

Faculdade de Engenharia da Universidade do Porto



**Optimization of an electricity-thermal system
participating in multi-energy markets**

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Abstract

There is a pressing need to decarbonize energy systems to combat climate change and align with the objectives of the European Union. This goal largely involves the integration of renewable energy sources. However, renewable production is inherently intermittent, which poses significant challenges to the stability and reliability of energy systems. At the same time, it is essential to increase the resilience of these systems in response to such variability.

Energy storage technologies emerge as a promising solution to address these challenges, with electric and thermal batteries standing out among the available options.

The main objective of this work is to develop an energy optimization methodology for an electric-thermal system, with thermal energy storage at its core, considering its participation in multi-energy markets. Three distinct methodologies are developed, differing primarily in how they handle uncertainty associated with certain inputs, such as load profiles or external weather conditions.

The proposed methodologies are evaluated from both economic and operational perspectives using the same case study. In addition to comparing the performance of the different approaches, the impact of participating in the reserve market and the contribution of the thermal battery to the overall system performance are also assessed.

Keywords: energy optimization, electric-thermal system, multi-energy markets, thermal energy storage, renewable energy sources.

Resumo

Há uma necessidade urgente de descarbonizar os sistemas energéticos, de forma a combater as alterações climáticas e alinhar com os objetivos da União Europeia. Este objetivo passa, em grande medida, pela integração de fontes de energia renovável. No entanto, a produção renovável é, por natureza, intermitente, o que levanta desafios significativos para a estabilidade e fiabilidade do sistema energético. Paralelamente, torna-se fundamental aumentar a resiliência dos sistemas energéticos face a essa variabilidade.

As tecnologias de armazenamento de energia surgem como uma solução promissora para enfrentar estes desafios, destacando-se, entre elas, as baterias elétricas e as baterias térmicas.

Neste contexto, o principal objetivo deste trabalho é desenvolver uma metodologia de otimização energética para um sistema eletrotérmico, considerando a sua participação em mercados de energia. No âmbito deste trabalho, são desenvolvidas três metodologias distintas, cuja principal diferença reside na forma como lidam com a incerteza associada a determinados dados, como, por exemplo, perfis de carga ou condições climáticas exteriores.

As metodologias propostas são avaliadas do ponto de vista económico e operacional, utilizando o mesmo caso de estudo. Para além da comparação do desempenho entre metodologias, é também analisado o impacto da participação do sistema no mercado de reservas, bem como o contributo da bateria térmica para a performance global do sistema.

Palavras-chave: otimização energética, sistema eletrotérmico, mercados de energia, baterias térmicas, fontes de energia renovável.

UN Sustainable Development Goals

This dissertation can contribute to the UN Sustainable Development Goals in the following manners:

SDG	Target	Contribution	Performance Indicators and Metrics
7	7.1	Promotes the integration of renewable energy sources into electricity-thermal systems	Increase in renewable energy penetration in the energy supply
	7.2	Enhances energy efficiency and reduces energy costs	Cost savings achieved through optimization
12	12.1	Encourages efficient resource utilization in multi-energy systems	Reduction in peak energy demand. Reduction in waste heat in thermal systems
13	13.1	Reduces greenhouse gas emissions by optimizing energy use and incorporating renewables	Reduction in greenhouse gas emissions. Percentage of energy derived from renewable sources

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List of Acronyms

AGC	Automatic Generation Control
AFRR	Automatic Frequency Restoration Reserve
CHP	Combined Heat and Power
DA	Day-ahead
DB	Demand Bidding
DER	Distributed Energy Resources
DLC	Direct Load Control
DMER	Distributed Multi-energy Resources
DR	Demand Response
EDR	Emergency Demand Reduction
ESS	Energy Storage System
EU	European Union
EV	Electric Vehicle
FCR	Frequency Containment Reserve
HP	Heat Pump
IC	Interruptible/Curtailment service
MES	Multi-energy System
MFRR	Manual Frequency Restoration Reserve
MIBEL	Iberian Electricity Market
MIBGAS	Iberian Gas Market
NEMO	Nominated Electricity Market Operator
OMIE	Operator of the Iberian Electricity Market
PCR	Price Coupling of Regions
PV	Photovoltaic
RES	Renewable Energy Source
RR	Replacement Reserve
SIDC	Single Intraday Coupling
SOC	State-of-charge
SVC	Static VAR Compensator
TES	Thermal Energy System
TOU	Time of Use
TSO	Transmission System Operator
VPP	Virtual Power Plant

Chapter 1

Introduction

There is an urgent need to reduce carbon dioxide emissions in order to achieve the global objective of limiting the increase in average temperature to below 2°C. In this context, the European Union (EU) has set a target to reduce emissions by 55% by 2030 [1]. A central approach to achieving this goal is the decarbonization of both electrical and thermal energy systems. This involves replacing fossil fuel-based sources with renewable energy and promoting the use of high-efficiency technologies, such as electric heat pumps (HPs) and combined heat and power (CHP) systems.

However, these types of renewable energy sources (RES) are characterized by intermittency in their production. Therefore, to ensure a stable and reliable energy supply, it is essential to integrate storage technologies, such as batteries and thermal energy storage (TES), to enhance the flexibility and resilience of the overall energy system.

In this context, energy aggregators can play a vital role. By leveraging and coordinating Distributed Multi-Energy Resources (DMER), aggregators can contribute to system flexibility, participate in multi-energy markets, and help stabilize the power grid. This dissertation proposes an optimization framework for the operation of an electric-thermal system within multi-energy markets. The goal is to provide energy aggregators with a decision-support tool to efficiently manage their resources and interact with energy markets. More specifically, the objectives of this work are the development of optimization models for both electrical and thermal resources, the development of optimization algorithms for participation in electricity and natural gas markets and testing and validation of the developed algorithms through case study simulations.

Ultimately, this work aims not only to provide energy aggregators with an optimization tool that enables economic benefits but also to contribute to the development of a resilient and integrated energy system aligned with the EU's emission reduction goals. By doing so, the system will be better equipped to respond to fluctuations in energy supply and demand.

The remainder of this dissertation is structured as follows:

Chapter 2 presents a state-of-the-art review, focusing on the structure and operation of electricity markets (including day-ahead, intraday, and ancillary services), natural gas markets, energy aggregators, and multi-energy systems (MES).

Chapter 3 describes the methodologies developed to optimize electric-thermal systems under different approaches to uncertainty. It details the optimization models created for electrical and thermal resources, as well as the algorithm design for market participation.

Chapter 4 presents the case study used for validation. It includes descriptions of the six case studies, the network and DMER data, market data, as well as building, weather, and inflexible load data.

Chapter 5 discusses and compares the outcomes of the various case studies. For each case, an analysis of the submitted bids and the resulting economic performance is provided.

Chapter 6 concludes the dissertation by summarizing the main findings and discussing their implications for future work and energy system planning.

Chapter 2

Context and State of the Art

2.1 - Introduction

This section presents a review of the state of the art, focusing on topics relevant to the objectives of this work. The review begins with an overview of the electricity market, which is divided into several key components, such as the market timeline and structure. Within the context of the electricity market, aspects such as bid types, the EUPHEMIA algorithm, ancillary services, and the dispatch timeline are also examined. The second major topic covered is energy aggregators, with particular emphasis on demand response programs and real-world aggregator implementations. A literature review is also conducted on commonly used optimization frameworks employed by aggregators. The final section of this chapter reviews multi-energy systems, highlighting their advantages as well as the challenges associated with their implementation.

2.2 - Electricity market

The electricity market in Portugal, known as Iberian Electricity Market (MIBEL), includes both Portuguese and Spanish control areas and is divided into future markets, bilateral contracts, the day-ahead (DA) and intraday markets, and ancillary services.

As exemplified in Figure 2.1, the electricity market organization involves multiple stakeholders and processes to manage the flow of power and ensure system reliability. Generators supply electricity to the market, either through bilateral physical contracts or via the market operator pool, which coordinates supply and demand. The Transmission System Operator (TSO) oversees the grid operation, managing congestion and ensuring power delivery through generator dispatch, ancillary services, and real-time communication with transmission networks. Power and congestion data are exchanged between the TSO and the market pool, influencing operational

and market decisions. Retailers and eligible consumers purchase electricity, while network constraints are constantly monitored to maintain stability and efficiency across the system.

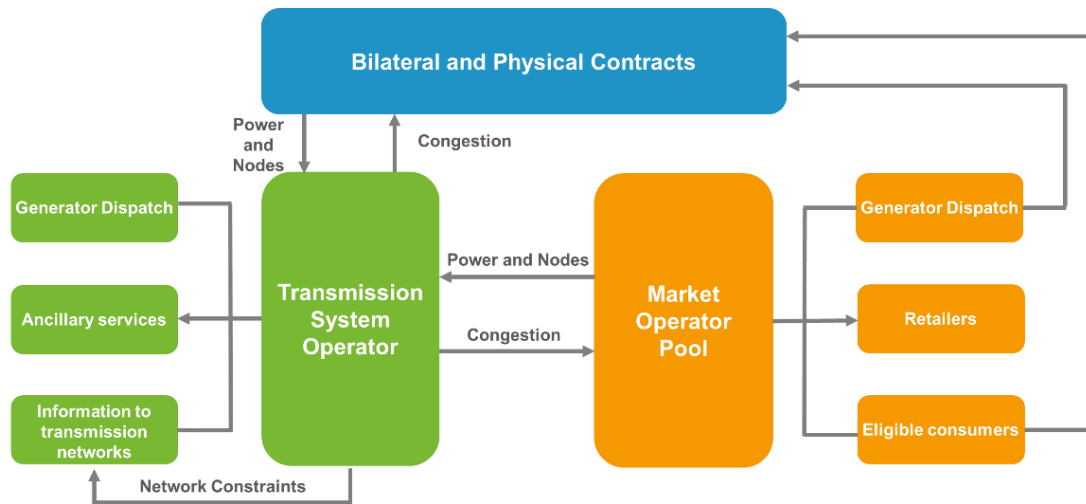


Figure 2.1. Structure of electricity markets. Adapted from [1].

Regarding the temporal organization of the energy market, it can be divided into four distinct time periods: well before Day D, Day D-1, Day D, and the Days after, as shown in Figure 2.2.

The first period occurs well before the delivery day, often referred to as D Day. During this phase, the focus is on planning and decision-making for future market activities. Transactions and agreements take place through future markets and bilateral contracts. These arrangements allow market participants to secure energy prices and quantities well in advance. This is primarily done for risk management and financial planning, helping participants avoid exposure to potential fluctuations in energy prices [2].

The second period is the DA market, which happens one day before the energy delivery. The DA market session opens at 12:00 p.m. and operates on a marginal pricing model. In this session, market participants submit their buy and sell offers for the 24-hour period of the following day. The intersection of supply and demand curves determines the quantity of energy traded and its hourly price, calculated using the EUPHEMIA algorithm [3].

In addition to energy trading, this phase includes ancillary services, which help maintain grid stability. These services range from frequency control and congestion management to voltage control and black start services.

On the day of energy delivery (Day D), the intraday energy market takes place. This market is divided into intraday capacity auctions and continuous trading sessions. These enable participants to adjust their positions to address any energy imbalances that may arise.

Finally, in the days following energy delivery, the market enters the settlement phase. During this phase, any deviations from scheduled energy transactions are calculated and compensated.

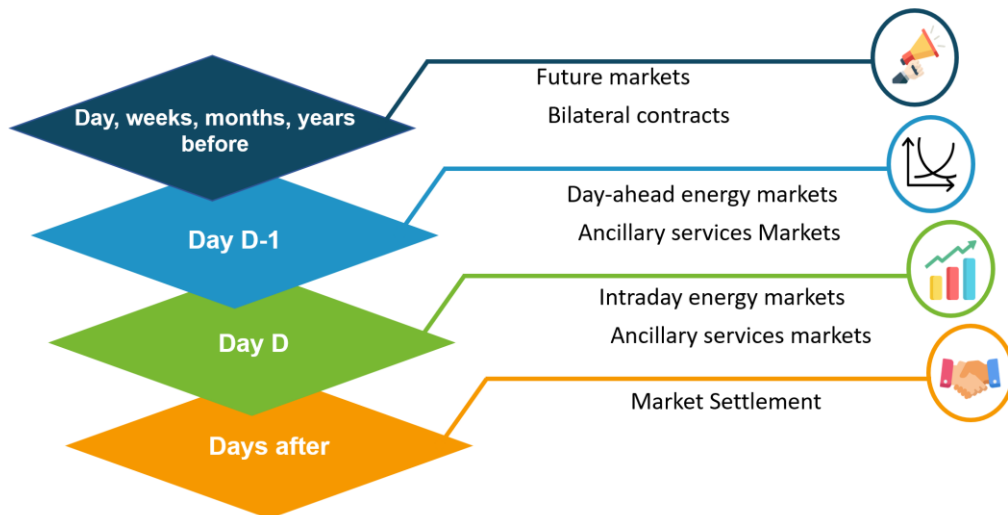


Figure 2.2. Electricity market timeline. Adapted from [3]

2.3 - Day-ahead market

The agents participating in the DA market present their offers through the Operator of the Iberian Electricity Market (OMIE), the sole Nominated Electricity Market Operator (NEMO) in the Iberian Peninsula.

MIBEL's DA market session happens at 12:00 p.m. every day of the year, follows a marginal pricing model, where market participants submit buy and sell offers for each of the 24 hours of the following day. Purchase and sale offers are made between 1 to 25 segments, each with the quantity and price of the offer [4].

Electricity producers make offers, which are then organized in ascending order. Retailers' bids are sorted in descending order according to purchase price. The quantity of transacted energy and the hourly price are determined by the intersection of supply and demand using the EUPHEMIA algorithm [5]. Figure 2.3 shows a typical graphical representation of the intersection of supply and demand curves.

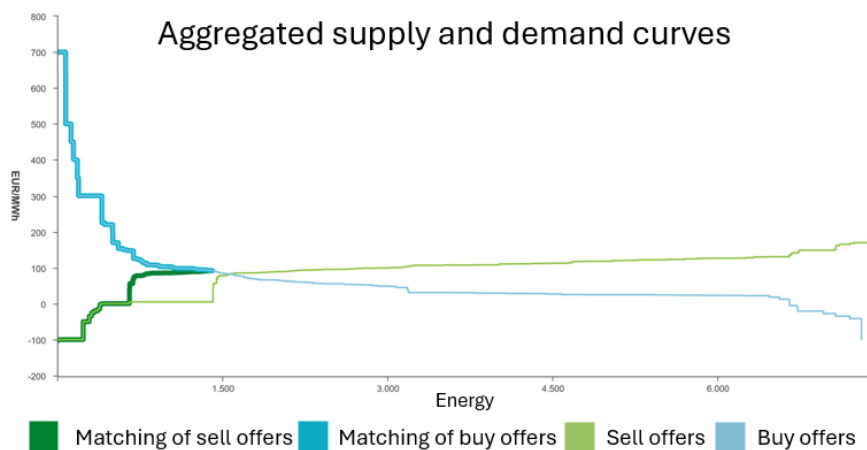


Figure 2.3. Graphical representation of the intersection of supply and demand curves. From [6]

Once the market clears, the TSO incorporates bilateral contracts into the cleared offers and performs a congestion management analysis [6], calculating feasible energy schedules following the guidelines established in UE Regulation 2015/1222 [7].

Congestion management can be of several types: intra-area, inter-area, and outer-area. Intra-area congestion management is done using market mechanisms whenever possible. Only after using these methods should other methods such as redispatch and curtailment of generation be used [8]. Inter-area congestion management is carried out through transmission capacity auctions or market splitting [9]. Outer-area control, in the case of the Iberian market, is managed through agreements with France and Morocco.

An inter-area congestion occurs in MIBEL due to a lack of transmission capacity in the connection between Portugal and Spain. Resolving this issue through market splitting creates two different price zones and generally leads to a price increase in the direction of the power flows.

In [10], an example of this situation in the Spain-to-Portugal direction is shown. With congestion, the power exported to Portugal is adjusted to the connection capacity, which results in a decrease in the Spanish price zone, signalling a reduction in generation and an increase in demand. In Portugal, however, there is a need for more generation and less demand, so higher bids are accepted, leading to an increase in the Portuguese zonal price.

2.3.1 - Bid type:

The bids that agents submit to the market can be of two types: simple or complex bids. Simple bids are those in which the agent specifies the quantity and price of the energy they intend to sell. On the other hand, offers incorporating complex sales conditions are those which, while meeting the requirements for simple offers, also incorporate the following technical or economic conditions [4], [11]:

- Load gradient: sets the maximum allowable difference between the energy produced in one hour and the energy produced in the following hour by a production unit. This limit ensures that the maximum energy offered in each hour is adjusted in relation to the previous and next hour, preventing abrupt changes in production units that technically cannot handle large fluctuations.
- Condition of minimum income: ensures that, while the production unit can make offers for every hour of the day, it will only be included in the daily pairing result if its total production meets a minimum yield threshold. This threshold must exceed a fixed amount in euros, along with a variable remuneration calculated in euros per each MWh paired.
- Condition of scheduled stop: allows that, if a production unit is excluded for not meeting the required minimum yield, a shutdown can be scheduled within a maximum of three hours. This prevents the unit from having to halt completely between the end of one day and the start of the next. Consequently, for the first three hours of the following day, the

unit's offers may be treated as simple offers, provided that the energy offered decreases progressively from one hour to the next.

2.3.2 - EUPHEMIA algorithm

The EUPHEMIA algorithm is a matching algorithm developed to optimize the coupling of DA electricity markets on the Price Coupling of Regions (PCR) perimeter. This algorithm determines the optimal allocation of electricity supply and demand across different interconnected regions while maximizing economic welfare. EUPHEMIA's primary goal is to enhance economic surplus comprising consumer surplus, producer surplus, and congestion rent, while respecting network limitations and maintaining stability in power flows across regions [3].

In this context welfare is defined as the sum of gains derived from purchase bids, sale bids, and any congestion charges that arise from transmission limitations between zones. For purchase bids, gain is defined as the difference between the bid price and the marginal price set by the market. For sale bids, gain is calculated as the difference between the market's marginal price and the sale bid price.

This algorithm accommodates two primary types of aggregate bidding curves [12]:

- Stepwise Aggregate Curves: That reflect situations where the starting price for the acceptance of a block of energy and the full acceptance price of that block coincide. Here, bid acceptance changes in discrete steps.
- Interpolated Aggregate Curves: These curves are more complex, with acceptance prices for a block of energy that change gradually over at least one minimum step between bid prices.

After matching bids, the algorithm allocates matched and unmatched energy blocks based on production zone bids while respecting transmission capacity limits. The algorithm ensures power flows do not exceed network capacity, using congestion rent as a regulatory mechanism.

2.3.3 - Ancillary services

Ancillary services ensure the proper functioning of the electrical system and include the automatic activation of frequency reserves (Frequency Containment Reserve (FCR) and automatic Frequency Restoration Reserve (aFRR), manual activation of reserves (manual Frequency Restoration Reserve (mFRR) and Replacement Reserve (RR)), voltage control, congestion management, and black start services [13]. The TSO is responsible for procuring and managing frequency reserves in their respective markets. Figure 2.4 shows the ancillary services market clearing timeline.

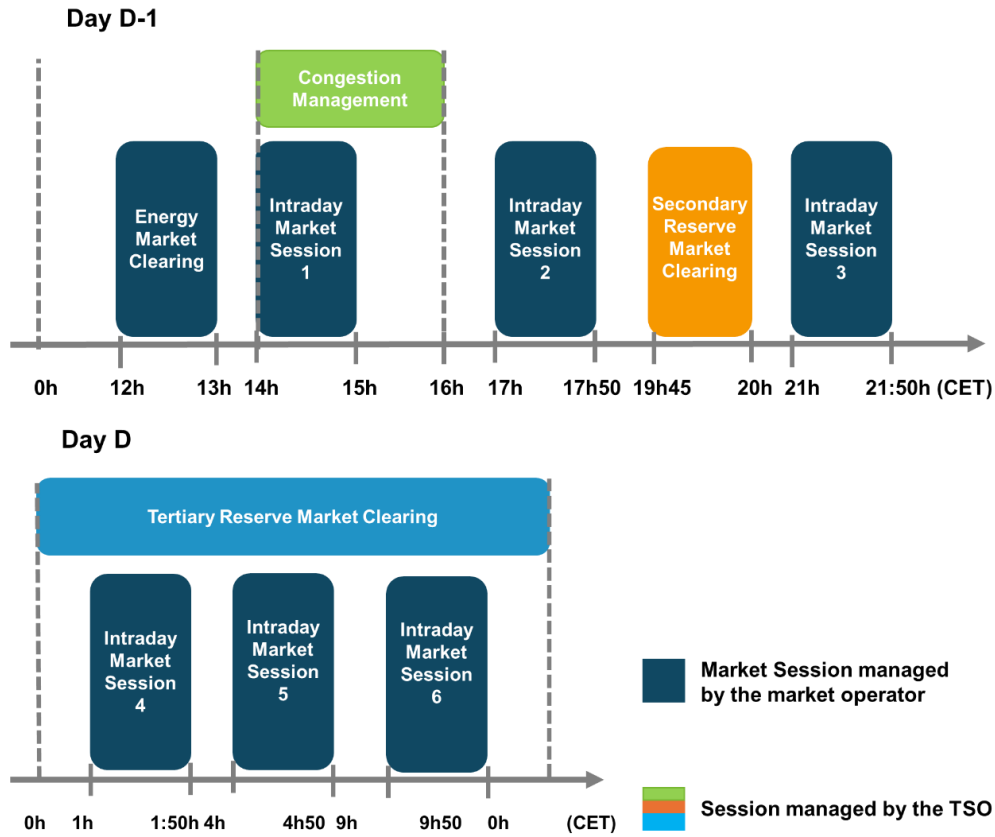


Figure 2.4. Ancillary services market clearing timeline. Adapted from [5], [15].

The frequency services help maintain the frequency levels within the stipulated limits mainly using generators and loads that have a flexible regime. These services can be split into primary services, secondary services and tertiary services, and are activated at different times as shown in Figure 2.5.

The primary reserve, or FCR, is automatically activated to correct frequency deviations, it does so by automatically adjusting the active power of loads and generators to restore load and supply balance [13]. It must respond within 15 seconds for disturbances below 100mHz, and between 15 and 30 seconds for disturbances up to 200mHz, with a linear response [14]. This reserve is mandatory and not remunerated [15].

The secondary reserve, or aFRR, consists of loads and generators that, through automatic generation control (AGC) increase or decrease generation and consumption within a very short time frame to restore frequency to its nominal value and maintain exchanges between neighbouring control areas.

The secondary reserve is remunerated by two factors: availability of capacity and usage. In Portugal, the secondary reserve is divided into 1/2 downward and 1/2 upward capacity [14]. Market agents that can participate in this service submit capacity offers, that must comply with the previous rule. The offers are made in power (MW) and are remunerated at the marginal price

(€/MW). The TSO is responsible for acquiring the secondary reserve and managing market clearing[5].

The tertiary reserve, or mFRR, is manually activated and replaces the secondary reserve. Loads and generators in this reserve must be capable of adjusting their output within 15 minutes. The need for this reserve is due to imbalances that can occur between generation and consumption, that deplete primary and secondary regulation reserves [16]. Therefore, the purpose of this reserve is to restore primary and secondary regulation reserve levels. It must be activated within a maximum of 15 minutes and sustained for at least two consecutive hours. Tertiary reserve bids are submitted in terms of power (MW) and compensated in €/MWh, with dispatch organized according to economic merit order [2], [11].

Voltage control is essential for maintaining voltage levels within specified ranges across the power system. This control is achieved through the injection or absorption of reactive power, utilizing both dynamic sources, such as generators and synchronous compensators, and static sources, such as static VAR compensators (SVCs) [14].

The voltage control service consists of two components: a voluntary component, for which service providers receive compensation according to specific regulations, and a mandatory, unpaid component, which all participating agents are required to provide [15].

