UNIVERSITAT POLITÈCNICA DE CATALUNYA (UPC) – BarcelonaTech

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MASTER IN INNOVATION AND RESEARCH IN INFORMATICS

Data Science

Master Thesis

Optimizing Energy Market Participation with Batteries

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Abstract

Due to the fact that the energy sector is in transition, there are goals for lowering the energy cost with the use of renewables and batteries. This presents challenges to the system and the solution is the issuing of energy communities that can be used to make electricity provision more clean and secure. It is also to see how energy flexibility elements or elements on the consumption side can make the system more efficient and cheaper, which is being done in this paper concerning the day-ahead bid and batteries. Traditional day-ahead bidding methods have become costly, mainly when the forecasted energy consumption differs from the actual consumption, which has to be resolved by penalizing with an imbalance cost. This thesis is part of a more significant project (Layered Energy System) that is to be deployed in Spain. Applying such changes to the electricity system first requires becoming familiar with and understanding Spain's context. The first part of this thesis provides research to understand the Spanish regulatory framework, how the market works, and the status of these technologies in Spain.

Following that, this thesis's primary work is to explore how day-ahead market bid could be improved through the use of batteries for better planning and error assumptions. It mentions several day-ahead bidding strategies in the context of energy and batteries. And then selects a subset (three) of the studied strategies and implements them, comparing their performance on actual electricity data. Finally, selects the one that best fits various scenarios and requirements. A particular objective function is opted to be minimized with respect to the battery constraints that involve the variables. A linear program will find the values that best fits those variables at every time step t of a single day. The methodology is an improvement over traditional predictive models. After comparing different strategies, Results show that strategy one, namely "Stochastic Chance-constraint optimization", yields the best results. In this strategy, the battery would have the freedom to maximize profit even if it sometimes increases imbalance. The preferred error distribution for this strategy is the Gamma distribution. Using a battery to offset imbalances can help to minimize total energy cost for a whole day (up to 26%).

The last part of the thesis is ongoing research about capacity traders and market performance. It surveys the literature on trading strategies in various contexts and markets relevant to capacity traders. The market performance in capacity trading needs to consider how well the buildings can reach their desired capacity through bidding and selling. Performance metrics that are typically used to evaluate those trading strategies were documented. This feature is being worked on with python, but it will not be able to be shown.

Collaboration

In collaboration with **i.LECO NV**

i.LECO is a company based in Geel, Belgium, conducted by a team with a long track record of successfully completing and providing value to challenging smart energy projects and products. "i.LECO" develops advanced solutions for a more sustainable world. They collaborate with both B2C and B2B customers to reduce CO2 emissions and enable the seamless integration of innovative technologies such as energy storage and electric vehicles into existing properties. i.LECO was founded in Q1-2019 with the aim of empowering and accelerating the necessary green energy transition through innovative software, with a final focus on the future expected network structure of "local energy communities." [87]

Acknowledgement

With this Master Thesis, I am at the end of an incredible journey. It has been both a beautiful and very demanding experience. I started this Master thesis with a lot of excitement and passion for investigating this topic, not only energy optimization, transition and flexibility but also the societal involvement in these crucial innovations. As with every process of learning, writing a thesis also had its ups and downs. In the past months, I had many moments of feeling completely lost in the complexity of this research, and I was unsure about my ability to work on such a challenging topic; however, everyone needs guidance and that is normal, we are all always learning. I believe I have great abilities and I can tackle any challenge. However, some of these low moments could not have been overcome without the invaluable support from my sister, Farah Cheaib and my most significant motivator who always made me believe I could do it.

I would like to thank i.LECO's CEO, Stefan Lodeweyckx, for giving me this opportunity to write my thesis with i.LECO and be part of their exciting work. With regards to the thesis, I cannot thank my supervisors enough. Working with Mike, Robbie and Fraser, has been a very wonderful experience. I would also like to thank my thesis tutor from UPC, Maria Arias, for being my tutor and providing some helpful feedback when most needed.

Many thanks my parents and big brother, Haitham, for their unconditional moral support from many kilometres away. I thank FIB who enabled me to take part in this interesting and challenging path. FIB gave me the chance to meet some of my dearest friends: Raul, Jorrit, Ferran, Marc, and Giovanni. A lot of appreciation is sent to my dear friends for having faith in me and the endeavours I take. We were with each other during the highs and the lows. Thank you to my friends at home and abroad that have been there for me, wherever I went. And lastly, thank you to my best friends Walid and Line, from back home, for the good times they always provided me when I was stressed out and needed to take my mind of things.

