3 Energy arbitrage in the day-ahead energy market

2.3.1 Concept

The day-ahead energy market serves the purpose to aid the system operator in balancing the supply and demand of the power system, for which it is responsible, by selecting beforehand which producers and consumers will operate during each hour of the following day, to reduce system costs and improve the social welfare. After receiving every producer and consumer bid to sell or buy energy, respectively, the market operator performs an optimal economic dispatch which determines the market price that is used for every energy transaction accepted (market clearing). It is assumed that the market clearing price corresponds to the value associated with the last bid accepted, that is, the operating cost of the most expensive generator scheduled.

2.3.2 Current scope

In this subsection, an overview of the current developments in Europe and in the United States regarding energy arbitrage in the day ahead market is presented.

2.3.2.1 Europe

According to a report published by the European Commission [20], [27], the main energy storage provider is still hydro pump systems, but new projects are being developed to increase the prevalence of BESSs across Europe, particularly regarding lithium-ion batteries. This rapid development is being made especially in the U.K., Germany and Italy (as seen in

Figure 2.4), which currently represent the countries with the largest power capacity of BESS installed in their respective grids.

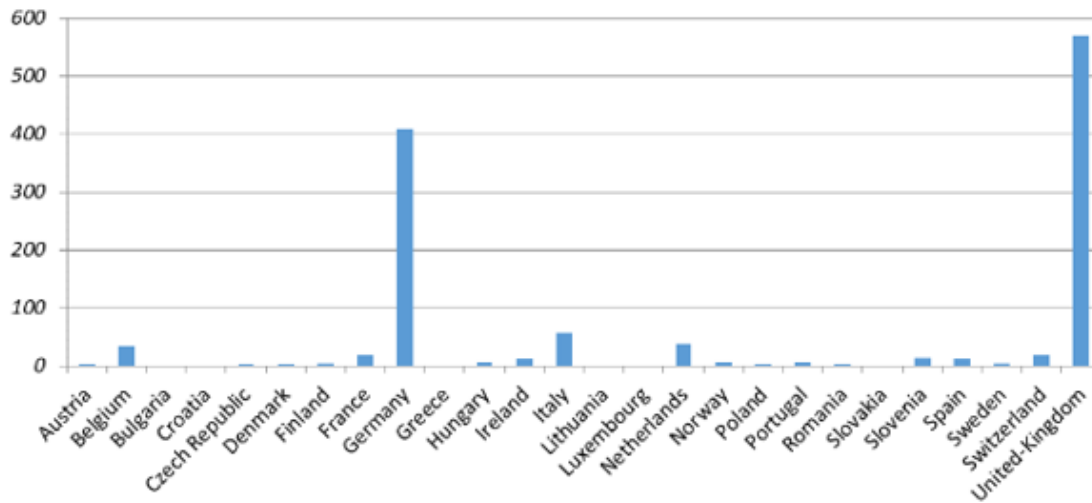


Figure 2.4 - Total installed power capacity (in MW) of operated BESS in European countries [27]

Previous research addresses the profitability of BESSs performing energy arbitrage in various European countries, considering the financial risks and fiscal issues of each country, where it is shown that, currently, the energy arbitrage operation is unprofitable across the board, with the U.K. and Ireland showing the best results and the worst being attributed to Portugal and Spain [22]. This can be attributed to the fact that the U.K. and Ireland are isolated power systems showing greater volatility in their day-ahead market prices (which implies greater viability for energy arbitrage), with the same happening in the “market zone” of Sicily when compared to the rest of the Italian energy market zones. The substantial amount of investments in Germany can, in turn, be attributed to the scarcity of flexibility in this local market mainly due to nuclear power and large coal plants (notoriously low flexibility) being the base of the production diagram. On the other hand, countries like Portugal and Spain rely on their hydroelectric power plants (with pumping capacity) to provide the flexibility needed, leading to the slow restructuring of these markets when faced with the emergence of BESS assets.

Despite these considerations regarding the profitability of energy arbitrage this paradigm is predicted to shift in Europe during the following years. This is due to the decrease in battery costs and increase in their round-trip efficiency, which may lead to profitable results for every European country.

2.3.2.2 United States

According to a report from EIA [25], between 2003 and 2019, there were installed more than 1000MW of new large-scale BESSs, with 80% of them being installed since 2015, which shows the increased prevalence of these systems in recent years. Of all the U.S. regions, BESSs installed in PJM have the most power capacity (around 30% of all existing U.S. BESS

power capacity), while the ones installed in CAISO have the most energy capacity (around 36% of all BESSs in the US). In terms of technology, the most common battery type in the United States is Lithium-ion batteries, being used in more than 90% of all existing BESS projects.

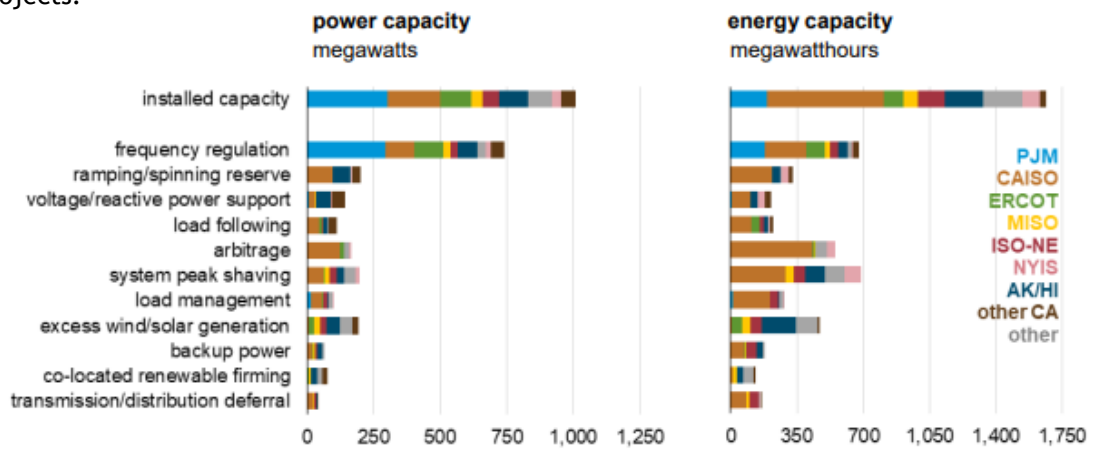


Figure 2.5 - Applications served by large scale battery storage (2019) [25].

Due to their characteristics regarding their power and energy capacities, the BESSs installed in PJM are more geared towards providing frequency regulation and other ancillary services, while the ones in CAISO are used more frequently for energy arbitrage, as shown in Figure 2.5. According to the research published in [30], the costs of investment related to the installation of BESSs need to decrease by approximately 80% for arbitrage to be economically viable as the only stream of revenue of a battery that participates in the CAISO market. The authors of [29] conclude that the current BESS costs also do not achieve profitability for their operator considering arbitrage as the only revenue and participation in the PJM market. Similar to Europe, the decline in battery costs is projected to bring viability to this operation in the near future.

2.3.3 Strategic bidding of a BESS in the DAM

Solely considering the provision of energy arbitrage in the day ahead energy market, a BESS can attempt to maximize its profitability by submitting strategic bids to the market. This strategic bidding is based on predicting the market prices for the day-ahead market, be it with a predictive algorithm or simply by analysing historical data, and bidding both charge and discharge bids in order to increase the profit generated. This optimization involves submitting charging bids during low-priced hours (characterized by prices slightly larger than the registered market price, so that the bids are accepted) in order to charge the battery for the minimum possible cost, and submitting discharge bids during the peak periods (characterized by prices slightly lower than the market prices).

If there was a perfect forecast for how the power system would behave during the following day, this optimization of profit generation would be straightforward, however, since the future is uncertain, the BESS operator must rely on accurate forecasting methods

(which are still not very reliable) or create robust bidding strategies that minimize the risk of economic losses. Depending on the BESS classification as a price-maker or a price-taker, as well as its electrical characteristics, a bidding strategy must be determined in order to maximize the profit generated by the BESS. The bidding strategy of the BESS is defined by the bids submitted by its operator, to the market. These bids have the following structure [32]:

- **Charging bids:** In order to charge itself, the battery must submit a bid to the energy market (normally the day ahead, where the prices are lower), containing the quantity of energy to be charged and the maximum price the operator is willing to pay for it.
- **Discharging offers:** To discharge the energy stored during lower-priced periods, the battery submits offers in the energy market, detailing the energy available for discharge and the minimum price accepted for it. Making use of the BESS fast response, the discharging offers are ideally submitted to the balancing market, where the price is usually higher than on the day-ahead and intraday market.
- **Capacity bids:** The BESS can also submit bids in the ancillary services market, offering to reserve a certain capacity (to be used when called by the system operator, for services like frequency regulation) and its respective price. Some TSO's also ask for an additional performance price bid. Despite the existence of these types of bids, they are not relevant for the bidding geared towards the performance of energy arbitrage.

After being submitted, these bids allow for the clearing of the market, that is, the determination of the winning bids (for each time-period considered) and the LMP. When every market is cleared for a certain time period, the BESS operating schedule is determined according to its winning bids. This schedule, in turn, allows the determination of the profit generated by the BESS.

Based on the forecasted data that the BESS operator has access to, the strategy for the operation of the BESS can be designed, that is, the prices and quantities of each charging and discharging bid can be determined. Considering the day-ahead energy market and a BESS that performs energy arbitrage, the bidding strategy of the latter can be interpreted as how the operator intends to manage the battery's SoC. The storage can define its discharge bids in a way that they are frequently accepted so that the energy previously stored is sold to create revenue, regardless of the value created, which can be useful to guarantee that the operator profits from the battery's operation but not when maximizing its profitability. On the other hand, the operator can consider future opportunities to discharge the battery for higher profit margins, tolerating, however, the risk of its bids not being accepted by the market operator.

2.3.4 Operating Costs

Operating the BESS has some associated costs, that can be interpreted as the marginal cost of operation. These costs are caused by the degradation of the BESS.

With repeated charging and discharging, the battery gets degraded, meaning that it is closer to its replacement date. The cost of replacement (along with maintenance costs), when divided for every expected charge/discharge cycle, represents the cost of operating the BESS during one full cycle.

It's important to acknowledge that the degradation of the battery is dependent on three factors: the Depth of Discharge (DoD), the initial level of the state of charge (SoC), and the discharge rate. The depth of discharge (% of maximum energy capacity) represents the difference between the initial and final SOC values, and according to [30] and [31], the life cycle of a battery that operates in shallower charging/discharging cycles is longer than that of a battery whose operation is based on deeper discharges. The initial SOC value is also of importance to determine the operating cost of the BESS, because the degradation of two similar batteries that discharge the same amount of energy (same DOD) is not the same if they have different starting points; with a higher initial SOC implying a lesser degradation of the BESS. The discharge rate of a battery represents the variation of the battery's SOC during a certain timeframe. Higher discharge rates (and therefore, higher discharge currents) are responsible for a higher life-cycle loss to the battery.

Despite these considerations, this work will not focus on the degradation costs of the battery when aiding the strategic bidding of the BESS operator, however, these costs could be added to the model proposed in future works in order to obtain a more accurate prediction of the profit generated by the battery.

2.4 Prediction models for day-ahead market uncertainty

2.4.1 Concept

The forecasting of the day-ahead market prices is critical for market participants to make better decisions regarding their approach to bidding with the objective of obtaining better results when it comes to scheduling energy production or consumption intended to generate higher profits. Due to the high volatility of market prices in power systems with high RES penetration, there is a need for predictive/forecasting methods to be employed by both suppliers and consumers. The main factor that affects the market prices of the DAM is the net load registered during the considered time period. The net load of a system is determined by the difference between the demand and the RES production, in other words, it is the amount of load that needs to be supplied by conventional generators. This parameter affects the day-

ahead market prices as when the net load is high, meaning that the demand is high and RES generation is low, the conventional generators must increase their production (or call other, more expensive, generators into operation) in order to supply the needed demand, which in turns increases the marginal cost of production leading to higher market prices.

2.4.2 Current scope

In recent years, research has been done regarding the use of several prediction models to forecast the system behaviour, be it the future market prices or other variables such as demand or RES generation. These prediction models can be divided into two clusters: statistical models and machine learning models.

A statistical model is based on mathematical and statistical methods to analyse historical data and identify patterns that relate the data analysed with the variable(s) it intends to forecast. These methods allow the BESS operator to use data regarding historical market prices, generation and consumption trends and other factors (e.g. weather conditions) to predict the behaviour of the BESS in the day-ahead market. One of these statistical models that is widely used in the literature concerning the day-ahead market is the Autoregressive Integrated Moving Average (ARIMA) model [32], [33].

Machine learning methods are based on algorithms that use historical data to configure their output-input correlation in order to identify patterns that may be too difficult for standard statistical methods. The most prevalent machine learning method is the artificial neural network (ANN) whose typical structure can be seen in Figure 2.6, which are modelled based on the behaviour of the human brain. These have three layers of neurons: an input layer, an output layer, and a hidden layer in between. The input layer receives data relevant to the correlation problem which is then passed to the hidden layer so that it can be processed, attributing a “weight” to each inputted variable based on its importance in predicting the forecasted variable and an associated “bias”. This processed data is in turn passed to the output layer resulting in the final prediction of the expected output variable. By using a training data set of inputs and targets (known outputs for the respective inputs), the weights and bias of each neuron are determined in order to minimize the difference between the neural network’s output and their respective target.

In the context of energy arbitrage in the day-ahead market, these methods can be used to forecast the following day’s electricity prices, the BESS operating behaviour, etc. They rely on inputs obtained by analysing the system’s current or historical behaviour, based on parameters such as the demand registered, the renewable energy generated, weather conditions, market prices, among others. The results of these forecasts can be used by the BESS operator in order to make better informed decisions regarding its bidding, as well as help to determine which system variables affect the operation of the battery the most, which in turn can be used to improve the data gathering capabilities of the system regarding these

relevant parameters. When considering future energy prices as the forecasted variable, the authors in [34] show that the most important explanatory variables (for the Iberian market) are the market prices registered previously, thermal generation and the load consumption, while [35] shows the importance of the forecasted wind speed as an input variable of the forecasting model. One consideration that must not be disregarded is the availability of the information regarding the input variables chosen, as the BESS operator is only able to collect data that's been made public.

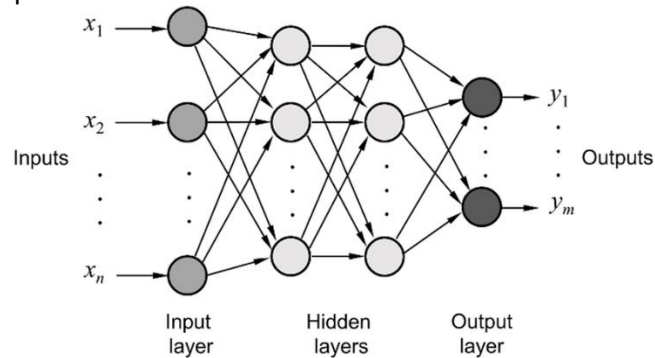


Figure 2.6 - Structural diagram of an artificial neural network.

While both methods make use of historical data to predict future outcomes, it has been shown that ANNs need fewer data (used in the training phase) to produce more accurate predictions, making it the most adequate prediction model to be used by a BESS operator [36]. Thus, this will be the method used in the work presented in this dissertation, considering the lack of extensive historical data that the BESS operator has access to. One must also consider that, despite the usefulness of this machine learning method, every ANN trained beforehand must be tested so that its assertiveness can be ascertained, otherwise the results obtained can lead to bad decision-making.

2.5 Main research conducted on energy arbitrage in the DAM by BESS

There is an extensive literature, particularly in recent years, that addresses the determination of maximizing the profit of a BESS that participates in the electricity markets. The majority of research papers focus on the provision of arbitrage and frequency control services. In [37], the Colombian market is considered as a case study, where several market forecasting methods are used and compared to determine the best arbitrage strategy to maximize the BESS profit, with statistical strategies presenting better results than ANN models and much better results than simple seasonal strategies that only use a small amount of historical data. This shows that higher precision in the market behaviour forecast (with smaller prediction errors) leads to better profits, but despite this, every strategy considered brings a negative net profit value, which means that a BESS solely providing arbitrage in the Colombian market is not yet economically viable. In ref [22], the viability of a BESS engaging

in energy arbitrage is analysed for several European countries (using 2019 data). A mixed-integer linear optimization method is used to maximize the cash flows that result from the BESS energy-only market participation, followed by the calculation of the highest possible profit generated during the battery's life cycle. The results show that energy arbitrage is not profitable for any country considered (with the UK and Ireland presenting the best results, and Spain and Portugal presenting the worst), mainly due to the high battery and inverter costs and the volatility of the prices in the considered market.

Ref. [38] addresses the techno-economic feasibility of BESSs performing energy arbitrage and providing energy arbitrage on the Iberian market. The study conducted shows that the range between maximum and minimum market prices (peak-off-peak price ratio) is crucial in the determination of the feasibility of the BESS when it comes to generate profit. The results also reveal that the energy arbitrage provision does not produce sufficient revenue for the BESS to justify investments of private firms, implying the need to employ the BESS in other applications, due to the high cycle costs and low variability of the DAM prices. This previous work also concludes that market prices are higher during winter months (mainly due to an increase in demand (e.g., the prevalent use of electrical heating), and that the transformer limitation and unavailability to sell energy does not affect the results. Ref. [39] examines the opportunities for investment in BESSs by private entities, concluding that a BESS with several days' supply is socially desirable (from a welfare point of view) but not commercially profitable. This study also concludes that for the regional market of Britain, the best time period to perform energy arbitrage would be during the day, as the market prices reveal a higher variation, and that predicting future prices is difficult more than 3-days ahead due to the inaccuracy of wind power forecasts, while considering the load a first-order determinant of market prices.

The work in [7] formulates a revenue maximization problem in CAISO's day ahead and real-time markets analysing 3 years of data to calculate arbitrage profits and concluding that solely providing energy in the DAM produces significantly less profit than the participation in both markets. In addition, it also shows that the location of the BESS affects the revenue generated in the CAISO market environment. Ref. [40] focuses on the energy arbitrage of BESSs in the Nordic countries which, despite belonging to the same market structure (Nord Pool), show different potential benefits in each bidding zone, showing the differences in the scarcity of flexibility and market value of said flexibility in each zone. It shows that Norway reveals the least economic value for energy storage performing energy arbitrage, which is due to their natural hydro reservoirs providing their needed flexibility (pump hydro). The results also reveal, and more importantly, that with the current market conditions, even aggregating revenue sources besides arbitrage, do not lead to the profitability of energy storage. The authors of [41] formulate an LMP-based day-ahead market model, in GAMS, the results of which show that the inclusion of BESS reduces marginal prices and increases social

welfare when they possess larger market power. The work presented in [42] provides a model to optimize the revenue of a BESS performing energy arbitrage using statistics of 5 years of historical PJM data, demonstrating that the revenue is determined by price data shape, mostly their range. In addition, it also concludes that the winter season provides more energy arbitrage opportunities due to their average market prices assuming two daily peaks rather than just one.

Ref. [20] concludes that under current battery costs, energy arbitrage is not profitable in the majority of EU countries, however, with the declining trend in battery costs, the potential for arbitrage profitability will increase rapidly in the studied countries. The study concludes that local markets such as the U.K., Germany, France and Italy show great promise regarding future profitability for BESSs performing energy arbitrage, while others such as Spain, Portugal and Norway still need a significant reduction in battery costs for this operation to be economically viable. The authors of [22] develop a MILP model to optimize the optimal bidding strategy for each EU country considered, and use the results to determine the profitability of a BESS performing energy arbitrage using economic indicators of net present value and internal rate of return (considering the relevant taxes and discount rates of each country), concluding that the U.K. and Ireland show the best results while Spain and Portugal show the worst.

The work in [43] focuses on the potential for energy arbitrage of Lithium-Ion batteries in the Spanish market, with the main conclusion being that the profit generated is always negative regardless of the considerations taken (e.g., inverter size and bidding strategy). The authors suggest that with the trend of declining battery costs this operation might be profitable in the future but meanwhile the BESS operators should participate in other markets and provide additional services. In [29], the potential of energy arbitrage in PJM interconnection was studied, revealing that with current battery-related costs, energy arbitrage is still not a viable option for profit generation.

The work presented in [44] is based on the uncertain lifetime of the BESS and how it affects its profit, with the results showing that for the regional ERCOT market, none of the BESS technologies considered will reach positive net present value by solely providing energy arbitrage.

The results presented in [45] show that BESSs performing energy arbitrage are rarely profitable as the investment costs of lithium-ion batteries are too high, implying the need to reduce these costs or provide other BESS services in order for a storage operator to reach profitable results. The authors also conclude that market restructuring could impact profits in the future, as the need for energy storage in the grid is expected to increase.

The authors of [32], [33], [46], [47] use several forecasting methods to forecast the day-ahead market prices. In [47], a BESS connected to a wind park is studied regarding its arbitrage profitability, where a forecasting algorithm based on ANN is used to predict market

prices obtaining better results than other statistical methods in the literature. in [46], time series analysis, ANNs and wavelets were used to forecast the 24 market prices for the day-ahead market using data from PJM, and after comparing the results the authors concluded that time-series techniques (particularly dynamic regression and transfer function algorithms) are more effective than ANNs. Attributing this to the fact that ANNs are difficult to tune in order to obtain an accurate forecast, implying the potential for improving this method if some adjustments are made.

Chapter 3

Methodology for the proposed predictive Tool

This chapter provides an overview of the methodology adopted for this dissertation. The problem addressed is described in detail, along with the mathematical formulation that serves as the basis for the day-ahead market simulations used throughout this work. Additionally, the concept and characteristics of a bidding strategy are presented along with three different approaches to the bidding process of a BESS operator performing energy arbitrage in the DAM.