Black start services are related to a generator's ability to start operating without the need for support from the power grid or any other energy source and having enough active and reactive power, along with the ability to control it effectively, to contribute to powering parts of the transmission network and initiating additional generators [17].

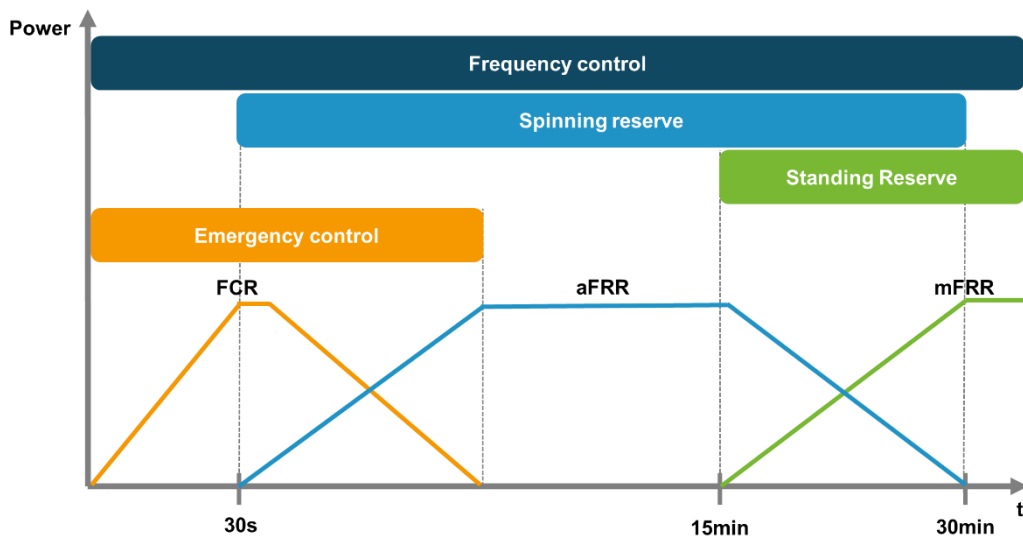


Figure 2.5. Primary, secondary and tertiary reserve activation timeline. Adapted from [14].

2.4 - Intraday market

The intraday market consists of intraday capacity auctions and continuous auctions, which aim to satisfy the demand and supply of energy arising after the DA market results.

The European intraday auction market currently operates in six sessions with different scheduling horizons, shown in Figure 2.6.

Like the DA market, the intraday auctions follow the marginal pricing model, and the hourly energy volume and price are set by the intersection of supply and demand [15].

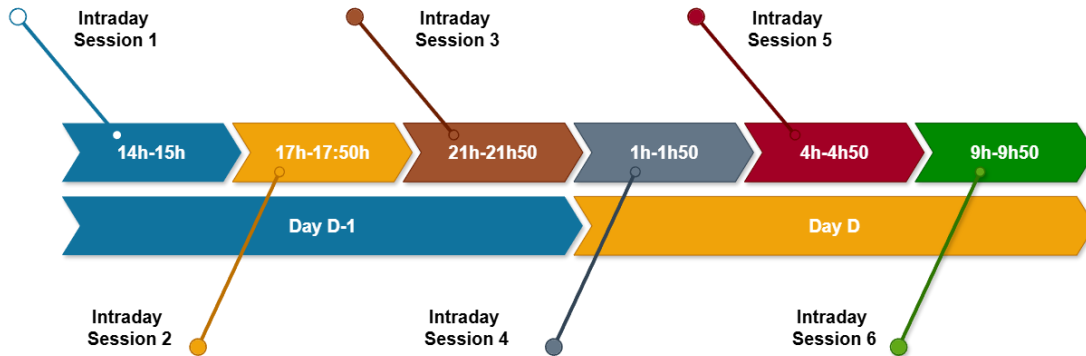


Figure 2.6. Intraday market timeline.

The continuous intraday market, also known as Single Intraday Coupling (SIDC) in the European context, allows trading between agents located in the same price zone or in different zones, if cross-zonal capacity is available. In this market, transactions can occur up to one hour before the energy delivery time. After that, other markets managed by the System Operator take over, ensuring continuous balance between production and consumption [18].

Like the intraday auction market, the continuous intraday market provides participants with the opportunity to adjust their energy imbalances. However, there are two key differences compared to the auction market:

- Agents, in addition to accessing local liquidity, can also benefit from liquidity available in other areas of Europe, if there is cross-border transmission capacity between zones.
- Adjustments can be made up to one hour before the energy delivery time.

The continuous intraday market is managed by the designated market operators. This market operates in accordance with Regulation (EU) 2015/1222, which aims to create a continuous and cross-border intraday market in Europe. The goal of SIDC is to facilitate the trade of energy between different European zones continuously, enhancing the overall efficiency of transactions in intraday markets across Europe [18].

2.5 - Natural gas market

In Portugal, the natural gas market is integrated with Spain, forming the Iberian Gas Market (MIBGAS). Trading in the natural gas market is organized into trading sessions, which are divided into two main types.

Firstly, there is the Daily Trading Session, where products such as Daily, Weekend, Rest of the Month, and Next Month are traded. Secondly, there is the Intraday Trading Session, where the Intraday product is traded.

Within a single trading session, two different trading methods may be available. In auction-based trading, participants submit buy and sell offers for a specific product. When the auction closes, MIBGAS compiles all received bids and offers to construct demand and supply curves for the product. The intersection point of these curves determines the auction's marginal price, which is then applied to all transactions completed in that session [15].

Alternatively, in continuous trading, offers are processed in real-time as they are submitted to the trading platform. If a new offer is competitive with existing opposing offers, it takes precedence, and the transaction is finalized. If not, the original offer remains valid on the platform [19] .

2.6 - Aggregators

An aggregator is a service provider that manages a group of customers, such as prosumers (individuals who both consume and produce energy) enabling them to buy and sell energy (thus taking on the roles of both retailer and generator) and reserve services in the electricity market [5]. The aggregator may also expand its operations into other markets, such as the natural gas market. In the electricity market, it can choose to participate solely in the energy market or in both the energy and reserve markets. The role of the aggregator emerges because small prosumers cannot directly participate in the markets, as the minimum bid is 1 MW [20] . Thus, the aggregator facilitates their entry. This role is represented in Figure 2.7.

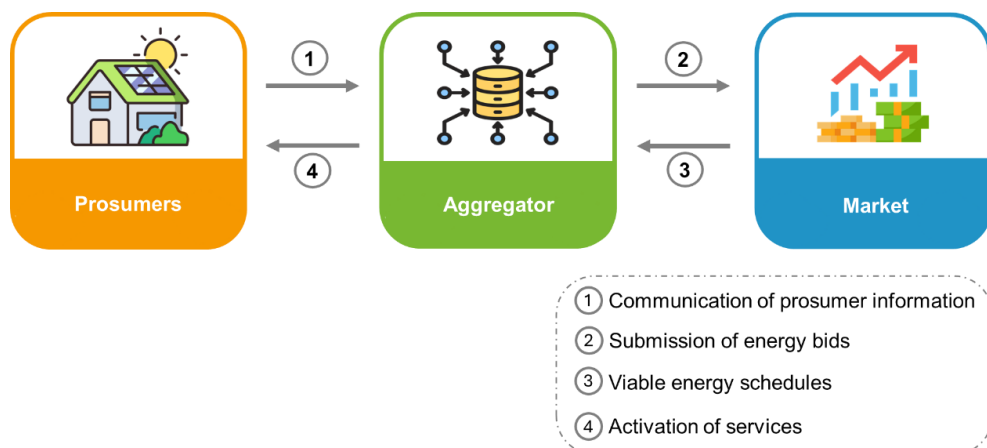


Figure 2.7. Aggregator's role in the energy market.

The aggregator leverages the flexibility of prosumers' resources to generate profit in the energy and ancillary services markets. Typically, due to its smaller size relative to the market, a multi-energy aggregator lacks the capacity to influence market prices, so it accepts prevailing market prices, participating as a price taker. Therefore, it submits offers in the DA market without a price, as well as in the ancillary services market [5]. During the day, the aggregator sets the operation of the flexible resources, based on DA market commitments and set points communicated by the TSO to deploy secondary/tertiary reserves. Figure 2.8 represents the tasks of the aggregator associated with its participation in the market.

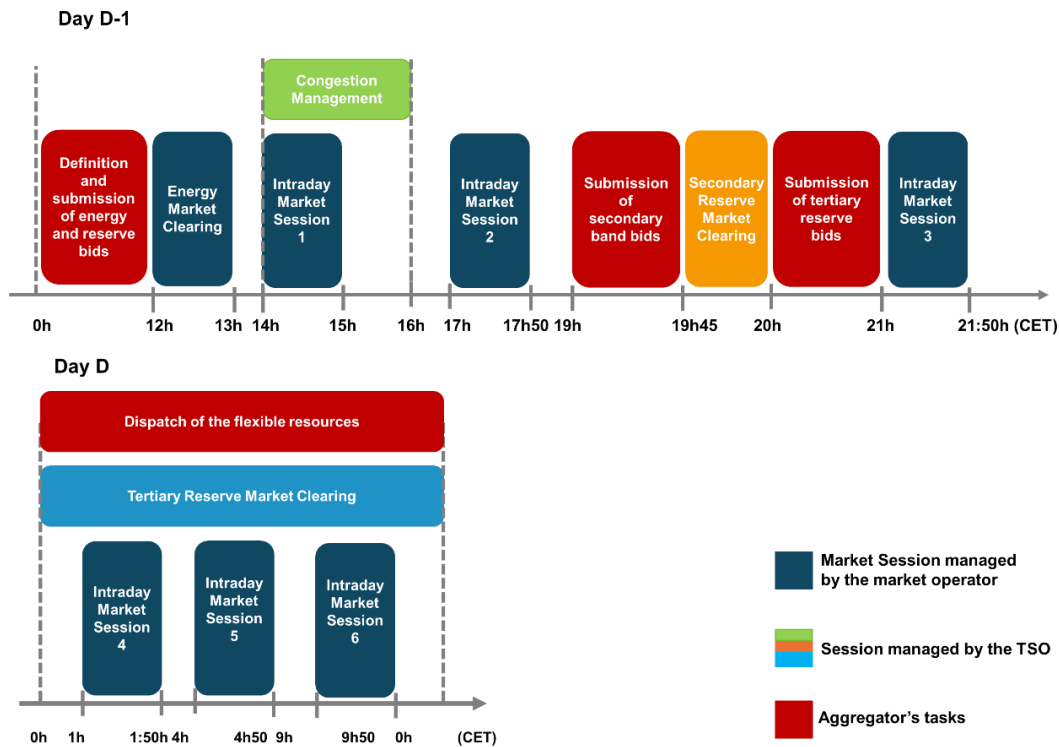


Figure 2.8. Aggregator's tasks in the market timeline. Adapted from [5], [15].

2.6.1 - Demand response programs

Demand response (DR) programs are designed to influence electricity consumption patterns to benefit both consumers and the broader energy system. These programs can be classified into two main categories: incentive-based DR and price-based DR.

In incentive-based DR programs, consumers are rewarded for adjusting their consumption according to the supply side's needs. Examples of incentive-based DR programs include Direct Load Control (DLC), Interruptible/Curtailable Service (IC), Demand Bidding (DB), and Emergency Demand Reduction (EDR).

In contrast, price-based DR programs, such as Time of Use (TOU), Real-Time Pricing, Critical Peak Pricing, and Capacity Market Programs, charge consumers different rates based on the time of their consumption [21].

Both incentive-based and price-based DR programs utilize price signals and incentive schemes to encourage shifts in electricity consumption, especially during periods of high market prices or when the grid faces reliability issues. These programs have the objective to reduce electricity demand during periods of high demand, which benefits both the consumers and the energy system[13].

Consumer inconvenience plays a critical role in DR programs, as it can directly impact consumer comfort and willingness to participate. As the magnitude of load increases, the inconvenience to consumers rises, which can reduce their participation in DR programs [22] .

2.6.2 - Real world aggregators

Several companies already aggregate multi-energy sources, managing a diverse range of clients and assets, including small producers, prosumers, and individual DMERs. These companies provide flexibility and offer valuable services both to the energy market and their clients. Based in Germany, Next Kraftwerke is a prominent European aggregator that operates one of the largest Virtual Power Plants (VPPs), actively participating in energy markets by aggregating decentralized assets like renewables, storage systems, and industrial demand response. It provides balancing and ancillary services, stabilizing the grid while trading energy and generating revenue [23].

Similarly, Enel X, connects a variety of resources, including industrial loads, batteries, and electric vehicles (EVs), to offer flexibility and participate in wholesale and capacity markets [24]. Tesla's VPP, operational in markets like California and Australia, aggregates solar panels, home batteries, and EVs into a flexible energy network that provides frequency regulation, and surplus energy sales back to the grid, actively earning revenue through market auctions [25]. GreenCom Networks integrates residential solar systems, batteries, EVs, and smart devices into a MES, participating in energy markets by delivering grid services like load balancing and flexibility optimization [26]. Kiwi Power, based in the UK, connects distributed resources such as commercial and industrial demand response, energy storage, and renewable generation, actively bidding into ancillary markets and providing critical grid services [27].

2.6.3 - Optimization tools for multi-energy aggregators

2.6.3.1 - Optimization frameworks

In this work, the optimization frameworks used will include deterministic, stochastic, and robust optimization. Although these three approaches share similar structures and objectives, there are significant differences between them.

The main difference between the deterministic and stochastic methodologies lies in how they deal with uncertainties. Deterministic models assume fixed values for input parameters, treating all variables as known and unchanging. In contrast, stochastic models explicitly account for

uncertainties by incorporating probability distributions or scenarios to represent variability in key parameters. The stochastic approach provides a more realistic representation of the unpredictable nature of critical factors such as photovoltaic (PV) generation, energy consumption, and outdoor temperatures. Unlike deterministic approaches, the stochastic model captures variability and randomness, enabling robust decision-making that accounts for a range of possible outcomes. Moreover, it also enables the evaluation of worst-case scenarios and risk mitigation strategies.

In addition to these methods, robust optimization offers a third approach to handling uncertainty. Rather than relying on probability distributions or numerous scenarios, robust optimization defines uncertainty sets that encapsulate the possible deviations of uncertain parameters within a bounded range. This approach seeks solutions that remain feasible under all realizations within the defined uncertainty set, thereby ensuring performance even in worst-case conditions. Robust models strike a balance between solution conservativeness and practical robustness, allowing decision-makers to guard against data variability without the need for extensive probabilistic information. This makes robust optimization particularly useful in environments where data is limited or where worst-case guarantees are essential.

2.6.3.2 - Literature review

This section reviews the literature on a set of optimization tools used by multi-energy aggregators to manage their resources in energy markets. The focus is on optimization tools designed for the DA market, with particular attention to how these tools handle uncertainty, whether through deterministic, stochastic, or robust optimization approaches.

The literature on this topic is extensive, with numerous studies exploring deterministic [28], [29], [30], [31], stochastic [32],[33],[5],[34] and robust [35], [36], [37] methods for optimizing DMERs and their participation in energy markets.

For example, [28] uses a deterministic approach to optimize the planning and operation of aggregated resources in the electricity market comparing it to a stochastic approach. The deterministic model considers both the average and the most likely scenarios. The methodology is evaluated through case studies under two conditions: one where the aggregated resources are large enough to act as a price-maker, and another where the aggregator behaves as a price-taker.

The work in [29] presents a deterministic optimization model for an aggregator representing a group of prosumers equipped with RES and an energy storage system (ESS). The objective is to minimize the cost of traded energy by submitting bids in both DA and intraday markets. The study includes a year-long case study based on the Iberian electricity market, to compare the deterministic approach with probabilistic strategies.

In another study [30], the authors develop a deterministic optimization model for the DA market that also considers secondary reserve provision and EV charging coordination. The model aims

to optimize market bids by minimizing deviations between DA commitments and actual outcomes. The input data includes forecasts of EV usage, availability, charging requirements, and market prices.

In [31], a deterministic modelling approach is employed to analyse the behaviour of multi-energy aggregators within the MES framework. By utilizing a bilevel optimization structure, the model captures the decision-making interactions between the players and the wholesale electricity market. This approach facilitates the analysis of how aggregators contribute to demand smoothing and price stabilization across local and wholesale markets.

Since uncertainty is a major factor that aggregators must contend with, it is only natural that there is a growing focus on methodologies that explicitly account for it. As such, several works in the literature implement stochastic optimization models to address the various uncertainties present in the optimization process.

The article [34] proposes a stochastic methodology for developing a bidding strategy for distributed energy resources (DER) aggregators, considering demand flexibility. In this work, the aggregator acts as an intermediary between the market and the leveraged DERs, which are organized into local energy systems. The goal is to maximize the aggregator's profit while meeting the multi-energy demands of the buildings.

In [32], a multi-stage stochastic optimization approach is proposed, using scenario-based price realizations to formulate optimal bids across sequential market stages. These include the flexibility reservation market, the DA spot market, and the flexibility adjustment market.

In [33], [5] and [34] the authors propose a two-stage stochastic approach to optimize aggregator participation in various electricity markets. Specifically, [33] focuses on the DA market, whereas [5] and [34] extend the analysis to ancillary services markets, targeting secondary and tertiary reserves, respectively. These models incorporate uncertainties related to the production of DERs managed by the aggregator, electrical demand, and outdoor temperature. The findings demonstrate the effectiveness of the stochastic approach, showing a minimum cost reduction of 40%.

Uncertainty in the optimization process can also be addressed through robust optimization. Several methodologies in the literature are based on this approach.

For instance, the authors of [35] propose an adjustable robust optimization method to determine the robust counterpart of a problem with uncertainties related to PV generation, electricity prices, and load. This approach aims to minimize the costs for residential aggregators in both energy and local flexibility markets. In [36] the same authors propose a similar framework to optimize the aggregation of electrical and thermal resources, including PV, EVs an ESS and, on the thermal side, a TES. Additionally, this work also focuses on modelling battery degradation based on the relationship between the depth of discharge and the total battery life cycles. The robust optimization approach is compared to a simple deterministic method, and the results show that the robust strategy can lead to cost reductions up to 5,7%.

Similarly, [37] presents a robust optimization-based strategy for DA bidding in energy and ancillary markets. This method models uncertainties in prices and DMER production using uncertainty sets generated via a Gaussian process method.

The work in [38] adopts a hybrid approach combining stochastic and robust optimization. Scenarios are used to capture uncertainties in resources and DA market prices, while robust optimization models the deviations between DA bids and actual realizations.

2.7 - Multi-energy systems

A MES is a structure that integrates various energy vectors, such as electricity, gas, heat, and hydrogen, aiming to optimize efficiency and resilience in the energy system. This integration enables coordinated management of generation, storage and consumption, which allows to maximize efficiency, reduce carbon emissions, and enhance energy security by leveraging the complementary characteristics of diverse sources.

The MESs are constituted by DMERs, which include systems such as PVs, HPs, CHPs, ESSs, TESs, and EVs. These distributed resources are characterized by their flexibility, allowing the MES to adjust consumption and generation according to the system's needs.

PVs convert sunlight into electricity, providing a renewable and cost-effective energy source during the day, and any surplus generation can be stored or sold to the market. HPs convert electricity into heat to provide heating or cooling, improving energy efficiency and reducing dependence on fossil fuels. CHPs simultaneously produce electricity and useful heat from a single energy source, maximizing energy efficiency and reducing overall energy waste. ESSs store electricity during periods of low demand or high renewable generation and discharge it during peak demand, enhancing grid stability and reliability. TESs store excess thermal energy in the form of heat or cold, which can be used later for heating or cooling applications, reducing energy costs and optimizing resource use. EVs act as both a mode of transportation and a flexible energy resource, as their batteries can store electricity and return it to the grid during peak demand, contributing to load balancing [39]. The typical structure of a MES with the mentioned DMERs is shown in Figure 2.9.

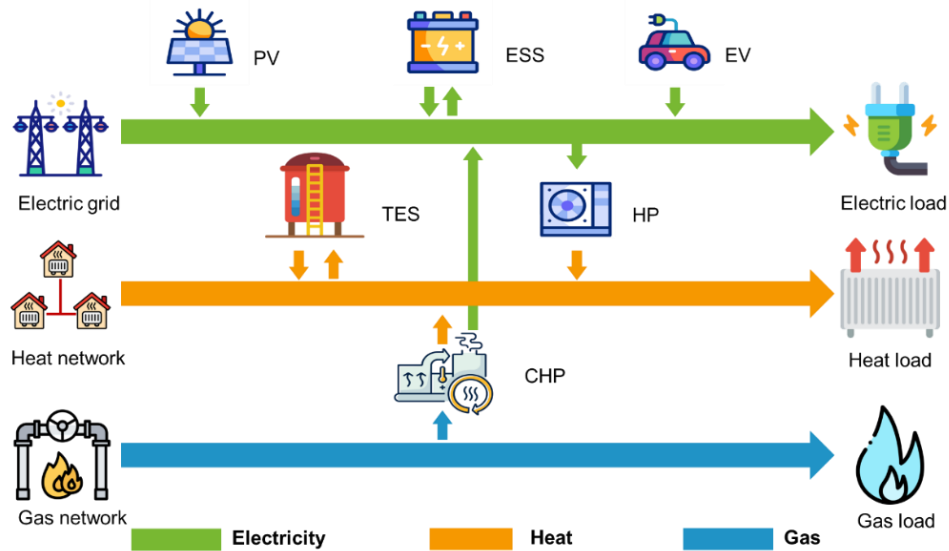


Figure 2.9. Typical MES structure.

2.7.1 - Advantages and challenges in MES

One of the key advantages of MES is their enhanced flexibility, allowing the system to quickly adjust to changes in energy supply or demand. For example, excess renewable energy from wind or solar can be stored and later used for heating or transportation, reducing strain on the electricity grid [40]. Similarly, when there's a high demand for heating or transportation, MES can shift energy resources to balance supply and demand, offering greater efficiency than traditional systems [41].

Additionally, MES improve the reliability and resilience of energy systems. By incorporating diverse energy sources and storage solutions, these systems are less vulnerable to disruptions. For instance, if a power grid experiences an outage, stored energy or renewable sources can continue to power critical services [42].

MES also contribute to decarbonization by integrating RES like wind, solar, reducing reliance on fossil fuels and lowering greenhouse gas emissions, supporting a transition to a low-carbon energy future [41].

However, implementing MES presents challenges, notably the complexity of coordinating multiple energy carriers and technologies. MES integration demands advanced control systems, algorithms, and real-time data analytics, alongside skilled personnel and robust infrastructure [43]. The reliance on real-time data management and communication also necessitates significant investments in data infrastructure and cybersecurity to ensure effective operation [43]. Also, regulatory barriers, fragmented energy market structures and inconsistent policies further impede MES adoption.

2.8 - Conclusions

The state-of-the-art review carried out in this chapter has made a significant contribution by providing knowledge that will serve as a foundation for the development of this dissertation. The initial study of energy markets, focusing on their structure and respective timeline, enabled the transition to a literature review on energy aggregators, emphasizing the aspects most relevant to this work. In this regard, the review helped to understand how energy aggregators interact with various market agents and mechanisms, both in terms of participation timeline and the actual delivery of their energy. This section was complemented by the study of some optimization methods commonly used by aggregators, which will be explored throughout the dissertation. Finally, the section on MES systems helped to identify not only their advantages but also some of the challenges that will need to be addressed during the development of this work.

Through the conducted literature review, some gaps in the existing literature were identified, which this work aims to address. There is a lack of studies exploring TES as a DMER integrated into a MES, both as an active participant in the energy market and as a resource that enables the participation of other resources. For instance, CHP systems, that can easily adjust their production, can benefit from the added flexibility provided by TES, enabling them to participate more effectively in the energy and reserve markets. Furthermore, the integration of TES within MES architecture can contribute to improve the overall system resilience and optimize energy flows. Despite these advantages, modelling approaches and real-world validation of these systems remains scarce in the literature, which justifies the need for further research in this area.