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Nomenclature

Battery Variables

Δt the time resolution (duration of time interval t)

η_c the charge efficiency

η_d the discharge efficiency

ν a Boolean variable

B^c the total battery capacity

B^e_{t+1} the battery energy availability in the next time-step $t+1$

B^e_t the battery energy available at time t

B^{SoC}_t the battery state of charge at t (0 - 100%)

P^B_t the battery power at t

P^C_t the charging power at t

P^D_t the discharging power at t

P^{max} the maximum power of the battery

t_beg the time t at the start of every day (t = 0, 96, ...)

Basic Definition

BESS Battery Energy Storage System

BRP Balance Responsible Party

CDA Continuous Double Auction

CSC Collective Self-Consumption

DA Day-Ahead

DAM Day-Ahead Market

EC Energy Cost

LEC Local Energy Community

LEM Local Energy Market

LES Layered Energy System

LES Renewable Energy Community

LME Local Market Entity

P2P Peer-to-Peer

SOC State of charge (for Battery)

ZIC Zero-Intelligence - Constraint

ZIP Zero-Intelligence Plus

General Variables

γ imbalance price

λ_t Day-Ahead Market price at time t

s a single scenarios

t Timestep

X Number of possible scenarios

Power Variables

p_t^f Forecasted power at time t

p_t^{aL} True demand load at time t

$p_t^{committed}$ Power committed at time t

p_t^{imb} imbalance power at time t

Chapter 1

Introduction

In the light of increasing populations, more significant energy demands, less abundant, and more costly traditional energy sources, it is becoming imperative to change the approach to energy usage. For decades, fossil fuels have been used to create electricity, but they have several drawbacks. They damage the environment, are non-renewable and unsustainable, and the extraction of fossil fuels is risky. The approach towards using renewable energy and energy storage systems is a must for a better and more sustainable future. If this target is reached, an expected reduction of a significant amount of greenhouse gas emissions will occur. Increasing the energy system's flexibility is necessary to make this transition possible to compensate for the variability of the renewables. Energy communities are essential to address the challenge of climate change. The strategy of the EU for 2050, defined as "Clean package", acknowledges the need for regulatory frameworks which empowers renewable-based self-consumers (also referred to as prosumers) to generate, consume, store, and sell electricity back to the grid.

The technology for households, businesses or buildings to generate their own energy has become readily accessible, called self-consumption. Understanding what is going on in the energy market has also become possible, thus allowing a household to optimize its intelligent energy system. At the same time, everyone wants to keep the energy system as reliable as possible. Due to the fact that the energy sector is in a transition phase, there are goals for lowering the energy cost with the use of renewable energy and the introduction of batteries. This presents challenges to the system and the solution is the issuing of energy communities that can be used to make electricity provision cleaner and more secure. It is how flexible elements or elements on the compensation side (like batteries) can make the system more efficient and cheaper, which has been done in this thesis in the day-ahead bid using a battery. Grid-scale battery energy storage systems are rapidly becoming realistic energy solutions as battery technology advances [117]. As a result, there has been an increase in interest in discovering new and efficient battery applications in power systems [82]. More industries will concentrate on the development and construction of the battery as a grid-scale energy storage system. The battery energy storage system (BESS) will engage in numerous marketplaces and profit from various services as its capacity grows [33].

Making bidding decisions and allocating BESS capacity have become critical challenges. In the energy sector, retailers usually buy energy on the day-ahead market. The **day-ahead market** is a financial market in which market players buy and sell energy at specific day-ahead prices for the upcoming day for every timestep of the day. For example, a retailer puts a bid on how much he thinks his clients will consume for the next day and during the next day if his forecast varies from the actual energy consumption, he is penalized with an imbalance cost. Traditional techniques are limited to forecasting the energy using historical data without considering the battery, which can be costly when there is a deviation between the forecasted data and the actual data of the next day. That is why a battery would be an excellent addition to this system; however, the battery can be used in various ways, which this thesis will mention. One of the goals of this thesis is to introduce, address and compare different day-ahead bidding strategies, considering a battery with constraints exists and the scheduling of the battery operation when the next day comes in order to minimize energy cost and maximize profit.