3.1 Problem description

The objective of the owner or operator of a BESS is to optimize its bidding process in order to maximize its profit. For this dissertation, this profit will be considered to be generated solely through the operation of energy arbitrage in the day-ahead market. However, this presents challenges as the operator must submit bids to the DAM without certainty if they will be accepted or rejected, due to not knowing how the market behaves in the future.

By submitting charge and discharge bids (containing both quantity and prices) the operator tries to charge at the lowest cost possible and discharge at the highest price possible. However, the unknown bids of competitors make it difficult to determine the optimal profitability beforehand, potentially resulting in sub-optimal profitability or even non-operation of the battery.

In this scope, there is a need for a model to correlate available information to the operator in order to predict how the BESS will perform under a given system scenario. This dissertation aims to fill this gap by developing a predictive tool based on forecasted system parameters. This tool should be able to provide the best bidding strategy for the maximization of profit for the DAM, among those considered. The development of the tool

takes into account the limited availability of data, forcing the BESS operator to only possess knowledge available prior to the bidding submission for the next day's market operation.

Ideally, the tool should be able to output the best bidding strategy possible for the next day. However, this dissertation will only consider three different bidding strategies (detailed in section 3.2). This work serves as a proof-of-concept for the presented tool, which can be slightly adapted in future work to be used for a broader scope of application, considering multiple strategies to be selected from (following different bidding approaches).

To this end, the flow of the presented work (depicted in Figure 3.1) can be divided into three steps:

- The development of different bidding approaches for the BESS and the establishment of possible scenarios for the behaviour of the power system where the BESS is located;
- The simulation of the BESS participation in the DAM, considering that each bidding strategy is adopted for the established system scenarios;
- The development of the predictive tool based on the results obtained by the simulations.

Furthermore, an analysis is conducted to evaluate the results of the tool when applied to some test cases. This structured approach pretends to conduct a comprehensive examination on the influence of each bidding strategy in the BESS operation, and on the influence of the tool in the decision making process of a BESS operator. Additionally, it also aims to provide insights into the relationship between system parameters and the tool's effectiveness.

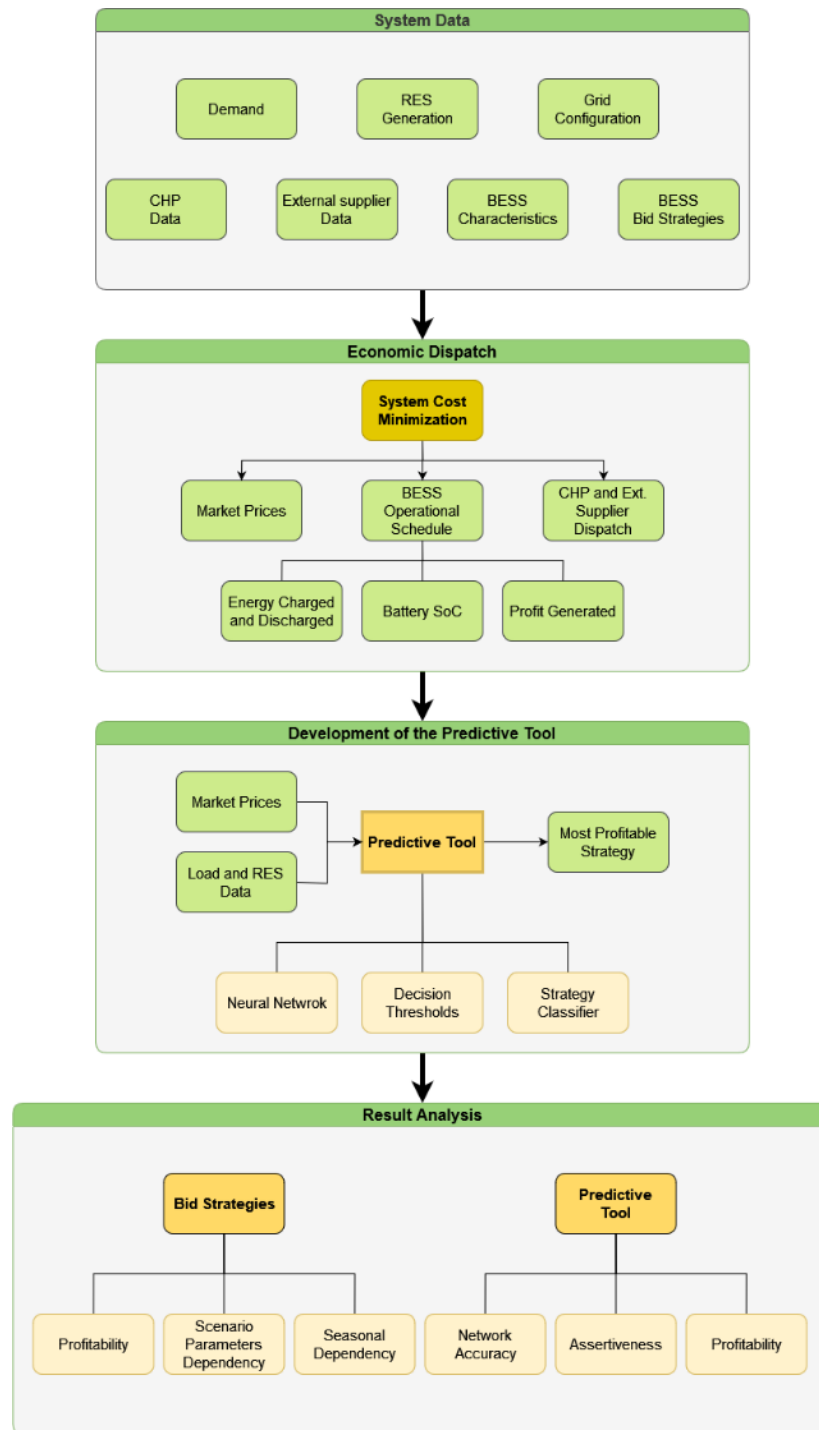


Figure 3.1 - Flow of the adopted methodology.

Section 3.2 provides an overview of what constitutes a bidding strategy and outlines the general approaches adopted in this dissertation. The specific bidding strategies used for the development of the tool will be designed in chapter 4, as section 3.2 only describes the thought process behind each strategy's approach to submitting bids to the market.

3.2 Bidding Strategy Formulation

The strategic bidding process of the BESS, aimed at energy arbitrage, can be seen as a means to influence the battery's behaviour to maximize the profit generated by its operation. The objective of a profitable energy arbitrage is to charge the battery during periods of low electricity prices (associated with low demand and/or high renewable generation) and discharge it during peak hours when prices are higher, thereby generating profit for its operator.

A bidding strategy for a BESS consists of two components: (i) the strategic approach regarding the charging of the battery; and (ii) the approach relative to its discharging. This work primarily focuses on the discharging strategy.

The charging behaviour of the BESS is considered implicit through the State-of-Charge (SoC) target established for the end of the day, as the BESS only submits bids to the market offering its full capacity at a null price. This approach induces the BESS to charge whenever the operating cost of the system is reduced through a complete charge cycle. For the discharge strategy of the BESS, its approach can be represented by two arrays with lengths equal to the delivery times, in this case, twenty-four delivery times with a duration of one hour each. These arrays contain the capacity bided and its respective selling price, for every hour of the following day. In Table 3.1 and Figure 3.2 the basic idea of a bidding strategy is represented.

Table 3.1 - charging and discharging bids for the day-ahead market, considering a basic bidding strategy

Hour		1	2	3	4	5	6	7	8	9	10	11	12
Charge Bids	Capacity [MW]	Max	Max	Max	Max	Max	Max	Max	Max	Max	Max	Max	Max
	Price [m.u.]	0	0	0	0	0	0	0	0	0	0	0	0
Discharge Bids	Capacity [MW]	-	-	-	-	-	-	-	10	10	10	10	10
	Price [m.u.]	-	-	-	-	-	-	-	100	100	100	100	100
Hour		13	14	15	16	17	18	19	20	21	22	23	24
Charge Bids	Capacity [MW]	Max	Max	Max	Max	Max	Max	Max	Max	Max	Max	Max	Max
	Price [m.u.]	0	0	0	0	0	0	0	0	0	0	0	0
Discharge Bids	Capacity [MW]	-	-	-	-	-	20	20	20	20	20	20	20
	Price [m.u.]	-	-	-	-	-	50	50	50	50	50	50	50

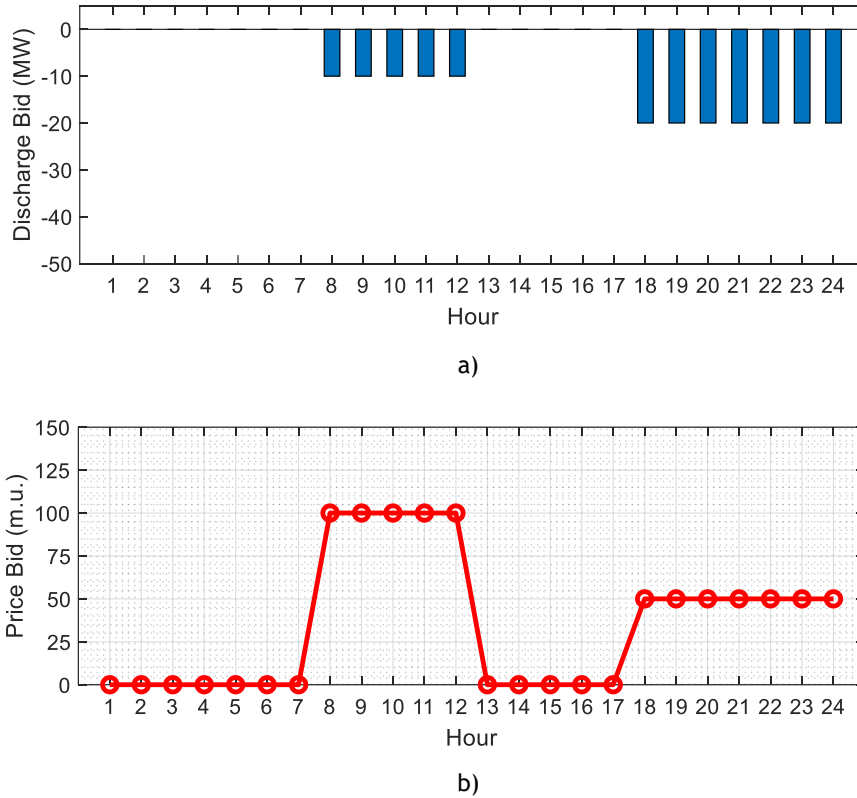


Figure 3.2 - Characteristics of both the capacity (a) and price (b) bids of the exemplary bidding strategy

When it comes to the strategic discharge of the battery, the BESS operator selects a bidding approach based on the level of risk that they are willing to undertake in order to generate profit. While discharging the full capacity of the BESS during the hour with the highest market price would yield the highest profit, the BESS operator lacks knowledge about the future behaviour of the power system and of the other market participants. Consequently, there is always a risk associated with bidding in the DAM, which may result in either a null profit or a suboptimal profit.

Two main approaches were considered in this dissertation, differing from each other in terms of the capacity bided, the prices coupled with each bid and the time slots during which the discharge bids are submitted. These approaches are as follows: (i) The conservative approach, and (ii) the aggressive approach. Sections 3.2.1, 3.2.2 and 3.2.3 will provide an overview of the advantages and disadvantages of each considered bidding approach.

3.2.1 Conservative approach

The first approach pretends to discharge the BESS every time that it is profitable for its operator, regardless of the profitability of each individual discharge, prioritizing the generation of a steady and relatively predictable daily profit. This strategy achieves this due to the characteristics of its bids:

- By submitting a low-priced bid, the BESS can discharge at any given hour (except when the market price is zero due to the excess of RES production), with the only requirement being a sufficient level of SoC for the performance of this operation;
- The low capacity of each bid leads the battery to discharge its stored energy across multiple periods instead of focusing on a single one.

The pros and cons of this approach are as follows:

- Pros:
 - Ensures the profitability of the BESS operation, for most days, as it is not affected by unexpected non-operations that result from undesired market outcomes;
 - Able to take advantage of every profitable discharge opportunity regardless of the specific period during which the opportunity arises.
- Cons:
 - Does not fully capitalize on the occurrence of high-priced periods due to its low energy discharges, which results in an expected lower profitability when compared to the maximum potential profit for any given day.

3.2.2 Aggressive approach

Another approach is focused on only discharging the BESS during periods with expected high market prices, preserving the SoC of the battery to take full advantage of these opportunities. The characteristics of the bids associated with this strategy are:

- High-capacity bids, which aim to influence the battery to discharge its full capacity, thereby maximizing the exploitation of high-priced periods;
- By submitting high-priced bids, this strategy ensures that the BESS only discharges when the cleared market price exceeds a certain threshold deemed to be the minimum price acceptable to its operator.

Similarly, to the conservative strategy, there are advantages and disadvantages to this type of approach when it comes to the performance of energy arbitrage by the BESS:

- Pros:
 - Allows the BESS to fully capitalize on high prices, by discharging large amounts of energy during these periods, and thus achieving high profits.

- Cons:
 - Does not allow the battery to capture every high-priced period, as its bids are focused on specific daily periods with a higher prevalence of high prices;
 - This may result in the non-operation of the battery, and thus a null profit. This occurs if there are no peak periods with market prices high enough to trigger the discharge of the BESS.

3.2.3 Moderate approach

Another bidding strategy was proposed whose approach combines elements of the previous two strategies. This strategy involves submitting discharge bids during periods with expected high prices while also considering other possibilities for discharging the battery outside of this timeframe. The characteristics of the bids of the moderate strategy are:

- Moderate capacity bids, with values in between those of the conservative and aggressive strategy;
- High-priced bids, although less exclusive than those submitted by the aggressive strategy.

This strategy also presents positive and negative aspects when it comes to generating profit from energy arbitrage.

- Pros:
 - Takes advantage of opportunities to discharge during hours with high market prices, while not presenting the same level of risk of non-operation as the aggressive strategy;
 - Allows the discharge of the BESS if an opportunity presents itself outside the typical high-priced periods.
- Cons:
 - There is still a risk of non-operation associated with this bidding approach, although lower than that of the aggressive strategy;
 - Due to the moderate capacity of each bid, this strategy does not take full advantage of peak periods, as it can not discharge the totality of its SoC during a single period.

Overall, the moderate strategy aims to strike a balance between maximizing profit from high-priced periods and maintaining some flexibility to discharge in other periods, reducing the risk of non-operation compared to the aggressive strategy. These will be the generic

approaches to the bidding of a BESS willing to perform energy arbitrage, in the day-ahead energy market. The specific characteristics of each strategy will be defined when presenting the case study addressed in this dissertation, which is described in Chapter 4.

3.3 Model for the day-ahead market operation

After designing the strategies and establishing the system scenarios based on the considered study case, the operation of the BESS that results from the adoption of each bidding strategy has to be determined so that each strategy can be evaluated. The operation of the BESS is obtained as a result of the simulation of an Economic Dispatch for the DAM, considering the distribution grid in which the BESS is located and all its characteristics.

3.3.1 Concept

The DAM is supervised by a market operator whose objective is to supply the maximum demand for the lowest cost possible, while making sure that the grid constraints are not violated. Both energy suppliers and consumers submit bids to the market, each characterized by their available capacity for that time period and by the minimum or maximum accepted price when selling or buying energy, respectively. Every submitted bid is considered by the market operator, and only the ones that will lead to the lowest system cost will be accepted. Each market player with accepted bids will pay or be compensated by the marginal market price registered during market clearing, which is the same for every bid during the considered time period under a pay-as-clear system (which is the one considered in this work). The formulation of both the objective problem for the economic dispatch simulation and the constraints associated with it, is presented in section 3.3.2.

3.3.2 Mathematical Formulation

The model for the economic dispatch of the day-ahead energy market used in the work developed for this dissertation was adapted from [48]. The mathematical formulation of this model is based on minimizing the objective function (system operational cost), while attending the constraints of the grid, generators and the BESS itself. The system operational cost is given by Eq. 1.1:

$$\min obj = \sum_{t=1}^H \left[\sum_{g=1}^{N_{Gen}} \left(P_{Gen}(g, t) * \pi_{Gen}(g, t) + P_{Gen}^{Cut}(g, t) * \pi_{Gen}^{Cut}(g, t) \right) - P_{Ext}^{export}(t) * \pi_{Ext}^{export}(t) \right. \\ \left. + \sum_{l=1}^{N_{Load}} \left(P_L^{Shed}(l, t) * \pi_L^{Shed}(l, t) \right) + \sum_{B=1}^{N_{BESS}} \left(P_{Dch}(B, t) * \pi_{Dch}(B, t) - P_{Ch}(B, t) * \pi_{Ch}(B, t) \right) \right] \quad (1.1)$$

where P_{Gen} is the power supplied by each generator, π_{Gen} the production cost of each generator, P_{Gen}^{Cut} is the generation curtailed and π_{Gen}^{Cut} its cost, P_L^{Shed} refers to the load shed and π_L^{Shed} the equivalent cost of load shedding, P_{Ch} is the energy charged by the BESS and P_{Dch} is the energy discharged, π_{Ch} is the bided price for charging the battery and π_{Dch} is the bided price for discharging. All these parameters refer to each interval $t \in H$, where H is the total amount of periods considered (in this case 24 hours).

This objective function is subjected to certain constraints which need to be considered:

- **Generation constraints:**

Regarding the constraints applied to the parameters of the objective function which concern the power supplied by each generator, their formulation is:

$$P_{Gen}(g, t) \leq P_{Gen}^{Max}(g, t), \quad \forall t; \forall g \in \{CHP \text{ generators and external connection}\} \quad (1.2)$$

$$P_{Gen}(g, t) = P_{Gen}^{Max}(g, t), \quad \forall t; \forall g \in \{Wind \text{ and Solar PV}\} \quad (1.3)$$

$$P_{Gen}^{Cut}(g, t) \leq P_{Gen}^{Max}(g, t), \quad \forall t; \forall g \quad (1.4)$$

$$Q_{Gen}(g, t) \leq (P_{Gen}(g, t) - P_{Gen}^{Cut}(g, t)) * \tan\varphi_{(g, t)}, \quad \forall t; \forall g \quad (1.5)$$

$$Q_{Gen}(g, t) \geq 0, \quad \forall t; \forall g \quad (1.6)$$

- **Export Constraints:**

When there is an excess of generation within the distribution grid, it needs to be exported to the external supplier through the interconnection between them. The constraint regarding this export is:

$$P_{Ext(t)}^{Export} \leq P_{Ext(t)}^{Max}, \quad \forall t \quad (1.7)$$

where $P_{Ext(t)}^{Max}$ is the maximum power which can be exported to the external supply according to the limits imposed by the max capacity of the interconnection.

- **Load Constraints:**

The loads present in the distribution grid are subjected to constraints regarding their active and reactive consumption as well as their shedding:

$$P_L^{Shed}(l, t) \leq P_L(l, t), \quad \forall t; \forall l \quad (1.8)$$

$$Q_L(l, t) = (P_L(l, t) - P_L^{Shed}(l, t)) \tan\varphi_{(l, t)}, \quad \forall t; \forall l \quad (1.9)$$

where $P_L(l, t)$ and $Q_L(l, t)$ are the active and reactive power associated with each individual load, respectively.

- **BESS constraints:**

The BESS installed in the grid is also subject to constraints which address its operating limits, as well as how the SoC of the BESS is determined for each time interval.

$$P_{Ch}(B, t) \leq P_{Ch}^{Max}(B, t) * C(t) \quad \forall t; \forall B \quad (1.10)$$

$$P_{Dch}(B, t) \leq P_{Dch}^{Max}(B, t) * D(t) \quad \forall t; \forall B \quad (1.11)$$

$$SoC^{Min}(B) \leq SoC(B, t) \leq SoC^{Max}(B) \quad \forall t; \forall B \quad (1.12)$$

$$SoC(B, t) = SoC(B, t - 1) + P_{Ch}(B, t) * \eta_{Ch}(B) - \frac{P_{Dch}(B, t)}{\eta_{Dch}(B)} \quad \forall t; \forall B \quad (1.13)$$

$$C_{(B,t)} \text{ binary}, \quad \forall t; \forall B \quad (1.14)$$

$$D_{(B,t)} \text{ binary}, \quad \forall t; \forall B \quad (1.15)$$

$$C_{(B,t)} + D_{(B,t)} \leq 1, \quad \forall t; \forall B \quad (1.16)$$

where $P_{Ch(B,t)}^{Max}$ and $P_{Dch(B,t)}^{Max}$ are the maximum charge and discharge capacities, respectively, for a given interval “t” and a given battery “B”. $SoC_{(B)}^{Max}$ and $SoC_{(B)}^{Min}$ are the minimum and maximum state of charge for the considered BESS, $\eta_{Ch(B)}$ and $\eta_{Dch(B)}$ are the efficiencies associated with the charging and discharging operation, which are considered to be constant regardless of the current SoC of the battery or the amount of energy charged/discharged. Finally, $C_{(B,t)}$ and $D_{(B,t)}$ are binary variables chosen to indicate if the battery is currently charging or discharging.

Equations 1.10 and 1.11 limit the charging and discharging of the BESS to what the maximum charge and discharge rates allow. Equation 1.13 determines the SoC for every interval “t” according to the SoC during the previous time interval and the operations performed by the battery “B” during “t”. Equation 1.12 limits the current SoC to the limits imposed by the technical characteristics of the BESS.