Chapter 3

Methodology

This chapter presents the deterministic, stochastic and robust methodologies developed and their mathematical formulations for an industrial hub that needs to meet thermal requirements. These methodologies optimize the DA operation of the industrial hub considering the buying and selling of electricity, the buying of natural gas, and the selling of secondary reserves.

The formulations developed in this section will be implemented using the Python programming language, employing the Pyomo library to define the optimization model, including the objective function and constraints. The case study data, listed in Chapter 4, serves as input to the code via an Excel file.

The mathematical formulations incorporate detailed operational constraints and relationships for each of these components. This includes equations governing energy generation, consumption, storage, and exchange across the system. The system includes a PV, HPs to satisfy the thermal needs of office buildings, an ESS, a solid-liquid TES, and a CHP, these last two connected to an industrial thermal load. The TES is a latent heat storage system. It operates at a constant temperature, ensuring a stable thermal output. This system can consume or inject electricity from the electricity network. In the next chapter a more in-depth analysis of the system and the case study will be provided.

Next subsections present the formulation developed. It ensures that the system operates efficiently, leveraging RES, the ESS and the TES to meet production targets and market opportunities.

3.1 - Optimization frameworks

This section aims to serve as a starting point for the formulation implemented for the industrial hub, intending to show how the approach evolved from a deterministic model to a stochastic and robust optimization model.

To this end, we begin with a canonical optimization problem to illustrate in a simple way the rationale behind the developed formulation.

The canonical optimization problem can be represented as follows:

$$\min c'x \quad (3.1)$$

Subject to:

$$Ax \leq b \quad (3.2)$$

$$x \geq 0 \quad (3.3)$$

Where x is a variable, A is a matrix such that $A = [a_{ij}]$ and b, c are vectors

In this form, the optimization problem is deterministic, the input parameters have fixed values, and all variables are known and unchanging.

To introduce uncertainty into this canonical optimization problem through a stochastic model, it is necessary to incorporate it into the parameters using probability distributions or scenarios. Since the modelling for the industrial hub considered uncertainty through scenarios, it will also be represented here using scenarios.

In this example, uncertainty is assumed to be present in the cost vector c . A finite set of scenarios $s \in S$ is considered, each with an associated probability of occurrence π_s such that $\sum_s \pi_s = 1$.

The optimization problem is then reformulated as follows:

$$\min \sum_s \pi_s \cdot c_s'x \quad (3.4)$$

Subject to:

$$Ax \leq b \quad (3.5)$$

$$x \geq 0 \quad (3.6)$$

To incorporate uncertainty in the context of robust optimization, uncertainty sets that account for the worst-case scenario are used. In the formulation created for the industrial hub, the uncertainty parameters are related to the right-hand side of the optimization problem. Thus, for the canonical optimization problem, considering that the uncertainty is related to parameter b and that the worst case occurs when b is at its maximum, the problem then takes the following form:

$$\min c'x \quad (3.7)$$

Subject to:

$$\sum_j a_{ij}x_j - \max\{b_i^{\max}\} \leq b_i, \quad \forall i \quad (3.8)$$

$$x_j \geq 0, \quad \forall j \quad (3.9)$$

The dual problem associated with the constraint is the following:

$$\min q_i + \Gamma z_i \quad (3.10)$$

Subject to:

$$q_i + \Gamma \cdot z_i \geq b_i^{max} \gamma_i, \quad \forall i \quad (3.11)$$

$$z_i, q_i \geq 0, \quad \forall i \quad (3.12)$$

$$\gamma_i \geq 1, \quad \forall i \quad (3.13)$$

Where z_i, q_i are dual variables, Γ is a robust control parameter and γ_i is an auxiliary variable.

After substituting the robust counter part of the constraint, the equivalent optimization problem is as follows:

$$\min c'x \quad (3.14)$$

Subject to:

$$\sum_j a_{ij} x_j \leq b_i + q_i + \Gamma z_i, \quad \forall i \quad (3.15)$$

$$q_i + \Gamma * z_i \geq b_i^{max} \gamma_i, \quad \forall i \quad (3.16)$$

$$z_i, q_i \geq 0, \quad \forall i \quad (3.17)$$

$$\gamma_i \geq 1, \quad \forall i \quad (3.18)$$

$$x_j \geq 0, \quad \forall j \quad (3.19)$$

3.2 - Deterministic

This subsection presents the deterministic formulation developed to optimize the participation of the industrial hub in the energy and gas markets.

3.2.1 - Objective function

The objective is to minimize the electricity and natural gas cost in the DA market. The objective function (3.20)-(3.22) is separated into different terms:

- The first term $\lambda_t^E \cdot E_t^{E,DA} \Delta t$ is the net cost of buying and selling energy in the DA energy market.

- The second term $\lambda_t^B (U_t^{E,DA} + D_t^{E,DA})$ is the income from selling upward and downward band in the DA secondary reserve market.
- The third term $(\lambda_t^{D,E} \cdot \phi_t^D \cdot D_t^{E,DA} - \lambda_t^{U,E} \cdot \phi_t^U \cdot U_t^{E,DA}) \Delta t$ is the revenue from activation of upward and downward secondary band.
- The fourth term $\lambda_t^G \cdot E_t^{G,DA} \Delta t$ is the net cost of buying and selling gas in the DA energy market.
- The fifth term $(\lambda_t^{U,G} \cdot \phi_t^U \cdot U_t^G - \lambda_t^{D,G} \cdot \phi_t^D \cdot D_t^G) \Delta t$ represents the gas deviations generated by the activation of secondary reserves.

$$\text{Min} \sum_{t \in T} f_t^E + f_t^G \quad (3.20)$$

$$f_t^E = \lambda_t^E \cdot E_t^{E,DA} - \lambda_t^B (U_t^{E,DA} + D_t^{E,DA}) \Delta t + (\lambda_t^{D,E} \cdot \phi_t^D \cdot D_t^{E,DA} - \lambda_t^{U,E} \cdot \phi_t^U \cdot U_t^{E,DA}) \quad (3.21)$$

$$f_t^G = \lambda_t^G \cdot E_t^{G,DA} + (\lambda_t^{U,G} \cdot \phi_t^U \cdot U_t^G - \lambda_t^{D,G} \cdot \phi_t^D \cdot D_t^G) \quad (3.22)$$

Table 3.1 presents the variables for the objective function.

Table 3.1. Variables for the deterministic objective function

Variable	Description
$E_t^{E,DA}$	DA electricity bids
$U_t^{E,DA}$	DA upward band bids
$D_t^{E,DA}$	DA downward band bids
$E_t^{G,DA}$	DA gas bids
U_t^G	Upward deviations from activation of secondary reserves
D_t^G	Downward deviations from activation of secondary reserves

Table 3.2 presents the objective function parameters.

Table 3.2. Parameters of the deterministic objective function

Parameter	Description
λ_t^E	Electricity price
λ_t^B	Secondary reserve band price
$\lambda_t^{U,E}$	Upward band activation price
$\lambda_t^{D,E}$	Downward band activation price
λ_t^G	Gas price
ϕ_t^U, ϕ_t^D	Upward and downward ratio

3.2.2 - Market constraints

Constraint (3.23) separates the band into upward and downward. Following MIBEL's secondary market rules, the band is split in two between upward and downward band.

$$U_t^{E,DA} = D_t^{E,DA}, \quad \forall t \in T \quad (3.23)$$

3.2.3 - Bidding constraints

Constraint (3.24) defines the electricity balance, aggregating contributions from inelastic loads, HPs, ESS, PV, CHP and TES. Constraint (3.25) defines the gas balance which comes from the consumption of the CHP. Constraints (3.26) and (3.27) define the upward and downward secondary reserve bids, accounting for the flexibility from the ESS, HPs, PVs, CHPs, and TES.

Constraints (3.28) and (3.29) define the impact of the upward and downward reserves band on the natural gas balance.

$$E_t^{E,DA} = \sum_{j \in J} P_{j,t}^{IL,E} + P_{j,t}^{HP} + P_{j,t}^{Sto,+} - P_{j,t}^{Sto,-} - P_{j,t}^{PV} - P_{j,t}^{CHP,E} + P_{j,t}^{TES,E,+}, \quad \forall j \in J, t \in T \quad (3.24)$$

$$E_t^{G,DA} = \sum_{j \in J} P_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.25)$$

$$U_t^E = \sum_{j \in J} U_{j,t}^{Sto,+} + U_{j,t}^{Sto,-} + U_{j,t}^{HP} + U_{j,t}^{PV} + U_{j,t}^{CHP,E} + U_{j,t}^{TES,E,+}, \quad \forall j \in J, t \in T \quad (3.26)$$

$$D_t^E = \sum_{j \in J} D_{j,t}^{Sto,+} + D_{j,t}^{Sto,-} + D_{j,t}^{HP} + D_{j,t}^{PV} + D_{j,t}^{CHP,E} + D_{j,t}^{TES,E,+}, \quad \forall j \in J, t \in T \quad (3.27)$$

$$U_t^G = \sum_{j \in J} U_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.28)$$

$$D_t^G = \sum_{j \in J} D_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.29)$$

Table 3.3 presents the variables for the bidding constraints.

Table 3.3. Variables for bidding constraints

Variable	Description
$P_{j,t}^{IL,E}, P_{j,t}^{HP}, P_{j,t}^{Sto,+}, P_{j,t}^{Sto,-}, P_{j,t}^{PV}, P_{j,t}^{CHP,E}, P_{j,t}^{TES,E,+}, P_{j,t}^{CHP,G}$	Electrical load, power generated by the heat pump, energy storage system charge power, energy storage system discharge power, power generated by PVs, electrical production by the CHP, TES electrical charging power, CHP gas consumption
$U_{j,t}^{CHP,G}, U_{j,t}^{Sto,+}, U_{j,t}^{Sto,-}, U_{j,t}^{HP}, U_{j,t}^{PV}, U_{j,t}^{CHP,E}, U_{j,t}^{TES,E,+}$	Upward CHP, ESS, HP, PV, CHP, TES imbalance caused by the activation of secondary reserves
$D_{j,t}^{CHP,G}, D_{j,t}^{CHP,E}, D_{j,t}^{Sto,+}, D_{j,t}^{Sto,-}, D_{j,t}^{HP}, D_{j,t}^{PV}, D_{j,t}^{TES,E,+}$	Downward CHP, ESS, HP, PV, TES imbalance caused by the activation of secondary reserves

3.2.4 - Resources constraints

This subsection presents the deterministic model developed for the PVs, HPs, CHP, ESS and TES.

3.2.4.1 - Photovoltaic constraints

The PVs are modelled by equations (3.30) to (3.32). Constraint (3.30) limits the PV generation through the generation profile (p_t^{PV}). Constraints (3.31) and (3.32) define the upward and downward band limits.

$$0 \leq P_{j,t}^{PV} \leq p_t^{PV}, \quad \forall j \in J, t \in T \quad (3.30)$$

$$0 \leq U_{j,t}^{PV} \leq p_t^{PV} - P_{j,t}^{PV}, \quad \forall j \in J, t \in T \quad (3.31)$$

$$0 \leq D_{j,t}^{PV} \leq P_{j,t}^{PV}, \quad \forall j \in J, t \in T \quad (3.32)$$

Table 3.4 presents the PVs parameters.

Table 3.4. Parameters for photovoltaic system

Parameter	Description
p_t^{PV}	PV production profile

3.2.4.2 - Heat pumps constraints

Heat pumps consume energy to produce heat. The HPs are modelled by constraints (3.33) to (3.43). The HPs power is limited by its minimum ($\underline{P_j^{HP}}$) and maximum power ($\overline{P_j^{HP}}$), constraint (3.33). Constraints (3.34) to (3.36) define the limits of the band. Constraint (3.37) defines the temperature of the building in relation to HPs production. Constraint (3.38) and (3.39) define the temperature deviations caused by the activation of the secondary reserves. Constraints (3.40) to (3.42) define the temperature limits.

$$\underline{P_j^{HP}} \leq P_{j,t}^{HP} \leq \overline{P_j^{HP}}, \quad \forall j \in J, t \in T \quad (3.33)$$

$$D_{j,t}^{HP} \leq \overline{P_j^{HP}} - P_{j,t}^{HP}, \quad \forall j \in J, t \in T \quad (3.34)$$

$$U_{j,t}^{HP} \leq P_{j,t}^{HP} - \underline{P_j^{HP}}, \quad \forall j \in J, t \in T \quad (3.35)$$

$$D_{j,t}^{HP}, U_{j,t}^{HP} \geq 0, \quad \forall j \in J, t \in T \quad (3.36)$$

$$\theta_{j,t+1}^E \leq \beta_j \cdot \theta_{j,t}^E + (1 - \beta_j)[\theta_{j,t}^O + R_j(\eta_{j,t}^{HP} \cdot P_{j,t}^{HP})] + \vartheta_{j,t}, \quad \forall j \in J, t \in T \quad (3.37)$$

$$\theta_{j,t+1}^U \leq \beta_j \cdot \theta_{j,t}^U + (1 - \beta_j)[\theta_{j,t}^O + R_j(\eta_{j,t}^{HP} \cdot P_{j,t}^{HP} - \eta_{j,t}^{HP} \cdot U_{j,t}^{HP})] + \vartheta_{j,t}, \quad \forall j \in J, t \in T \quad (3.38)$$

$$\theta_{j,t+1}^D \leq \beta_j \cdot \theta_{j,t}^D + (1 - \beta_j)[\theta_{j,t}^O + R_j(\eta_{j,t}^{HP} \cdot P_{j,t}^{HP} - \eta_{j,t}^{HP} \cdot D_{j,t}^{HP})] + \vartheta_{j,t}, \quad \forall j \in J, t \in T \quad (3.39)$$

$$\underline{\theta}_j \leq \theta_{j,t+1}^E \leq \overline{\theta}_j, \quad \forall j \in J, t \in T \quad (3.40)$$

$$\underline{\theta}_j \leq \theta_{j,t+1}^U \leq \overline{\theta}_j, \quad \forall j \in J, t \in T \quad (3.41)$$

$$\underline{\theta}_j \leq \theta_{j,t+1}^D \leq \overline{\theta}_j, \quad \forall j \in J, t \in T \quad (3.42)$$

Table 3.5 presents the variables of the HPs constraints.

Table 3.5. Variables for HPs

Variable	Description
$\theta_{j,t+1}^E$	Building temperature
$\theta_{j,t+1}^U, \theta_{j,t+1}^D$	Upward and downward temperature deviations caused by the activation of secondary reserves

Table 3.6 presents the HPs parameters.

Table 3.6. Parameters for heat pumps

Parameter	Description
$P_j^{HP}, \overline{P_j^{HP}}$	Minimum and maximum HP power
$P_{j,t}^{load,H}$	HP heat load
η_j^{HP}	HP electrical to heat efficiency
$\underline{\theta}_j, \overline{\theta}_j$	Minimum and maximum temperature
$\theta_{j,t}^O$	Outside temperature
β_j	Thermal constant
R_j	Thermal Resistance
$\vartheta_{j,t}$	Heat gains and losses

3.2.4.3 - Energy storage system constraints

The ESS is modelled by constraint (3.43) to (3.58). Constraints (3.43) and (3.44) define the state-of-charge (SOC) and its limits, constraint (3.45) defines that the initial SOC is equal to SOC at the end of the day. Constraints (3.46) to (3.48) define the charging/discharging power.

Constraints (3.49) through (3.58) ensure the correct operation of the ESS in the secondary reserve market.

$$SOC_{j,t+1}^{Sto,E} = SOC_{j,t}^{Sto,E} + \left(P_{j,t}^{Sto,E,+} \cdot \eta_j^{Sto,E} - \frac{P_{j,t}^{Sto,E,-}}{\eta_j^{Sto,E}} \right) \Delta t, \quad \forall j \in J, t \in T \quad (3.43)$$

$$\overline{SOC_j^{Sto,E}} \leq SOC_{j,t+1}^{Sto,E} \leq \overline{SOC_j^{Sto,E}}, \quad \forall j \in J, t \in T \quad (3.44)$$

$$SOC_{j,0}^{Sto,E} = SOC_{j,-1}^{Sto,E}, \quad \forall j \in J \quad (3.45)$$

$$0 \leq P_{j,t}^{Sto,E,-} + P_{j,t}^{\dot{Sto,E,-}} \leq (1 - b_{j,t}^{Sto,E}) \cdot \overline{P_j^{Sto,E,-}}, \quad \forall j \in J, t \in T \quad (3.46)$$

$$0 \leq P_{j,t}^{Sto,E,+} + P_{j,t}^{\dot{Sto,E,+}} \leq b_{j,t}^{Sto,E} \cdot P_j^{Sto,E,+}, \quad \forall j \in J, t \in T \quad (3.47)$$

$$P_{j,t}^{Sto,E,-}, P_{j,t}^{\dot{Sto,E,-}}, P_{j,t}^{Sto,E,+}, P_{j,t}^{\dot{Sto,E,+}} \geq 0, \quad \forall j \in J, t \in T \quad (3.48)$$

$$0 \leq U_{j,t}^{Sto,E,-} \leq \overline{P_j^{Sto,E,-}} - P_{j,t}^{Sto,E,-}, \quad \forall j \in J, t \in T \quad (3.49)$$

$$0 \leq U_{j,t}^{Sto,E,+} \leq P_{j,t}^{Sto,E,+}, \quad \forall j \in J, t \in T \quad (3.50)$$

$$0 \leq D_{j,t}^{Sto,E,+} \leq \overline{P_j^{Sto,E,+}} - P_{j,t}^{Sto,E,+}, \quad \forall j \in J, t \in T \quad (3.51)$$

$$0 \leq D_{j,t}^{Sto,E,-} \leq P_{j,t}^{Sto,E,-}, \quad \forall j \in J, t \in T \quad (3.52)$$

$$\left(\frac{U_{j,t}^{Sto,E,-}}{\eta_j^{Sto,E}} + U_{j,t}^{Sto,E,+} \cdot \eta_j^{Sto,E} \right) \Delta t \leq SOC_{j,t+1}^{Sto,E} - \overline{SOC_j^{Sto,E}}, \quad \forall j \in J, t \in T \quad (3.53)$$

$$\left(\frac{D_{j,t}^{Sto,E,-}}{\eta_j^{Sto,E}} + D_{j,t}^{Sto,E,+} \cdot \eta_j^{Sto,E} \right) \Delta t \leq \overline{SOC_j^{Sto,E}} - SOC_{j,t+1}^{Sto,E}, \quad \forall j \in J, t \in T \quad (3.54)$$

$$U_{j,t}^{Sto,E,+} + U_{j,t}^{Sto,E,-} + D_{j,t}^{Sto,E,+} + D_{j,t}^{Sto,E,-} \leq P_{j,t+1}^{\dot{Sto,E,+}} + P_{j,t+1}^{\dot{Sto,E,-}}, \quad \forall j \in J, t \in T \quad (3.55)$$

$$U_{j,t}^{Sto,E,+} + U_{j,t}^{Sto,E,-} + D_{j,t}^{Sto,E,+} + D_{j,t}^{Sto,E,-} \leq b_{j,t}^{\dot{Sto,E}} \cdot M, \quad \forall j \in J, t \in T \quad (3.56)$$

$$P_{j,t}^{\dot{Sto,E,+}} + P_{j,t}^{\dot{Sto,E,-}} \leq (1 - b_{j,t}^{\dot{Sto,E}}) \cdot M, \quad \forall j \in J, t \in T \quad (3.57)$$

$$U_{k,j,-1}^{Sto,E,+}, U_{k,j,-1}^{Sto,E,-}, D_{k,j,-1}^{Sto,E,+}, D_{k,j,-1}^{Sto,E,-} = 0, \quad \forall j \in J, t \in T \quad (3.58)$$

Table 3.7 presents the variables for ESS constraints.

Table 3.7. Variables for energy storage system

Variable	Description
$SOC_{j,t}^{Sto,E}$	ESS state of charge
$P_{j,t}^{Sto,E,+}, P_{j,t}^{Sto,E,-}$	ESS charging and discharging power
$P_{j,t}^{\dot{Sto,E,+}}, P_{j,t}^{\dot{Sto,E,-}}$	ESS availability for charging and discharging
$b_{j,t}^{Sto,E}$	Binary variable that indicates charge or discharge mode

$b_{j,t}^{Sto,E}$	Binary variable that indicates the capacity for upward and downward reserve provision
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Table 3.8 presents the ESS parameters.

Table 3.8. Parameters for energy storage system

Parameter	Description
$\eta_j^{Sto,E}$	Charging and discharging efficiency
$\underline{SOC_j^{Sto,E}}, \overline{SOC_j^{Sto,E}}$	Maximum and minimum SOC

3.2.4.4 - Combined heat and power constraints

Constraint (3.59) defines the CHP production limits. Constraints (3.60) and (3.61) define electricity and heat generation, respectively. Constraint (3.62) defines the CHP production through its load. Constraints (3.63) to (3.69) define the upward and downward reserve bands provided by the CHP.

$$\underline{P_j^{CHP,G}} \leq P_{j,t}^{CHP,G} \leq \overline{P_j^{CHP,G}}, \quad \forall j \in J, t \in T \quad (3.59)$$

$$P_{j,t}^{CHP,E} = \eta_j^{CHP,E} \cdot P_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.60)$$

$$P_{j,t}^{CHP,H} = \eta_j^{CHP,H} \cdot P_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.61)$$

$$P_{j,t}^{CHP,H} + P_{j,t}^{TES,H,-} = P_{j,t}^{IND,H}, \quad \forall j \in J, t \in T \quad (3.62)$$

$$0 \leq U_{j,t}^{CHP,G} \leq \overline{P_j^{CHP,G}} - P_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.63)$$

$$0 \leq D_{j,t}^{CHP,G} \leq P_{j,t}^{CHP,G} - \underline{P_j^{CHP,G}}, \quad \forall j \in J, t \in T \quad (3.64)$$

$$D_{j,t}^{CHP,H} = \eta_j^{CHP,H} \cdot D_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.65)$$

$$D_{j,t}^{CHP,E} = \eta_j^{CHP,E} \cdot D_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.66)$$

$$U_{j,t}^{CHP,H} = \eta_j^{CHP,H} \cdot U_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.67)$$

$$U_{j,t}^{CHP,E} = \eta_j^{CHP,E} \cdot U_{j,t}^{CHP,G}, \quad \forall j \in J, t \in T \quad (3.68)$$

$$U_{j,t}^{CHP,G}, D_{j,t}^{CHP,G} \leq \mu^{CHP} \cdot \overline{P_j^{CHP,G}}, \quad \forall j \in J, t \in T \quad (3.69)$$

Table 3.9 presents the cogeneration parameters.