Locally produced energy can be used for self-consumption, fed into the grid at specific rates, stored in energy storage systems, or traded with other local consumers and vice versa. In recent history, energy markets have been utilized as a reliable means of connecting buyers and sellers. Since the late 1990s, computers have increasingly been employed as intelligent agents to trade on behalf of human operators [66]. This viewpoint is similar to the resource allocation difficulties seen in real-time trading marketplaces. Another goal of this thesis is to look into the use of algorithmic trading as an efficient mechanism for managing energy demand for households with variable power supplies. Zero-intelligence (ZI) and Zero-Intelligence Plus (ZIP) trading algorithms are applied to this problem in a continuous double auction environment (more to read about it in section 5.1).

This thesis is part of a more significant project (Layered Energy System (LES) model [37]) that is yet to be pilot in Spain. This topic is essential to address, and much work is being done on it with regards to batteries in the day-ahead markets in the context of energy communities in Spain. The rules and regulations need to be understood and analyzed in order to pilot this project in Spain (the technical work). **Research has been done to understand the Spanish Regulatory framework, to understand how the market works and to understand the status of these technologies in Spain**. This should help apply the concepts being developed by **i.LECO** then transfer how they can be implemented in the Spanish context. Once familiar with these, the technical task comes next, which is **exploring how the battery can be used for a battery and cheaper bidding strategies in the day-ahead energy markets in Spain**. After obtaining an algorithm that allows the battery to optimize interaction with the day-ahead energy market, ways to use this algorithm in the context of energy trading have been explored. Following that, the thesis will **introduce capacity traders and analyze traders' performance and findings when a python simulation is applied. It will also discuss ZIC and ZIP traders in a capacity trading setting**. The whole point of this is to make energy cheaper for the consumers and prosumers and maximize profit.

1.1 Contributions

- The Spanish regulatory framework chapter introduces definitions, rules, and regulations in the Spanish context. These define what is currently possible in Spain and how it will possibly improve in the near future. It also mentions how projects like the LES (section 4) can be applied in Spain and what still needs to be improved.

- Following that, the literature review chapter provides an introduction to the domain. Day-ahead bidding, battery operation and capacity trading are presented, thereby highlighting influential papers while paying attention to work focusing on bidding strategies, battery operation and trading mechanisms.

- The LES bidding chapter is then introduced to show the work that has been done in this thesis. The chapter shows different strategies on how the battery can be used to improve the day-ahead bidding stage and how the battery, considering its constraints, can be optimally scheduled for the following day at every timestep t in order to minimize energy cost and maximize profit eventually.

- When addressing the Continuous Double Auction, it is important to keep in mind that many publications proposing new trading methods used their own version. However, it is not always visible how they compare to one another; thus a summary of the overview is provided along with the key auction characteristics.

- When a household or a business, generates its own energy or receives energy from its retailer, there will be three conditions. Condition one is when the household does not use all its energy, there will be excess energy at a specific timestep t. Condition two is when the household has consumed all of its energy, it still needs more energy at a specific timestep t. Condition three is when the household uses up all of its energy and does not need any extra. A trading mechanism can happen in that case. If a household needs extra energy at timestep t, another household with extra energy can undergo a trade and provide him with what is necessary. Following that, different metrics that market performance of capacity trading are looked into. This is still an ongoing research.

1.2 Problem Statement

Spain is a phase where there is a huge transition in the energy sector. Because of the growing use of renewable energy sources, the existing energy system is experiencing imbalances, and the expenses to address them are expensive. There are possibilities for congestion, high dispatch, surplus and shortage, forecasting challenges, and less typical reserves. The energy crisis refers to the concern that the world's demands on the finite natural resources needed to power the world today are decreasing as demand increases. Natural resources are in limited supply. Energy is also becoming more costly, so the goal is to minimize energy costs and maximize profit in Spain. The objectives of this thesis are as follows.

1.2.1 Objectives

1. Identify the Spanish energy context in relation to i.Leco's Layered Energy System (LES) model.
2. Explore how the day-ahead market bid could be improved through use of batteries for better planning and error compensation. Opt to solve the problem from a mathematical programming perspective. A particular objective function is opted to be minimized with respect to constraints that involve the variables. A Linear program will find the values that best fit those variables at every time step t.
3. Ongoing research: discuss capacity traders and delve into different metrics for measuring market performance in capacity trading.

1.3 Thesis Outline

Chapter 2 draws light upon the Spanish regulatory framework for local energy communities and collective self-consumption. It introduced how the Spanish regulations have improved and the current regulations and markets, roles and operators concerning i.LECO's LES model.

Chapter 3 provides an introduction to the domain where relevant related work is described.