- **Power Flow Constraints:**

A crucial step in determining the optimal economic dispatch for a grid is the calculation of the power flow for each time interval, to verify if the current economic solution violates any grid constraints or if it is admissible to be used in the actual dispatch. The formulation for the active and reactive power flows are:

$$\begin{aligned} V_{i(t)}^2 G_{ii} + V_{i(t)} \sum_j [V_{j(t)} (G_{ij} \cos(\theta_{j(t)} - \theta_{i(t)}) + B_{ij} \sin(\theta_{j(t)} - \theta_{i(t)}))] \\ = \sum_{g \in N_{gen}} (P_{gen(g,t)}^i - P_{Gen(g,t)}^{Cut,i}) - P_{Ext(t)}^{Export} \\ - \sum_{l \in N_{Load}} (P_{Load(l,t)}^i) + \sum_{B \in N_{Bess}} (P_{Dch(B,t)}^i - P_{Ch(g,t)}^i), \quad \forall t; \forall i \end{aligned} \quad (1.17)$$

$$\begin{aligned} V_{i(t)}^2 B_{ii} + V_{i(t)} \sum_j [V_{j(t)} (G_{ij} \sin(\theta_{j(t)} - \theta_{i(t)}) - B_{ij} \cos(\theta_{j(t)} - \theta_{i(t)}))] \\ = \sum_{g \in N_{gen}} (Q_{gen(g,t)}^i) - Q_{Ext(t)}^{Export} - \sum_{l \in N_{Load}} (Q_{Load(l,t)}^i), \quad \forall t; \forall i \end{aligned} \quad (1.18)$$

where $V_{i,j(t)}$ and $\theta_{i,j(t)}$ are the voltage magnitude and angle for buses “i” and “j”. Equations 1.17 and 1.18 represent the active and reactive power balances for the bus “i” and interval “t”, considering that “j” represents every other bus connected to bus “i”.

This formulation of this economic dispatch involves non-linear equations, whose complexity calls for the use of solvers capable of solving Mixed-Integer Nonlinear Programming (MINLP) problems. The modelling software used for this optimization was the software GAMS, which relied on a CPLEX optimizer to solve the minimization problem.

The economic dispatch was simulated considering that the considered BESS adopts each of the three established bidding strategies for every system scenario. The results obtained can be subsequently used as historical data to train the predictive tool.

3.4 Model for the predictive tool

A BESS operator willing to engage in energy arbitrage in the DAM faces the challenge of submitting optimal charge and discharge bids (composed of both quantity and price values) in order to maximize their profit. However, the BESS operator lacks accurate knowledge of the future best opportunities that may arise to either charge or discharge the battery, which hinders their ability to maximize their profit according to the market's outcome. The profit (and therefore its maximization) realized by the performance of energy arbitrage relies solely on the market prices, which are given by the bidding price of the most expensive generator in operation for any given hour when considering the DAM. These market prices depend on the prices bided by every market competitor, as well as the capacities coupled with each of these bids (due to their influence on the operating cost of the system which determines its acceptance by the market operator). Evidently, this knowledge is private to each competitor up to the moment of the market clearing. As a price-taker, the BESS operator's profit is dependent on these market prices, making it difficult to predict which bids will maximize their profit. To address this issue and mitigate this problem, a predictive method could be adopted by the market participant to correlate available information prior to the bidding process with the outcome of the DAM. In this dissertation, this information is correlated to the profitability of the BESS operation of energy arbitrage.

Throughout the following work, the optimal bidding for the BESS will be narrowed down to a certain number of pre-established strategies, so that the prediction only has to culminate in one of these approaches instead of generating a completely new one predicted to be the best. This has some implications, such as: (i) the predictive capacity of the method is expected to increase, as the number of possible strategies for maximization of the BESS profit is narrowed from a virtual infinite number of possibilities to only a few deterministic options, and (ii) each bidding strategy must be designed in an effective manner in order to capture profits close to the maximum achievable, considering the unpredictability of future opportunity costs.

The predictive method chosen for this work was a feedforward neural network, as this method is particularly adequate to correlate data to certain expected outcomes. These networks are designed to output a value correlated to a set of weighted inputs, which in the

context of this work, allow the operator of a BESS to predict the best decision regarding the bidding of the battery when provided with a set of system parameters regarding its demand and production.

In order to be used in a practical scenario, the ANN must be trained beforehand so that its weights and bias are calibrated. This allows the ANN to effectively correlate the input variables with the desired outputs. To ensure reliable predictions, the trained ANN must be tested using a new dataset of input-target pairs so that its accuracy can be ascertained with minimal selection bias. Therefore, the development of the ANN has two distinct phases: (i) the training phase and (ii) the testing phase. Each of these phases will be described in sections 3.4.1 and 3.4.2, respectively.

3.4.1 Training phase

The training phase of the ANN involves the adjustment of the weights and bias of its neurons in order to reduce the error between the outputs of the ANN and their desired targets (while considering the same set of inputs). An adequate training of the ANN requires a suitable dataset that contains input parameters paired with desired outputs. These input-target pairs must demonstrate an actual correlation between them otherwise the ANN cannot establish accurate associations and thus produce undesired results.

In the context of aiding the BESS operator in their decision-making for the DAM, the parameters chosen (both inputs and targets) must follow the following criteria:

- Parameters whose data is available to the BESS operator at the time of the market bidding (considered for this work to be at 12h00 during the day before the actual operation, following the regulation of the MIBEL);
- Must be correlated to each other, that is, the parameter used as output should depend on the parameters used as inputs.

As the intended purpose of the predictive tool is to predict the most profitable strategy, the output of the ANN must give an indication of which strategy is in fact the best to be adopted the following day. Taking this into consideration, the set of outputs chosen was a 24-hour array composed of the binary decision variables regarding the charging and discharging of the BESS, obtained as a result from the operation of the battery that follows the optimal bidding strategy.

The operation of the battery heavily relies on the market prices registered during the operating day, which in turn are correlated to the netload present in the system (since a higher netload implies the use of more expensive conventional generators to supply the needed demand, and vice versa). Neither the market prices nor the netload of the system for the following day are known during the bidding process, however, forecasts or historical data can be used to solve this non-availability problem. Based on these considerations, and the

objective proposed by this dissertation of proving a correlation between available parameters and the best bidding strategy, the set of inputs chosen consider an array containing the 24-hour forecasts for the market prices and for the system parameters that define the netload, that is, the demand and renewable energy production(wind and solar PV).

The ANN used in the work presented in this dissertation was trained using the Levenberg-Marquardt backpropagation method, by making use of MatLab's machine learning toolkit.

3.4.2 Testing phase

After adequately training the ANN, its accuracy needs to be tested while using a new dataset containing input-target sets not used during the training phase, in order to acquire unbiased results. The accuracy of the ANN is determined by the mean squared error between the outputs and their respective targets.

Regardless of the parameter chosen as the target for the outputs of the ANN, the latter will be non-integers despite the targets being rounded values. This implies that two decision thresholds must be implemented to classify each output as a class associated with each integer decision variable (-1, 0 or 1). These thresholds are selected based on a statistical analysis that compares the true output rates for different threshold values. The chosen thresholds are those that achieve a balance between the true rates of the two classifications that they aim to separate.

The outputs of the trained ANN, after being processed by the other tool components (i.e., thresholds and the strategy classifier.), will lead to the expected most profitable strategy for the following day among those previously established. This strategy will then be used by the operator of the BESS during the bidding process for the DAM.

3.4.3 Strategy Classifier

After inputting the system parameters into the trained neural network, the resulting output provides the decision variables for the battery's operating Schedule for the next 24 hours. However, these results do not provide information on the quantities and prices of each bid; to address this, a strategy classifier algorithm was implemented. This algorithm is based on an heuristic method that counts the number of discharges in one specific time periods where discharges are expected to commonly occur based on the time slot and quantity bids of each strategy (16h-24h). Based on the number of discharges outputted in each of these periods, a certain bidding strategy is selected. The classifier algorithm follows this ruleset:

- Aggressive Strategy: Selected if 2 or fewer discharges take place during the 16h-24h period.
- Moderate Strategy: Selected if between 3 or 5 (included) discharges take place during the 16h-24h period.

- **Conservative Strategy:** Selected if the sum of 8 or more discharges are outputted by the neural network during the whole day, as no other strategy usually discharges as often; or if the criteria for the selection of the other strategies are not met.

3.5 Summary

Overall, the methodology employed throughout this dissertation relies on historical or forecasted data available to the operator of a BESS pretending to perform arbitrage. This data is used as inputs for the tool, which then indicates the most suitable strategy to employ during the bidding process of the DAM. To this end, and before assessing the tool's effectiveness in aiding the decision-making process of the BESS operator, a specific case study needs to be established and characterized. Only after these factors have been determined can the bidding strategies be developed.

It is important to note that this specific case study narrows the scope of application for the developed tool. Therefore, the current work serves as a proof of concept for the effectiveness of this predictive model.

Chapter 4

Assessment of BESS participation in an energy-only market

The purpose of the tool developed in this work is to predict the best bidding strategy to generate profit for its operator during the following day's market operation. To verify the effectiveness of the proposed methodology, it first must be tested in a simulated practical scenario. This chapter is dedicated to establishing the case study adopted throughout the work presented for this dissertation, which is divided into:

- The characterization of the distribution grid used as a reference for this study, including information about its topology, energy providers and consumers, as well as their profiles;
- The design of the three bidding strategies, considering: (i) the characteristics of the studied BESS, (ii) the characteristics of the power system and (iii) the previously described general bidding approaches;
- The development of the tool specifically designed to be used for these system's characteristics, and considering the established strategies.

4.1 System characterization

The power system that is used as the foundation for this work is a distribution grid based on the design of the IEEE 37-bus grid, as depicted in Figure 4.1. This grid consists of 37 buses at 11kV. This system is made up by a set of 22 loads installed in some of those buses to represent consumption points, and their location is represented by circles in Figure 4.1. This system also contains several power plants, including 2 wind turbines and 22 solar PV plants (responsible for RES production), as well as 3 CHP generators. Additionally, There is an external connection to the upstream grid which is used to supply the load during a deficit of

Figure 4.1 - 37-bus MV distribution grid.

The technical characteristics of each energy resource are represented in Table 4.1, providing information on their quantity, as well as their availability (in pu) and operating cost (in m.u.). Additionally, the BESS installed in the grid is defined by the characteristics outlined in Table 4.2.

Table 4.1 - Characteristics of the energy resources in the grid.

Energy Resource		Availability [pu]	Production cost [m.u./pu]	Quantity
External Supply		35	100-300	1
1		2	30	
CHP	2	2	20	3
	3	2	10	
Wind Turbines		2.5	0	2
Solar PV		0 - 8	0	22

Table 4.2 - Technical characteristics of the BESS.

Bus Location	Capacity	State of Charge	
		Min.	Max.
2	1MW/1MWh	10%	90%

The production cost of wind and solar PV plants is null due to their renewable nature. On the other hand, the rest of the energy sources have an associated production cost which will be used as their price bids. For the CHP generators, their production cost (and thus their bids) are constant throughout the day, although different across the 3 available generators. For the external supplier, the production cost varies depending on the load present on the distribution grid. The production cost of the external supplier follows the rule presented in Table 4.3.

Table 4.3 - Correlation between the system load and the operating price of the external supplier.

Load Value [MW]	Price of the external supply [m.u.]
<10	100
10-15	150
15-20	200
>20	300

As stated in section 3.4, for the tool to be developed and then tested for this case study, a set of scenarios representing the operating behaviour of the characterized power system needs to be established. These will serve as potential historical data for the system and will be used to both develop the bidding strategies and the tool considered in this work.

4.1.1 Typical System Scenario

A system scenario is hereby considered to be defined by the value for the demand and renewable production for every hour of a single operating year, as these are the most relevant parameters pertaining to this power system that affect the operation of the BESS. Therefore, throughout the presented work these will be referred simply as system parameters. This scenario creation process begins by selecting a base scenario to represent a typical year for the behaviour of the system.

4.1.1.1 Demand profiles

To represent different behaviour for the consumers, the demand of the system in question must be defined for each of the consumption points of the grid. This was accomplished by relying on an adapted data set previously used in other research [48]

To represent the variability intrinsic to the real-life operation of a power system, different types of variations were considered for this system parameter. These were:

- Seasonal profiles that define the load for each of the four clusters of days;
- Hourly variations are applied to similar days within the same seasonal cluster.

The data set adapted from [48] already contains seasonal variations to the demand of each consumption point of the reference power grid considered in this case study, meaning that for a single year, there are 4 distinct typical load diagrams (defining the profile for the cluster of days belonging to each of the seasons) for every single load. The load diagrams for the total demand of this power system are represented in Figure 4.2.

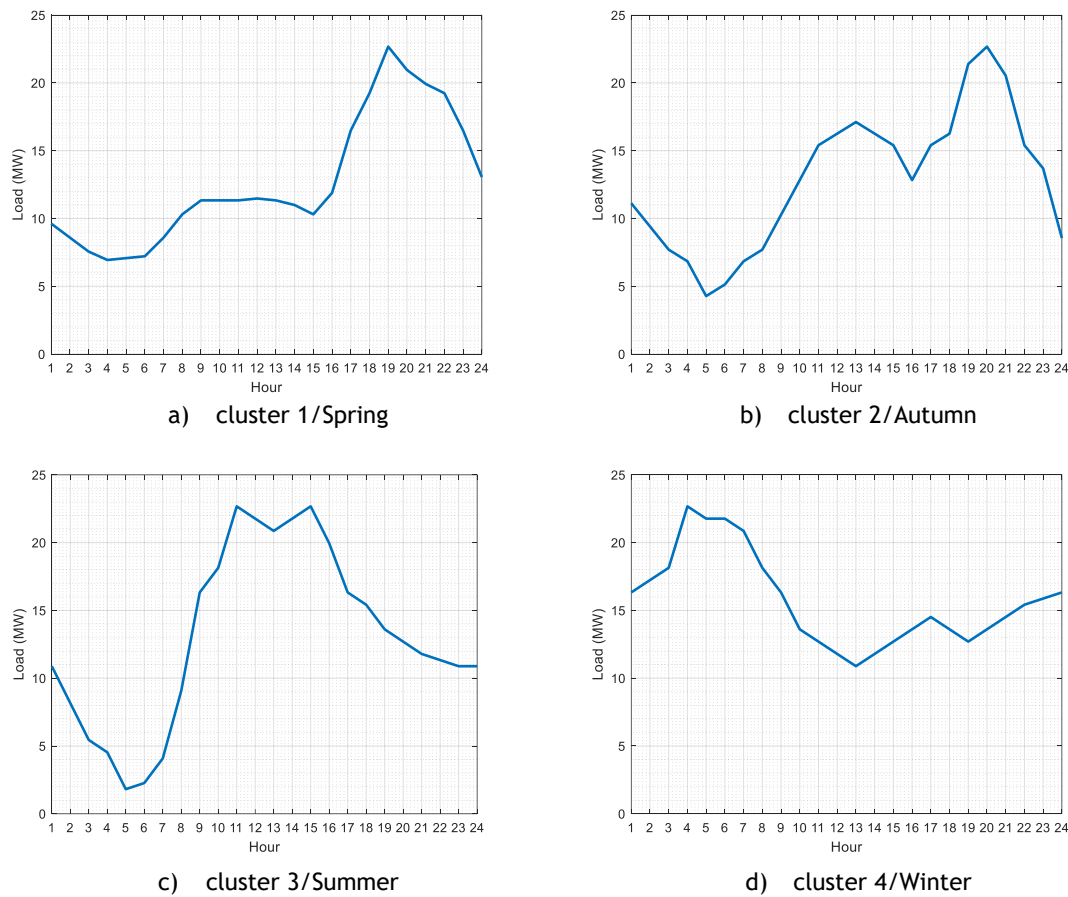


Figure 4.2 - Load diagrams that characterize each seasonal cluster of the year

To account for the daily variation in the system's demand, assuming that each day is slightly different from the previous one (even when belonging to the same season, and thus sharing the same load profile), a daily variation factor was introduced to the demand profile values for every hour of the year. This variation factor was chosen randomly for every hour of each day, following a uniform distribution of values between $[-10,10]\%$. By introducing these variations, the established scenarios are able to more accurately represent the dynamic nature of the system's demand patterns that are seen in real life. Figure 4.3 illustrates the difference in the hourly system's demand for two consecutive days belonging to the same season.

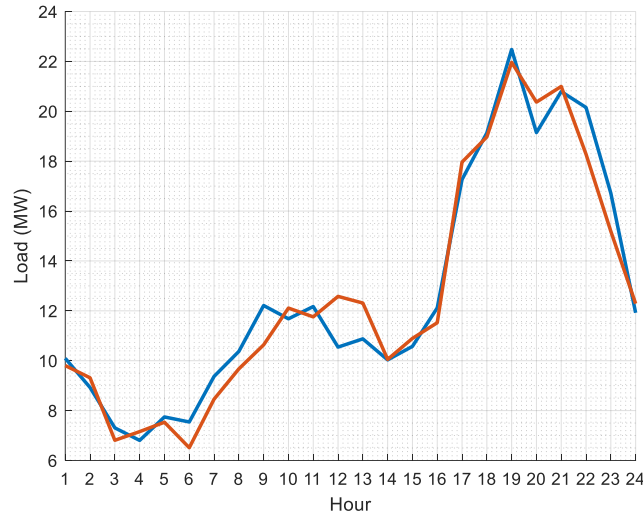


Figure 4.3 - Comparison of the hourly load data of two consecutive days belonging to the same seasonal cluster.

4.1.1.2 Renewable energy generation profiles

The data used to model the profiles for the wind production was taken from [49], in which a data set for 43-hours of point predictions under 100 possible scenarios was used. When creating possible system scenarios, a set of 24 hours of wind data is selected for each day. This hourly data is then multiplied by the capacity of each turbine in order to acquire the actual wind production for each of these, taking into consideration their maximum production capacity.

Regarding the solar PV production, PV data from [50], [51] were used to obtain a data set that contains 24-hours of point predictions for the PV production of each solar plant for 100 different scenarios. Similar to the process applied for the determination of the wind production data, a solar PV scenario is chosen at random to represent the solar production for every day of the year.

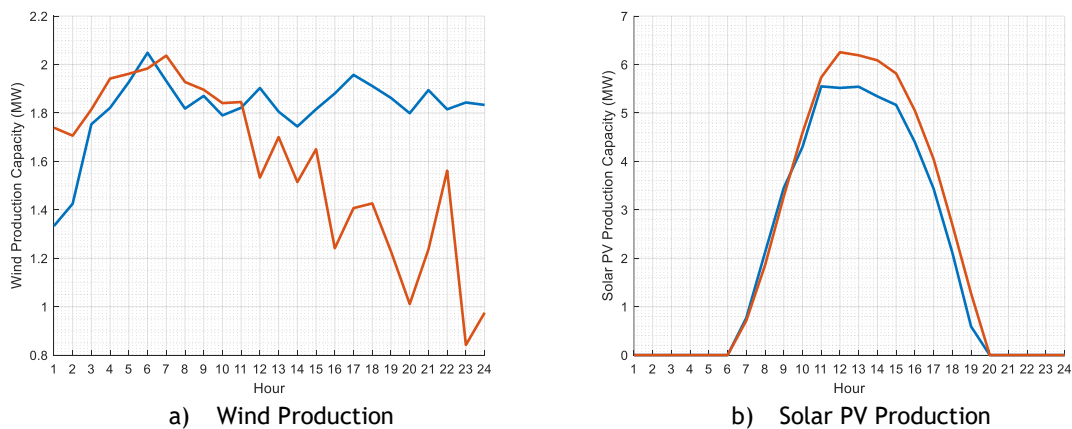


Figure 4.4 - Comparison of the hourly wind production (a) and solar PV (b) production data of two consecutive days belonging to the same seasonal cluster.

Once the base scenario has been established, the seasonality of its parameters (associated with the operation of a typical year) can be examined. To this end, the graphical representation of each of the relevant system parameters as well as the netload of the system is shown in Figure 4.5.

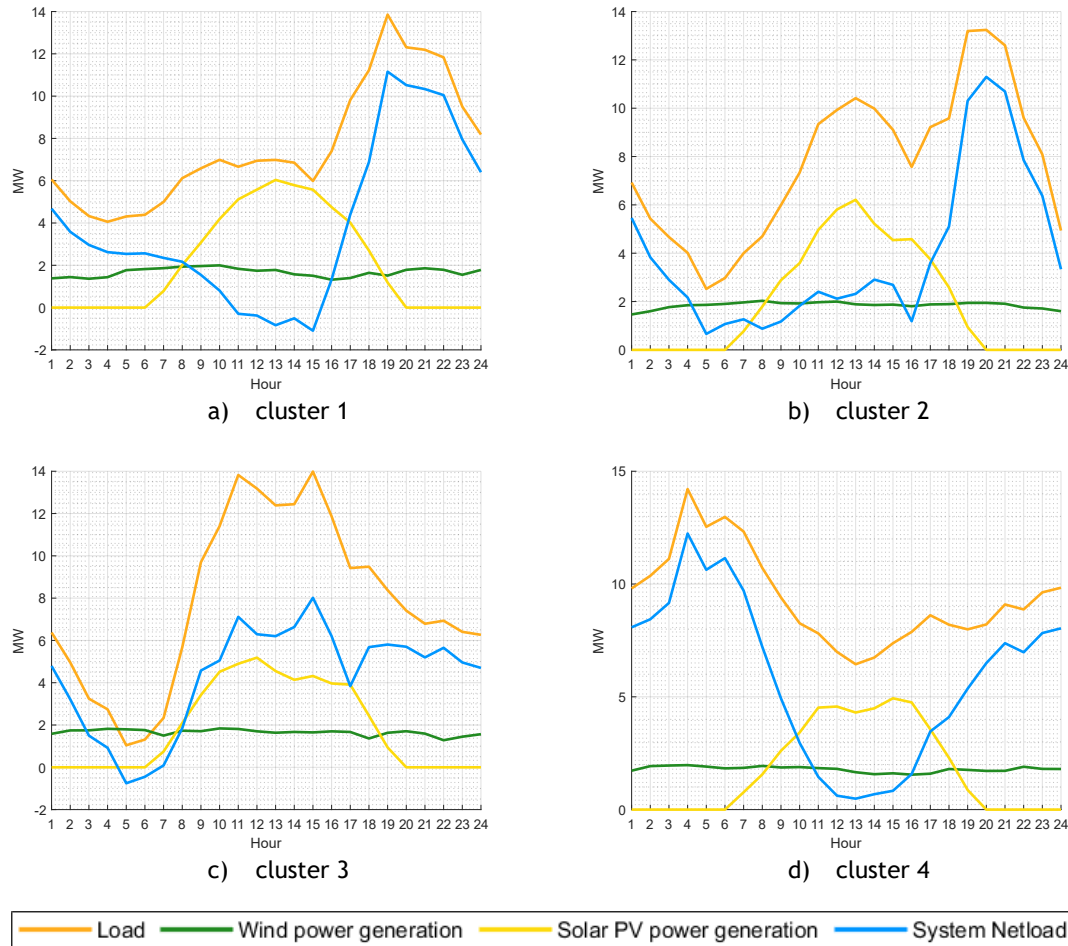


Figure 4.5 - Load, wind, PV and netload data for sample days of each cluster.