Table 3.9. Parameters for cogeneration

Parameter	Description
$\overline{P_{j,t}^{CHP,G}}, \underline{P_j^{CHP,G}}$	Maximum and minimum gas power
$\eta_j^{CHP,E}, \eta_j^{CHP,H}$	Gas to electricity and gas to heat efficiency
$P_{j,t}^{IND,H}$	Industrial load
μ^{CHP}	Participation factor

3.2.4.5 - Thermal energy storage constraints

The TES is modelled by constraints (3.70) to (3.81). Constraints (3.70) and (3.71) define the SOC and its limits. Constraint (3.72) defines the TES charging power. Constraints (3.73) and (3.74) set the range of charging and discharge power. Constraint (3.75) sets the SOC at the end of the day is equal to the initial SOC. Constraints (3.76) and (3.77) define and limit the upward band while constraints (3.78) and (3.79) limit the downward band. Constraints (3.80) and (3.81) guarantee that the storage only supplies upward and downward band if the SOC is within the limits.

$$SOC_{j,t+1}^{TES,H} = SOC_{j,t}^{TES,H} + \left(P_{j,t}^{TES,H,+} \cdot \eta_j^{TES,H} - \frac{P_{j,t}^{TES,H,-}}{\eta_j^{TES,H,-}} \right) \Delta t - \gamma_j \cdot SOC_{j,t}^{TES,H}, \quad \forall j \in J, t \in T \quad (3.70)$$

$$\underline{SOC_j^{TES,H}} \leq SOC_{j,t+1}^{TES,H} \leq \overline{SOC_j^{TES,H}}, \quad \forall j \in J, t \in T \quad (3.71)$$

$$P_{j,t}^{TES,H,+} = \eta_j^{TES,E2H} \cdot P_{j,t}^{TES,E,+}, \quad \forall j \in J, t \in T \quad (3.72)$$

$$0 \leq P_{j,t}^{TES,H,-} \leq (1 - b_{j,t}^{TES,H}) \cdot \overline{P_j^{TES,H,-}}, \quad \forall j \in J, t \in T \quad (3.73)$$

$$0 \leq P_{j,t}^{TES,H,+} \leq b_{j,t}^{TES,H} \cdot \overline{P_j^{TES,H,-}}, \quad \forall j \in J, t \in T \quad (3.74)$$

$$SOC_{j,0}^{TES,H} = SOC_{j,-1}^{TES,H}, \quad \forall j \in J \quad (3.75)$$

$$U_{j,t}^{TES,H,+} = \eta_j^{TES,H} \cdot U_{j,t}^{TES,E}, \quad \forall j \in J, t \in T \quad (3.76)$$

$$0 \leq U_{j,t}^{TES,E,+} \leq P_{j,t}^{TES,E,+}, \quad \forall j \in J, t \in T \quad (3.77)$$

$$D_{j,t}^{TES,H,+} = \eta_j^{TES,H} \cdot D_{j,t}^{TES,E}, \quad \forall j \in J, t \in T \quad (3.78)$$

$$0 \leq D_{j,t}^{TES,E,+} \leq \overline{P_j^{TES,E,+}} - P_{j,t}^{TES,E,+}, \quad \forall j \in J, t \in T \quad (3.79)$$

$$(U_{j,t}^{TES,H,+} \cdot \eta_j^{TES,H}) \Delta t \leq SOC_{j,t+1}^{TES,H} - \underline{SOC_j^{TES,H}}, \quad \forall j \in J, t \in T \quad (3.80)$$

$$(D_{j,t}^{TES,H,+} \cdot \eta_j^{TES,H})\Delta t \leq \overline{SOC_j^{TES,H}} - SOC_{j,t+1}^{TES,H}, \quad \forall j \in J, t \in T \quad (3.81)$$

Table 3.10 presents the variables for TES constraints.

Table 3.10. Variables for TES constraints

Variable	Description
$SOC_{j,t}^{TES,H}$	SOC of the TES

Table 3.11 presents the TES parameters.

Table 3.11. Parameters for TES constraints

Parameter	Description
$b_{j,t}^{TES,H}$	Binary variable indicating the charging (1) or discharging (0) mode
$\eta_j^{TES,E2H}$	Electricity to heat efficiency
$\overline{SOC_j^{TES,H}}, \underline{SOC_j^{TES,H}}$	Minimum and maximum state-of-charge
$P_j^{TES,H}$	Maximum charging/discharging power
γ_j	Discharging rate

3.3 - Stochastic

This subsection presents the stochastic formulation developed to optimize the participation of the industrial hub in the energy and gas markets.

3.3.1 - Objective function

The first three terms of constraint (3.82) define the costs of buying/selling electricity, selling secondary reserve band and buying natural gas. The fourth term defines the realizations of the electricity and natural gas scenarios. Constraint (3.83) considers the value of the deviations between the electricity DA bids and the realizations of scenario k ($\Delta E_{k,t}^{E,-}$ and $\Delta E_{k,t}^{E,+}$); the value of the activation of upward and downward reserve for scenario k ($D_{k,t}^E$ and $U_{k,t}^E$); and also the value of the upward and downward secondary band not supplied ($\Delta U_{k,t}^E$ and $\Delta D_{k,t}^E$). Constraint (3.84) considers the value of the deviations between natural gas DA bids and realizations of scenarios k ($\Delta E_{k,t}^{G,-}$ and $\Delta E_{k,t}^{G,+}$) and the value of the activation of upward and downward reserve for the natural gas ($D_{k,t}^G$ and $U_{k,t}^G$).

$$\text{Min} \sum_{t \in T} [\lambda_t^E \cdot E_t^{E,DA} - \lambda_t^B (U_t^{E,DA} + D_t^{E,DA})\Delta t + \lambda_t^G \cdot E_t^{G,DA} + \sum_{k \in K} \tau_k (f_{k,t}^E + f_{k,t}^G)] \quad (3.82)$$

$$f_{k,t}^E = \lambda_t^{E,-} \Delta E_{k,t}^{E,-} - \lambda_t^{E,+} \Delta E_{k,t}^{E,+} + (\lambda_t^{D,E} \cdot \phi_t^D \cdot D_{k,t}^E - \lambda_t^{U,E} \cdot \phi_t^U \cdot U_{k,t}^E + \lambda_t^{B,-} \Delta U_{k,t}^E + \lambda_t^{B,-} \Delta D_{k,t}^E)\Delta t \quad (3.83)$$

$$f_{k,t}^G = \lambda_t^{G,-} \Delta E_{k,t}^{G,-} - \lambda_t^{G,+} \Delta E_{k,t}^{G,+} + (\lambda_t^{U,G} \cdot \phi_t^U \cdot U_{k,t}^G - \lambda_t^{D,G} \cdot \phi_t^D \cdot D_{k,t}^G) \Delta t, \quad (3.84)$$

Table 3.12. Variables of the stochastic objective function

Variable	Description
$E_t^{E,DA}$	DA energy bids
$U_t^{E,DA}$	DA upward band bids
$D_t^{E,DA}$	DA downward band bids
$E_t^{G,DA}$	DA gas bids
U_t^G	Upward deviations from activation of secondary reserves
D_t^G	Downward deviations from activation of secondary reserves
$\Delta E_{k,t}^{E,-}, \Delta E_{k,t}^{E,+}$	Negative and positive deviations between the DA bids and the realizations for scenario k
$U_{k,t}^E, D_{k,t}^E$	Value of the activation of upward and downward reserve for scenario k
$\Delta U_{k,t}^E, \Delta D_{k,t}^E$	Value of the upward and downward secondary band not supplied
$\Delta E_{k,t}^{G,-}, \Delta E_{k,t}^{G,+}$	Deviation between the DA bis and realizations of scenarios k
$D_{k,t}^G, U_{k,t}^G$	Value of the activation of upward and downward reserve for natural gas

Table 3.13. Parameters of the stochastic objective function

Parameter	Description
λ_t^E	Electricity price
λ_t^B	Secondary reserve band price
$\lambda_t^{U,E}, \lambda_t^{D,E}$	Upward and downward band activation price
λ_t^G	Gas price
ϕ_t^U, ϕ_t^D	Upward and downward ratio
τ_k	Scenario probability
$\lambda_t^{E,+}, \lambda_t^{E,-}$	Positive and negative electricity imbalance price
$\lambda_t^{B,-}$	Price for the secondary reserve band not supplied
$\lambda_t^{G,+}, \lambda_t^{G,-}$	Positive and negative gas imbalance price
$\lambda_t^{U,G}, \lambda_t^{D,G}$	Upward and downward reserve natural gas activation price

3.3.2 - Market constraints

Constraint (3.85) defines the energy balance between the electricity DA market commitments and the realizations of scenario k. Constraints (3.86) and (3.87) define the upward and downward secondary band not supplied. Constraints (3.88) and (3.89) define that the upward band must be equal to the downward band. Constraint (3.90) defines the energy balance between the natural gas DA market commitments and the realizations of scenario k. Constraint (3.91) ensures that both the deviations and the variables involved are non-negative.

$$\Delta E_{k,t}^{E,-} - \Delta E_{k,t}^{E,+} = E_{k,t}^E - E_t^{E,DA}, \quad \forall t \in T, k \in K \quad (3.85)$$

$$\Delta D_{k,t}^E = D_t^{E,DA} - D_{k,t}^E, \quad \forall t \in T, k \in K \quad (3.86)$$

$$\Delta U_{k,t}^E = U_t^{E,DA} - U_{k,t}^E, \quad \forall t \in T, k \in K \quad (3.87)$$

$$U_{k,t}^E = D_{k,t}^E, \quad \forall t \in T, k \in K \quad (3.88)$$

$$U_t^{E,DA} = D_t^{E,DA}, \quad \forall t \in T \quad (3.89)$$

$$\Delta E_{k,t}^{G,-} - \Delta E_{k,t}^{G,+} = E_{k,t}^G - E_t^{G,DA}, \quad \forall t \in T, k \in K \quad (3.90)$$

$$\Delta D_{k,t}, \Delta U_{k,t}, \Delta E_{k,t}^{E,-}, \Delta E_{k,t}^{E,+}, \Delta E_{k,t}^{G,-}, \Delta E_{k,t}^{G,+}, D_{k,t}^E, U_{k,t}^E, D_{k,t}^G, U_{k,t}^G > 0, \quad \forall t \in T, k \in K \quad (3.91)$$

3.3.3 - Bidding constraints

The bidding constraints (3.92) to (3.97) are the same as those in the deterministic model, the key difference from the deterministic formulation is that the index k is considered.

$$E_{k,t}^E = \sum_{j \in J} P_{k,t}^{IL,E} + P_{k,j,t}^{HP} + P_{k,j,t}^{Sto,+} - P_{k,j,t}^{Sto,-} - P_{k,j,t}^{PV} - P_{k,j,t}^{CHP,E} + P_{k,j,t}^{TES,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.92)$$

$$E_{k,t}^G = \sum_{j \in J} P_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.93)$$

$$U_{k,t}^E = \sum_{j \in J} U_{k,j,t}^{Sto,+} + U_{k,j,t}^{Sto,-} + U_{k,j,t}^{HP} + U_{k,j,t}^{PV} + U_{k,j,t}^{CHP,E} + U_{k,j,t}^{TES,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.94)$$

$$D_{k,t}^E = \sum_{j \in J} D_{k,j,t}^{Sto,+} + D_{k,j,t}^{Sto,-} + D_{k,j,t}^{HP} + D_{k,j,t}^{PV} + D_{k,j,t}^{CHP,E} + D_{k,j,t}^{TES,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.95)$$

$$U_{k,t}^G = \sum_{j \in J} U_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.96)$$

$$D_{k,t}^G = \sum_{j \in J} D_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.97)$$

Table 3.14. Variables for bidding constraints

Variable	Description
$P_{k,t}^{IL,E}, P_{k,j,t}^{HP}, P_{k,j,t}^{Sto,+}, P_{k,j,t}^{Sto,-}, P_{k,j,t}^{PV}, P_{k,j,t}^{CHP,E}, P_{k,j,t}^{TES,E,+}, P_{k,j,t}^{CHP,G}$	Electrical load, power generated by the HP, ESS charge power, ESS discharge power, power generated by PVs, electrical production by the CHP, TES electrical charging power, CHP gas consumption
$U_{k,j,t}^{CHP,G}, U_{k,j,t}^{Sto,+}, U_{k,j,t}^{Sto,-}, U_{k,j,t}^{HP}, U_{k,j,t}^{PV}, U_{k,j,t}^{CHP,E}$	Upward CHP, ESS, HP, PV, CHP, TES imbalance caused by the activation of secondary reserves

$U_{k,j,t}^{TES,E+}$ $D_{k,j,t}^{CHP,G}, D_{k,j,t}^{CHP,E}, D_{k,j,t}^{Sto,+}$ $D_{k,j,t}^{Sto,-}, D_{k,j,t}^{HP}, D_{k,j,t}^{PV}$ $D_{k,j,t}^{TES,E+}$	Downward CHP, ESS, HP, PV, CHP, TES imbalance caused by the activation of secondary reserves
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3.3.4 - Resources constraints

This subsection presents the stochastic model developed for the PVs, HPs, CHPs, ESSs and TES. The formulation is the same as in the deterministic formulation, the key difference is that index k is considered.

3.3.4.1 - Photovoltaic constraints

The PVs are modelled by equations (3.98) to (3.100). Constraint (3.98) limits the PV generation through the generation profile (p_t^{PV}) and its maximum power ($\overline{P_j^{PV}}$). Constraints (3.99) and (3.100) define the upward and downward band limits.

$$0 \leq P_{k,j,t}^{PV} \leq p_{k,t}^{PV} \quad \forall j \in J, t \in T, k \in K \quad (3.98)$$

$$0 \leq U_{k,j,t}^{PV} \leq p_{k,t}^{PV} - P_{k,j,t}^{PV} \quad \forall j \in J, t \in T, k \in K \quad (3.99)$$

$$0 \leq D_{k,j,t}^{PV} \leq P_{k,j,t}^{PV} \quad \forall j \in J, t \in T, k \in K \quad (3.100)$$

Table 3.15 presents the PVs parameters.

Table 3.15. Parameters for photovoltaic system

Parameter	Description
$p_{k,t}^{PV}$	PV production profile

3.3.4.2 - Heat pumps constraints

HPs consume energy to produce heat. The HPs are modelled by constraints (3.101) to (3.110). The HPs power is limited by its minimum ($\underline{P_j^{HP}}$) and maximum power ($\overline{P_j^{HP}}$) in constraint (3.101). Constraints (3.102) to (3.104) define the limits of the band. Constraint (3.105) defines the temperature of the building in relation to HPs production. Constraint (3.106) and (3.107) define the temperature deviations caused by the activation of the secondary reserves. Constraints (3.108) to (3.109) define the temperature limits.

$$\underline{P_j^{HP}} \leq P_{k,j,t}^{HP} \leq \overline{P_j^{HP}}, \quad \forall j \in J, t \in T, k \in K \quad (3.101)$$

$$D_{k,j,t}^{HP} \leq \overline{P_j^{HP}} - P_{k,j,t}^{HP} \quad \forall j \in J, t \in T, k \in K \quad (3.102)$$

$$U_{k,j,t}^{HP} \leq P_{k,j,t}^{HP} - \underline{P_j^{HP}}, \quad \forall j \in J, t \in T, k \in K \quad (3.103)$$

$$D_{k,j,t}^{HP}, U_{k,j,t}^{HP} \geq 0, \quad \forall j \in J, t \in T, k \in K \quad (3.104)$$

$$\theta_{k,j,t+1}^E \leq \beta_j \cdot \theta_{k,j,t}^E + (1 - \beta_j)[\theta_{k,j,t}^O + R_j(\eta_{j,t}^{HP} \cdot P_{k,j,t}^{HP})] + \vartheta_{k,j,t}, \quad \forall j \in J, t \in T, k \in K \quad (3.105)$$

$$\theta_{k,j,t+1}^U \leq \beta_j \cdot \theta_{k,j,t}^U + (1 - \beta_j)[\theta_{k,j,t}^O + R_j(\eta_{j,t}^{HP} \cdot P_{k,j,t}^{HP} - \eta_{j,t}^{HP} \cdot U_{k,j,t}^{HP})] + \vartheta_{k,j,t}, \quad \forall j \in J, t \in T, k \in K \quad (3.106)$$

$$\theta_{k,j,t+1}^D \leq \beta_j \cdot \theta_{k,j,t}^D + (1 - \beta_j)[\theta_{k,j,t}^O + R_j(\eta_{j,t}^{HP} \cdot P_{k,j,t}^{HP} + \eta_{j,t}^{HP} \cdot D_{k,j,t}^{HP})] + \vartheta_{k,j,t}, \quad \forall j \in J, t \in T, k \in K \quad (3.107)$$

$$\underline{\theta_{k,j}} \leq \theta_{k,j,t+1}^E \leq \overline{\theta_{k,j}}, \quad \forall j \in J, t \in T, k \in K \quad (3.108)$$

$$\underline{\theta_{k,j}} \leq \theta_{k,j,t+1}^U \leq \overline{\theta_{k,j}}, \quad \forall j \in J, t \in T, k \in K \quad (3.109)$$

$$\underline{\theta_{k,j}} \leq \theta_{k,j,t+1}^D \leq \overline{\theta_{k,j}}, \quad \forall j \in J, t \in T, k \in K \quad (3.110)$$

Table 3.16 presents the variables for the HPs constraints.

Table 3.16. Variables for HPs

Variable	Description
$\theta_{k,j,t+1}^E$	Building temperature
$\theta_{k,j,t+1}^U, \theta_{k,j,t+1}^D$	Upward and downward temperature deviations caused by the activation of secondary reserves

Table 3.17 presents the HPs parameters.

Table 3.17. Parameters for HPs

Parameter	Description
$\underline{P_j^{HP}}, \overline{P_j^{HP}}$	Minimum and maximum HP power
$P_{j,t}^{load,H}$	HP heat load
η_j^{HP}	HP electrical to heat efficiency
$\underline{\theta_{k,j}}, \overline{\theta_{k,j}}$	Minimum and maximum temperature
$\theta_{k,j,t}^O$	Outside temperature
β_j	Thermal constant
R_j	Thermal Resistance
$\vartheta_{k,j,t}$	Heat gains and losses

3.3.4.3 - Energy storage system constraints

The ESS is modelled by constraint (3.111) to (3.126). Constraints (3.111) and (3.112) define the SOC and its limits, constraint (3.113) defines that the initial SOC is equal to SOC at the end of the day. Constraints (3.114) to (3.116) define the charging/discharging power.

Constraints (3.117) through (3.126) ensure the correct operation of the ESS in the secondary reserve market.

$$SOC_{k,j,t+1}^{Sto,E} = SOC_{k,j,t}^{Sto,E} + \left(P_{k,j,t}^{Sto,E,+} \cdot \eta_j^{Sto,E} - \frac{P_{k,j,t}^{Sto,E,-}}{\eta_j^{Sto,E}} \right) \Delta t, \quad \forall j \in J, t \in T, k \in K \quad (3.111)$$

$$\underline{SOC}_j^{Sto,E} \leq SOC_{k,j,t+1}^{Sto,E} \leq \overline{SOC}_j^{Sto,E}, \quad \forall j \in J, t \in T, k \in K \quad (3.112)$$

$$SOC_{k,j,0}^{Sto,E} = SOC_{k,j,-1}^{Sto,E}, \quad \forall j \in J, k \in K \quad (3.113)$$

$$0 \leq P_{k,j,t}^{Sto,E,-} + P_{k,j,t}^{\dot{Sto},E,-} \leq (1 - b_{k,j,t}^{Sto,E}) \cdot \overline{P}_j^{Sto,E,-}, \quad \forall j \in J, t \in T, k \in K \quad (3.114)$$

$$0 \leq P_{k,j,t}^{Sto,E,+} + P_{k,j,t}^{\dot{Sto},E,+} \leq b_{k,j,t}^{Sto,E} \cdot \overline{P}_j^{Sto,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.115)$$

$$P_{k,j,t}^{Sto,E,-}, P_{k,j,t}^{\dot{Sto},E,-}, P_{k,j,t}^{Sto,E,+}, P_{k,j,t}^{\dot{Sto},E,+} \geq 0, \quad \forall j \in J, t \in T, k \in K \quad (3.116)$$

$$0 \leq U_{k,j,t}^{Sto,E,-} \leq \overline{P}_j^{Sto,E,-} - P_{k,j,t}^{Sto,E,-}, \quad \forall j \in J, t \in T, k \in K \quad (3.117)$$

$$0 \leq U_{k,j,t}^{Sto,E,+} \leq P_{k,j,t}^{Sto,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.118)$$

$$0 \leq D_{k,j,t}^{Sto,E,+} \leq \overline{P}_j^{Sto,E,+} - P_{k,j,t}^{Sto,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.119)$$

$$0 \leq D_{k,j,t}^{Sto,E,-} \leq P_{k,j,t}^{Sto,E,-}, \quad \forall j \in J, t \in T, k \in K \quad (3.120)$$

$$\left(\frac{U_{k,j,t}^{Sto,E,-}}{\eta_j^{Sto,E}} + U_{k,j,t}^{Sto,E,+} \cdot \eta_j^{Sto,E} \right) \Delta t \leq SOC_{k,j,t+1}^{Sto,E} - \underline{SOC}_j^{Sto,E}, \quad \forall j \in J, t \in T, k \in K \quad (3.121)$$

$$\left(\frac{D_{k,j,t}^{Sto,E,-}}{\eta_j^{Sto,E}} + D_{k,j,t}^{Sto,E,+} \cdot \eta_j^{Sto,E} \right) \Delta t \leq \overline{SOC}_j^{Sto,E} - SOC_{k,j,t+1}^{Sto,E}, \quad \forall j \in J, t \in T, k \in K \quad (3.122)$$

$$U_{k,j,t}^{Sto,E,+} + U_{k,j,t}^{Sto,E,-} + D_{k,j,t}^{Sto,E,+} + D_{k,j,t}^{Sto,E,-} \leq P_{k,j,t+1}^{\dot{Sto},E,+} + P_{k,j,t+1}^{\dot{Sto},E,-}, \quad \forall j \in J, t \in T, k \in K \quad (3.123)$$

$$U_{k,j,t}^{Sto,E,+} + U_{k,j,t}^{Sto,E,-} + D_{k,j,t}^{Sto,E,+} + D_{k,j,t}^{Sto,E,-} \leq b_{j,t}^{\dot{Sto},E} \cdot M, \quad \forall j \in J, t \in T, k \in K \quad (3.124)$$

$$P_{k,j,t}^{\dot{Sto},E,+} + P_{k,j,t}^{\dot{Sto},E,-} \leq (1 - b_{k,j,t}^{\dot{Sto},E}) \cdot M, \quad \forall j \in J, t \in T, k \in K \quad (3.125)$$

$$U_{k,j,-1}^{Sto,E,+}, U_{k,j,-1}^{Sto,E,-}, D_{k,j,-1}^{Sto,E,+}, D_{k,j,-1}^{Sto,E,-} = 0, \quad \forall j \in J, t \in T, k \in K \quad (3.126)$$

Table 3.18 presents the variables for the ESSs constraints.

Table 3.18. Variables for ESS

Variable	Description
$SOC_{k,j,t}^{Sto,E}$	ESS SOC
$P_{k,j,t}^{Sto,E,+}, P_{k,j,t}^{Sto,E,-}$	ESS charging and discharging power
$P_{j,t}^{Sto,E,+}, P_{k,j,t}^{Sto,E,-}$	ESS availability for charging and discharging
$b_{k,j,t}^{Sto,E}$	Binary variable that indicates charge or discharge mode
$b_{k,j,t}^{Sto,E}$	Binary variable that indicates the capacity for upward and downward reserve provision

Table 3.19 presents the ESSs parameters.

Table 3.19. Parameters for ESS

Parameter	Description
$\eta_j^{Sto,E}$	Charging and discharging efficiency
$SOC_j^{Sto,E}, SOC_j^{Sto,E}$	Maximum and minimum SOC

3.3.4.4 - Combined heat and power constraints

Constraint (3.127) defines the CHP production limits. Constraints (3.128) and (3.129) define electricity and heat generation, respectively. Constraint (3.130) defines the CHP production through its load. Constraints (3.131) to (3.137) define the upward and downward reserve bands provided by the CHP.

$$\underline{P_j^{CHP,G}} \leq P_{k,j,t}^{CHP,G} \leq \overline{P_j^{CHP,G}}, \quad \forall j \in J, t \in T, k \in K \quad (3.127)$$

$$P_{k,j,t}^{CHP,E} = \eta_j^{CHP,E} \cdot P_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.128)$$

$$P_{k,j,t}^{CHP,H} = \eta_j^{CHP,H} \cdot P_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.129)$$

$$P_{k,j,t}^{CHP,H} + P_{k,j,t}^{TES,H,-} = P_{k,j,t}^{IND,H}, \quad \forall j \in J, t \in T \quad (3.130)$$

$$0 \leq U_{k,j,t}^{CHP,G} \leq \overline{P_j^{CHP,G}} - P_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.131)$$

$$0 \leq D_{k,j,t}^{CHP,G} \leq P_{k,j,t}^{CHP,G} - \underline{P_{j,t}^{CHP,G}}, \quad \forall j \in J, t \in T, k \in K \quad (3.132)$$

$$D_{k,j,t}^{CHP,H} = \eta_j^{CHP,H} \cdot D_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.133)$$

$$D_{k,j,t}^{CHP,E} = \eta_j^{CHP,E} \cdot D_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.134)$$

$$U_{k,j,t}^{CHP,H} = \eta_j^{CHP,H} \cdot U_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.135)$$

$$U_{k,j,t}^{CHP,E} = \eta_j^{CHP,E} \cdot U_{k,j,t}^{CHP,G}, \quad \forall j \in J, t \in T, k \in K \quad (3.136)$$

$$U_{k,j,t}^{CHP,G}, D_{k,j,t}^{CHP,G} \leq \mu^{CHP} * \overline{P_j^{CHP,G}}, \quad \forall j \in J, t \in T, k \in K \quad (3.137)$$

Table 3.20 presents the cogeneration parameters.