Chapter 4 introduces, discusses, and compares the strategies applied to the day-ahead bidding and battery operation to minimize energy cost. That done, a sample of results is demonstrated.

Chapter 5 introduces the concept of auctions and delves more into continuous double auctions (CDA). Out of many trading agents, two agents are mentioned more in detail: ZIC and ZIP. Following that, an ongoing research is about capacity traders and the market performance metrics are discussed.

Chapter 6: provides the conclusion that reflects what has been done and what was learned.

Chapter 7: provides all the references used for this thesis.

Chapter 2

Spanish Energy Regulatory Framework

2.1 Self-consumption and Local Energy Communities

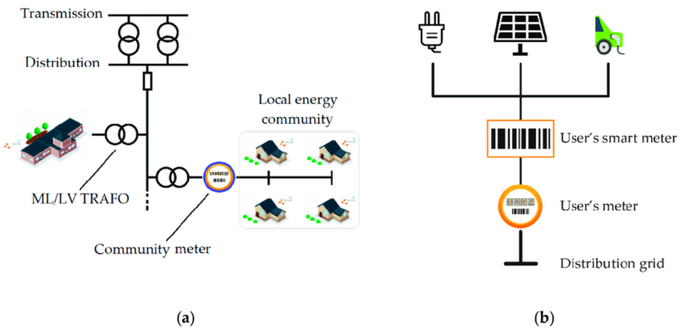


Figure 2.1: An (local) Energy Community
[9] taken with permission

In light of energy production through renewable energy sources, an individual can produce his energy. Self-consumption is when an individual fulfils his energy needs through his own energy production, preferably renewable energy sources like PV solar panels. 100% self-consumption is when the individual can provide all of his energy needs through solar and not need the grid. The evolution and production of locally consumed electricity are becoming a must with the initiative to battle climate change and avoid using fossil fuels and significant investments in grid infrastructure. An energy community is where citizens participate in the energy system and engage in various cooperative energy actions [16]. A *local energy community* (LEC) is, for example, when people who live on the same street can come together and install a collective number of solar cells, or a group of friends can invest in wind turbines and start sharing this generated energy among each other. If there is an excess of local energy production, selling power to the main grid or other nearby consumers is an option. Local energy communities involve citizens and public and private actors who produce, sell and consume sustainable energy. The local power is shared within the community and can also be sold to the grid. Figure 2.1 is an example of what an (local) energy community is. A group of houses can produce their energy and be connected to the main grid if they need more energy from the primary source. Community energy projects are characterised by varying degrees of community involvement in decision-making and benefits sharing [120]. The role of the local energy community is to facilitate the proactive participation of the broad sectors of society on the chain of energy value, always from a local position regarding the territory where they operate and the socio-economic benefit they generate [58].

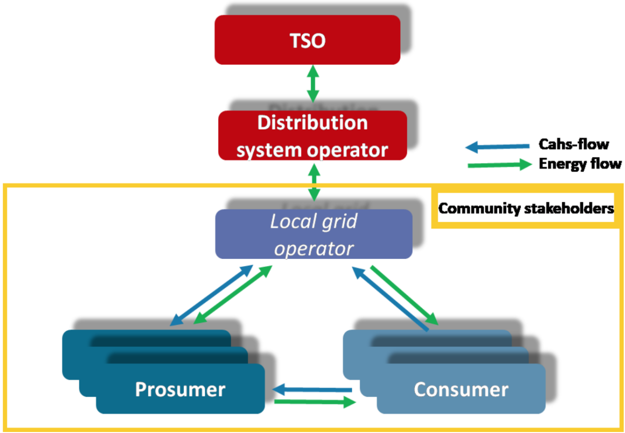


Figure 2.2: How an (local) Energy Community works
[110] taken with permission

2.1.1 European definition and framework

A European Union (EU) package called the "Clean Energy Package" identifies some categories of energy community initiatives as 'energy communities' in European legislation [16]. Another way energy communities are defined is that it is a way to somehow 'organise' collective energy actions around open, democratic participation and governance and the provision of benefits for the local community members [16]. In the Clean Energy Package, there are two legal definitions of energy communities. Citizen energy community contained in the revised Internal Electricity Market Directive (EU) 2019/944 and renewable energy community contained in the revised Renewable Energy Directive (EU) 2018/2001 [16].