4.1.2 Atypical years for the system's behaviour

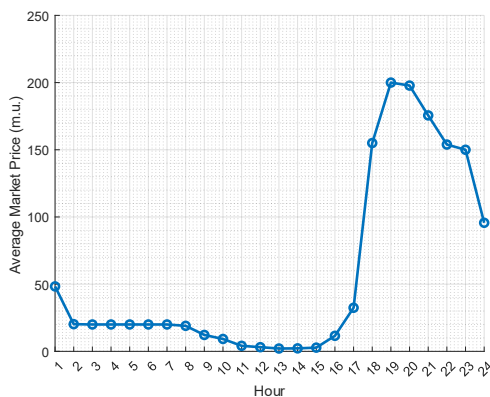
Despite the consideration of a base system scenario to represent a typical year, it is important to acknowledge that every year demonstrates unique characteristics in regard to their demand and renewable generation. In order to represent these yearly variations, new system scenarios were created by applying known percentual variations to each individual parameter, or in some cases to a combination of parameters. The characteristics of these newly established scenarios are outlined in Table 4.4, presenting a reference number to each of them (which will be used throughout the presented work), alongside the variations applied to each parameter (normalized to the values of the base scenario).

Table 4.4 - Description of the scenarios that represent the behaviour of the power system, with each parameter normalized to the base scenario.

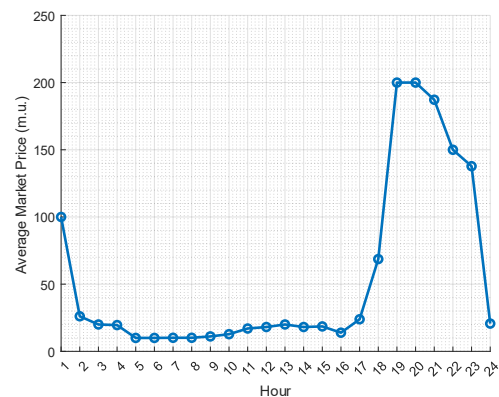
Scenario	Load	PV	Wind
1 [Base]	1	1	1
2	1.1	1	1
3	0.9	1	1
4	1	1.1	1
5	1	0.9	1
6	1	1	1.1
7	1	1	0.9
8	1.2	0.8	1
9	1.2	1.2	1
10	0.8	1.2	1
11	0.8	0.8	1
12	1.2	1	0.8
13	1.2	1	1.2
14	0.8	1	1.2
15	0.8	1	0.8
16	1.1	1.1	1
17	1.1	0.9	1
18	0.9	1.1	1
19	0.9	0.0	1
20	1	1.3	1
21	1	0.7	1
22	1.15	1	1

4.2 Development of the bidding strategies for this case study

Seasonal variations have a significant impact on market prices compared to variations within days belonging to the same seasonal cluster. Figure 4.6 displays the average hourly market prices for each season, based solely on the results of the economic dispatch simulations considering the base scenario (typical year). These results aid the BESS operator in designing each strategy following the approaches outlined in Section 3.2.



a) cluster 1



b) cluster 2

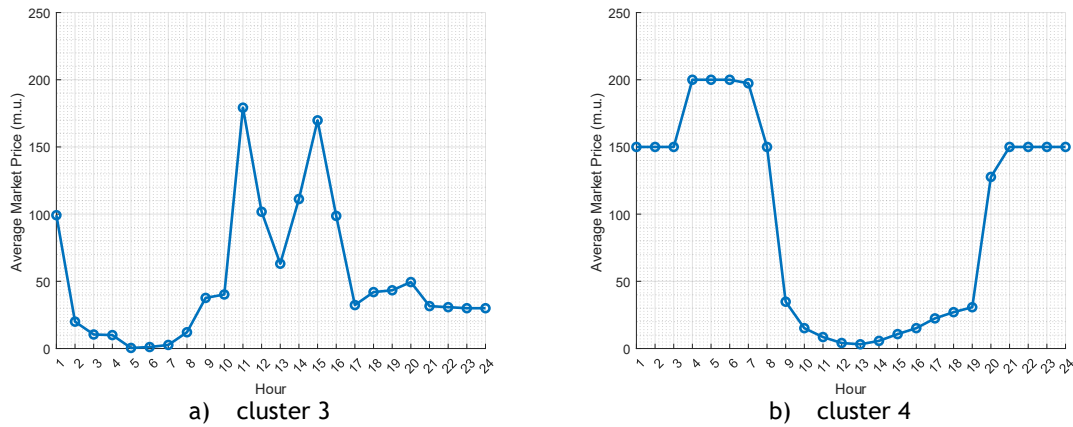


Figure 4.6 - Comparison of the hourly market prices for clusters 1 (a), 2 (b), 3 (c) and 4 (d), based on the condition of the base scenario.

4.2.1 Conservative bidding strategy

For the conservative strategy, the operator of the BESS submits small volumes of energy (i.e., 0.1 MW for each hour) for every time slot of the day. The intention is to discharge every time that it is profitable, therefore the price coupled with each discharge bid has to be above the charging cost but lower than the next possible market price (least expensive CHP generator - 10 m.u.). The characteristic of the discharge bidding strategy A can be seen in Figure 4.7.

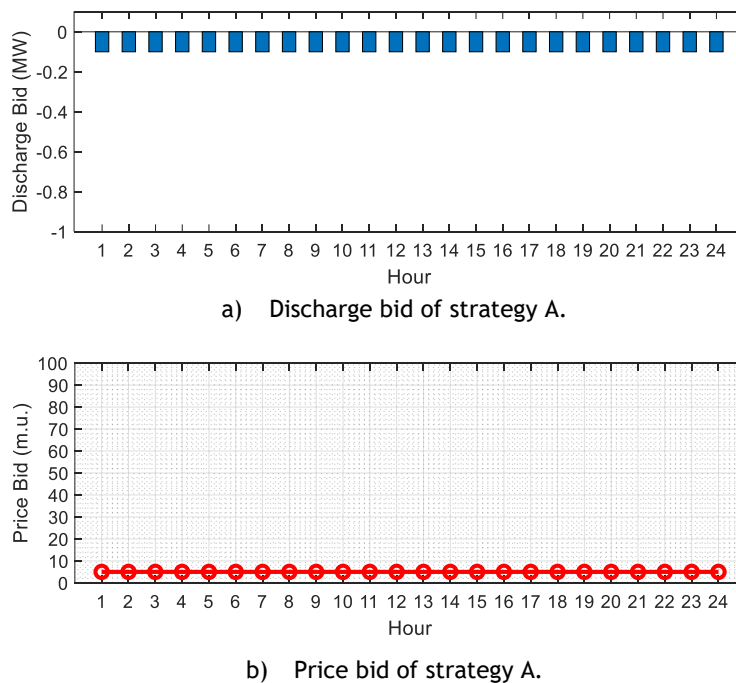


Figure 4.7 - Characteristics of strategy A's bids, in terms of capacity (a) and price (b).

4.2.2 Aggressive bidding strategy

The aggressive strategy aims to preserve the SoC to profit by fully discharging it during high-priced periods, implying that the bids submitted by this strategy have a capacity of 0.72 MWh (full discharge capacity when considering the charging and discharging efficiencies of the BESS). Analysing Figure 4.8, it can be observed that the average prices for the days of clusters 1, 2 and 3 start rising at 16h00, exhibiting peaks during the 19h-21h period. The average prices for these periods are consistently above 150 m.u., therefore this strategy submits bids characterized by prices of 150 m.u. This is done to ensure that the BESS is only dispatched when the prices are very high, and due to variations in the system parameters, these peak prices may occur in adjacent periods to the mentioned previously. So, the operator bids during time slots starting from 16h00 until the end of the day. The characteristic of the discharge bidding strategy B can be seen in Figure 4.8.

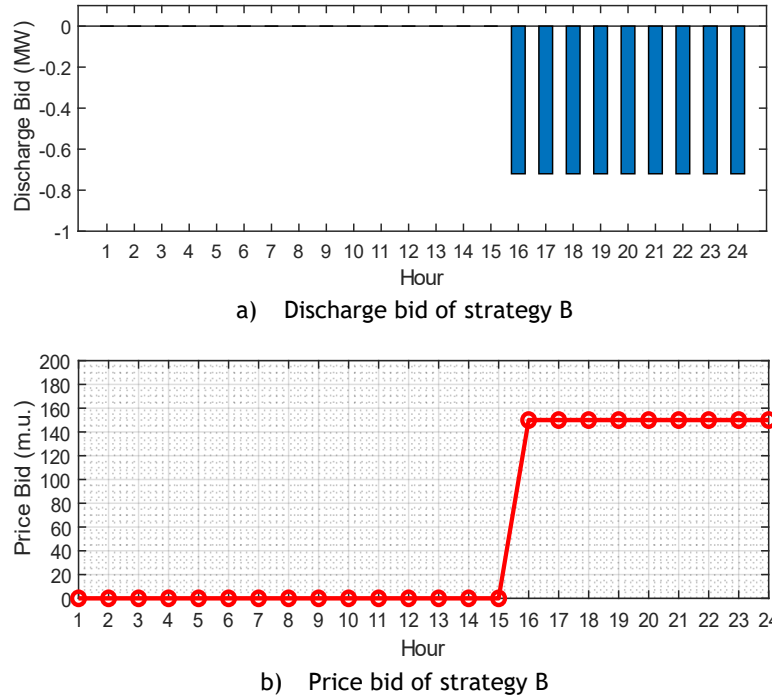


Figure 4.8 - Characteristics of strategy B's bids, in terms of capacity (a) and price (b).

4.2.3 Moderate bidding strategy

The moderate strategy's approach is to bid during two different periods with potential high prices: (i) the late afternoon (after 16h00) and (ii) the morning (7h-10h).

During the afternoon, this approach is characterized by submitting bids with moderate volumes of energy, equal to 25% of the total discharge capacity of the BESS considering the round-trip efficiency of the battery. These bids of 0.18 MWh allow flexibility, which can capture potential variations in the timing of high-priced periods throughout the operating

day. The prices paired with each bid of this strategy were set as 100 m.u., ensuring that the battery only discharges when the external supplier defines the marginal price of the system.

During the morning period (7h-11h) there is no high prevalence of peak period, so in order to capture them whenever possible, the BESS offers its full available capacity to be discharged at 75 m.u., expecting to increase the rate of acceptance of its bids during these events. The discharge strategy for the moderate approach (strategy C) is represented in Figure 4.9.

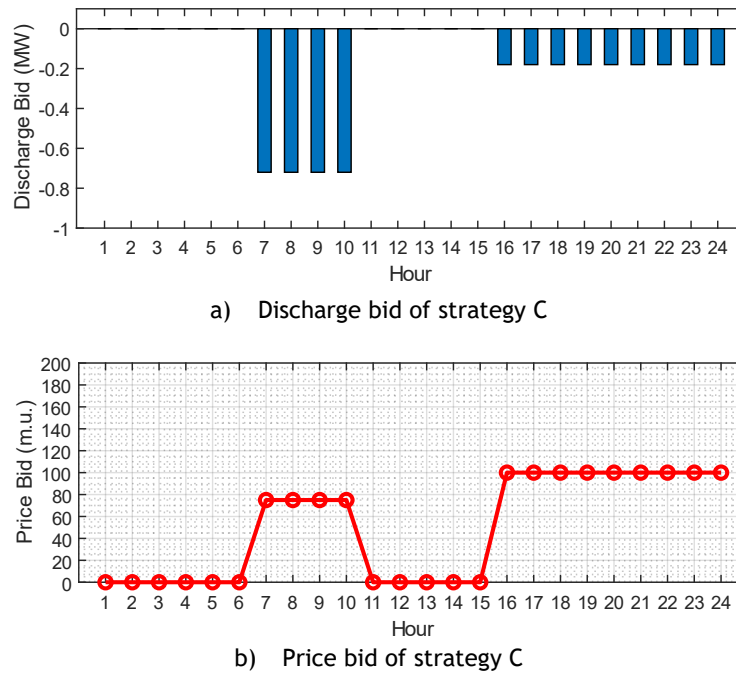


Figure 4.9 - Characteristics of strategy C's bids, in terms of capacity (a) and price (b).

The economic dispatch simulation for the DAM is performed by using the CPLEX optimizer implemented in the software GAMS (as detailed in section 3.3). These simulations take into account the several established scenarios to represent a sample of the multitude of potential system behaviours. During these simulations the BESS operator adopts a single bidding strategy among those previously established in the present section, using it as its bidding approach for the entire year. The data resulting from these simulations will allow the development of the predictive tool as well as a more detailed analysis of the impact of each parameter on the operation and profitability of the BESS.

4.3 Simulation of a BESS in an energy market

The behaviour of the BESS, regardless of the bidding strategy adopted by its operator, is expected to be influenced by the system parameters that directly affect the market prices. The operating schedule of the battery is determined by the accepted bids and offers

submitted to the energy market, which are intrinsically connected to the relationship between the market price and the price component of the battery's bid, for any given period. The same dependence on the accepted bids and the market price registered during the BESS's operating hours is seen for the profit generated by the BESS.

Hence, the results presented in this section are divided into 2 components according to the behaviour of the system parameters that affect the operation of the BESS:

- The seasonality aspect of the system parameters;
- The daily variations of the system parameters.

4.3.1 Seasonality of the system parameters

The residual demand present in the system, for any given time period, evidently impacts the number of energy resources that need to be in operation to supply the aforementioned demand. This, in turn, can potentially affect the characteristics of peak and off-peak periods. Therefore, the seasonal variations of the system parameters are expected to strongly influence the operating schedule of the battery, however, this needs to be validated by recurring to the dispatch simulations results.

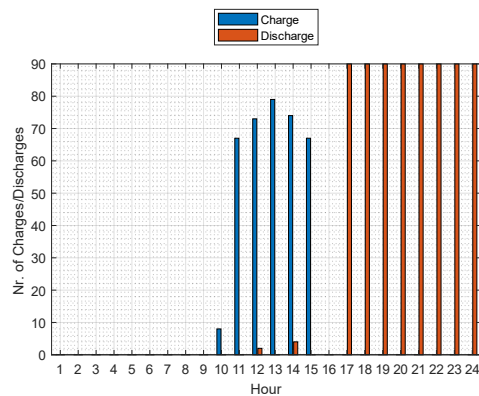
The following results related to the seasonality aspect of the system parameters are divided into:

- The operating schedule of the BESS, considering every bidding strategy;
- The profit generated by the BESS through the performance of energy arbitrage.

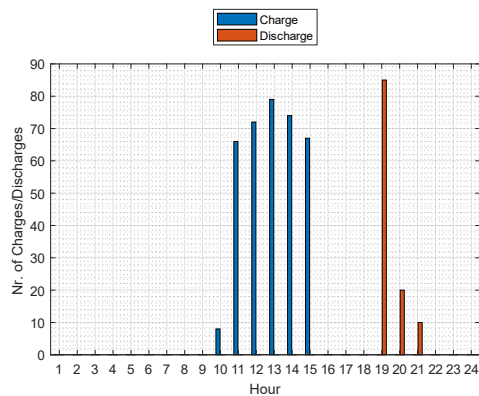
4.3.1.1 Operating schedule of the BESS

When considering the performance of energy arbitrage for a single day, the operating schedule of the BESS is interpreted as during which hours the battery charges and discharges its storage capacity. As discussed previously, this operation is dependent on the behaviour of the system parameters on the specific operating day. So, to evaluate the overall seasonal influence on the arbitrage of the BESS, the complete set of days of each season was used as data for the results presented in this subsection. Figure 4.10 represents the number of charges and discharges performed by the BESS during each hour of the day, for every day that encompasses seasonal cluster 1, while Figure 4.11, Figure 4.12 and Figure 4.13 represent the same parameter for seasonal clusters 2, 3 and 4 respectively.

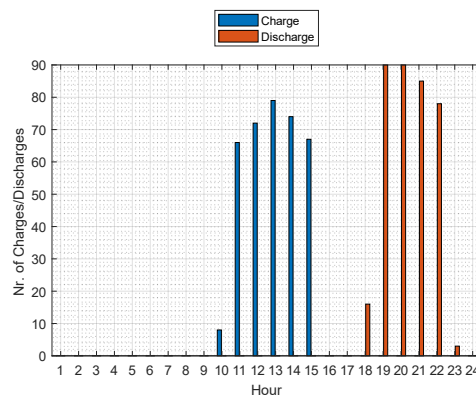
- Results for Cluster 1:



a) Conservative strategy



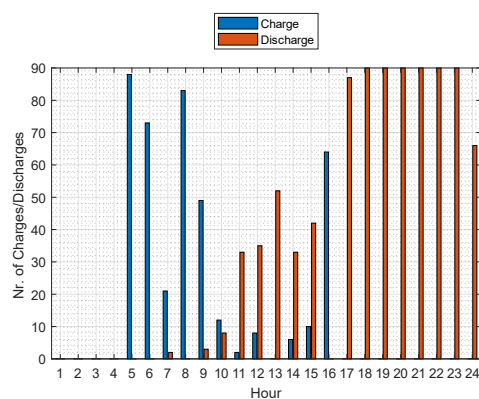
b) Aggressive strategy



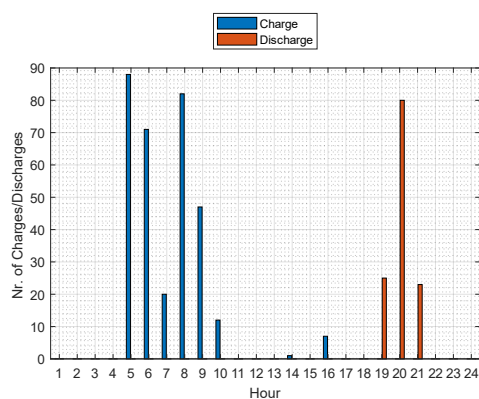
c) Moderate strategy

Figure 4.10 - Hourly number of charges and discharges for the days of seasonal cluster 1, considering the base scenario and the conservative (a), aggressive (b) and moderate (c) bidding strategies.

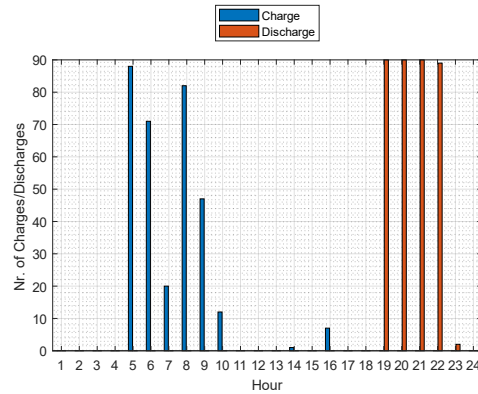
- Results for Cluster 2:



a) Conservative strategy



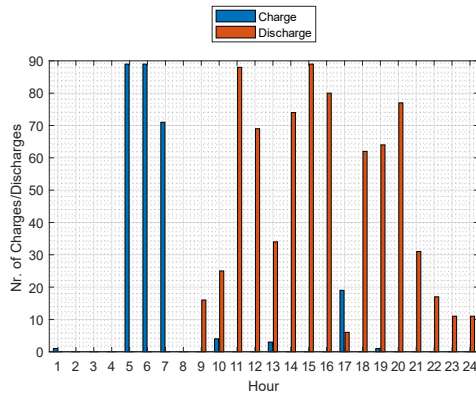
b) Aggressive strategy



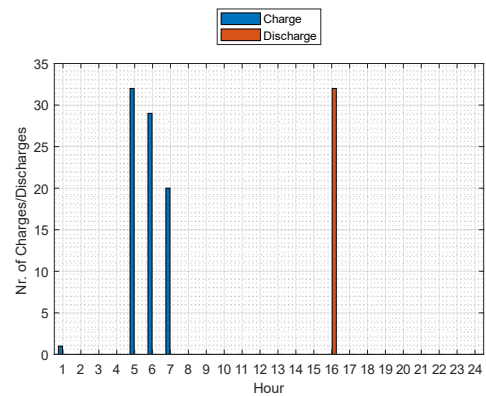
c) Moderate strategy

Figure 4.11 - Hourly number of charges and discharges for the days of seasonal cluster 2, considering the base scenario and the conservative (a), aggressive (b) and moderate (c) bidding strategies.