Table 3.20. Parameters for cogeneration

Parameter	Description
$\underline{P_j^{CHP,G}}, \overline{P_j^{CHP,G}}$	Maximum and minimum gas power
$\eta_j^{CHP,E}, \eta_j^{CHP,H}$	Gas to electricity and gas to heat efficiency
$P_{k,j,t}^{IND,H}$	Industrial load
μ^{CHP}	Participation factor

3.3.4.5 - Thermal energy storage constraints

The TES is modelled by constraints (3.128) to (3.139). Constraints (3.128) and (3.129) define the SOC and its limits. Constraint (3.130) defines the TES charging power. Constraints (3.131) and (3.132) set the range of charging and discharge power. Constraint (3.133) sets that the SOC at the end of the day is equal to the initial SOC. Constraints (3.134) and (3.135) define and limit the upward band while constraints (3.136) and (3.137) limit the downward band. Constraints (3.138) and (3.139) guarantee that the storage only supplies upward and downward band if the SOC is within the limits.

$$SOC_{k,j,t+1}^{TES,H} = SOC_{k,j,t}^{TES,H} + \left(P_{k,j,t}^{TES,H,+} \cdot \eta_j^{TES,H} - \frac{P_{j,k,t}^{TES,H,-}}{\eta_j^{TES,H,-}} \right) \Delta t - \gamma_j \cdot SOC_{k,j,t}^{TES,H}, \quad \forall j \in J, t \in T, k \in K \quad (3.128)$$

$$\underline{SOC_j^{TES,H}} \leq SOC_{k,j,t+1}^{TES,H} \leq \overline{SOC_j^{TES,H}}, \quad \forall j \in J, t \in T, k \in K \quad (3.129)$$

$$P_{k,j,t}^{TES,H,+} = \eta_j^{TES,E2H} \cdot P_{k,j,t}^{TES,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.130)$$

$$0 \leq P_{k,j,t}^{TES,H,-} \leq (1 - b_{k,j,t}^{TES,H}) \cdot \overline{P_j^{TES,H}}, \quad \forall j \in J, t \in T, k \in K \quad (3.131)$$

$$0 \leq P_{k,j,t}^{TES,H,+} \leq b_{k,j,t}^{TES,H} \cdot \overline{P_j^{TES,H}}, \quad \forall j \in J, t \in T, k \in K \quad (3.132)$$

$$SOC_{k,j,0}^{TES,H} = SOC_{k,j,-1}^{TES,H}, \quad \forall j \in J, t \in T, k \in K \quad (3.133)$$

$$U_{k,j,t}^{TES,H,+} = \eta_j^{TES,H} \cdot U_{k,j,t}^{TES,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.134)$$

$$0 \leq U_{k,j,t}^{TES,E,+} \leq P_{k,j,t}^{TES,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.135)$$

$$D_{k,j,t}^{TES,H,+} = \eta_j^{TES,H} \cdot D_{k,j,t}^{TES,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.136)$$

$$0 \leq D_{k,j,t}^{TES,E,+} \leq \overline{P_j^{TES,E}} - P_{k,j,t}^{TES,E,+}, \quad \forall j \in J, t \in T, k \in K \quad (3.137)$$

$$(U_{k,j,t}^{TES,H,+} \cdot \eta_j^{TES,H}) \Delta t \leq SOC_{k,j,t+1}^{TES,H} - \underline{SOC_j^{TES,H}}, \quad \forall j \in J, t \in T, k \in K \quad (3.138)$$

$$(D_{k,j,t}^{TES,H,+} \cdot \eta_j^{TES,H}) \Delta t \leq \overline{SOC_j^{TES,H}} - SOC_{k,j,t+1}^{TES,H}, \quad \forall j \in J, t \in T, k \in K \quad (3.139)$$

Table 3.21 presents the variables for the TES constraints.

Table 3.21. Variables for TES constraints

Variable	Description
$SOC_{k,j,t}^{TES,H}$	TES SOC

Table 3.22 presents the TES parameters.

Table 3.22. Parameters for TES constraints

Parameter	Description
$b_{k,j,t}^{TES,H}$	Binary variable indicating the charging (1) or discharging (0) mode
$\eta_j^{TES,E2H}$	Electricity to heat efficiency
$\underline{SOC_j^{TES,H}}, \overline{SOC_j^{TES,H}}$	Minimum and maximum SOC
$\overline{P_j^{TES,H}}$	Maximum charging/discharging power
γ_j	Discharging rate

3.4 - Robust optimization

This subsection presents the robust formulation developed to optimize the participation of the industrial hub in the DA market.

The robust approach accounts for uncertainties in PV generation, the hub's electrical load, the industrial load, and the outdoor temperature, all of which need to be properly modelled through uncertainty sets. The way this sets are modelled is explained in subsection 3.1 -Optimization frameworks.

The robust and deterministic formulations are almost identical. For clarity and to avoid redundancy, only the additional constraints introduced to handle uncertainties are detailed in this

section. For the remaining constraints, references are provided to their corresponding formulations in the deterministic model.

3.4.1 - Objective function

The objective function used in the robust optimization formulation is identical to that of the deterministic model and can be found in Equations (3.20) to (3.22).

3.4.2 - Market constraints

The market constraint used in the robust optimization formulation is identical to that of the deterministic model and can be found in Equation (3.23).

3.4.3 - Bidding constraints

In the robust optimization model, the formulation of the bidding constraints includes an uncertain parameter represented by an uncertainty set: the electrical load.

The remaining bidding constraints used in the robust optimization formulation are identical to those of the deterministic model and can be found in Equations (3.24) to (3.29).

$$P_t^E = \sum_{j \in J_n} \left(P_t^{IL,E,forecast} + \Delta P_{j,t}^{IL,E,forecast} \right) + P_{j,t}^{HP} + P_{j,t}^{Sto,+} - P_{j,t}^{Sto,-} - P_{j,t}^{PV} - P_{j,t}^{CHP,E} + P_{j,t}^{TES,E,+}, \quad \forall j \in J, t \in T \quad (3.140)$$

$$\Gamma_t^{IL,E} * z_t^{IL,E} + q_t^{IL,E} \geq (u_t^{IL,E}) \gamma_t^{IL,E}, \quad \forall t \in T \quad (3.141)$$

$$z_t^{IL,E}, q_t^{IL,E} \geq 0, \quad \forall t \in T \quad (3.142)$$

$$\gamma_t^{IL,E} \geq 1, \quad \forall t \in T \quad (3.143)$$

$$\Delta P_{j,t}^{IL,E,forecast} = q_t^{IL,E} + \Gamma_t^{IL,E} \cdot z_t^{IL,E}, \quad \forall j \in J, t \in T \quad (3.144)$$

Table 3.23 presents the bidding constraints variables.

Table 3.23. Variables for bidding constraints

Variable	Description
$q_t^{IL,E}, z_t^{IL,E}$	Electrical load dual variables
$\gamma_t^{IL,E}$	Electrical load auxiliary variable

Table 3.24 presents the bidding constraints parameters

Table 3.24. Parameters for bidding constraints

Variable	Description
$\Gamma_t^{IL,E}$	Electrical load robust control parameter

$\mathcal{U}_t^{LL,E}$ Electrical load uncertainty set

3.4.4 - Resources constraints

This subsection presents the robust optimization formulation developed for the PVs, HPs, CHPs, ESSs and TES.

3.4.4.1 - Photovoltaic constraints

In the robust optimization model, the formulation of the PV constraints includes an uncertain parameter represented by an uncertainty set: the PV generation profile.

$$0 \leq p_{j,t}^{PV} \leq p_t^{PV,forecast} - \Delta p_t^{PV,forecast}, \quad \forall j \in J, t \in T \quad (3.145)$$

$$\Delta p_t^{PV,forecast} = q_t^{PV} + \Gamma_t^{PV} * z_t^{PV}, \quad \forall j \in J, t \in T \quad (3.146)$$

$$\Gamma_t^{PV} * z_t^{PV} + q_t^{PV} \geq (\mathcal{U}_t^{PV})\gamma_t^{PV}, \quad \forall t \in T \quad (3.147)$$

$$z_t^{PV}, q_t^{PV} \geq 0, \quad \forall t \in T \quad (3.148)$$

$$\gamma_t^{PV} \geq 1, \quad \forall t \in T \quad (3.149)$$

$$0 \leq U_{j,t}^{PV} \leq p_t^{PV,forecast} - \Delta p_t^{PV,forecast} - p_{j,t}^{PV}, \quad \forall j \in J, t \in T \quad (3.150)$$

Table 3.25 presents the PV variables.

Table 3.25. Variables for PV constraints

Variable	Description
q_t^{PV}, z_t^{PV}	PV profile dual variables
γ_t^{PV}	PV profile auxiliary variable

Table 3.26 presents the PV parameters.

Table 3.26. Parameters for PV constraints

Variable	Description
Γ_t^{PV}	Robust control parameter
$\mathcal{U}_t^{PV}$	PV profile uncertainty set

The remaining PV constraint used in the robust optimization formulation is identical to that of the deterministic model and can be found in Equation (3.32).

3.4.4.2 - Heat pump constraints

In the robust optimization model, the formulation of the HPs constraints includes an uncertain parameter represented by an uncertainty set: the outside temperature.

$$\theta_{j,t+1}^E \leq \beta_j \cdot \theta_{j,t}^E + (1 - \beta_j) \left[\theta_{j,t}^{O,forecast} - (q_t^O + \Gamma_t^O \cdot z_t^O) + R_j(\eta_{j,t}^{HP} \cdot P_{j,t}^{HP}) \right] + \vartheta_{j,t}, \quad \forall j \in J, t \in T \quad (3.151)$$

$$\theta_{j,t+1}^U \leq \beta_j \cdot \theta_{j,t}^U + (1 - \beta_j) \left[\theta_{j,t}^{O,forecast} - (q_t^O + \Gamma_t^O \cdot z_t^O) + R_j(\eta_{j,t}^{HP} \cdot P_{j,t}^{HP}) \right] + \vartheta_{j,t}, \quad \forall j \in J, t \in T \quad (3.152)$$

$$\theta_{j,t+1}^D \leq \beta_j \cdot \theta_{j,t}^D + (1 - \beta_j) \left[\theta_{j,t}^{O,forecast} - (q_t^O + \Gamma_t^O \cdot z_t^O) + R_j(\eta_{j,t}^{HP} \cdot P_{j,t}^{HP}) \right] + \vartheta_{j,t}, \quad \forall j \in J, t \in T \quad (3.153)$$

$$\Delta \theta_t^O = q_t^O + \Gamma_t^O \cdot z_t^O, \quad \forall j \in J, t \in T \quad (3.154)$$

$$q_t^O + \Gamma_t^O \cdot z_t^O \geq (U_t^O) \gamma_t^O, \quad \forall j \in J, t \in T \quad (3.155)$$

$$z_t^O, q_t^O \geq 0, \quad \forall t \in T \quad (3.156)$$

$$\gamma_t^O \geq 1, \quad \forall t \in T \quad (3.157)$$

The remaining HP constraint used in the robust optimization formulation is identical to that of the deterministic model and can be found in Equations (3.33) to (3.36) and (3.40) to (3.42).

Table 3.27 presents the HP variables.

Table 3.27. Variables for HP constraints

Variable	Description
q_t^O, z_t^O	Dual variables for outside temperature
γ_t^O	Auxiliary variable for outside temperature

Table 3.28 presents the HP parameters.

Table 3.28. Parameters for HP constraints

Variable	Description
Γ_t^O	Outside temperature robust control parameter
U_t^O	Outside temperature uncertainty set

3.4.4.3 - Energy storage system constraints

The ESS constraints used in the robust optimization formulation are identical to those of the deterministic model and can be found in Equation (3.43) to (3.58).

3.4.4.4 - Combined heat and power constraints

In the robust optimization model, the formulation of the CHPs constraints includes an uncertain parameter represented by an uncertainty set: the industrial load.

$$P_{j,t}^{CHP,H} + P_{j,t}^{TES,-} = P_{j,t}^{load,CHP,forecast} + q_t^{CHP} + \Gamma_t^{CHP} \cdot z_t^{CHP}, \quad \forall j \in J, t \in T \quad (3.158)$$

$$\Gamma_t^{CHP} \cdot z_t^{CHP} + q_t^{CHP} \geq (u_t^{CHP})\gamma_t^{CHP}, \quad \forall t \in T \quad (3.159)$$

$$z_t^{CHP}, q_t^{CHP} \geq 0, \quad \forall t \in T \quad (3.160)$$

$$\gamma_t^{CHP} \geq 1, \quad \forall t \in T \quad (3.161)$$

The remaining CHP constraints used in the robust optimization formulation are identical to those of the deterministic model and can be found in Equation (3.59) to (3.69).

Table 3.29 presents the CHP variables.

Table 3.29. Variables for CHP constraints

Variable	Description
q_t^{CHP}, z_t^{CHP}	Dual variables for industrial load
γ_t^{CHP}	Auxiliary variable for industrial load

Table 3.30 presents the CHP parameters.

Table 3.30. Parameters for CHP constraints

Variable	Description
Γ_t^{CHP}	Industrial load robust control parameter
u_t^{CHP}	Industrial load uncertainty set

3.4.4.5 - Thermal energy storage constraints

The TES constraints used in the robust optimization formulation are identical to those of the deterministic model and can be found in Equation (3.70) to (3.81).

Chapter 4

Case study

This chapter presents the case study used to evaluate the methodology developed in the previous chapter. The analysis was performed for a week. It describes the characteristics of the network considered, the DMERs, the electricity and gas markets, and the buildings, weather and inflexible load data.

4.1 - Case studies

The methodology developed was evaluated considering three main characteristics: the way the algorithm deals with uncertainty (stochastic vs deterministic vs robust optimization), the use of TES, and the participation in secondary reserves. The following scenarios were considered:

- A-real - the algorithm uses a deterministic formulation using real values, with TES and participation in reserves.
- A-forecast – the algorithm uses a deterministic formulation using forecasts, with TES and participation in reserves.
- B – the algorithm uses a stochastic formulation, with TES and participation in reserves.
- B-NTES – the algorithm considers a stochastic formulation, without TES and with participation in reserves.
- B-NRES - the algorithm considers a stochastic formulation, with TES and without participation in reserves.
- C- the algorithm uses a robust optimization formulation, with TES and participation in reserves

The Table 4.1 presents all the case studies considered:

Table 4.1. Case studies

Cases	A-real	A-forecast	B	B-NTES	B-NRES	C
Stochastic	No	No	Yes	Yes	Yes	No
Deterministic	Yes	Yes	No	No	No	No
Robust Optimization	No	No	No	No	No	Yes
Thermal Storage	Yes	Yes	Yes	No	Yes	Yes
Secondary market participation	Yes	Yes	Yes	Yes	No	Yes

4.2 - Network and DMER data

The industrial hub under study is the Sonae industrial hub, located in Maia. The internal network of the hub was not considered in the study and was instead represented as a single node. The industrial hub includes a set of DMERs, which are: PV systems, HPs, a CHP, an ESS, and a TES. Additionally, the hub has two types of energy loads: electrical load and thermal load.

All DMERs are interconnected through their respective networks. The PVs, ESSs, HPs, CHP, and TES are connected to the electrical network. The CHP is connected to the gas network. The TES, HPs, and CHP are also connected to the thermal network. The electrical load is supplied by the PV generation, the ESS, the CHP produced electricity or directly from the electrical grid.

The heat produced by the HPs is used to meet the thermal demand of the hub's buildings, mainly the office areas. In contrast, the heat produced by the TES and the CHP is used to supply the hub's industrial thermal load.

Figure 4.1 illustrates the schematic representation of the industrial hub and the interconnection of its components.

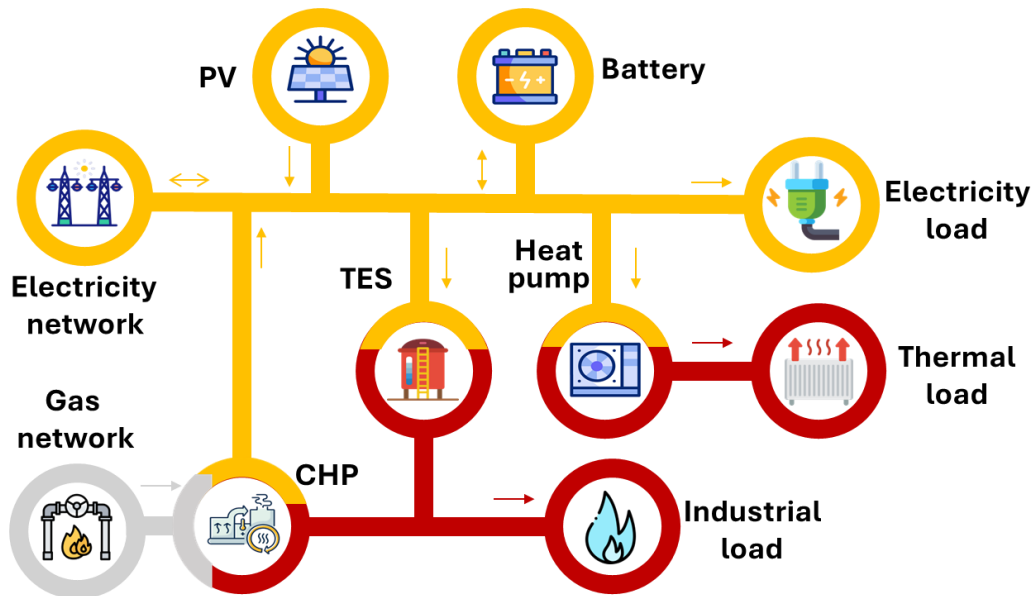


Figure 4.1. Industrial hub energy scheme.

The DMER data is the following: The PV peak power $\overline{P^{PV}}$ is 1500 kW. The HPs parameters are 850 kW of maximum production $\overline{P^{HP}}$ and 3.4 of COP. The CHP as 10MW of maximum gas power $\overline{P^{CHP,G}}$, 0.35 electric efficiency $\eta_j^{CHP,E}$, 0.45 of heat efficiency $\eta^{CHP,H}$ and a participation factor μ^{CHP} of 1/3. The ESS parameters are 100 kW of maximum power $\overline{P^{Sto,E}}$, 0.9 of charge efficiency $\eta^{Sto,E}$ and 300kWh of capacity $\overline{SOC^{Sto,E}}$. For the TES the charge efficiency η_j^{TES} is 0.9, the maximum power $P^{TES,E}$ is 600 kW, and the capacity $\overline{SOC^{TES,H}}$, is 1000 kWh.

Table 4.2 presents the DMERS characteristics.

Table 4.2. DMERs characteristics

Resource	Efficiency	Maximum Power (kW)	Capacity (kWh)	Discharging rate (%)
PV	-	1500	-	-
HP	3.4	850	-	-
CHP	0.35 (electricity) 0.45 (heat)	10000	-	-
ESS	-	100	300	-
TES	0.9	600	1000	0.01

4.3 - Market data

In this section the electricity and natural gas market data is presented. The data is all fixed and the data for one market week was directly taken from the Portuguese TSO website, REN [44]. The data refers to the period from December 14 to 21, 2024.

The data retrieved from the DA market includes energy price λ_t^E and positive $\lambda_t^{E,+}$ and negative $\lambda_t^{E,-}$ imbalance prices, as shown in Figure 4.2 to Figure 4.6 respectively.

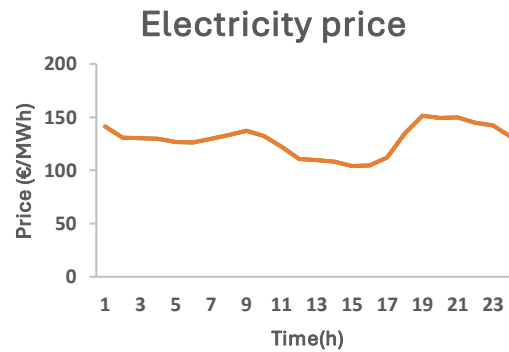


Figure 4.2. Electric energy daily price.

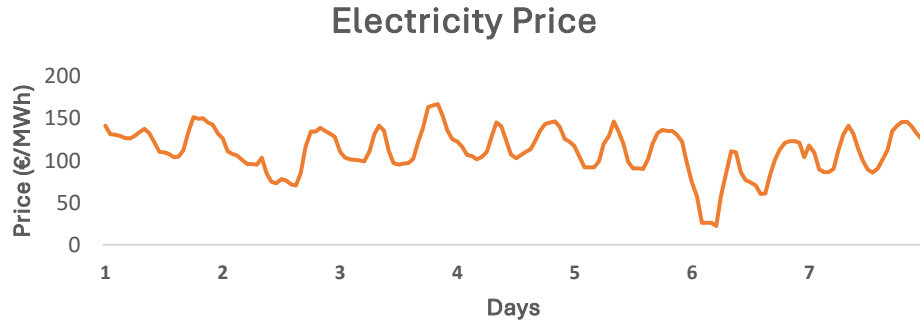


Figure 4.3. Electric energy weekly price.

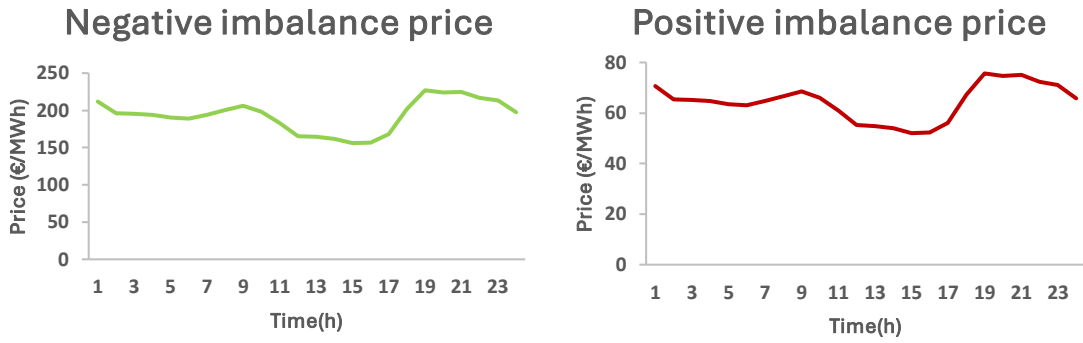


Figure 4.4. Energy positive and negative imbalance price for a day

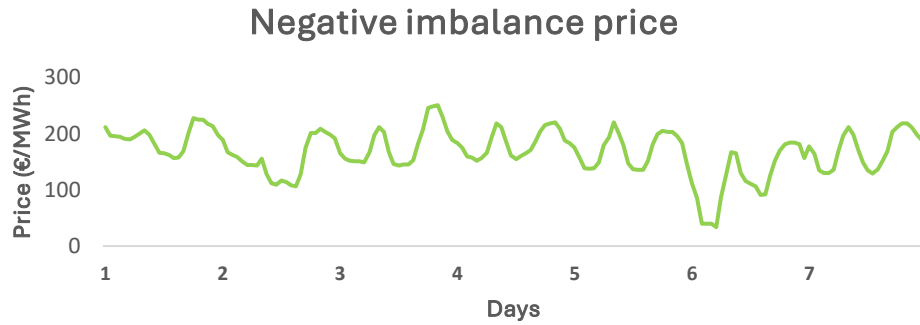


Figure 4.5. Negative energy imbalance weekly price

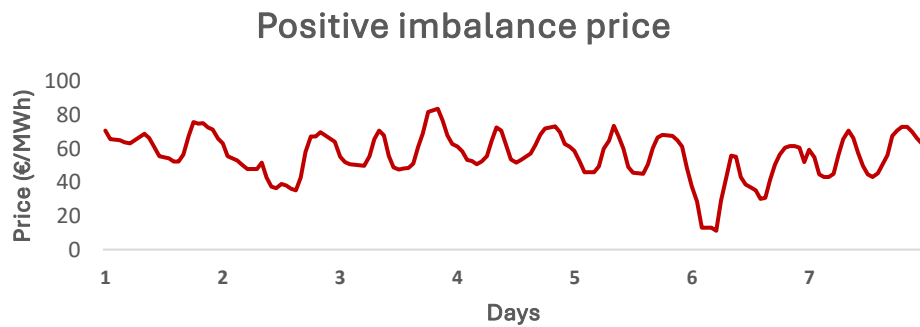


Figure 4.6. Positive energy imbalance weekly price

In the secondary reserve market, the data includes the secondary reserve price λ_t^B , the not supplied band price $\lambda_t^{B,-}$, and the upward ϕ_t^U , and downward ϕ_t^D band activation ratios, which are

calculated as the ratio between activated and contracted reserves. This data is represented in Figure 4.7 to Figure 4.10.