Article 2(16) Renewables Directive defines '**Renewable Energy Community (REC)**' as an autonomous legal entity, based on open and voluntary participation, and effectively controlled by shareholders or members that are located in the proximity of the renewable energy projects that are owned and developed by that legal entity[102]. In the RECs, the shareholders or members of which are natural persons, SMEs or local authorities, including municipalities and the primary purpose of which is to provide environmental, economic or social community benefits for its shareholders or members or for the local areas where it operates, rather than financial profits. The RECs are entitled to produce, consume, store and sell renewable energy (without using fossil fuels) [102].

Article 2(11) Electricity Directive defines '**Citizen Energy Community (CEC)**' as a legal entity that is based on voluntary and open participation and is controlled effectively by members or shareholders that are natural persons, local authorities, including municipalities, or small enterprises [102]. Its primary purpose is to provide environmental, economic or social community benefits to its members or shareholders or to the local areas where it operates rather than to generate financial profits [102]. The CECs may engage in generation, including from renewable sources, distribution, supply, consumption, aggregation, energy storage, energy efficiency services or charging services for electric vehicles or provide other energy services to its members or shareholders [102].

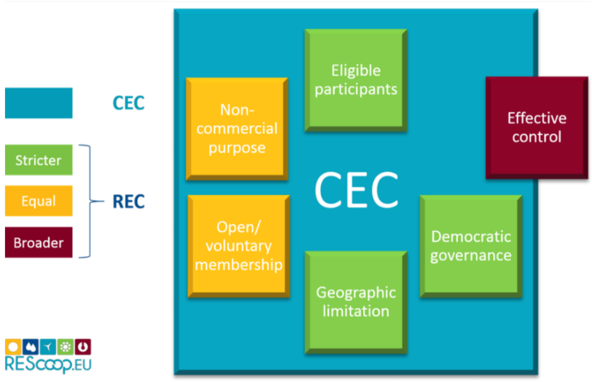


Figure 2.3: Comparing REC and CEC
[102] taken with permission

Trading energy within communities needs a digital system for counting, negotiating and communicating. The work aims to define market mechanisms that can be a tool to match preferences. Energy communities face legal and commercial barriers, but new EU directives will make it possible in the future.

2.1.2 Current regulatory framework in Spain

In Spain, the framework duplicates the rights, privileges and responsibilities from the EU directives for citizen and renewable energy communities [51]. Royal Decree 244/2019 completes the Royal Decree-Law 15/2018 by extending self-consumption to a group of people beyond single owners. A self-consumption facility may now be located in more than one dwelling. Power surpluses may be shared with nearby consumers located in other buildings or fed into the grid [102].

Collective Renewable self-consumption:

- Article 2(14) - Renewables Directive defines Renewables self-consumer as a customer that operates within his property (allowed by the state) who generates renewable energy for his consumption and may sell or store his excess of energy to another household that is not a renewable self-consumer (energy generation is not the consumer's primary profession) [102].
- Article 2(15) - Renewables Directive defines jointly acting renewables self-consumer or, in other words, collective self-consumption as a group of two or more renewables self-consumers collectively functioning in fulfilment of the point in Article 2(14) who are located in the same building or multi-apartment block [102].

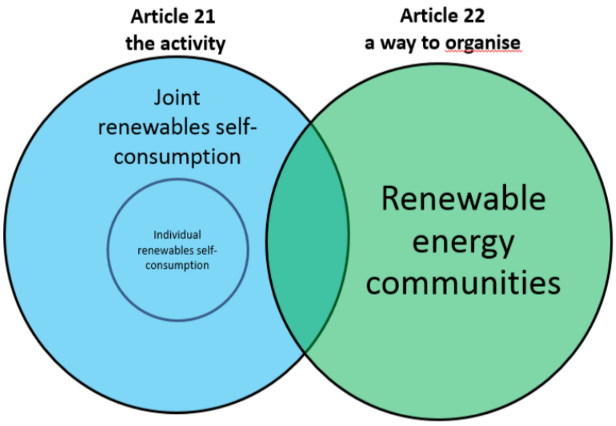


Figure 2.4: The link between renewables self-consumption as an activity and renewable energy communities as a way to organise
[102] taken with permission

According to the elEconomista.es, the government is going to amend self-consumption (whether single or collective). It will give further benefits to the local energy communities (a new type of legal figure derived from European regulations) with the ability to produce, consume, store and sell energy (principally renewable green energy) using its facilities, without its participants losing their status as final customers [32]. According to Spanish Government (Gobierno De España) and the minister council, it approves the Royal Decree that regulates the conditions of self-consumption of electricity [40]. This means that the standard enables the figure of collective self-consumption, which will promote this formula in neighbouring communities.