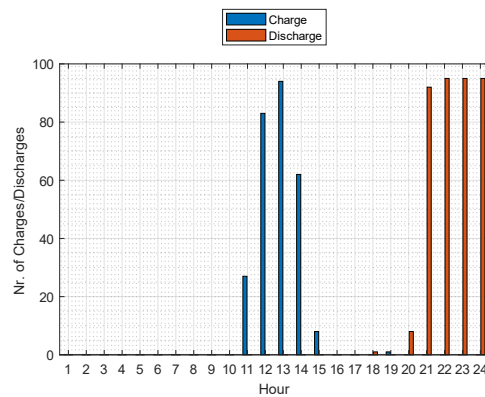
- Results for Cluster 3:**



a) Conservative strategy



b) Aggressive strategy



c) Moderate strategy

Figure 4.12 - Hourly number of charges and discharges for the days of seasonal cluster 3, considering the base scenario and the conservative (a), aggressive (b) and moderate (c) bidding strategies.

- **Results for Cluster 4:**

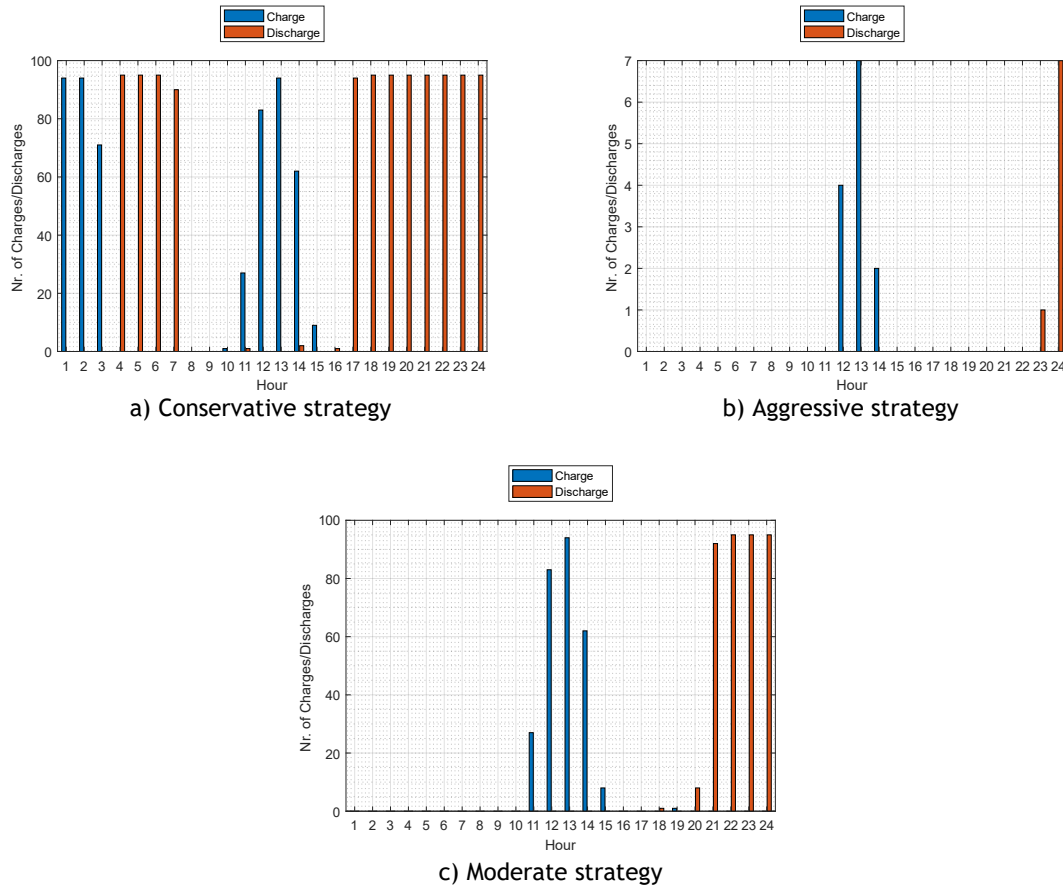


Figure 4.13 - Hourly number of charges and discharges for the days of seasonal cluster 4, considering the base scenario and the conservative (a), aggressive (b) and moderate (c) bidding strategies.

4.3.1.2 Profitability of the BESS

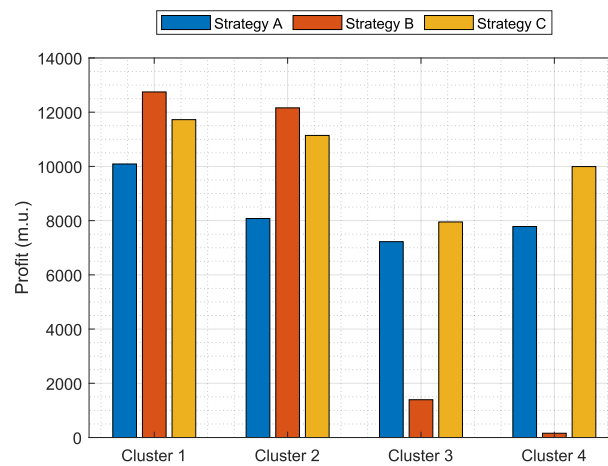
The accumulated profits obtained by the BESS operator for each bidding strategy are presented in Table 4.5, categorized by season. The system parameters affect the operation of the BESS, consequently impacting its profitability under different bidding approaches. The profit generated by the BESS is determined in two phases:

- The calculation revenue is determined by multiplying the amount of energy discharged by the battery and the market price registered during the discharge period;
- The calculation of the incurred costs, by multiplying the amount of energy charged at the market price registered during the charging period.

Table 4.5 - Accumulated profit from energy arbitrage for each strategy, divided per season.

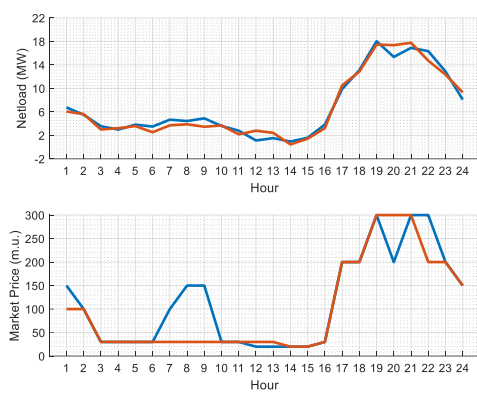
Scenario	Strategy	Profit [m.u.]			
		Cluster 1	Cluster 2	Cluster 3	Cluster 4
1	A	10091	8078	7225	7782
	B	12747	12160	1395	158
	C	11725	11143	7952	9995

Figure 4.14 illustrates the results pertaining to Table 4.5 where it can be seen that different seasonality profiles for the system variables lead to not only different profits but to different rankings regarding the most optimal strategies for each cluster. This demonstrates the impact that different peak and off-peak periods have on the profitability of the BESS.

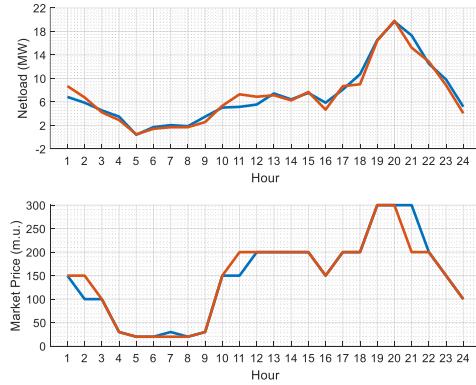
**Figure 4.14** - Accumulated profit by strategy, divided per seasonal cluster when considering the Base Scenario.

4.3.2 Daily variations of the system parameters

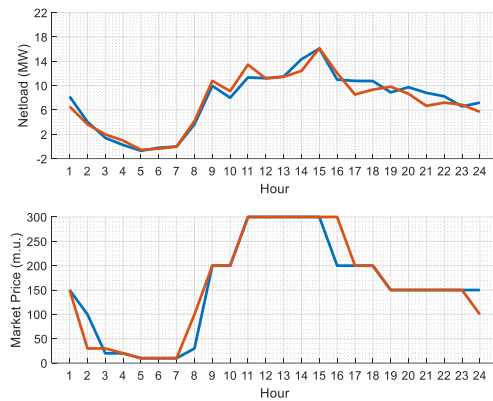
A single system scenario is affected not only by seasonal variations, whose impact was shown in section 4.3.1, but also by daily variations applied throughout the year. These daily variations result in distinct outcomes for the operation of the BESS when comparing consecutive days within the same season. Slight variations in the system parameters during each hour of the day may require the use of more expensive energy sources to meet the residual demand, leading to higher market prices for that specific hour, and vice-versa. This can be verified by comparing both the hourly market prices and the system's netload for each hour of the day, for consecutive days. These comparisons are represented in Figure 4.15.



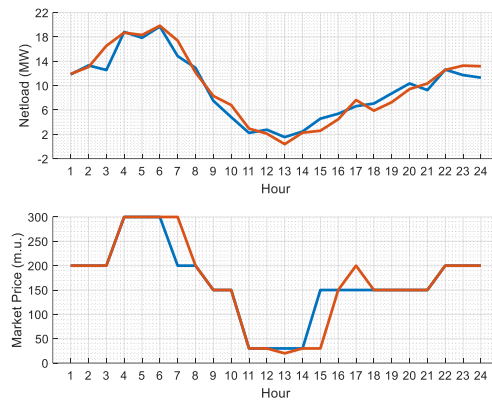
a) Netload (above) and market price (below) for two days of cluster 1



b) Netload (above) and market price (below) for two days of cluster 2



c) Netload (above) and market price (below) for two days of cluster 3



d) Netload (above) and market price (below) for two days of cluster 4

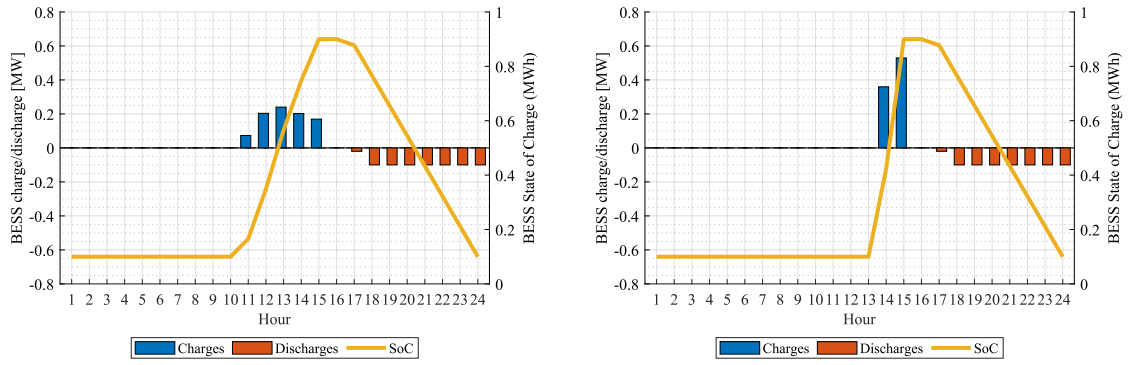
Figure 4.15 - Hourly Netload and Market price for two consecutive days of cluster 1 (a), cluster (2), cluster 3 (c) and cluster 4 (d).

The presented results focus on these daily variations and address three key aspects of the operation of the BESS:

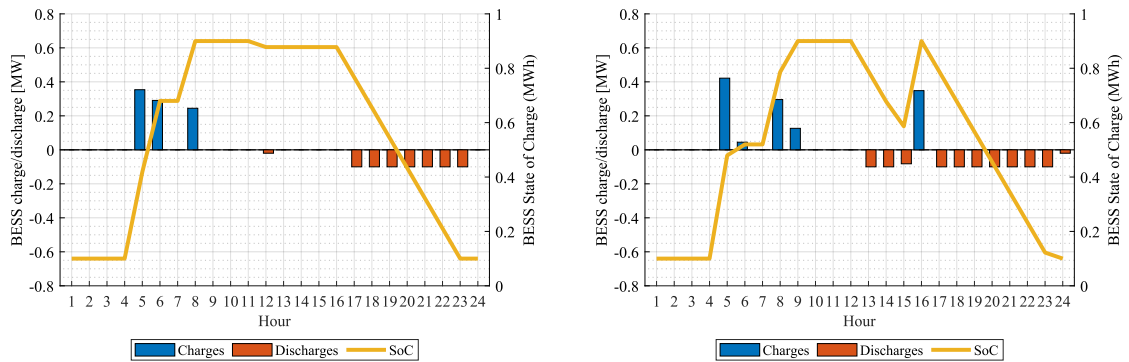
- The operating schedule of the BESS;
- The daily profit generated for each strategy;
- The ranking of the most profitable strategy for a given day.

4.3.2.1 Operating schedule of the BESS

As discussed previously, the daily variations in netload and hourly market prices can significantly influence BESS's operation, depending on the extent of these variations, as well as the bidding strategy selected by the BESS operator. Figure 4.16 and Figure 4.17 shows the charging and discharging operation and SoC of the BESS for two consecutive operating days for each cluster, respectively.

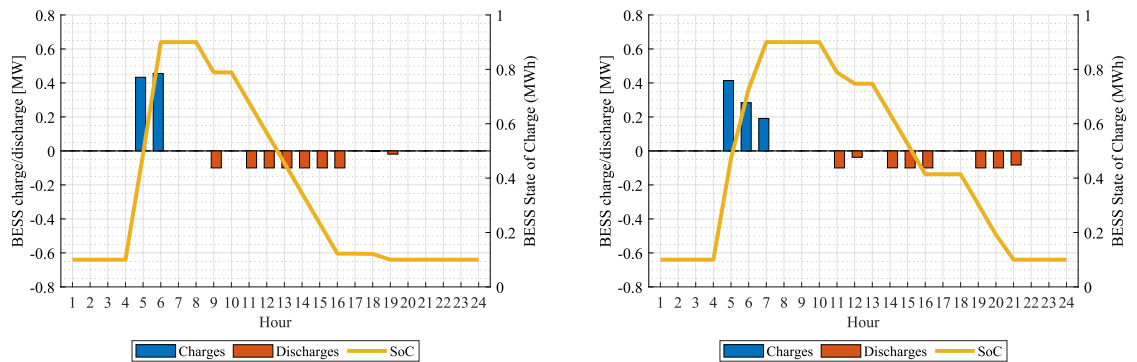


a) Two days of seasonal cluster 1

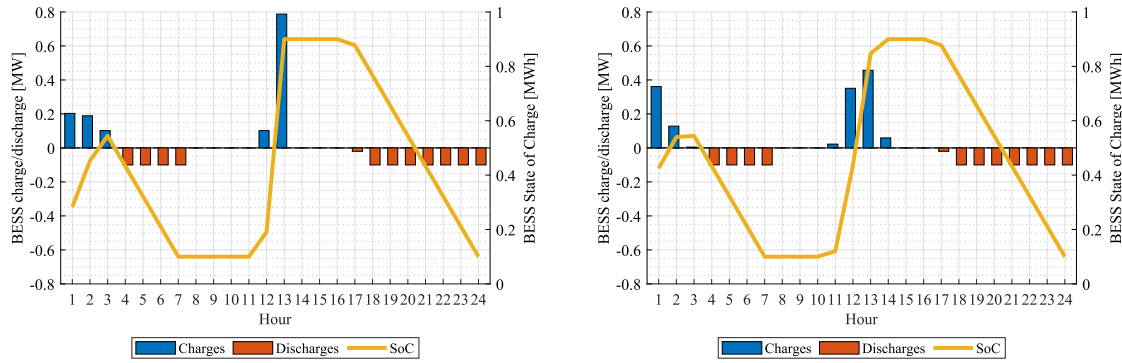


b) Two days of seasonal cluster 2

Figure 4.16 - Comparison of the SoC and operating schedules of the BESS for two different days of seasonal cluster 1 (a) and seasonal cluster 2 (b)



a) Two days of seasonal cluster 3



b) Two days of seasonal cluster 4

Figure 4.17 - Comparison of the SoC and operating schedules of the BESS for two different days of seasonal cluster 3 (a) and seasonal cluster 4 (b)

4.3.2.2 Profitability of the BESS

The change in the charge and discharge hours of the BESS, along with the prices registered during those periods, obviously have an impact on the profitability of the energy arbitrage performed by the BESS. These variations impact each strategy differently due to their distinct characteristics. Table 4.6 provide information regarding the average profits generated by the adoption of each strategy for each seasonal cluster, as well as the maximum positive and negative deviations to the average profit.

Table 4.6 - Average profit and the average positive and negative deviations, for each strategy divided per season.

Cluster	Strategy	Average daily profit [m.u.]	Average Positive variations [m.u.]	Average Negative Variations [m.u.]
1	A	111,95	6,39	5,11
	B	141,63	2,37	9,46
	C	130,28	6,14	5,37
2	A	89,76	6,79	4,33
	B	135,11	0,00	0,00
	C	123,81	2,30	6,70
3	A	80,28	30,55	23,36
	B	15,50	78,87	13,32
	C	88,35	63,58	66,46
4	A	81,92	4,13	5,67
	B	1,66	20,93	1,66
	C	105,21	2,86	5,63

Moreover, the daily variations can potentially influence the ranking of the most profitable strategy for any given day, influencing the decision-making process of the BESS operator. To assess this, the frequency of each strategy being the most profitable was determined for

every day of each season. Furthermore, the same test was conducted under different parameters pertaining to different yearly system scenarios, to determine how the variation of each parameter influences the ranking of the established bidding strategies.

Table 4.7 - Frequency of each strategy leading to the highest daily profit, divided per season, for the test scenarios.

Scenario	Strategy	Cluster			
		1	2	3	4
Base	A	0,0	0,0	43,3	0,0
	B	88,9	100,0	6,7	0,0
	C	11,1	0,0	50,0	100,0
1	A	1,1	6,7	17,8	20,0
	B	0,0	68,9	1,1	26,3
	C	98,9	24,4	81,1	53,7
2	A	0,0	0,0	98,9	100,0
	B	0,0	0,0	0,0	0,0
	C	100,0	100,0	1,1	0,0
3	A	0,0	0,0	80,0	0,0
	B	91,1	100,0	1,1	0,0
	C	8,9	0,0	18,9	100,0
4	A	0,0	0,0	4,4	0,0
	B	90,0	100,0	2,2	0,0
	C	10,0	0,0	93,3	100,0
5	A	0,0	0,0	63,3	0,0
	B	88,9	100,0	2,2	0,0
	C	11,1	0,0	34,4	100,0
6	A	0,0	0,0	18,9	0,0
	B	87,8	100,0	6,7	0,0
	C	12,2	0,0	74,4	100,0

Table 4.7 show a strong correlation of the most profitable strategy with the seasonality of the system parameters. This implies that despite existing daily variations, these do not influence the ranking of the strategies in most of the seasons of the analysed scenarios, which improves the ability to correlate more efficiently the seasonality aspect of the tool's inputs with the most profitable strategy. However, it worsens the capability of predicting occasional alterations in the ranking of the strategies. This, however, is not true for all cases, particularly for days of cluster 3, which shows a high daily variation in the ranking of the strategies due to the variations of the system parameters during the traditional operating hours of the BESS.

Figure 4.18 shows a sample week taken from cluster 3 of the base scenario where the daily variation in the ranking of the most profitable strategy is clearly visible, which adds to the justifications of a decision-making aiding tool.

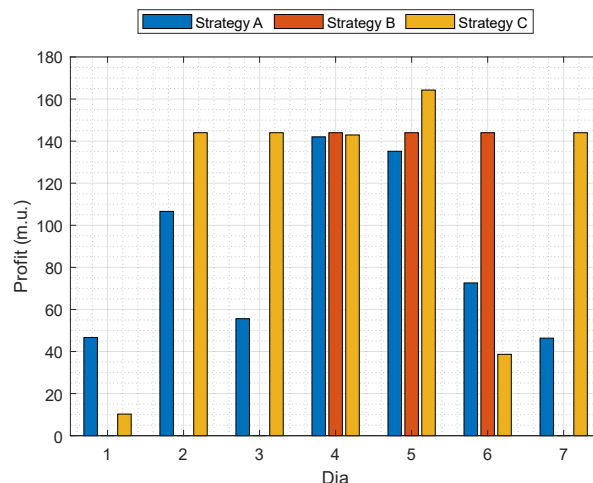


Figure 4.18 - Daily profit of each established bidding strategy for a sample week of the base scenario.

4.3.3 Influence of system scenario in the results

Subsections 4.3.1 and 4.3.2 were mainly focused on the performance of energy arbitrage by the BESS under the base scenario, which is considered to represent a typical year for the behaviour of the power system. To explore the influence of the system parameter variations on the operation of the BESS, other tests were conducted using atypical scenarios for the behaviour of the system.

When considering the same daily pattern, despite being expected that an increase in netload (either by increasing demand or reducing renewable energy generation) leads to higher market prices and vice versa, it is necessary to examine these potential system scenarios. For example, while the increase in prices could lead to higher revenues, by increasing the number of discharges at higher market prices, it can also lead to higher charging prices. In Table 4.8, detailed information regarding the accumulated profits during each season for each bidding strategy is presented, considering each system scenario that will be used as a test case for the application of the tool.

Table 4.8 - Accumulated profits for each strategy and season, for different system scenarios.