Secondary reserve price

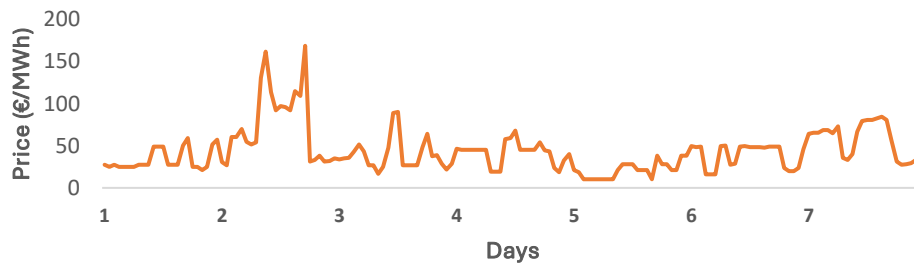


Figure 4.7. Secondary reserve weekly price

Band not supplied price

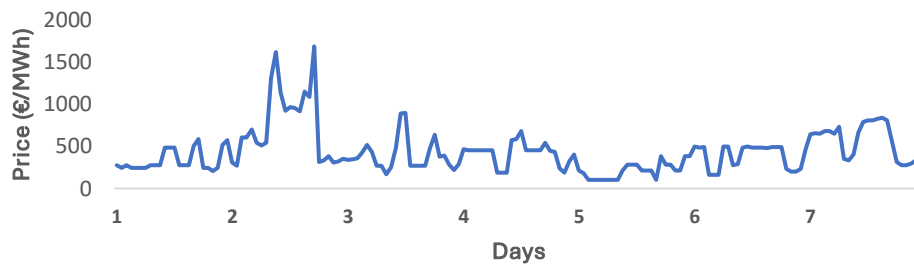


Figure 4.8. Band not supplied weekly price

Upward band activation ratio

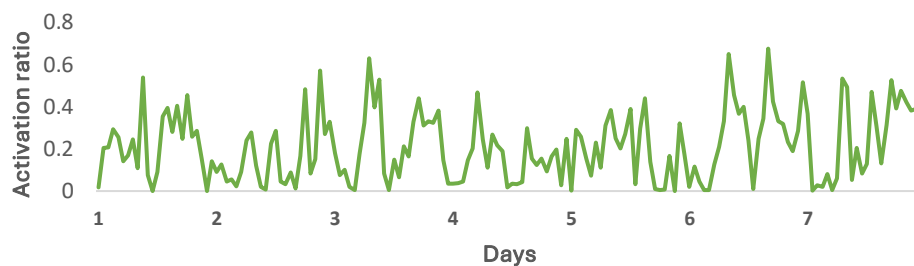


Figure 4.9. Upward band activation ratio

Downward band activation ratio

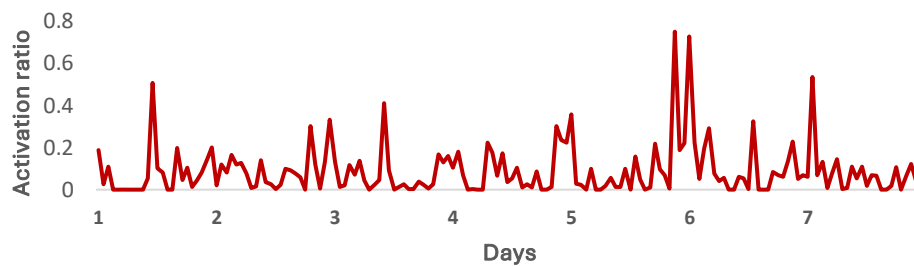


Figure 4.10. Downward band activation ratio

Additionally, the market data includes the upward $\lambda_t^{U,E}$ and downward $\lambda_t^{D,E}$ tertiary reserve prices, as shown in Figure 4.11 and Figure 4.12.

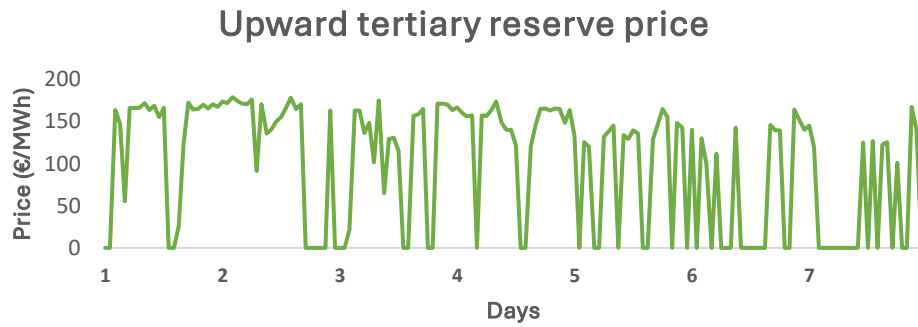


Figure 4.11. Upward tertiary reserve weekly price

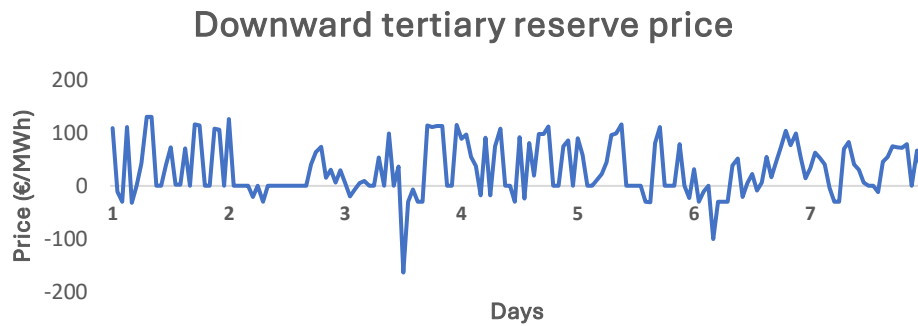


Figure 4.12. Downward tertiary reserve weekly price

As for the natural gas market data, it includes the daily market price λ_t^G , the positive $\lambda_t^{G,+}$ and negative $\lambda_t^{G,-}$ gas imbalance price, represented in Figure 4.13 to Figure 4.15, respectively. The value for one week was taken from the MIBGAS website [45].

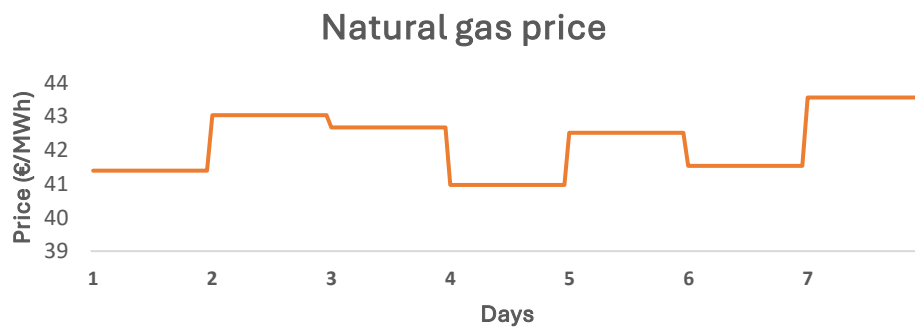


Figure 4.13. Natural gas weekly price

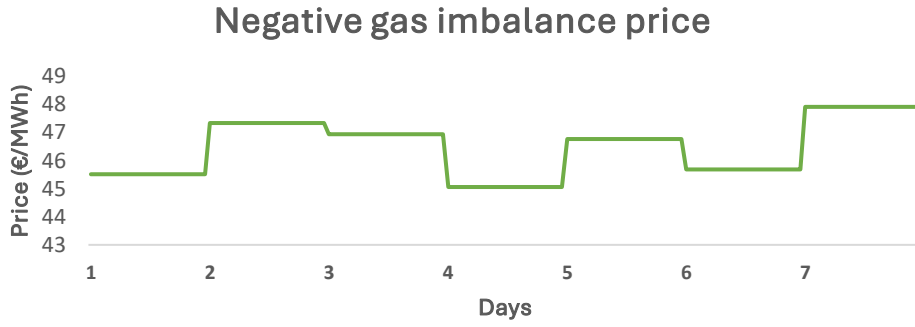


Figure 4.14. Negative gas imbalance weekly price

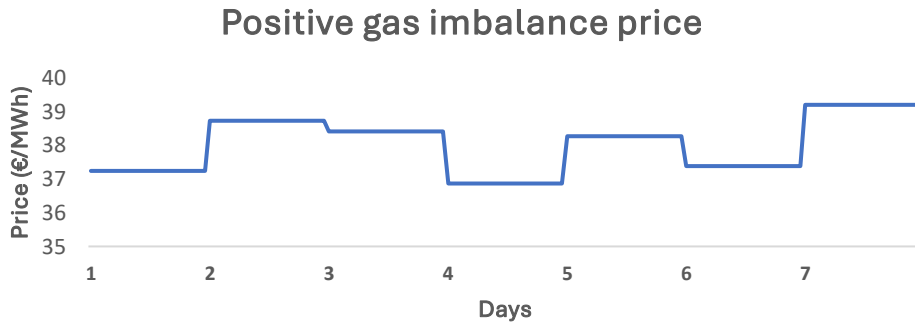


Figure 4.15. Positive gas imbalance weekly price

4.4 - Buildings, weather and inflexible load data

This section presents the building data, as well as the weather data and inflexible load profiles. The latter two are not fixed and take on different values in the stochastic and robust optimization cases. Therefore, the method used to obtain these values is also explained.

The buildings connected to the HPs have a thermal constant β of 0.9 and a thermal resistance R of 0.081°C/kWh. The comfort range for the interior building temperature was set to be between 18°C and 21°C.

To optimize the operation of the industrial hub using a stochastic formulation, a set of ten scenarios was generated to represent the uncertainties in electrical load, industrial load, outdoor temperature, and photovoltaic production. It is assumed that all scenarios have the same probability of occurrence, 10%. Although the scenario generation process is beyond the scope of this work, the scenarios were created using the Gaussian copula method based on probabilistic forecasts. These scenarios also served as the foundation for constructing the uncertainty sets used in the robust optimization formulation. Figure 4.16 and Figure 4.17 present the daily and weekly actual, forecasted and ten generated scenarios of electrical load, respectively.

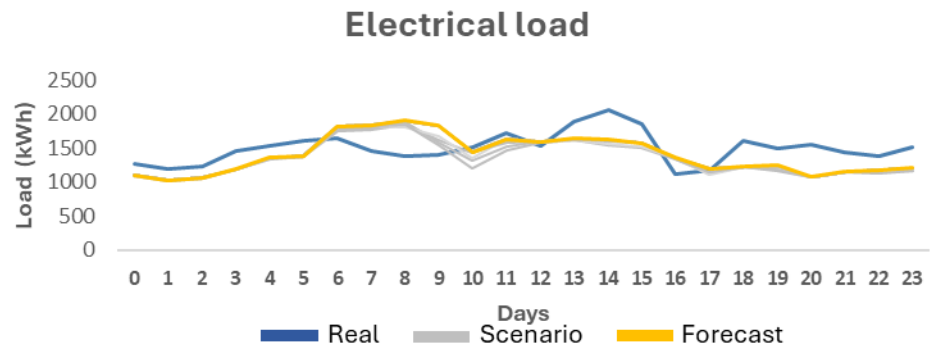


Figure 4.16. Daily electrical profile: real, scenario and forecast

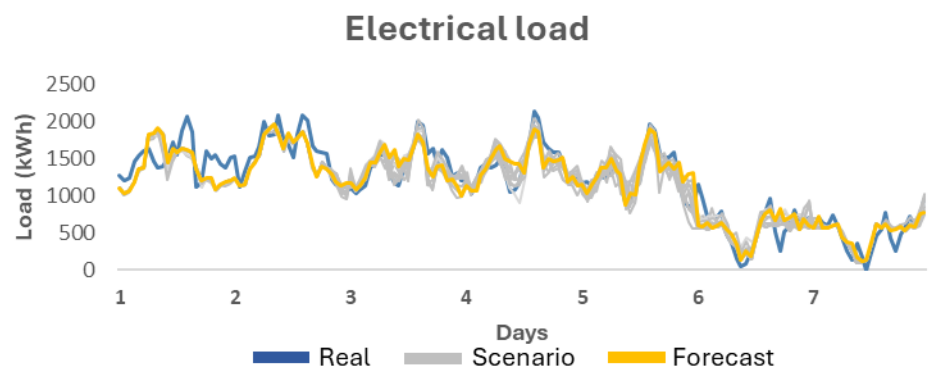


Figure 4.17. Weekly electrical load profile: real, scenario and forecast

Figure 4.18 and Figure 4.19 present the daily and weekly actual, forecasted and ten generated scenarios of PV generation, respectively.

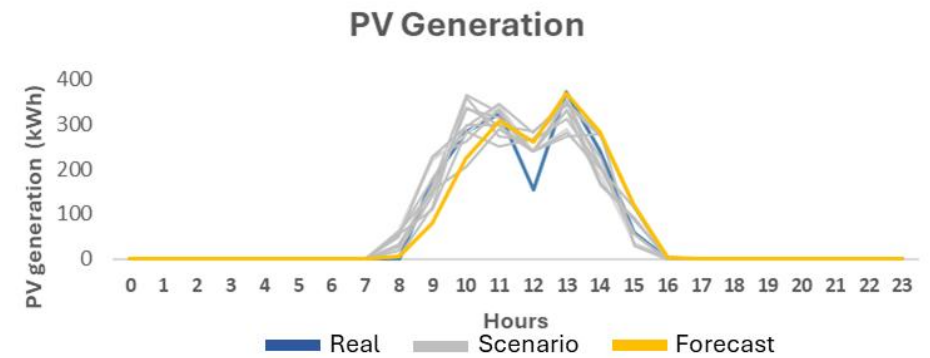


Figure 4.18. Daily PV generation profile: real, scenario and forecast

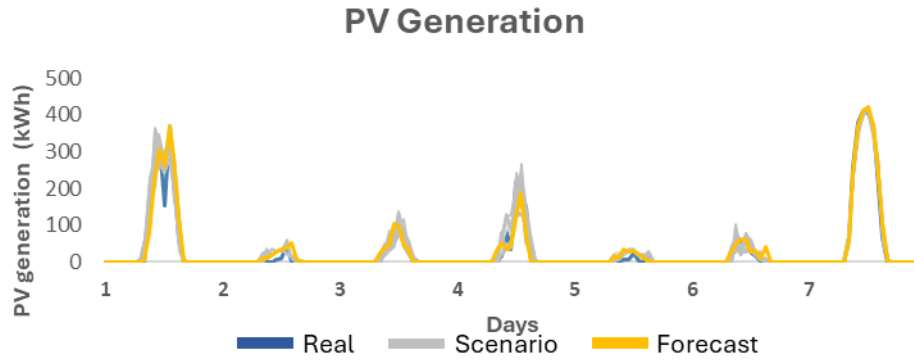


Figure 4.19. Weekly PV generation profile: real, scenario and forecast

Figure 4.20 and Figure 4.21 present the daily and weekly actual, forecasted and ten generated scenarios of outside temperature, respectively.

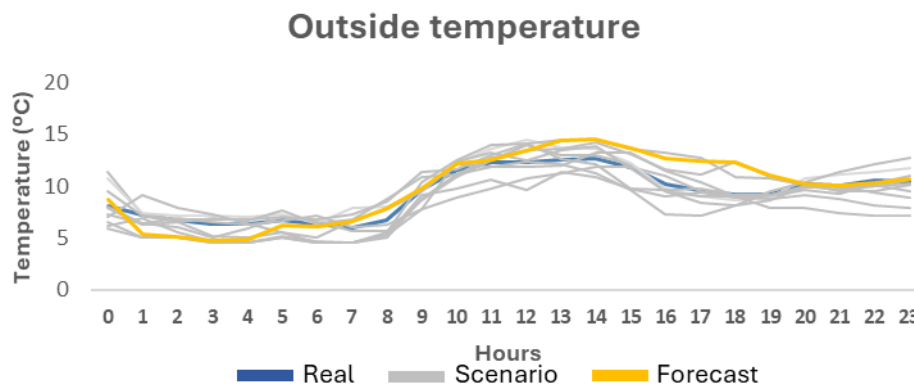


Figure 4.20. Daily outside temperature profile: real, scenario and forecast

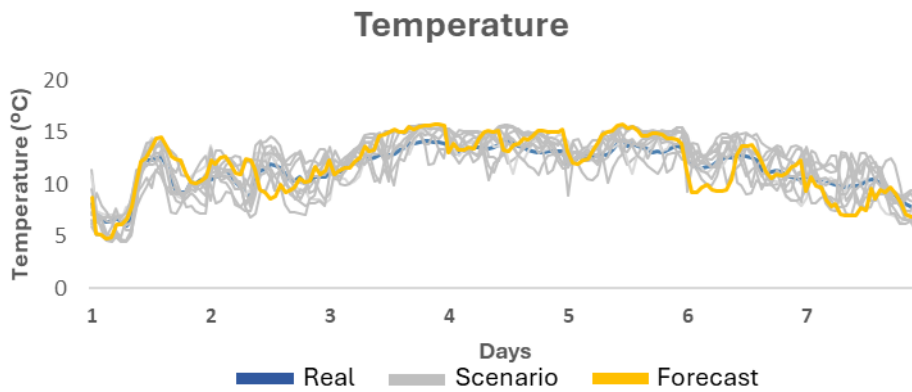


Figure 4.21. Weekly outside temperature profile: real, scenario and forecast

Figure 4.22 and Figure 4.23 present the daily and weekly actual, forecasted and ten generated scenarios of industrial load, respectively.

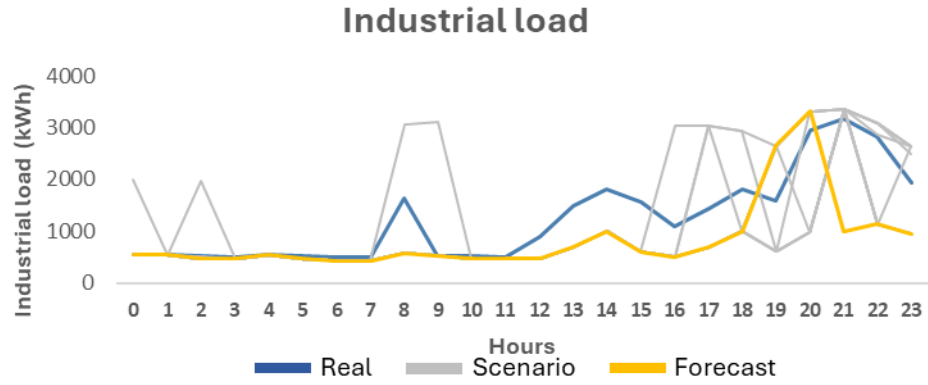


Figure 4.22. Daily industrial load profile: real, scenario and forecast

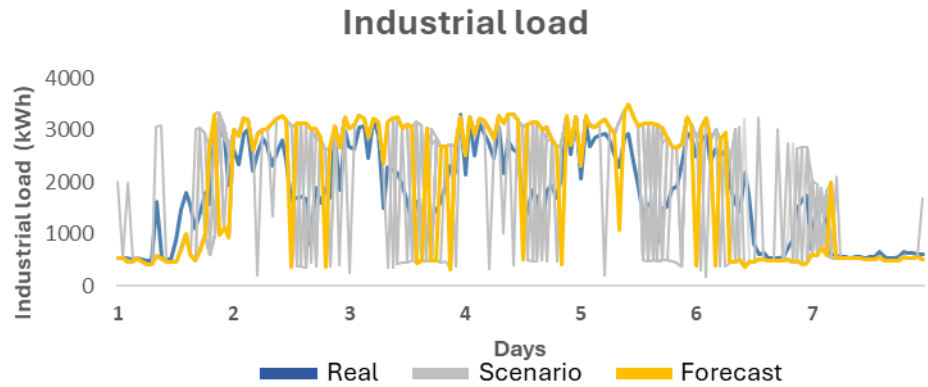


Figure 4.23. Weekly industrial load profile: real, scenario and forecast

In the robust optimization modelling the same data is subject to uncertainty. To incorporate these variables within the context of robust optimization, it is necessary to create an uncertainty set for each of them, defining the limits of variation each variable may assume.

The time interval used for market bidding computation and for defining the production schedule of energy resources was one hour. Therefore, for each hour of the day, the uncertain parameters are associated with an hourly uncertainty set. To construct the uncertainty sets, a quantile-based approach was adopted. Based on the 10 scenarios and using the python library scikit-learn, the non-parametric Conditional Kernel Estimator method was used to estimate the conditional probability distribution of the parameters associated with the scenarios.

With the conditional probability distributions estimated, the extreme quantiles 10% and 90% were calculated for each hour. The uncertainty set was then defined as the difference between the 90% and 10% quantiles. Figure 4.24 to Figure 4.27 present the created uncertainty sets.

The conservativeness of the robust optimization model can be adjusted by manipulating the uncertainty sets. For a more conservative model, the previously calculated full uncertainty set is used. Conversely, for a less conservative modelling approach, scaled subsets of the original uncertainty set may be employed.