2.1.3 Development of Self-Consumption in Spain

Retailers in Spain have an active role in the development of self-consumption. Many retailers offer their clients the installations and resolution of procedures for a self-consumption PV solar panel installation as a service [90, 43, 13]. These offers are mainly made at an individual level. As the regulations regarding collective self-consumption and local energy communities progress, self-consumption projects for energy communities are beginning to be explored and implemented [28, 99]. Schemes regarding compensation for extra energy put back into the grid are now available. The retailer is then free to offer another price or formula for compensation of surplus energy to be specified in the contract with the client. Generally speaking, retailers put a fixed price per every kWh imported back into the grid; other retailers apply the market price, which on average is 0.05 euro/kWh. There are many examples from different retailer offices like Factor Energia, Iberdrola, Estabanell Energia, Holaluz, Bon Preu Energia and others [90, 43, 13, 44].

From the financial point of view, self-consumption deployment entails additional resources mainly stemming from consumers, which helps diversify centralised energy investments [46]. At the socioeconomic level, distributed generation increases the number of actors that share the benefits of electricity generation activity, historically concentrated in a reduced number of large companies [46]. Distributed PV is associated with higher rates of jobs creation per MW than other energy sources, including large-scale PV [11]. For example in Iberdola [57], if the customer is a prosumer and there is an energy surplus, they compensate their customer at a rate of 0.051 euro/kWh. How to pay:

- If the contracted power is equal or less than 10kW:

Power Term (fixed)		Energy term (Consumption)		
Without Taxation	With Taxation	Without Taxation	Promotion Hour?	With Taxation
€ 45.00 kW / year	€ 57.23 kW / year	0.089800 €/kWh	yes	0.114213 €/kWh
		0.138101 €/kWh	no	0.175646 €/kWh

- If the contracted power is between 10kW and 15kW:

Power Term (fixed)		Energy term (Consumption)		
Without Taxation	With Taxation	Without Taxation	Promotion Hour?	With Taxation
€ 50.00 kW / year	€ 63.59 kW / year	0.117840 €/kWh	yes	0.149876 €/kWh
		0.171590 €/kWh	no	0.218239 €/kWh

2.2 Collective Self-Consumption in Spain

European directives in relation to the "Clean Energy" have been translated to a national legal framework in addition to "self-consumption" and "energy communities" [60]. This framework made a big change in Spain because the past legislation was a barrier for self-consumption [95, 80]. There is no detailed legislation on energy communities that exists in Spain yet [45]. Self-consumption and Collective self-consumption (CSC) is a concept that allows citizens to organise their participation in the energy system and open the way for new types of energy initiatives in Spain.

2.2.1 Regulatory Developments and Requirements for CSC

With the rise of the Royal Decree-Law 15/2018, it represents three main points related to collective self-consumption which are:

- Cancellation of the sun tax [115, 41, 45] (A tax that was imposed on instantaneously consumed locally PV generation)
- Simplification of the classification of self-consumption facilities.
- Authorization of collective self-consumption.

The Royal decree 23/2020 (23 June 2020) mentions energy communities and aggregators, only defining their general purpose and nature [45]. In addition to that, with respect to the Royal Decree 244/2019, energy fed to the main grid is economically remunerated and self-consumption installations shared by several customers are permitted [41, 45]. This means that it is possible to share solar panel installations with other self-consumers. However, in order to share energy with others in the form of collective self-consumption, at least ***one*** of the following requirements must be met [6, 45, 46]:

- Self-consumers must be in a low voltage distribution grid in the same transformation center.
- There must be a max distance of 500 meters between the PV plant and the self-consumers.
- The production of the PV system and the self-consumers must be registered in the same cadastral reference (taking into account the first 14 digits)

In all ways of self-consumption, the consumer and the owner may be different natural or legal persons and storage elements are allowed to be installed [45]. It must be noted that consumers who are sharing a self-consumption installation (most probably a PV solar panel), must communicate together and send to the distribution company (individually or through a marketer) a *contrato de acuerdo de reparto* which is mentioned in more detail in Section 2.2.3. The Royal Decree 244/2019 establishes two types of connection modalities: [6]:

- **Through the public network**: where the participants are connected to a low voltage distribution and a bidirectional meter will be placed. The bidirectional smart meter will be in charge of accounting for the production and consumption of energy from the installation.
- **Through direct connection to the internal network**: the system is connected to the internal network of the associated self-consumers.