Scenario	Strategy	Profit by Cluster [m.u.]			
		1	2	3	4
Base	A	10076	8100	7225	7782
	B	12747	12169	1395	158
	C	11725	11143	7952	9995
1	A	11518	9839	12857	9052
	B	12131	12064	12515	3658
	C	12131	11554	12788	9555
2	A	7077	4666	1820	3706
	B	214	287	23	35
	C	9711	7032	261	689

3	A	10132	7797	4087	7939
	B	12932	12180	471	136
	C	11696	11154	2881	10188
4	A	9533	8559	10855	7238
	B	12129	12160	5511	48
	C	11121	11134	13356	9390
5	A	9834	7573	5715	7400
	B	12848	12169	976	141
	C	11800	11143	5526	9879
6	A	10192	8473	8210	7784
	B	12564	12160	3049	227
	C	11603	11134	10733	9850

Figure 4.19 illustrates the impact that the variation of the system parameters has on the annual profit generated by the BESS for different yearly system scenarios. This justifies the correlation of these parameters to the profitability of the performance of energy arbitrage which can be exploited to assist the decision-making of the BESS operator during the bidding process.

These results help to illustrate the necessity for a tool that can aid the BESS operator in its decision-making process regarding which strategy to adopt during the bidding process of the DAM.

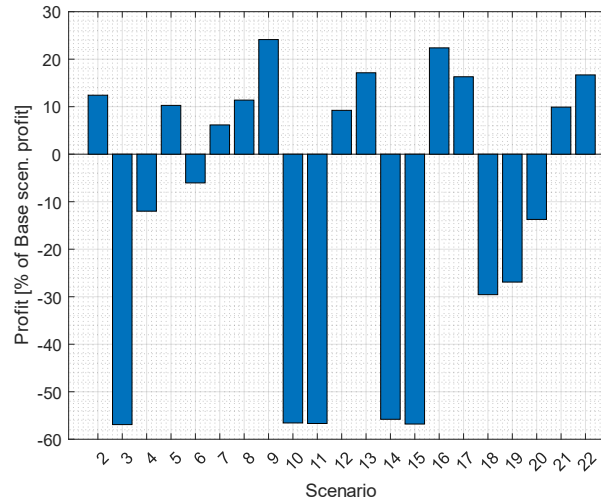


Figure 4.19 - Percentual variation of the annual profit for different system scenarios compared to the Base scenario.

4.4 Development of the Predictive Tool for this Case Study

After both the distribution grid considered for the case studied and the bidding strategies capable of being adopted by the BESS operator were established, the development of the predictive tool capable of supporting the aforementioned decision-making process can be developed. The present section consists of the application of the previously defined

methodology to this study case, culminating in the development of a predictive tool adapted for the characteristics of the system and the bidding strategies considered in this chapter.

4.4.1 Configuration of the predictive model

The data resulting from the economic dispatch simulations were used to train and test the ANN for the proposed predictive tool. The present subsection covers the training and testing of the ANN as well as the implementation of the decision thresholds. Additionally, an example of the application of the ANN is done for a single day.

The data set used for the development of the ANN (containing data for 8030 days, equivalent to 22 simulated years) is divided into 2 data groups: (i) one to be used in the training process and the other (ii) to test the network's accuracy. The training data set consists of 80% of the data pertaining to the previous dataset, while the test data set contains the remaining 20%, with this selection being random to avoid selection bias in the results.

The selected input data are the forecasted hourly values for the load, wind and solar production and market prices. These values are arranged in an array with 96 positions (24 hours of each parameter) to be used during the training of the ANN. Due to not having an available forecast for these parameters, the historical values pertaining to the previous day were used instead, assuming that the deviations across them were in the same level of magnitude as the differences between forecasted and actual data for the following day. The targets selected are the decision variables representing the operation of the BESS for the day defined by the correspondent input set. Table 4.9 shows the characteristics of each data set.

Table 4.9 - Characteristics of each data set used in the development of the ANN.

Data Set	Nr. Days	Nr. Charges	Nr. Non Operations	Nr. Discharges	Nr. of times each strategy is used	
Training	6424	22851	28248	103077	Strategy A	1338
					Strategy B	1719
					Strategy C	3367
Test	1606	5808	6958	25778	Strategy A	315
					Strategy B	456
					Strategy C	835

To classify the outputs of the ANN into three categories (charges, discharges, and non-operations), two decision thresholds are implemented due to non-integer nature of the outputs of the ANN. These two thresholds can be defined as the “positive” and the “negative threshold, with the latter separating the negative and zero decision zones, and the former separating the zero and positive decision zones. These thresholds are selected based on a

statistical analysis, aiming to reach a balance between the true rates regarding the two classifications (positive, negative and zero) delimited by the respective threshold.

The classification of each output in regards to the accuracy of the predictive ANN is determined by their relation to both the threshold and their respective targets:

- An output is considered as a positive, negative or zero depending on if its value is above the positive threshold, below the negative threshold or in between them, respectively;
- Each output is considered as true or false depending on their relation to their respective targets. If they are located in the same decision zone, they're considered as being "true", otherwise they are considered as false.

To determine the optimal threshold values for this ANN, several threshold values were considered and tested, aiming to achieve the best accuracy for the network's predictions. The test data set was divided into two subsets: (i) one containing every non-negative output and their respective targets, and (ii) another containing every non-positive output and their respective targets.

The effect that the value of each threshold has on the accuracy and sensitivity of the ANN (which are a product of the true positive/negative rate and the false positive/negative rate, respectively), can be visualized by plotting a Receiver Operating Characteristic (ROC) curve. Each point of the ROC curves corresponds to a different threshold value. The point located in this curve whose coordinates are closer to the "optimal coordinates" (with a True Rate of 1 and a False Rate of 0, indicating a perfect accuracy) reveals the best threshold value for the considered data set. The ROC curves obtained by testing 1000 different values for the positive and negative thresholds (from 0 to 1, with an increment of 0.001), are plotted in Figure 4.20.

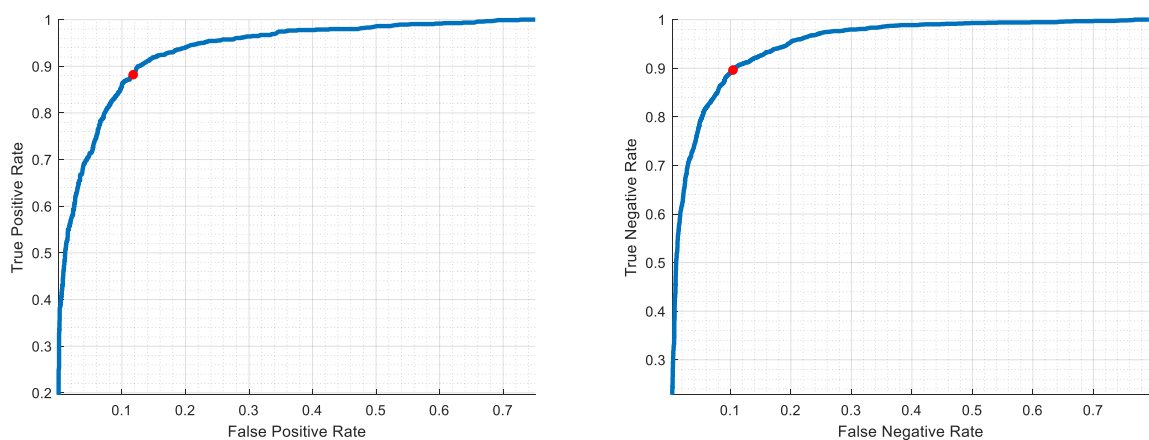


Figure 4.20 - ROC curves for the positive (left) and negative (right) thresholds

The red dots depicted in Figure 4.20 are the optimal points when considering the results of the true positive/negative rates in conjunction with the false positive/negative rates. The red dot in the left ROC curve of Figure 4.20 implies that the best value for the positive threshold is 0.365. For the negative threshold, the best results are achieved when its value is -0.359.

Table 4.10 - Characteristics of the optimal thresholds chosen to be implemented in the tool.

Thresholds		Output Classification						Rate of True Outputs			Accuracy [%]
Positive	Negative	TP	FP	TZ	FZ	TN	FN	TPR	TZR	TNR	
0,365	-0,359	5211	1082	23442	1302	6227	1280	0,90	0,91	0,89	90,5

After implementing the optimal threshold values for the ANN, the results regarding the accuracy of the network are presented in Table 4.10. This table provides an overview of the accuracy achieved by the ANN in classifying the outputs for the full data set, as well as the corresponding true positive, true negative, and true zero rates.

In section 4.4.2, some relevant results regarding the developed ANN are presented.

4.4.2 Results

4.4.2.1 Neural network accuracy

The test data set was then used to perform an analysis regarding the accuracy of the trained network. This was done by inserting the inputs of the test data set in the trained network and comparing every output of the network to its respective target of the data set. Then, the numeric error between them was determined. These errors were arranged in a histogram in order to visualize their probabilistic distribution, depicted in Figure 4.21.

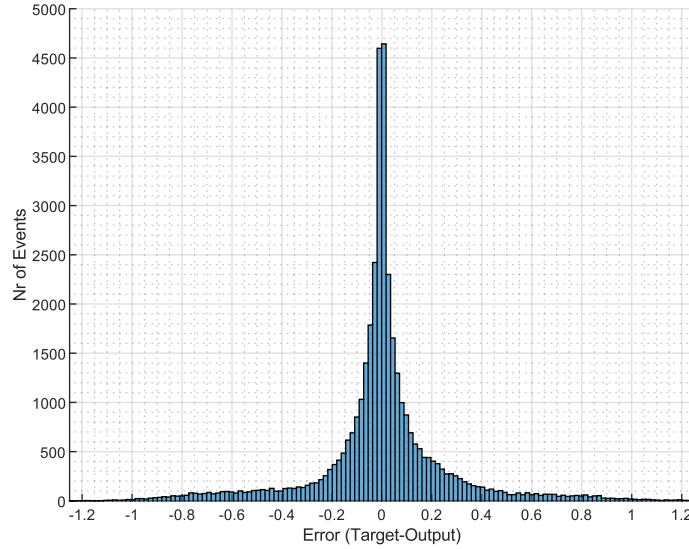


Figure 4.21 - Histogram of the distribution of errors for the neural network.

Analyzing the histogram of Figure 4.21, it can be concluded that the majority of errors are located around the 0 mark, meaning that for almost the entirety of the test data, the error is minimal. A parameter that can be used to represent the accuracy of the network's results is the Mean Squared Error, given by eq. 4.1.

$$MSE = \frac{1}{n} \sum_{i=1}^n (Output_i - Target_i)^2 \quad (4.1)$$

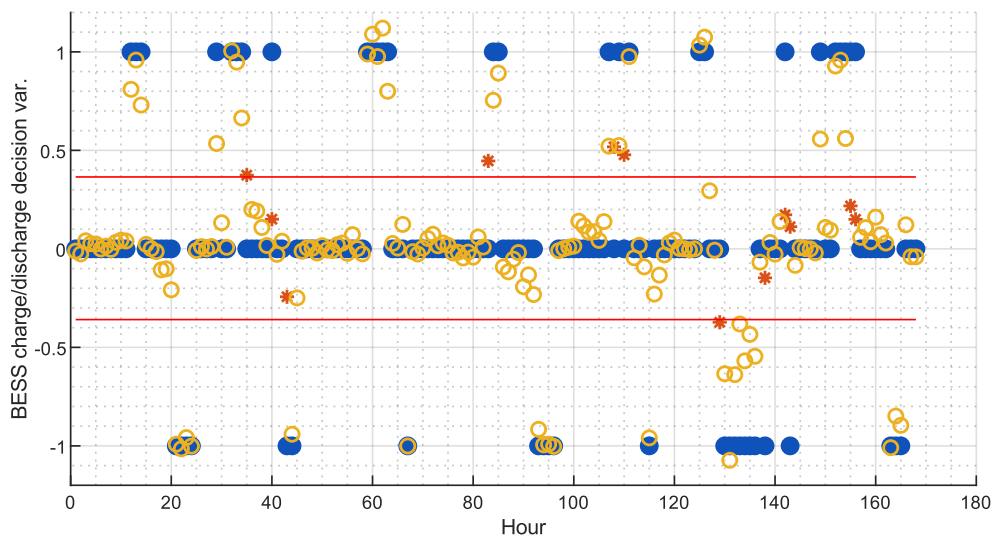
4.4.2.2 Network assertiveness

The assertiveness of the ANN can be interpreted as the accuracy in predicting the behaviour of the battery qualitatively, that is, the ability to correctly identify charges, discharges or non-operations of the battery for a certain time period. After implementing the thresholds (whose value was determined previously in Section 4.4.1), the test data set was used to determine the assertiveness of the network.

The classification of each target is determined for the test data set with the results being represented in Table 4.11. In Figure 4.22, the outputs and targets of 7 random days selected from the test data set were used to represent the impact of the thresholds.

Table 4.11 - Confusion matrix for the outputs of the neural network when the test data set is used

		Output		
		1	0	-1
Target	1	5211	579	18
	0	1074	23442	1262
	-1	8	723	6227

**Figure 4.22** - Comparison between the outputs of the neural network and their targets for 7 days of the test data set.

It is shown in Figure 4.22 that the large majority of the incorrect outputs generated by the ANN are located near the thresholds, indicating proximity to the “decision zone”, which suggests that the ANN is functioning well, as only a few outputs deviate significantly from their respective targets. The previous observation is reinforced by the fact that the network, for the test dataset of 1606 days, only commits 26 large errors, that is, a “charge” output corresponds to a “Discharge” target, or vice versa.

Figure 4.23 illustrates the distribution of errors between the output of the ANN and their respective target (same data set used in the distribution of Figure 4.21), however, for this case the true and false outputs are differentiated.

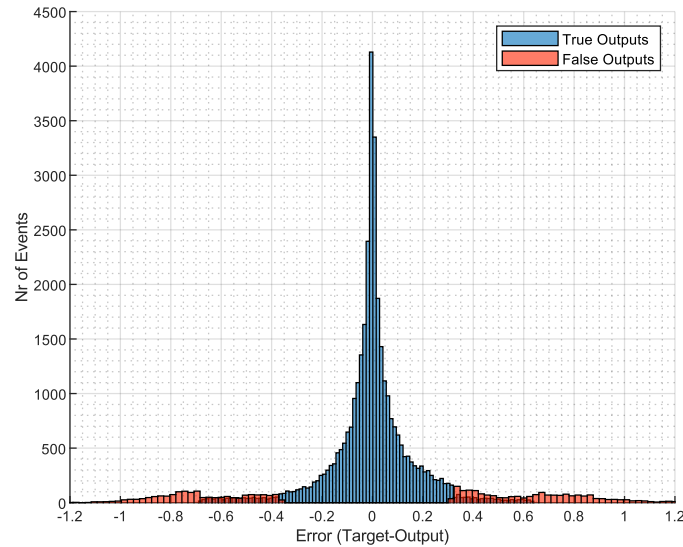


Figure 4.23 - Histogram of the error distribution considering the effect of the thresholds.

The lack of false outputs with errors between $[-0.36, 0.37]$ is due to the effect of the thresholds:

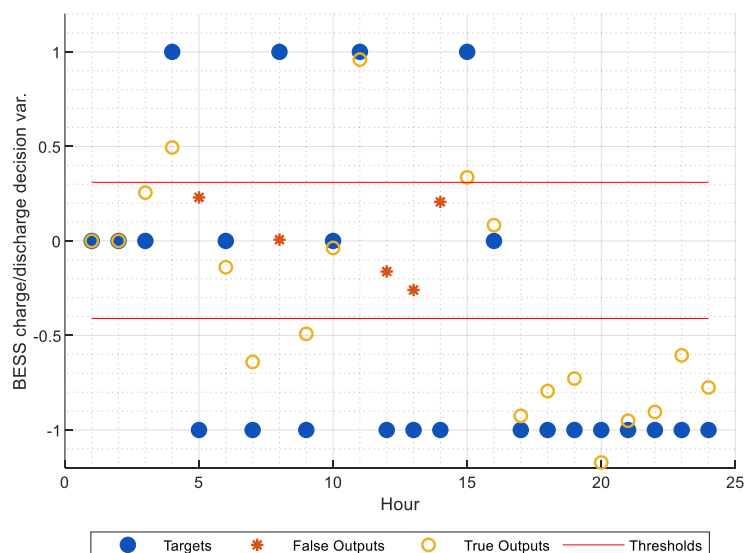
- If the target is positive (1): errors less than 0.63 would mean that the output would also be classified as positive, explaining the slight peak around this value.
- If the target is negative (-1): errors that lead to false outputs need to be higher than the difference between the target and the highest (in absolute value) possible output classified as false zero, therefore these errors are always below -0.64.
- If the target is zero (0): the absolute error must be above the threshold values in order for the corresponding output to be considered false, that is, any false output must be higher than 0.36 and lower than -0.37 (these values are symmetrical to the threshold values due to the way the error is calculated).

4.4.2.3 Example of the application of the ANN for a single day

To exemplify how the ANN behaves when inputs from the test data set are used, a random sample day belonging to this set was selected. The target for the BESS's decision variables for the selected sample day is shown in Table 4.12, alongside the outputs obtained when system data, relative to the previous day, was used as input of the ANN. In Figure 4.24, the comparison between the outputs of the ANN for this day and their respective targets is illustrated.

Table 4.12 - Comparison between the outputs of the neural network and their respective outputs for a sample day of the test data set.

Hour	Target	Network Output	
		Before Thresholds	After Thresholds
1	0	0	0
2	0	0	0
3	0	0.255	0
4	1	0.494	1
5	-1	0.230	0
6	0	-0.139	0
7	-1	-0.640	-1
8	1	0.007	0
9	-1	-0.492	-1
10	0	-0.037	0
11	1	0.959	1
12	-1	-0.162	0
13	-1	-0.260	0
14	-1	0.207	0
15	1	0.336	1
16	0	0.084	0
17	-1	-0.925	-1
18	-1	-0.794	-1
19	-1	-0.728	-1
20	-1	-1.172	-1
21	-1	-0.951	-1
22	-1	-0.904	-1
23	-1	-0.605	-1
24	-1	-0.775	-1

**Figure 4.24** - Target output comparison for the sample day of the test data set.

The scatter plot of Figure 4.24 illustrates the dispersion of both the outputs generated by the trained ANN and their respective targets for the selected sample day of the test data set.

The outputs are then categorized into true and false depending on the relation between their obtained classification and respective target.

The outputs obtained after thresholds imply a certain bidding strategy among those previously established, in this case, strategy A, whose reference bid values will be used for the day-ahead market's bidding process.

Chapter 5

Application of the tool for some test cases

The developed tool was used in several test scenarios that were excluded during its development to ensure unbiased results. These test cases aim to assess the tool's efficacy in supporting the decision-making process of the BESS operator. By using diverse scenarios for these test cases, the robustness of the tool can also be ascertained. Furthermore, these scenarios offer insights regarding the best cases for its use. Through a sensitivity analysis, these tests also allow to identify correlations between each input parameter and the tool's efficiency.

The current chapter presents the application of the tool to multiple test scenarios, presenting the corresponding results and the subsequent analysis of the implemented work.

5.1 Annual results for the application of the developed tool

The tool utilized the input parameters for each daily scenario to determine the most profitable strategy for the following day. These predictions were then compared to the results of economic dispatch simulations of the DAM, in order to assess the accuracy of said predictions, and thus, gaining valuable insights of its effectiveness.

To this end, the profitability of the BESS was evaluated by using two reference points:

- The maximum potential profit achievable by a 100% accurate tool;
- The profitability resulting of relying in a single strategy throughout the entire year, disregarding any dynamic decision-making approach. This static approach served as a benchmark for evaluating the performance of the operator's decision-making process when using the proposed tool.

5.1.1 Results for a typical system year (Base Scenario)

Table 5.1 shows the comparison between the accumulated annual profit of the same BESS when using different approaches; these regard the use of the developed tool, and the use of a single strategy (among the three previously established), throughout the entire year.

Table 5.1 - Profits generated for different cases, under the conditions of the Base Scenario.

Case studied	Profit [m.u.]	Deviation to the tool's profit [%]
Applying the tool	41052	-
Max. Profit (100% Assertiveness)	44923	+9.4
Strategy A	33161	-19.2
Strategy B	26460	-35.5
Strategy C	40815	-0.6

The tool has demonstrated to be effective for this specific scenario, representing a typical year for the studied system. It has achieved an annual profit that is at least 0.6% higher compared to static-bidding approaches. This efficacy is increased if the operator adopts either a conservative or aggressive strategy.

To further evaluate the tool's robustness, it was tested under some atypical scenarios for the system considered. Six extreme scenarios were tested, with each having one of its system parameters altered. Each of the three independent system parameters (Load, Wind Gen. and Solar PV Gen.), gave way to two test cases:

- One with a variation of +20% of the base value;
- One with a variation of -20% of the base value.

These scenarios are considered to be test cases 1 through 6, whose defining characteristics are presented in Table 5.2.

Table 5.2 - Test cases and their characteristic variation when compared to the base scenario.

Test Case	Variation to Base Scenario
1	+20% Load
2	-20% Load
3	+20% Wind Gen.
4	-20% Wind Gen.
5	+20% Solar PV Gen.
6	-20% Solar PV Gen.

5.1.2 Results for Scenarios with load variations

The analysis of this subsection was focused on the load variation scenarios (test cases 1 and 2). The results of effectiveness of the tool in aiding the decision-making of the BESS operator can be seen in Table 5.3 and Table 5.4. These show that for these extreme load variations, the developed tool generates profits that surpass those obtained by the three non-dynamic approaches that rely on a single strategy throughout the year.

Table 5.3 - Comparison of the profits generated for different cases, considering test case 1 (+20% Load).

Case studied	Profit [m.u.]	Deviation to the tool's profit [%]
Applying the tool	46501	-
Max. Profit (100% Assertiveness)	47705	+2.6
Strategy A	43231	-7.0
Strategy B	40363	-13.2
Strategy C	46013	-1.0

Table 5.4 - Comparison of the profits generated for different cases, considering test case 2 (-20% Load).