Electrical load uncertainty set

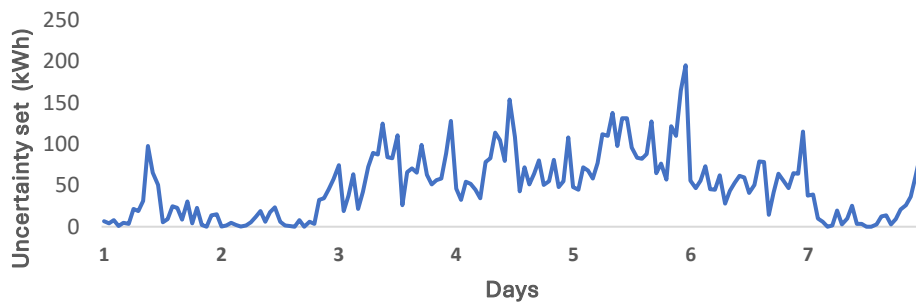


Figure 4.24. Weekly electrical load uncertainty set

PV generation uncertainty set

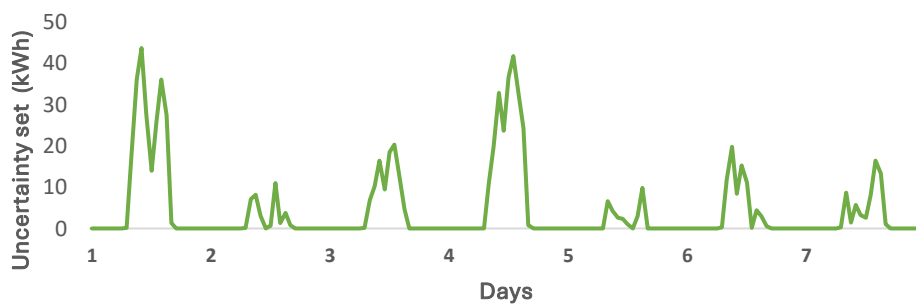


Figure 4.25. Weekly PV generation uncertainty set

Outside temperature uncertainty set

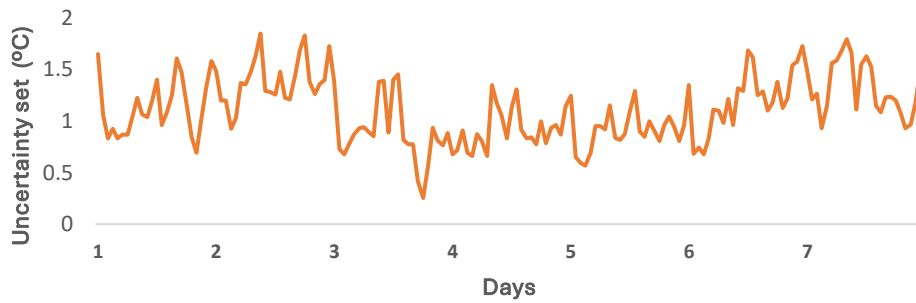


Figure 4.26. Weekly outside temperature uncertainty set

Industrial load uncertainty set

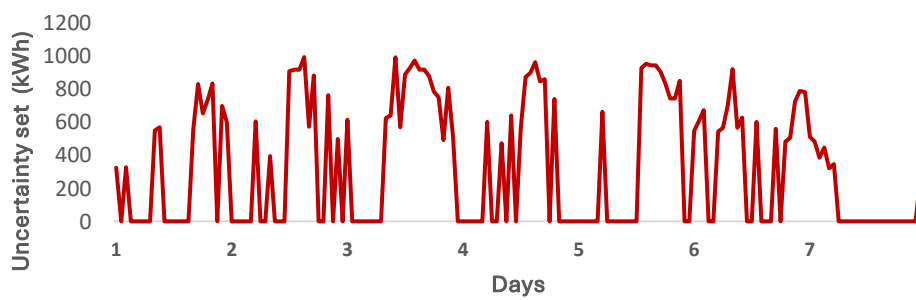


Figure 4.27. Weekly industrial load uncertainty set

Chapter 5

Results

This section presents a comparison and discussion of the different optimization methodologies and the impact that TES and participation in the reserve market have on the operation of the industrial hub. For each of the above-mentioned cases, the results of the bids submitted by the aggregator to the market are analysed, including the economic performance. Furthermore, to better characterize the hubs operation an hourly analysis will be conducted for a day focusing on energy resource operation.

5.1 - Optimization methodologies analysis

In this subsection a comparison of the different optimization methodologies is made using case studies A-Real, A-Forecast, B and C.

5.1.1 - Multi-energy bids

Table 5.1 presents the total number of bids submitted by the aggregator in the DA market for electricity, gas, upward, and downward reserve bands for the four case studies. Figure 5.1 shows the daily bids submitted for the same four cases.

Since the optimization strategy is the same for cases A-real and A-forecast, the differences between the result in Table 5.1 are from varying industrial load profiles.

In the DA electricity market, the robust optimization case (Case C) shows significantly higher supply bids compared to the other cases. This is particularly noticeable in Figure 5.1 on days 1, 6, and 7 of the week. These days correspond to periods of lower industrial load, with especially large differences on days 1 and 7. On these days, due to the way uncertainty sets are constructed, the uncertain industrial load values in Case C can exceed the fixed industrial load. As a result, Case C assumes much higher industrial load values than the other case studies. The increased gas generation to meet this assumed load leads to higher electricity production. Since this

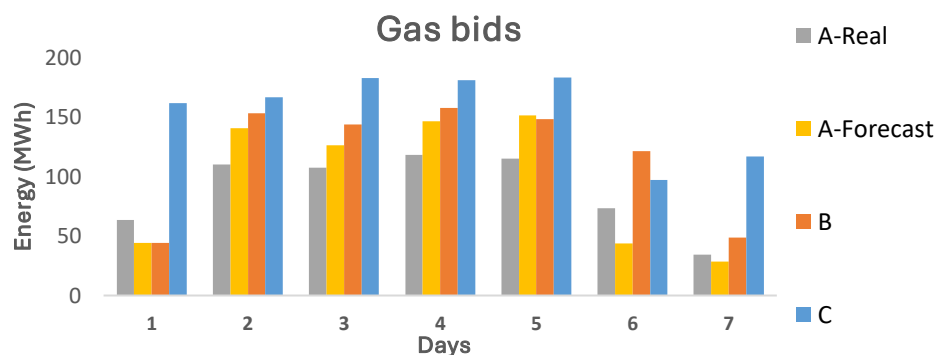
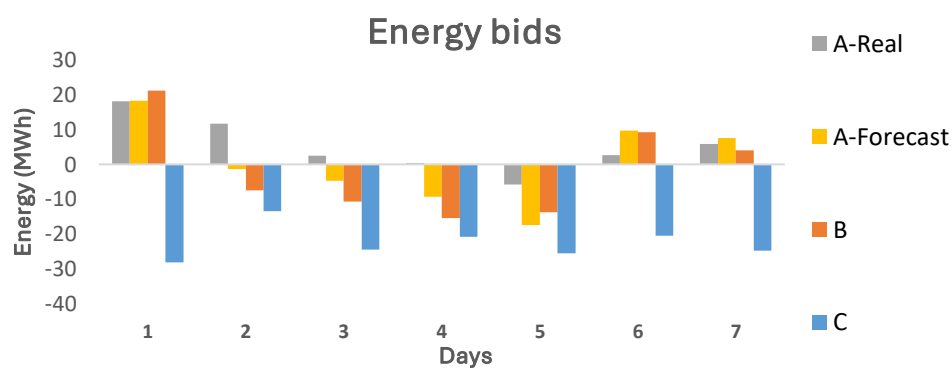
coincides with lower actual electricity demand, the excess electricity is offered as supply bids in the DA market.

Table 5.1 shows that both Case B and Case C show significantly higher natural gas bids compared to the other two cases. In Case B, this is due to the higher industrial load values in the scenarios, while in Case B it is, as explained, a result from the high-load scenarios defined in the uncertainty sets.

Regarding reserve band bids, all four strategies show similar behaviour. However, it's worth noting that Case B includes penalties for deviations between DA band offers and actual realizations. Consequently, Case B submits the lowest amount of reserve band bids (193.96) in the DA market.

Table 5.1. Total weekly bids for Case A-Real, A-Forecast, B and C

Bids (MW)	A-Real	A-Forecast		B		C	
Electricity supply bids	37.8	57.8	+53%	64.02	+69%	134.89	+257%
Electricity demand bids	73.1	60.4	-17%	51.09	-30%	22.94	-69%
Gas bids	621	681	+10%	816.71	+31%	1088.13	+75%
Band bids	214.5	202.2	-6%	193.96	-10%	205.44	-4%



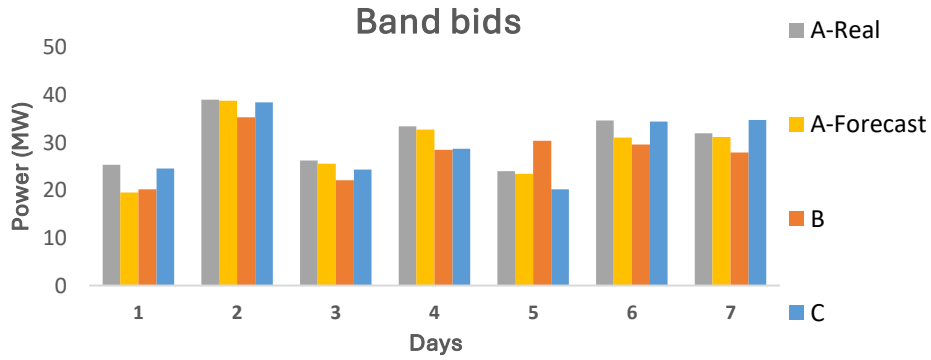


Figure 5.1. Aggregator's daily bids

Figure 5.2 shows the individual contribution of each DER to upward reserve. The data used in the figure is taken only from Case A, but since the characteristics of the resources remain unchanged across cases, the analysis presented here can be extrapolated to other cases.

From the figure, it can be seen that the CHP is the resource with the highest contribution to upward reserve bids. This is due to the fact that it is the largest resource. The CHP supplies both industrial and electrical loads, and when these loads are met and there is still production capacity available, this surplus is used for upward reserve. The HP and TES are the second and third DERs with the highest upward reserve contributions, respectively, although their values are considerably lower. The significant participation of TES in the upward reserve has a notable positive economic impact, which will be further explored in the following section.

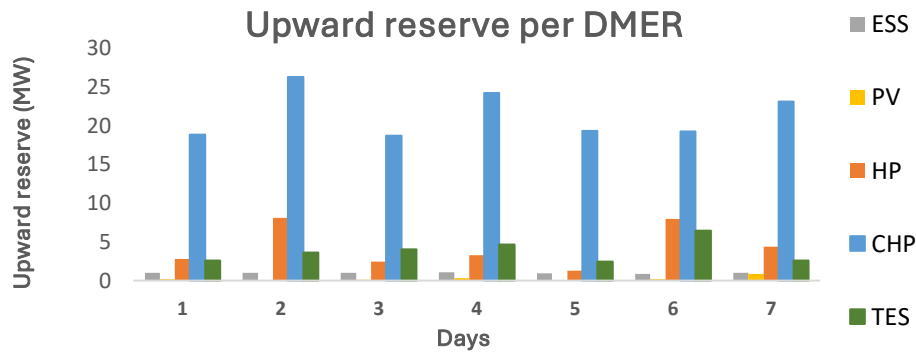


Figure 5.2. Weekly upward reserve per DMER

5.1.2 - Economic performance analysis

Table 5.2 presents the overall economic performance of the four case studies during the week analysed. Figure 5.3 represents the daily economic performance for the four case studies.

Due to the previously explained differences in the DA market participation for Case C, there was an increase in gas demand bids and electricity supply bids. This case study incurred a higher natural gas cost (€19.755) more than the real situation. However, the additional electricity supply bids in the DA market almost fully compensated for the increased gas cost, generating an additional €18.400 in revenue.

Case B shows the highest cost of participation in the DA market (€13.335), mainly due to lower revenue from reserve band sales and especially the high gas costs. Similarly, it also has the highest total energy market participation cost. Nevertheless, the revenue from reserve band mobilization and gas imbalance settlements helped reduce the total cost by 15%.

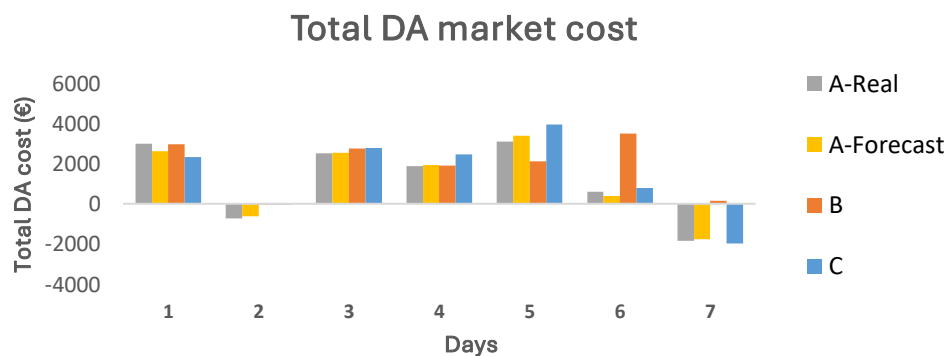
In Figure 5.3, days 2, 6, and 7 show lower total operating costs for the industrial hub across all four case studies when compared to the other days of the week.

The reduced cost on Day 2 can be explained by the fact that, as shown in Figure 5.3 in the “Income from selling band” graph, this day stands out across all case studies as the one with the highest income from selling band in the DA market. This increase in income is due to an exceptionally high secondary reserve band price on that day compared to the rest of the week.

For Days 6 and 7, the reduced operating costs can be attributed to significantly lower electricity and thermal load values compared to other days. When comparing Days 6 and 7 directly, the lower cost on Day 7 is also due to much higher photovoltaic production, which decreases energy demand bids and allows for increased downward bids, thus further reducing overall costs.

Table 5.2. Total weekly economic performance analysis: Case A-Real, A-Forecast, B and C

Economic performance (€)	A-Real		A-Forecast		B		C	
Electricity cost	3611	18	-100%	-1885	-152%	-14796	-510%	
Gas cost	26182	28756	10%	34456	32%	45937	75%	
Band revenue	21285	20271	-5%	19234	-10%	20831	-2%	
Total DA cost	8509	8503	-0.10%	13335	57%	10310	21%	
Band mobilization revenue	2516	2176	-14%	2290	-9%	2541	1%	
Band activation gas imbalance cost	2359	2301	-2%	2610	11%	1817	-23%	
Expected electricity imbalance cost	-	-	-	1610	-	-	-	
Expected gas imbalance cost	-	-	-	-3923	-	-	-	
Cost of band not supplied	-	-	-	0	-	-	-	
Forecasted Total cost	8353	8684	4%	11342	36%	9584	15%	



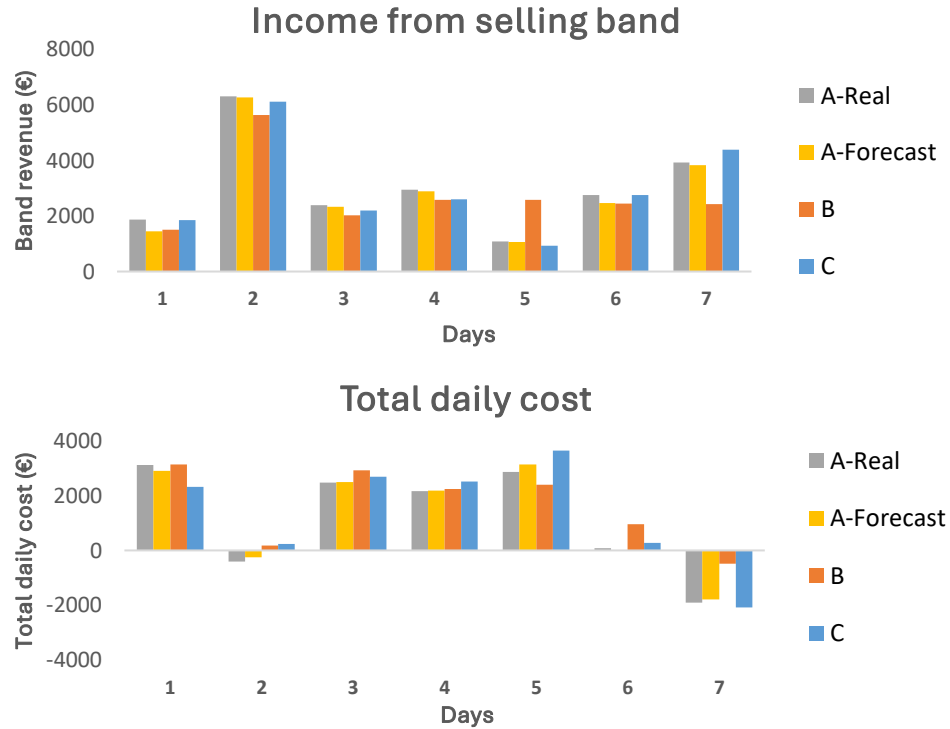


Figure 5.3. Economic performance graphical analysis: Case A-Real, A-forecast, B and C

5.2 - Impact of participating in secondary reserve

In this section the impact of the aggregator participation in the secondary reserve market is studied for this purpose study cases B and B-NRES are compared.

5.2.1 - Multi-energy bids

Figure 5.4 represents the daily energy bids for cases B and B-NRES. Both cases exhibit similar behaviour over the 7 days in the DA market in terms of energy and gas bids, with a higher number of electricity supply bids and gas demand bids on days with higher industrial load. Conversely, there are more demand bids on days with lower industrial load. Table 5.3 represents the weekly energy bids for cases B and B-NRES. In Table 5.3 it is visible that the total number of supply bids is higher in case B-NRES. This is because, unlike case B, B-NRES does not participate in the reserve market and therefore submits all excess produced energy as supply bids in the DA market. In contrast, case B splits the excess energy between supply bids and band bids. For the same reason, even though industrial load is the same in both cases, case B submits more gas bids in the DA market. This occurs because there are situations where purchasing gas is advantageous for generating electricity to be sold later as band bids in the DA market or to ensure fulfilment of DA commitments.

Table 5.3. Total weekly energy bids for cases B and B-NRES

Bids (MW)	B	B-NRES	
Electricity supply bids	64.02	90.87	+42%
Electricity demand bids	51.09	32.51	-36%
Gas bids	816.71	805.73	-1%
Band bids	193.96	-	-

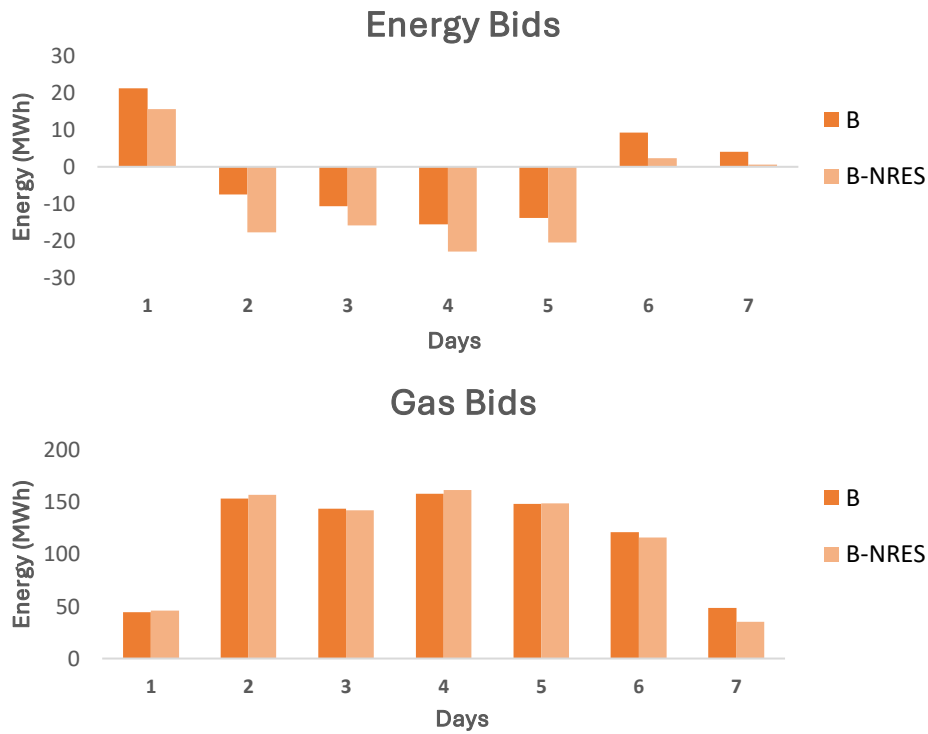


Figure 5.4. Daily energy bids for cases B and B-NRES

When comparing the two cases, it is also relevant to assess the operation of the TES to evaluate its involvement in reserves. The results of this comparison are shown in Figure 5.5, where it can be observed that on 5 out of the 7 days of the week, the TES is more heavily loaded in Case B than in Case B-NRES. On the remaining two days, although the TES is more loaded in Case B-NRES, the difference is not significant. Over the entire week, the total difference between the two cases is 4.34 MW more loaded in Case B. This result indicates that the TES is a DMER that actively contributes to the provision of reserves.

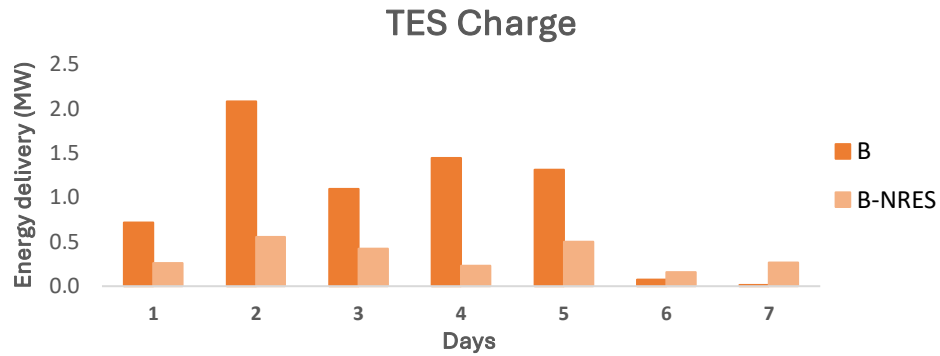


Figure 5.5. Comparison of TES participation for cases B and B-NRES

5.2.2 - Economic performance analysis

In Table 5.4, since B-NRES submitted more electricity supply bids in the DA market and fewer gas demand bids, its electricity and gas costs are significantly lower compared to Case B, €4.777 and €439, respectively.

Furthermore, selling reserve capacity in the DA market reduces operational costs in the DA market by 51%. Additionally, activating the reserves submitted further decreases the overall operational cost from €13.335 to €11.342, increasing the total cost reduction to 56%.

For both cases there is high revenue values coming from the expected gas imbalances. This revenue arises from the difference between gas bids placed in the DA market and the actual gas consumption. As represented in Figure 5.6 the main driver is the industrial load profile on day 6, which shows a sudden drop in thermal load. This abrupt change leads to discrepancies in the forecasted scenarios, resulting in positive gas imbalances that, from a cost perspective, translate into revenue.

To conclude the analysis, it should be noted that the revenues from participating in the reserves are subject to price fluctuations and vary throughout the year, so their return may not always be high. However, participation in this type of market is expected to be consistently advantageous, as demonstrated in this case.

It should also be noted that resource sizing has a significant impact on the benefits related to participation in the secondary reserves market. In this case study, the high revenue from the secondary reserves market is also due to the occurrence of days with very high thermal load peaks (industrial load). During those times, the CHP unit was producing excess electricity relative to the system's electrical demand, which could then be used to submit bids in the reserves market.

The high thermal load also led to a more generously sized CHP unit, which, combined with the factors mentioned above and the fact that it was the main resource submitting bids, further contributed to the high economic benefit.