2.2.2 Energy Surplus Compensation and Billing Schemes for CSC

The way Spain implements the net billing scheme and the several forms of collective self-consumption is as follows [6, 45, 46]:

1. **CSC without surpluses**: Participants are implementing self-consumption installation and using up all the energy without sending back excess energy into the electric network.
2. **CSC with surpluses not eligible for compensation**: Energy surplus is sold to the electricity market. The producer is the installation owner, and he will formalize the sale of the energy surplus.
3. **CSC with surpluses under compensation**: Consumers get financial compensation for the surplus that they gave back to the electricity grid. The marketer, for whom each user has contracted the supply, is in charge of compensating its customer for the excess energy cost at the end of each billing period.

People producing less than 100kW will be exempt from the obligation to register as an electricity supplier and will be subject only to technical regulations [45, 46]. The generation installations are connected to associated consumers' internal network (direct lines) or the low voltage network. The law says those with the methods of supply with self-consumption with a surplus may inject excess energy into the distribution network from their production facility. Those without surplus must install an anti-fouling mechanism to prevent the injection of surplus energy into the distribution network [45, 46, 6]. Regarding grid access, production facilities of up to 15 kW located on urbanized land and meeting the urban legislation requirements will be exempt from the need for access and connection permits [45].

An interested person must inform the distributor of the type of self-consumption they have at the time and their interest in the compensation modality. In addition to that, if the installation produces more energy than is consumed, the marketer with which they have contracted the electricity supply will compensate them financially for the kWh put back into the grid at the end of each billing period. Some requirements to benefit from the surplus compensation mechanism are [1, 45, 46]:

1. The energy must be renewable
2. The installation power cannot exceed 100kW (if exceeded, it is sold through the wholesale market).

3. The consumer must sign a single supply contract for consumption with a marketer.

4. There must be an agreement on 'surplus compensation' between the consumer and producer.

5. The consumer will not have a financial benefit; it will only be compensated for the energy it did not consume.

At the end of each billing period (max one month), the bidirectional meter of the corresponding installation is read, and the marketer applies a discount on the electricity bill based on the KWh that it has discharged [1, 46]. The electricity exported to the grid, at times when PV generation exceeds local demand, is rewarded at a price that depends on the wholesale market price. Every month, the retailer charges the consumer the resulting net amount, together with capacity-dependent costs and taxes. Net balance cannot be negative. Suppose the remuneration for the electricity exported to the grid is greater than the cost of the imported electricity. In that case, the balance is zero, and, in practice, the consumer is giving away the excess of generation at no cost [46].

Examples of collective self-consumption and local energy communities (LEC) are going to be mentioned in section 2.3.

2.2.3 Contrato de Acuerdo de Reparto

As mentioned earlier, the Royal Decree 244/2019 of April 5 mentions, within other features, collective self-consumption, which is where consumers can group and share, in an agreed manner, an energy production facility that is built close to them (based on renewable energy production like PV solar panels). For the locally generated energy to be adequately distributed among the participants, the Royal Decree 244/2019 sets up a set of definitions for these modalities of self-consumption [6, 39]. Participants in collective self consumption have to sign a deal which is the *Contrato de Acuerdo de Reparto* which is a deal agreement contract signed by the participants of the installation including the conditions of how the energy will be distributed, prices set and others [6, 39]. In relation with the provisions of Law 24/2013, Royal Decree 244/2019 and the prior Agreement of the Delegate Commission of the Government for Economic affairs, it follows the conditions in the contract [39]:

The net hourly energy generated individually from those participants i who carry out collective self-consumption or consumers associated with the facility through a network, ENG $_{h,i}$, will be:

$$ENG_{h,i} = \beta_{h,i} * ENG_h$$

Where ENG_h is the total hourly net energy produced by the generators and $\beta_{h,i}$ is the hourly distribution coefficient in hour h among consumers who participate in the collective self-consumption of the energy generated in hour h [39].

- For each consumer and participant in collective self-consumption, this coefficient will take the values that appear in an agreement signed by all participants of the collective self-consumption and notify the distribution company in charge of reading the consumption. The value of these coefficients may be determined based on the power to be billed for each of the participating consumers, of the economic contribution of each consumer for the generation installation, or any other criteria provided that there is an agreement signed by all participants and provided that the sum of these coefficients $\beta_{h,1}$ of all consumers participating in the collective self-consumption is the unit for each hour of the billing period. The coefficient will take the value of 1 for each hour of the billing period in cases where there is only one consumer associated with a nearby installation via a network [39].