Case studied	Profit [m.u.]	Deviation to the tool's profit [%]
Applying the tool	21966	-
Max. Profit (100% Assertiveness)	22332	+1.7
Strategy A	17239	-21.5
Strategy B	554	-97.5
Strategy C	17666	-19.6

For test case 1, the tool can generate profits at least 1% higher than the static use of bidding strategy C (best case scenario for an operator without any support to the decision making process regarding its strategic bidding). However, this slight increase in profitability is modest when compared to that achieved by the tool for test case 2. In this low demand scenario, the static bidding of a single strategy leads to profits at least 19,6% lower than those of the tool, showing its particular effectiveness in scenarios such as this. Furthermore, in both test cases, the annual profit generated by the tool are closer to the maximum possible profit for that respective year when compared to what occurs for the base scenario

5.1.3 Results for Scenarios with Wind production variations

Table 5.5 and Table 5.6 present the results for the test cases 3 and 4, respectively. The results for test case 3 demonstrate that for scenarios with increased wind generation, the tool is effective in correlating the system parameters with the optimal strategy for the BESS

and supporting the decision making process of its operator. This is proven by the tool being able to generate profits at least 3,9% higher than those of the three static approaches.

Additionally, the profit generated by its use is closer to the maximum than what occurs for the base scenario.

Table 5.5 - Comparison of the profits generated for different cases, considering test case 3 (+20% Wind production).

Case studied	Profit [m.u.]	Deviation to the tool's profit [%]
Applying the tool	39886	-
Max. Profit (100% Assertiveness)	42789	+7.3
Strategy A	30498	-23.5
Strategy B	26125	-34.5
Strategy C	38348	-3.9

Table 5.6 - Comparison of the profits generated for different cases, considering test case 4 (-20% Wind production).

Case studied	Profit [m.u.]	Deviation to the tool's profit [%]
Applying the tool	40444	-
Max. Profit (100% Assertiveness)	46685	+15.4
Strategy A	34645	-14.3
Strategy B	28000	-30.8
Strategy C	43330	+7.1

However, for test case 4, the tool's profitability is reduced when compared to the best static alternative (strategy C). The deviation to the maximum profit is also higher relative to that of the typical system year. This suggests that the tool's effectiveness varies depending on the specific conditions of the system parameters, and that a static bidding approach can sometimes yield better results than the employment of the tool.

5.1.4 Results for Scenarios with Solar PV production variations

When examining the solar PV variation scenarios (test cases 5 and 6), the tool proves to be effective in assisting the BESS operator when there is an increase in PV generation, according to the results of Table 5.7.

Table 5.7 - Comparison of the profits generated for different cases, considering Test Case 5 (+20% Solar PV production).

Case	Profit [m.u.]	Deviation to the tool's profit [%]
Applying the tool	38581	-
Max. Profit (100% Assertiveness)	40592	+5.2
Strategy A	29931	-22.4
Strategy B	25710	-33.4
Strategy C	35919	-6.9

Table 5.8 - Comparison of the profits generated for different cases, considering Test Case 6 (-20% Solar PV production).

Case	Profit [m.u.]	Deviation to the tool's profit [%]
Applying the tool	41259	-
Max. Profit (100% Assertiveness)	47511	+15.2
Strategy A	36183	-12.3
Strategy B	29848	-27.7
Strategy C	45009	+9.1

For test case 5, the tool's profitability is at least 6,9% higher than that of strategy C, when adopted for the entire year, and even higher when compared to the other alternatives. Additionally, the annual accumulated profit is also closer to the max than for the Base scenario.

In contrast, the application of the tool for test case 6 led to ineffective results. The tool's profitability in this scenario was 9.1% lower than that of using a single strategy (strategy C) and 15.2% lower than the maximum potential profit. These results are represented in Table 5.8.

5.2 Seasonal results for the application of the developed tool

In this section, the analysis was extended to evaluate the effectiveness of the tool in different seasonal clusters, in order to assess how the tool improves the decision-making process for the BESS operator during each of these. As seen in section 5.1, among the three static approaches, strategy C yielded the best results; therefore, the effectiveness of the tool in assisting the decision-making process was compared to the non-dynamic bidding approach while using the moderate strategy.

5.2.1 Seasonal results for the Base Scenario

In the present subsection, the results of the comparison between the tool and the use of strategy C are analyzed. These are shown in Table 5.9, alongside the difference between them (in a percentage relative to the tool's profit), referred to as error. Additionally, the prediction errors committed by the tool for the respective seasonal cluster are also shown.

Table 5.9 - Comparison between the profit generated by the tool and by the non-dynamic bidding of the moderate strategy alongside the tool's prediction errors, for each cluster - Base Scenario.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Non-dynamic bidding [m.u.]	11725.1	11142.9	7951.9	9995.0
Tool's profit [m.u.]	12567.6	11875.3	6614.0	9995.0
Error [%]	7.2	6.6	-16.8	0.0
Prediction errors [%]	20.0	16.7	35.6	0.0

Based on these results, the tool demonstrates a higher profit for the first two clusters of the year. However, for cluster 3, the tool's profit is nearly 17% lower, which coincides with the cluster where there are more daily variations in the ranking of the strategies. During days of cluster 4, the tool could accurately predict the best strategy for every day of the season; however, the best strategy for every day of this season is the moderate one, resulting in no improvement in profit.

Regarding the tool's assertiveness, it shows the lowest level of accuracy for days of cluster 3 due to the aforementioned higher variance in the ranking of the most profitable strategy that occurs in this season. For clusters 1 and 2, the tool exhibits identical assertivenesses.

The profit generated by the tool, when normalized to the max daily profit (obtained by a 100% accuracy), is illustrated in Figure 5.1

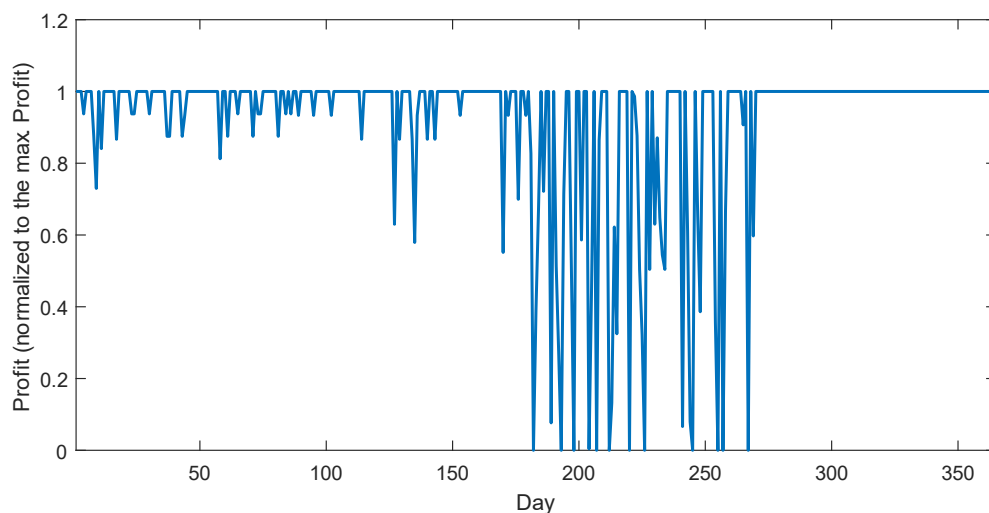


Figure 5.1 - Tool's profit normalized to the maximum profit possible for every day of the Base scenario.

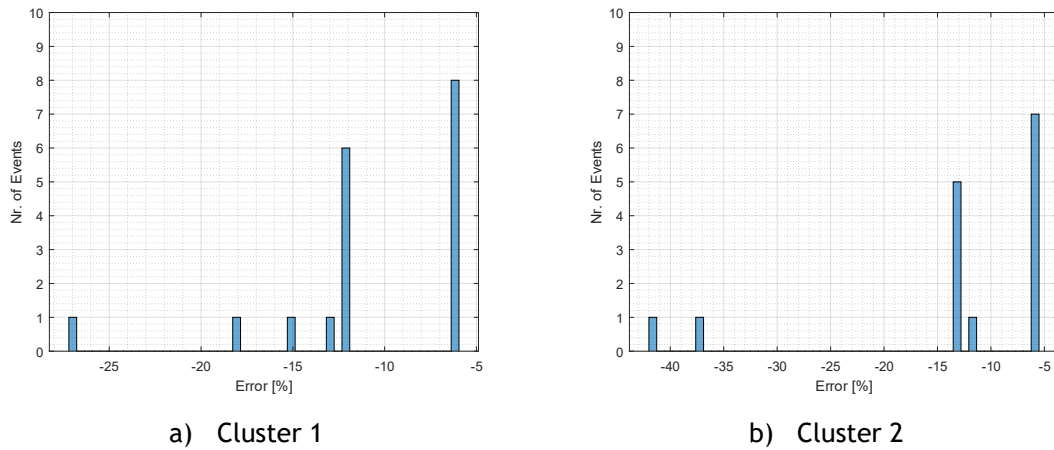


Figure 5.2 - Histograms for the distribution of the deviations between the tool's profit and the daily maximum profit (for seasonal clusters 1 and 2).

For cluster 3, the application of the tool stands out in terms of its results, as it is in this cluster that the larger number of prediction errors occurs. Additionally the tool also exhibits the largest variation in its profitability. This can be attributed to the larger variations in input parameters within this cluster, which can be justified by the overlap of the highest demand period with the peak solar PV production period. This leads to more variations in the market prices during the BESS's most prevalent discharge periods, which in turn causes a higher variance in the ranking of the most optimal strategy for each day, as seen in Figure 4.18.

With a focus on this cluster, the normalized profit generated by the tool concerning the maximum daily profit can be observed in Figure 5.3. Figure 5.4 illustrates the distribution of the percentual prediction errors committed by the tool.

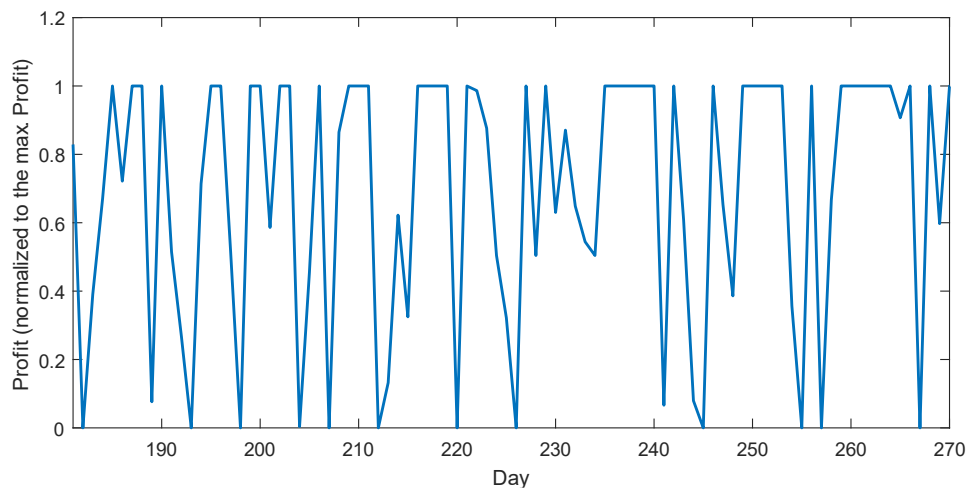


Figure 5.3 - Tool's profit normalized to the maximum profit possible for every day of cluster 3 of the Base scenario.

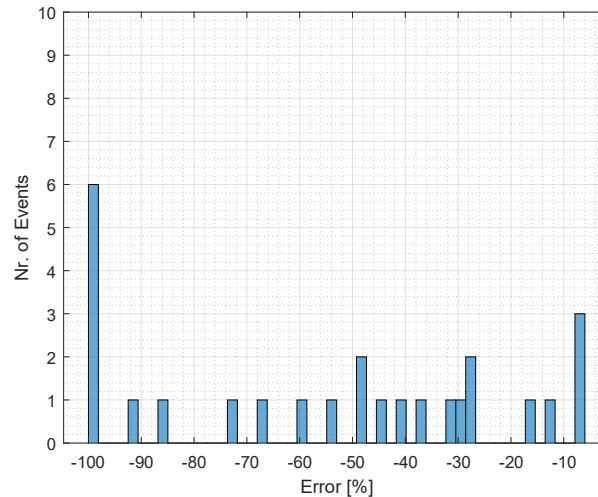


Figure 5.4 - Histogram for the distribution of the deviations between the tool's profit and the daily maximum profit (for seasonal cluster 3), represented in a percentage of the maximum profit.

The purpose of the tool is to assist the BESS operator in its decision-making. To visualize its effectiveness in achieving this, the seasonal profit obtained by the operator while using the tool is compared to another potential competitor that employs a single bidding strategy (strategy C) throughout the entire year. The comparative seasonal results are shown in Table 5.10, with the one highlighted in bold being the highest for the respective cluster (obviously disregarding the max profit).

Table 5.10 - Seasonal profit obtained by the application of the tool, by a single strategy approach, and the max profit obtainable, for the Base Scenario.

Profit [m.u.]	Cluster			
	1	2	3	4
Max.	12805.1	12168.9	9962.5	9995.0
Tool	12567.6	11875.3	6614.0	9995.0
Strategy C	11725.1	11142.9	7951.9	9995.0

The tool demonstrates to be effective in aiding the decision-making process of the BESS operator when applied for a full year (as seen in Section 5.1). However, when considering each season separately, the effectiveness of the tool is limited to only some clusters (as shown in Table 5.10). This limitation can be attributed to one main factor:

- The lack of daily variations in the ranking of the best strategy in the training dataset makes it difficult for the tool to accurately predict them.

However, the small variations across similar days that actually lead to different rankings of the most profitable strategy were already more frequent in cluster 3. Therefore, even if the tool was trained more adequately, there is already an inherent difficulty in the decision-making regarding which bidding strategy to use for days belonging to this season.

5.2.2 Seasonal results for the load variation scenarios

The seasonal assertiveness and profitability of the tool was analysed for the load variation scenarios corresponding to test cases 1 and 2. The results for these cases are shown in Table 5.11 and Table 5.12, respectively.

Table 5.11 - Comparison between the profit generated by the tool and by the non-dynamic bidding of the moderate strategy, alongside the tool's prediction errors, for each cluster of test case 1 (+20% Load).

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Non-dynamic bidding [m.u.]	12131.5	11554.1	12787.5	9554.6
Tool's profit [m.u.]	12131.5	11902.9	12871.2	9610.2
Error [%]	0.0	3.0	0.7	0.6
Prediction errors [%]	1.1	27.8	68.9	41.1

Table 5.12 - Comparison between the profit generated by the tool and by the non-dynamic bidding of the moderate strategy, alongside the tool's prediction errors, for each cluster of test case 2 (-20% Load).

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Non-dynamic bidding [m.u.]	9711.1	7032.2	261.4	688.8
Tool's profit [m.u.]	9711.1	7005.4	1820.4	3456.3
Error [%]	0.0	-0.4	596.4	401.8
Prediction errors [%]	0.0	1.1	1.1	11.6

For both test cases, the tool can improve the decision-making regarding the bidding of the BESS operator. In test case 1, the tool provides assistance to the BESS operator for all seasons of the year, resulting in a slight improvement in profitability compared to the alternative strategy. For test case 2, the tool's profit is only slightly lower (0.4%) than the alternative strategy for cluster 2. Due to the decrease in load and the reduction in market prices observed in this test case, the alternative strategy C (with its moderate risk of non-operation) shows a significant decrease in profits for clusters 3 and 4. These results shows the effectiveness of the tool in these test cases.

It must be considered that for clusters 3 and 4, another alternative among the three established strategies would be better suited for the BESS operator (as seen in Table 5.13). However, in order for a BESS to choose which strategy would be the best to use during each season, its operator would require another form of support to the decision making process in regard to its bidding (possibly through historical data analysis); this once again justifies the existence of a tool that would simplify this process, as the one developed for this dissertation aims to.

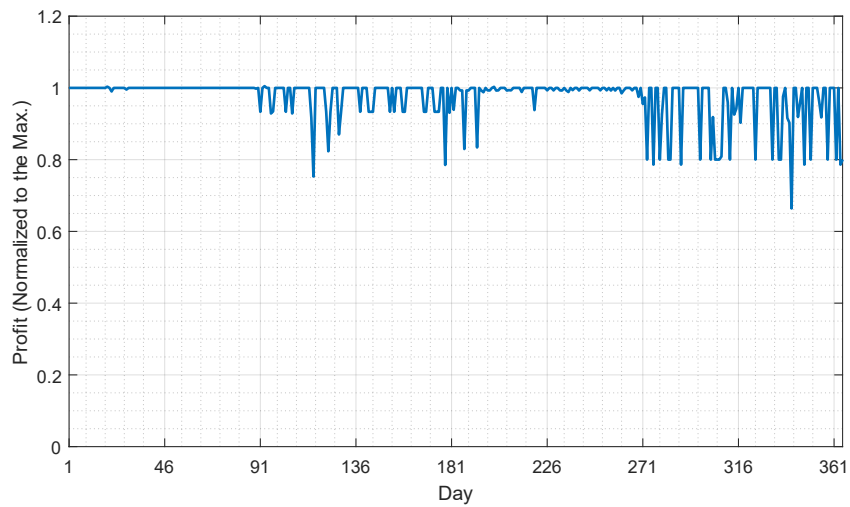
Table 5.13 - Seasonal profit considering the application of the tool, a single strategy approach, and the max profit, for test case 1.

Profit [m.u.]	Cluster			
	1	2	3	4
Max.	12133.7	12207.7	12993.0	10375.5
Tool	12131.5	11902.9	12871.2	9610.2
Strategy A	11518.2	9838.6	12857.2	9052.1
Strategy B	12131.5	12063.8	12515.4	3658.0
Strategy C	12131.5	11554.1	12787.5	9554.6

Table 5.14 - Seasonal profit considering the application of the tool, a single strategy approach, and the max profit, for test case 2.

Profit [m.u.]	Cluster			
	1	2	3	4
Max.	9711.1	7032.2	1909.8	3706.0
Tool	9711.1	7005.4	1820.4	3456.3
Strategy A	7076.7	4665.8	1820.4	3706.0
Strategy B	214.5	287.2	23.1	35.0
Strategy C	9711.1	7032.2	261.4	688.8

In terms of the assertiveness of the tool, Figure 5.5 and Figure 5.6 show the daily profit of the tool when normalized to the max possible daily profit for every day of the year.

**Figure 5.5** - Tool's profit normalized to the maximum profit possible for every day of the test case 1.

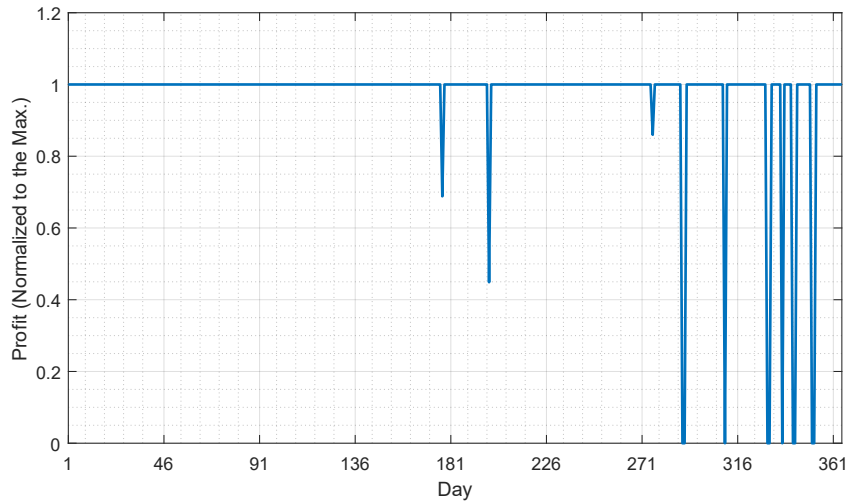


Figure 5.6 - Tool's profit normalized to the maximum profit possible for every day of the test case 2.

5.2.3 Seasonal results for the wind variation scenarios

The seasonal assertiveness and profitability of the tool was analysed for the wind variation scenarios, which correspond to test cases 3 and 4.

Table 5.15 - Comparison between the profit generated by the tool and by the non-dynamic bidding of the moderate strategy alongside, the tool's prediction errors, for each cluster of test case 3 (+20% wind production).

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Non-dynamic bidding [m.u.]	11799.8	11142.9	5526.4	9878.8
Tool's profit [m.u.]	12609.8	11720.2	5711.8	9835.4
Error [%]	6.9	5.2	3.4	-0.4
Prediction errors [%]	23.3	25.6	33.3	2.1

Table 5.16 - Comparison between the profit generated by the tool and by the non-dynamic bidding of the moderate strategy, alongside the tool's prediction errors, for each cluster of test case 4 (-20% Wind production).

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Non-dynamic bidding [m.u.]	11603.0	11134.0	10733.4	9850.3
Tool's profit [m.u.]	12134.3	11972.8	6468.4	9850.3
Error [%]	4.6	7.5	-39.7	0.0
Prediction errors [%]	43.3	11.1	25.6	0.0

For the wind increase scenario (test case 3), the tool demonstrates a better profitability than the alternative for clusters 1, 2 and 3. For cluster 4, its effectiveness is only slightly inferior due to predicting a sub-optimal strategy for 2 days of this cluster.

For test case 4, previously shown to be one of the worst cases for the application of the tool, the tool is still able to aid in the decision-making of the BESS operator for 3 out of the 4

clusters. Only in cluster 3 does the alternative produce higher profits. However, these errors tend to lead to the choice of strategy B as the alternative, which is associated with a high risk of non-operation. This leads to prediction errors that significantly impact the profitability of the tool, as seen in Figure 5.7 and Figure 5.8. Despite this, the tool still correctly foresees the best strategy for almost 75% of the days of this cluster.