Table 5.4. Economic performance analysis: Case B and B-NRES

Economic performance (€)	B	B-NRES	
Electricity cost	-1885	-6662	+253%
Gas cost	34456	33977	-1%
Band revenue	19234	-	-
Total DA cost	13335	27314	+105%
Band mobilization revenue	2290	-	-
Band activation gas imbalance cost	2610	-	-
Expected electricity imbalance cost	1610	1975	+23%
Expected gas imbalance cost	-3923	-2966	-24%
Cost of band not supplied	0	-	-
Forecasted Total cost	11342	26323	+132%

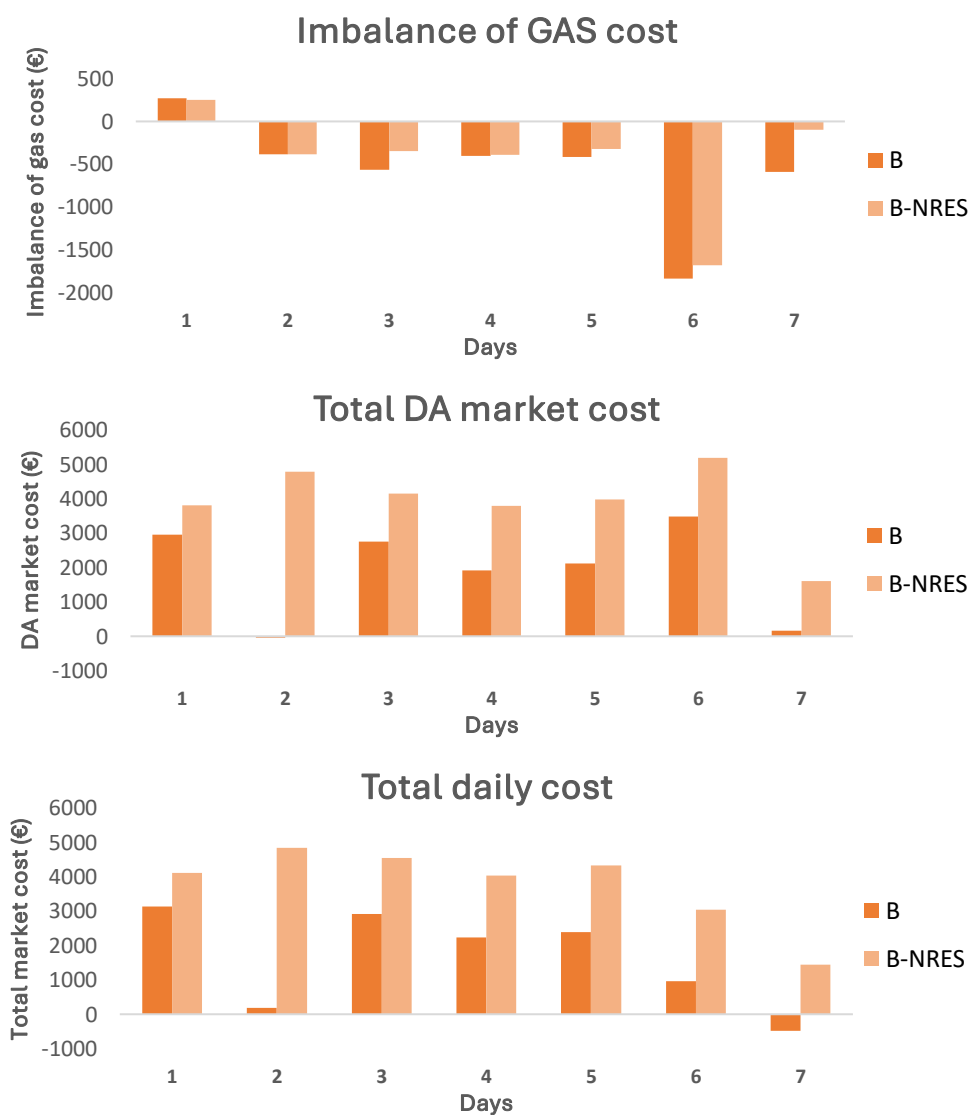


Figure 5.6. Economic performance graphical analysis: Case B and B-NRES

5.3 - Thermal storage impact

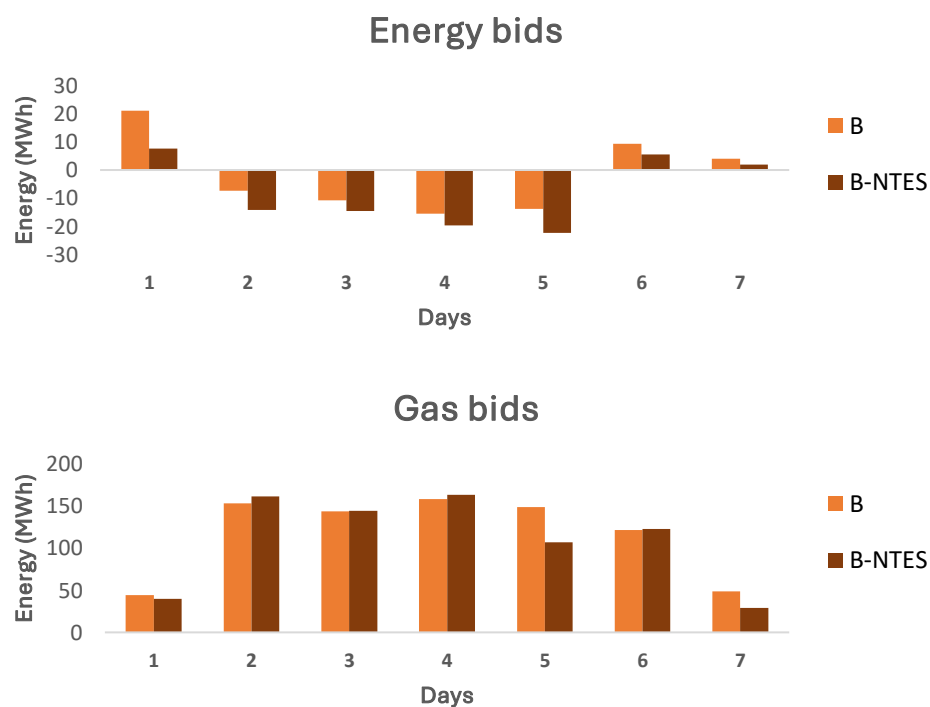
The impact of TES is analysed based on its influence on participation in the DA market and its performance in meeting requirements made during the DA phase. For this purpose, study cases B and B-NTES are compared.

5.3.1 - Multi-energy bids

In Figure 5.7 it is visible that both cases exhibit similar bid structures. However, the results in Table 5.5 indicate that with TES, electricity supply bids are 18% lower, while electricity demand bids are 70% higher. Additionally, both gas and reserve band bids increase with TES, by 7% and 12%, respectively. In Case B, the increase in reserve band bids is directly related to the enhanced capacity of TES to participate in the reserve market.

Table 5.5. Total weekly energy bids: Cases B and B-NTES

Bids (MW)	B	B-NTES	
Electricity supply bids	64.02	85.85	+34%
Electricity demand bids	51.09	29.91	-41%
Gas bids	816.71	765.79	-6%
Band bids	193.96	172.86	-11%



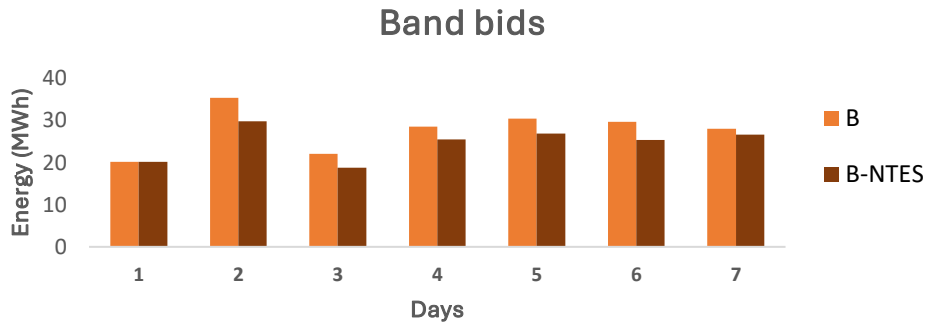


Figure 5.7. Weekly energy bids graphical representation: Case B and B-NTES

It is also important to analyse the contribution of the TES in ensuring the industrial load, as shown in Figure 5.8. As can be seen in the figure, the TES contribution never exceeds 10%. The days with higher industrial load correspond to the days with greater TES contribution to the heat supply (days 1, 2, 3, 4, and 5), while the days with lower load show a smaller TES contribution (days 6 and 7).

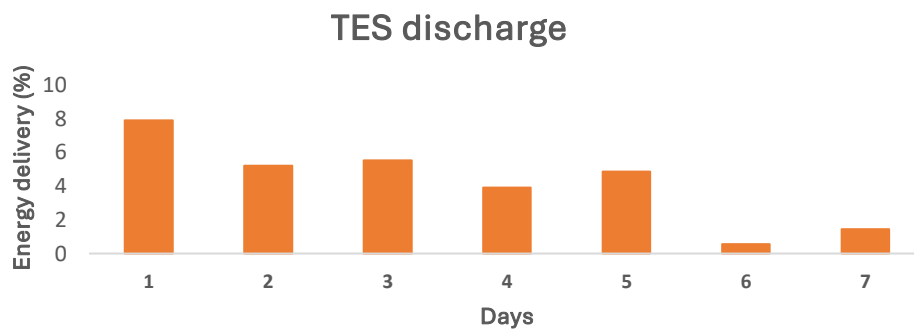


Figure 5.8. TES discharge to supply industrial load

5.3.2 - Economic performance

Table 5.6 presents the costs and revenues associated with market participation in the DA and reserve markets for the two cases. Case B-NTES shows a lower DA market participation cost compared to Case B (€8.798 vs. €13.335), primarily due to significantly lower electricity costs. This reduction is a result of Case B-NTES submitting a higher number of supply bids in the DA market.

However, despite the lower DA costs, the total market participation cost is higher in Case B-NTES (€13.515 vs. €11.342). This is mainly because Case B-NTES received lower band mobilization revenue, since it submitted fewer band bids, and incurred higher electricity and gas imbalance costs. The difference in imbalance costs is especially notable on Days 1 and 5, as shown in Figure 5.9. On these days, due to big changes in the load profile and the absence of TES, the aggregator was unable to complete the committed energy deliveries.

Table 5.6. Economic performance analysis: Case B and B-NTES

Economic performance (€)	B	B-NTES	
Electricity cost	-1885	-6669	+254%
Gas cost	34456	32273	-6%
Band revenue	19234	16806	-13%
Total DA cost	13335	8798	-34%
Band mobilization revenue	2290	1826	-20%
Band activation gas imbalance cost	2610	2826	+8%
Expected electricity imbalance cost	1610	4081	+153%
Expected gas imbalance cost	-3923	-367	-91%
Cost of band not supplied	0	2	-
Forecasted Total cost	11342	13515	+19%

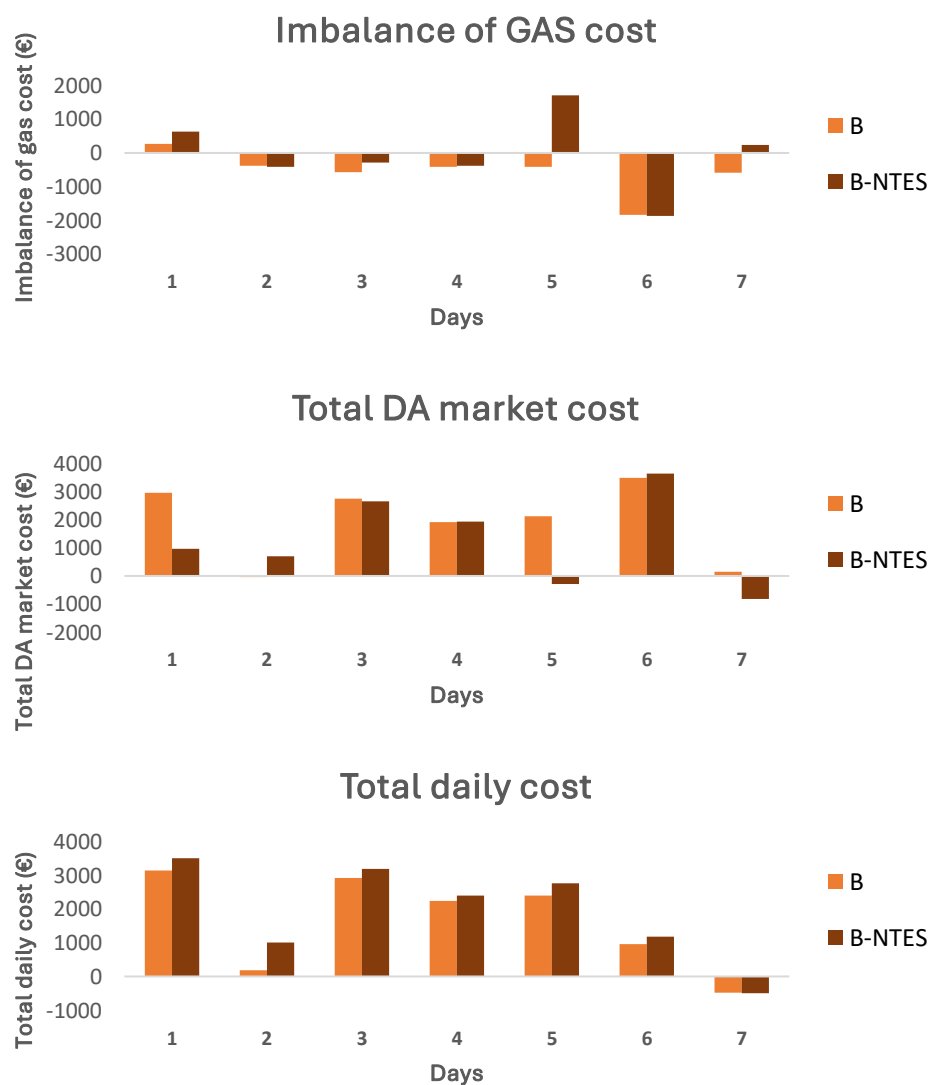


Figure 5.9. Economic performance graphical analysis: Case A and A-NTES

5.4 - Daily operation

This section analyses the daily operation, for the fourth day of the industrial hub using an hourly time resolution to better understand the individual behaviour of each DMER, focusing on their contribution to the bids submitted in the DA market and on meeting the hub's load requirements.

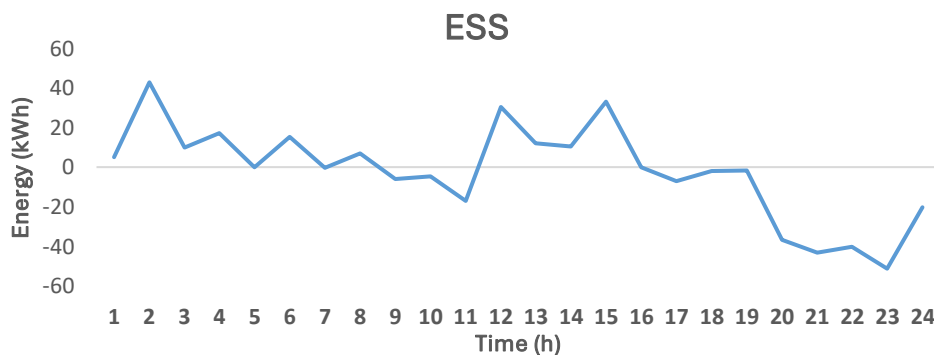
5.4.1 - DMERs multi-energy bids

As shown in Figure 5.10, the ESS alternates between consuming and injecting energy during most hours of the day. This behaviour occurs not only to help meet load requirements, but also because its charging/discharging availability is offered in the secondary reserve market. In the last four hours of the day, the submitted bids are for supply. This happens because the ESS is fully charged due to an excess of demand bids during the day, and equation (3.113) from the employed formulation imposes a constraint that the ESS's state of charge (SOC) must be equal at the beginning and end of the day.

The PV system only generates energy during daylight hours. On the selected day, the generation is relatively low during the expected peak hours, which is due to factors outside the scope of this work. During hours when PV generation does not match the predefined profile, the difference is submitted to the market as an upward secondary reserve bid. The PV also submits downward reserve bids during production hours.

The TES and CHP exclusively submit electricity and gas demand bids, respectively, throughout the day. The hours in which TES consumption is higher coincide with those of higher industrial load demand, thereby complementing the CHP to meet the load.

The output of the HPs is higher during colder hours (e.g., hours 4, 6, 7) or during periods with significant temperature variation (e.g., hours 11, 12, 13), to comply with the established temperature constraints.



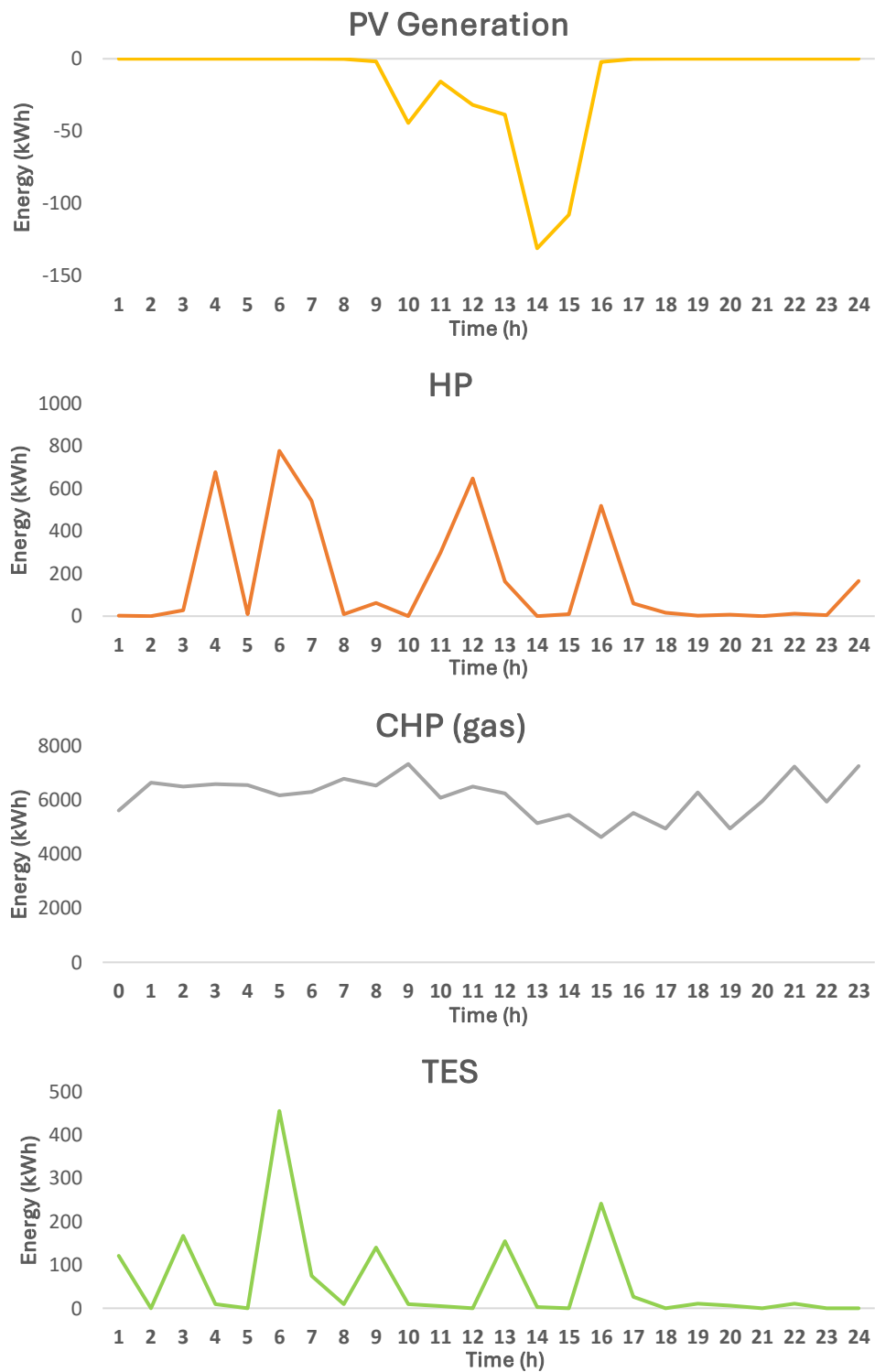


Figure 5.10. Daily energy bids per resource

5.5 - Discussion

This chapter presents different optimization strategies for industrial hubs participating in the DA electricity energy market, secondary reserve markets, and the gas market. The optimization

models define both the optimal operation of the hub's resources and the bids to be submitted to the DA markets.

The numerical results show that methodologies accounting for parameter uncertainty in the bidding process, namely, stochastic and robust optimization, lead to more conservative bids and higher operational costs compared to the deterministic approach. Furthermore, among the two uncertainty-based methods, the stochastic approach results in more conservative bids for both energy and reserves than robust optimization. This is because the stochastic method considers deviations between the energy and reserve bands sold in the DA market and the actual transacted quantities. In contrast, robust optimization only accounts for uncertainty in system parameters, not market-related uncertainties. This results in an 18% increase in operational costs.

Regarding participation in the secondary reserve market, numerical results show that this participation has a positive impact on the hub's operational costs. In fact, without participation in reserve markets, the system's operational costs more than doubled (increased by 132%). The main cost impact comes from the sale of reserve capacity in the DA market rather than the actual activation of the offers.

As for the impact of the TES on operations, while its effect is not as significant as that of reserve market participation, its absence still leads to substantial cost increases in the DA market by about 19%.

It should be noted that the true impact of either reserve market participation or TES can only be assessed by considering the activation phase, as this is when some penalties for energy deviations, which are not accounted for in the day-ahead market come into effect. Moreover, although there is a forecast in the day-ahead market, the actual activation of secondary reserves is very difficult to calculate, and the associated gains or losses can have a significant economic impact.

Chapter 6

Conclusion

This chapter presents the contributions, main findings of the dissertation and potential future work based on this research.

6.1 - Main contributions

The work developed in this dissertation contributes to the existing literature through the development of three optimization frameworks. Although different in nature, these frameworks share the common characteristic of being applicable by aggregators to participate in energy markets (electricity, gas, and secondary reserves), while considering market constraints and dispatch limitations associated with submitted bids.

Furthermore, the proposed frameworks characterize the operation of each DMER, considering its individual contribution to the bids submitted to the market. Among the DMERs, the participation of a thermal battery is considered, both for supplying industrial load and for participation in the energy markets, including the secondary reserve market, an aspect that remains underexplored in the existing literature.

The main distinctions between the three frameworks are as follows:

The deterministic framework employs a deterministic optimization methodology and does not consider uncertainties in the system parameters. All parameters are assumed to be fixed.

The stochastic framework accounts for the existence of uncertainty by modelling multiple scenarios with equal probability of occurrence. It considers deviations between the bids submitted to the DA market and their real-time realizations. These realizations are not actual observed values but forecasted estimates.

The robust framework also addresses uncertainty, but using uncertainty sets developed from the scenarios used in the stochastic model. This approach provides a more conservative decision-making process that ensures feasibility across a range of possible future conditions.

Based on the work conducted, a paper was published: A. Cunha, A. Coelho, F. Soares, "Stochastic Optimization of Industrial Hubs with Thermal Energy Storage and Reserves Provision," Powertech Conference, June 2025.

6.2 - Main findings

The analysis of the optimization frameworks showed that frameworks with lower complexity (those that did not consider uncertainties in the system parameters) resulted in more favorable economic outcomes regarding the system's operating cost. Nevertheless, the stochastic and robust frameworks, despite yielding worse results, represent the system's behavior more accurately.

From the analysis of the influence of the TES on system operation, it was concluded that its use offers advantages both operationally, by helping to reduce peak loads that the CHP unit must handle, thereby increasing system resilience, and economically, as the optimization of TES charging times contributes to economic benefits for the aggregator by reducing costs by 19%.

The analysis of participation in the secondary reserve market also showed that it has a very advantageous economic impact for the aggregator. Without participation in the secondary reserves market, costs would increase by 132%

6.3 - Future work

Although the work developed in this dissertation has demonstrated the effectiveness of the proposed methodologies, several possibilities remain unexplored due to time constraints, and these could positively complement the results achieved. The following points highlight some of the main directions for future research and development:

- **Real-time Simulation:** The study and the developed optimization methodologies focused on optimizing the system by generating operational setpoints for the following day. As such, real-time performance analysis of these methodologies was not considered. However, evaluating their real-time performance is highly relevant, as there are numerous factors, both positive and negative, that can affect results and were not accounted for in this study. Therefore, this constitutes an important direction for future work.
- **Broader case studies:** This work considered a limited number of case studies. Future work could involve exploring a broader set of case study combinations involving different optimization frameworks and system DMERs as well as extending the temporal scope of the analyses. This would allow for a deeper understanding of how the various system components and optimization approaches influence overall system performance.
- **Progressive Edging:** This work used a fixed set of constraints for the formulated problem. A potential direction for future work is the application of progressive edging techniques to develop more precise models of the system and characterized resources. These techniques

involve gradually tightening constraints or refining model parameters over time or in sequential stages, allowing the system to progressively adapt to real-world conditions. This approach would improve the accuracy of the optimization process, especially when considering uncertainty and operational variability.

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