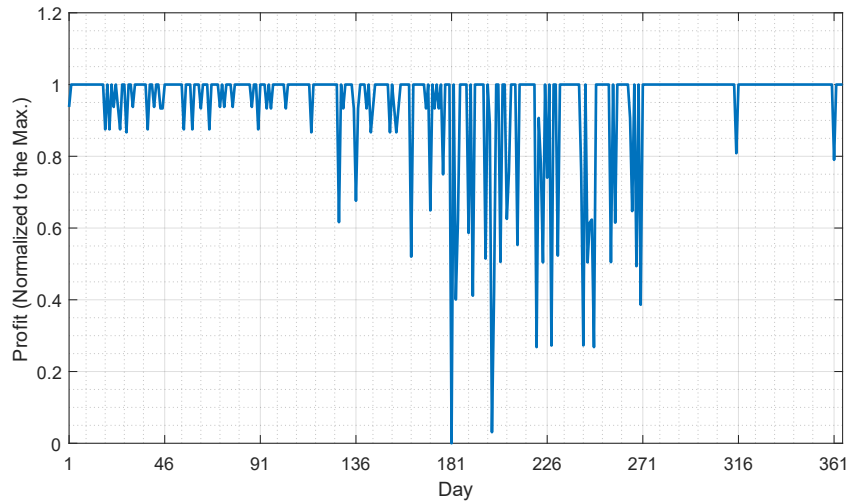


Figure 5.7 - Tool's profit normalized to the maximum profit possible for every day of the test case 3.

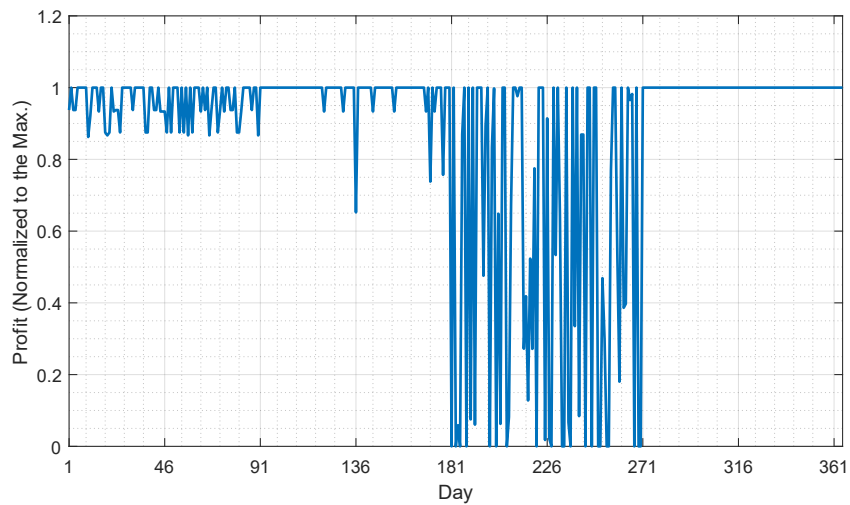


Figure 5.8 - Tool's profit normalized to the maximum profit possible for every day of the test case 4.

5.2.4 Seasonal results for the PV variations scenarios

The effectiveness of the tool is now analysed for test cases 5 and 6, where the solar PV production was changed in comparison to the base scenario. Table 5.17 and Table 5.18 show the seasonal profit of the tool compared to the alternative.

Table 5.17 - Comparison between the profit generated by the tool and by the non-dynamic bidding of the moderate strategy alongside the tool's prediction errors, for each cluster of test case 5 (+20% Solar PV production).

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Non-dynamic bidding [m.u.]	11696.0	11153.9	2880.7	10188.1
Tool's profit [m.u.]	12509.3	11895.1	4021.5	10154.5
Error [%]	7.0	6.6	39.6	-0.3
Prediction errors [%]	25.6	17.8	24.4	1.1

Table 5.18 - Comparison between the profit generated by the tool and by the non-dynamic bidding of the moderate strategy alongside the tool's prediction errors, for each cluster of test case 6 (-20% Solar PV production).

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Non-dynamic bidding [m.u.]	11120.5	11134.0	13355.8	9389.6
Tool's profit [m.u.]	11894.5	11915.5	8050.6	9389.6
Error [%]	7.0	7.0	-39.7	0.0
Prediction errors [%]	21.1	14.4	24.4	0.0

The tool can generate higher seasonal profit for every season of test case 5, except for cluster 4, due to a single failed prediction. For test case 6, the tool's profitability and effectiveness follows the same behaviour as they do for test case 4 (subsection 5.2.3). For this test case the tool is effective for clusters 1, 2 and 4. However, due to the strong variations verified in cluster 3, the tool lowers its profit enough (when compared to the alternative strategy C) to no longer be deemed effective in this test case.

Figure 5.9 and Figure 5.10 show the normalized daily prices for test cases 5 and 6, illustrating the variations in the daily profit of each season with the max values for each day used as reference. One can see the low profitability of the tool for cluster 3 of test case 6.

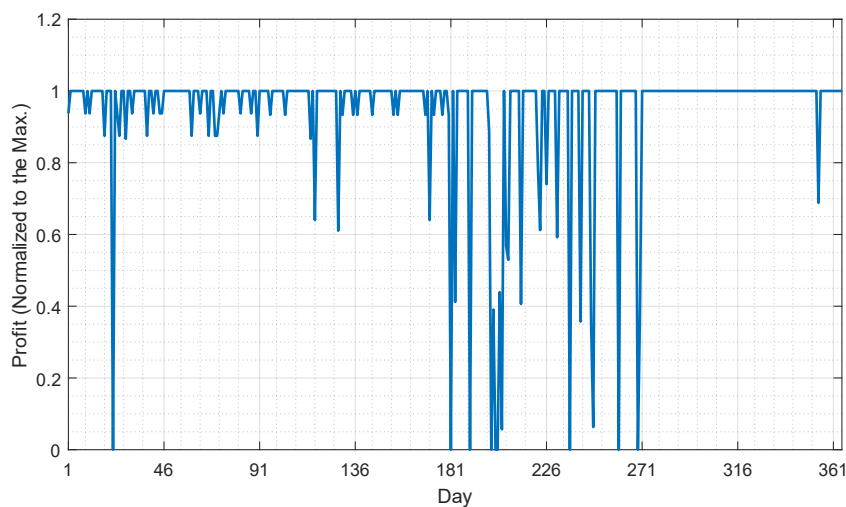


Figure 5.9 - Tool's profit normalized to the maximum profit possible for every day of the test case 5.

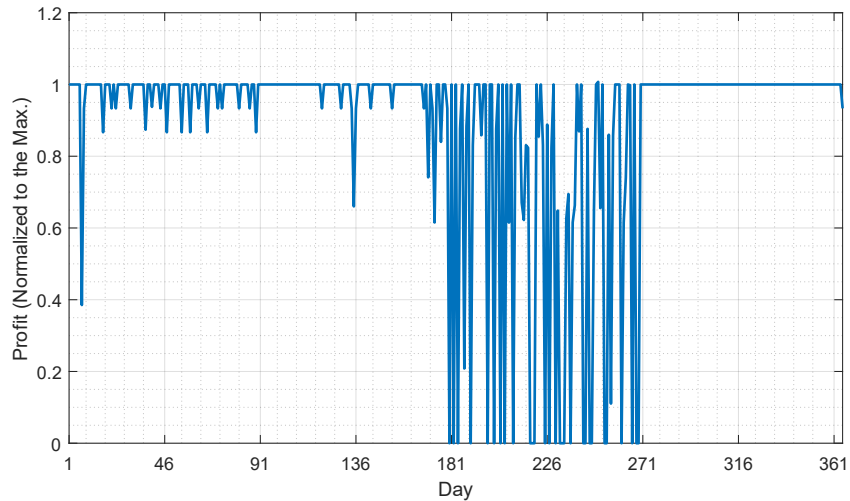


Figure 5.10 - Tool's profit normalized to the maximum profit for every day of the test case 6.

5.2.5 Summary

The previous results demonstrate the effectiveness of this predictive method in determining the optimal bidding strategy to be used in the DAM. Even if only by a slight margin, the tool can correlate the input parameters with the most effective strategy for the following day, for a year considered to be typical. This leads to higher profits than the alternative, even when considering that the alternative would be the best case scenario (moderate strategy). When considering a more risk-taking or risk-averse BESS operator, the tool would always be able to guarantee a better profitability, at least when used annually.

By testing other possible scenarios for the system's behaviour, a robustness analysis was performed, where it was shown that for 4 out of 6 test cases, the tool is able to help in the decision-making process regarding the bidding of the BESS operator.

5.3 Sensitivity analysis of the application of the tool

In order to make assertions on the impact of each system parameter on the assertiveness and profitability of the tool, a sensitivity analysis was conducted. This analysis compared the results obtained, identifying which variations in the inputs of the tool would lead to the most changes in the results. This allows us to analyze the sensibility of the tool to each of the independent system parameters used as inputs.

The inputs considered for this analysis suffered the same variations as those used for the test cases of the previous analysis. That is, each system parameter was affected with an increase and decrease of 20% to their base value.

Table 5.19 shows the impact of each input variation on the assertiveness of the tool compared to that obtained by the tool for the base scenario. The aforementioned table also presents the deviation between these assertivenesses.

Table 5.19 - Sensitivity analysis for the assertiveness of the tool.

Input Scenario		Assertiveness [%]	Deviation to base [%]
Base	-	82.19	-
Load	+20%	51.2	-37.7
	-20%	16.4	-80.0
Solar PV Production	+20%	76.4	-7.0
	-20%	87.1	6.0
Wind Production	+20%	74.8	-9.0
	-20%	83.0	1.0

In addition, Table 5.19 shows that the load has the highest impact on the assertiveness of the tool, which was expected (but still necessary to be simulated and proven), as the same percentual variation affects this parameter the most due to its higher base value when compared to the others. In turn, this affects the netload of the system and therefore the hourly market price, leading to more divergences in the outcome of the ranking of the most profitable strategy for each day (as seen in Table 4.8), which the tool was trained to predict. The variance in Solar PV input led to the next most pronounced effect on the assertiveness of the tool, followed by variations in the wind production input.

In terms of the profitability of the tool, the variance in the inputs led to slightly different results than the ones for assertiveness, which are shown in Table 5.20.

Table 5.20 - Sensitivity analysis of the profitability of the tool.

Input Scenario		Profit [m.u]	Deviation to base [%]
Base	-	41051.91	-
Load	+20%	39672.53	-3.4
	-20%	38115.21	-7.2
Solar PV Production	+20%	41565.36	1.3
	-20%	38278.41	-6.8
Wind Production	+20%	41285.09	0.6
	-20%	39457.26	-3.9

Table 5.20 shows that the profit obtained by the tool is most sensitive to the increase in the load input, followed by the decrease in solar PV production with similar results. However, when taking into consideration both the effect of increasing and decreasing the input value, the ranking of sensibilities is the same as for the assertiveness of the tool. The tool is more

sensitive to wind production, solar PV production and load inputs, when ordered from least to most impactful.

Table 5.21 resumes this analysis by illustrating the absolute percentual deviation that the increase and decrease of 20% in each input parameter leads to for both the assertiveness and profitability of the tool. It is relevant to say that, although these input variations always affect the trained predictability capacities of the tool, the impact of these variations is not always negative. This occurs as a wrong prediction when it comes to the trained output of the tool may lead to a correct prediction in the actual day-ahead market operation leading to higher assertivenesses and profits for the tool.

Table 5.21 - Absolute deviation of the tool's assertiveness and profitability for each input scenario.

		Absolute Deviation to Base Scenario	
Input Scenario		Assertiveness	Profitability
		[%]	[%]
Load	+20%	37.7	3.4
	-20%	80.0	7.2
Solar PV Production	+20%	7.0	1.3
	-20%	6.0	6.8
Wind Production	+20%	9.0	0.6
	-20%	1.0	3.9

5.4 Summary of the results

The main conclusions regarding the effectiveness of the tool can be ascertained based on the results resumed in Table 5.22 for the 7 scenarios analysed previously.

Table 5.22 - Results regarding the use of the predictive tool for every test case

Test Case.	Variation relative to the Base scenario			Assertiveness [%]	max profit [m.u.]	tool profit [m.u.]	Profitability [%]
	Load	Wind Gen.	Solar Gen.				
Base	-	-	-	82.2	44922.6	41051.9	91.4
1	+20%	-	-	64.9	47704.5	46501.4	97.5
2	-20%	-	-	96.4	22332.1	21966.2	98.4
3	-	-	+20%	79.5	42789.0	39886.3	93.2
4	-	-	-20%	80.5	46685.1	40443.8	86.6
5	-	+20%	-	83.0	40591.9	38580.5	95.0
6	-	-20%	-	85.2	47511.4	41259.3	86.8

The assertiveness of the tool is primarily affected by variations in the load, followed by variations in PV production and then wind generation. This corresponds to how much each

variable affects the operating schedule of the battery, and thus the variability in the ranking of the best bidding strategy to be submitted to the DAM, as seen in Table 4.7.

After testing the tool in a typical system scenario, and conducting a robustness analysis for other 6 test scenarios, the efficiency of the tool in assisting the BESS operator in its bidding process for the day ahead market is proven . This implies that the tool is able to find a correlation between the optimal bidding strategy for the following day and the system parameters used as inputs. However, the tool is not very effective in predicting the daily variations in the ranking of the most profitable strategy when these occur frequently (as is the case for Cluster 3). This is attributed to the development of the system scenarios and the establishment of the bidding strategies.

Despite this, the tool is still able to increase the profitability of the BESS operator for the majority of the seasons in the cases tested throughout this chapter, demonstrating its efficiency in supporting the decision making process concerning the bidding of the BESS to the DAM in both an annual and seasonal timeframe.

Chapter 6

Main findings

This chapter contains the main conclusions drawn during the development of this work. An analysis of the simulation results and the application of the predictive model is conducted, and the key findings are discussed. Some considerations regarding the results obtained and their interpretation are also provided. Additionally, the main contributions of this dissertation are highlighted, and some proposals for potential future developments related to this work are outlined.

6.1 Conclusions

The drive for carbon neutrality across the major world power grids is increasing the challenge of balancing the energy supply and demand, mainly due to the intermittent nature of RES. To mitigate these imbalances and to aid the integration of RES in the grid, the need for flexibility in the grid has been rising in recent years. BESSs offer a potential solution to this due to their capacity to both store excess energy and inject it into the grid when needed. A BESS operator can potentially profit through the provision of flexibility by charging during off-peak periods and discharging during peak periods in a process called energy arbitrage. Although currently unprofitable, declining battery costs and the growing need for flexibility is expected to change this paradigm, which implies that decision-making models for optimizing a BESS profit generation will become prevalent in the near future.

To this end, this dissertation was focused on developing a predictive model to support the decision-making process of a BESS operator, by evaluating and forecasting the most profitable bidding strategy to be submitted to the DAM. This model correlates forecasted or historical system data, available to the BESS operator, with the most profitable strategy among the three established. In this context, the work developed in this dissertation can be divided into two parts. The first was dedicated to the establishment of the bidding strategies and system

scenarios considered during each simulation, which culminate in the development of a case study for the application of the tool. The second part of this work was focused on the development of the tool based on the parameters of the established case study, its application and the subsequent analysis of its results. This analysis mainly concerns the impact of the tool on the decision-making process of a BESS operator regarding its bidding to the DAM, considering both its assertiveness and profitability.

The development of the predictive tool involved establishing three bidding strategies with different approaches to their bidding (conservative, moderate and aggressive) and evaluating their profitability by conducting simulations of the day-ahead energy market. These simulations considered different scenarios for the system's demand and RES generation. These scenarios were all based on a single system scenario considered to represent the typical behaviour of each parameter for an entire year, and were created by applying percentual variations to each of the system's parameters or a combination of them. The predictive tool, based on an ANN, was trained using the results of the simulations to correlate the system parameters of each established scenario with the operating schedule of the BESS that results from the adoption of the most profitable strategy.

The analysis of the results of each simulation, conducted in the first part of this dissertation, revealed that the operating schedule of a BESS is affected by both seasonal and daily variations in the hourly DAM prices. These prices are dependent on the system's residual load, which is determined by the demand and RES generation (wind and solar PV). More importantly, the simulation results allowed to assert that the profitability of energy arbitrage for each bidding strategy is affected by the combination of the battery's operating schedule and the DAM market prices. Therefore, the ranking of these bidding strategies in terms of most profitable is also influenced by the variations in the system parameters. Based on this, it can be concluded that the demand and RES production are good explanatory variables for the prediction of the most profitable strategy for the future, and therefore are suitable to be used as input parameters for a predictive tool.

The second part of the analysis addressed the results obtained by the application of the tool in some test scenarios. These results allowed to draw some conclusions regarding the effectiveness of the tool in supporting the decision-making of a BESS operator. To achieve this, the profitability of a BESS operator that relied on the results of the tool to dictate its bidding for the DAM was compared to the profitability of the same operator using the same bidding strategy across the entirety of the analyzed time frame. The analysis was conducted both on an annual basis and seasonal basis, allowing for conclusions to be drawn regarding the tool's effectiveness in different time frames. The annual analysis results allowed to affirm that for a system scenario deemed as typical, the tool was able to slightly improve (0.6%) the profitability of the BESS operator, when compared to the best-case scenario for an operator that relied on a static bidding strategy for the whole year. The profit margins for the tool

when compared to a more conservative or a more aggressive strategy are much more significant (19.2% and 35.5% for the conservative and aggressive strategies, respectively). To test the robustness of the tool, six extreme system scenarios were used as test cases for the application of the tool. For these cases, the tool's usage was proven effective except for the scenarios where the RES generation of the system was decreased.

The results of the seasonal analysis allow concluding that for a typical system year, the application of the tool improved the profitability of a BESS operator for the spring and autumn seasons. For these seasons, the tool was capable of generating at least 6.6% more revenue than if the BESS operator adopted a moderate bidding approach for the whole season. When considering all the test cases for the atypical scenarios, the tool also showed consistency in improving the profitability of the battery's operator in relation to the benchmark profit (sole use of the moderate strategy).

For the summer season, which for this study case was the season where the daily variations most impacted the rank of the best bidding strategy, the tool was shown to be ineffective. For this season, the profitability of the tool was 17% lower than the benchmark profit. When considering the rest of the test cases, the tool was only effective for this season when the system's netload suffered a decrease, which can be attributed to the reduction in the profitability of the moderate strategy and not to the improvement of the tool's prediction capabilities. This can be clearly seen in the solar PV variation scenarios, where the tool commits the same number of prediction errors but its profitability shows both a large increase and a large decrease when compared with the profit of the static bidding approach. This allows concluding that the tool was ill-prepared to deal with a higher degree of variations in the rank of most profitable strategy for days within the same season.

For the winter season, the results implied that the moderate strategy was the optimal strategy for every day of this season (except for the test scenario with an increase in the system's load). The results of the application of the tool led to an almost perfect assertiveness in the prediction of the most profitable strategy for the following day, when considering the majority of the test cases. This implies that the tool is capable of accurately correlating the seasonal characteristics of its input parameters with its expected outputs when there are few variations of the most profitable bidding strategy ranking for days belonging to the same season.

The sensitivity analysis conducted revealed that the system's load had the greatest impact on both the tool's assertiveness and profitability, followed by solar PV and wind production. This implies that for a BESS operator relying on the proposed tool, the most crucial parameter is the accurate forecast of the system's demand. Therefore, investing in improving data gathering capabilities to enhance the reliability of demand forecasts should be prioritized to overall improve the tool's effectiveness in supporting the decision-making process for the BESS operator.

An important conclusion reached during the development of this dissertation is that, according to the results obtained, the forecast of the system's demand and RES generation are suitable explanatory variables for a predictive model aiming to predict the optimal operating behaviour of a BESS for the following day. This can be applied to future developments in this area regardless of the specifications of the prediction model. However, the most important contribution of this dissertation is the development of a predictive model capable of correlating system data (available to a BESS operator) to the most profitable strategy for the following day. Despite the occurrence of some prediction errors associated with its application, which are to be expected due to its nature, this tool is able to increase the profitability of a BESS's participation in the DAM compared to one that disregards the decision-making associated with the bidding process.

Overall, the tool demonstrates that it is capable of supporting and improving the decision-making of the BESS operator regarding its bidding process. This serves as the proof of concept for the methodology used in the development of the presented tool, which can be adapted to be applied to similar systems, considering different bidding strategies and a growing number of them. By relying on the tool, a private BESS operator can increase its profitability (in some cases by a significant margin) when performing energy arbitrage in the DAM. In the near future, assuming a continuous decline in battery costs, this will prove to be a significant advantage over other competitors that do not use decision-making support models such as the one developed in this dissertation.

6.2 Future Work

While realizing the work developed for this dissertation, and after acquiring their results, some topics seemed relevant to be considered during future research. These include:

- Consideration of the use of other available data to use as inputs of the predictive model for the optimal bidding strategy parameters, as well as considering an increased number of bidding strategies;
- Development of a tool that, despite using the same type of approach as the one developed in this dissertation could be used to adjust the specific bids submitted. This could be done by using targets other than the decision variables for the BESS operation;
- The consideration of the participation of the BESS in other markets. This should involve the development of more complex bidding strategies;
- Reformulation of the objective function to include multiple criteria, such as the life cycle of the BESS. This would add a layer of complexity to the problem, as the high profitability of a certain strategy may not justify its use when considering its effect on battery degradation.

- The reformulation of the strategy classifier component of the tool to be able to consider different cases. Future work could explore alternative approaches, such as using another neural network to correlate the outputs of the initial ANN with the most suitable strategy for the BESS operator

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