- The distribution coefficient's value may differ for each hour of the billing period as provided in the agreement signed by all the participants. The sum of the coefficients of all the consumers who participate in collective self-consumption is the unit for every hour by itself [39].
- The value of the coefficient can be changed once a year [39].

If there is an agreement on the hourly energy distribution between the participants, the information must be sent to the company distributor with the following [39]:

1. The consumers must send a plain text file (.txt) containing the value of their coefficients with the value of all the year's hours. The file name will be the corresponding year with ".txt", with a field separator ";", and the decimal character will be the comma ","

Field	Information and/or units	Long.	Kind	long. fixed	Example
CUPS	Universal point Code Supply	22	Chain	No	
Time	Time that will take integer values 1 to 8760	4	Whole	No	543
Coefficient	Coefficient that will be a number	8	Decimal	No	0.134564

Table 2.1: CSC Contract format

2. Consumers may cancel the value of the coefficient in the current year and up to the next 20 years.
3. If, at the beginning of the next year, the distributor doesn't send a new set of coefficients, it will use the one of the year before.

Suppose all participants in self-consumption agree on constant coefficients throughout the year. In that case, the same procedure has to happen as mentioned earlier, except that it will be a single value instead of a different value for every hour of every consumer. [39, 6].

Field	Information and/or units	Long.	Kind	long. fixed	Example
CUPS	Universal point Code Supply	22	Chain	No	
Coefficient	Coefficient that will be a number	8	Decimal	No	0.134564

Table 2.2: CSC Contract with a single constant coefficient

The distribution company in charge must apply the distribution of energy with accordance to the coefficient $\beta_{h,i}$ as mentioned by the participant's signed agreement. In a case where this agreement was not done, the distribution coefficients will be calculated accordingly: $\beta_{h,i_i} = \frac{Pc_i}{\sum Pc_j}$ where Pc_i is the maximum power contracted to the associated consumer i and $\sum Pc_j$ is the sum of maximum powers contracted by all consumers who participate in collective self-consumption [39]. In other words, the energy will be spread out equally among the participants because they would have equal coefficients.

Examples of the contract are found in Section 2.3

2.2.4 Main challenges and developments of local energy communities in Spain

With continuous development in the Spanish regulations, there is still a lot to regulate concerning local energy communities and collective self-consumption. For example, one of the requirements for CSC is that there must be a maximum distance of 500m between the energy resource and the self-consumers. Another example is the agreements for CSC, where the energy spread among the participants is based on a fixed coefficient that can be only changed once a year. These mentioned CSC requirements (including the ones in section 2.2.1) are limiting. There needs to be more flexibility in this sense in order to maximize the benefit of local energy communities.

There have not been many experiences in order to make rules and regulations in the local energy communities sector. Spain is still in a phase where many pilot projects are happening, and as more projects happen, the rules and regulations are expected to evolve in the following years. Two significant differences, however, remain; an energy community represents an organizational format that requires a legal entity underlying several governance-related rules, and its potential activities go beyond self-consumption [45]. With increasing projects, the regulations are expected to become more apparent since local energy communities are new in Spain. Projects will closely be followed, and step by step, upgrade the regulations for local energy communities. Based on these Pilot projects, maybe better and clearer regulations will be put in one or two years, including taxation and others.

2.3 Examples of applications in Spain

With the examples below and the surplus regulations mentioned in 2.2.2, if there is a surplus, participants can either return the energy to the grid or sell it to neighbours with compensation on the bill at the end of the month (registered to return surplus of energy).

2.3.1 Agreement of Contrato de Acuerdo de Reparto

Assume three houses live on a residential street just like the figure 2.7 or three apartments in a building just like in figure 2.5. These three houses decided to share an installation and place it on one of the houses' roof. As mentioned in the contract, the participants have to agree on how the energy be distributed on an hourly basis for the whole coming year.

- The coefficient can different for every hour of every day with sum of the coefficients at every hour across the participants in a single CSC is equal to one. Different people/houses use electricity differently and the table below is an example of how the coefficients could be.

CUPS: ES12345678910121314152			
Hour	Coef. of Participant 1	Coef. of Participant 2	Coef. of Participant 3
1	0.200000	0.300000	0.500000
2	0.350000	0.450000	0.300000
.	.	.	.
.	.	.	.
8759	0.543210	0.123456	0.333334
8760	0.200000	0.300000	0.500000

- The coefficient can be a constant having the sum of all the coefficients across the participants in a single CSC at every hour is equal to exactly one.

CUPS: ES12345678910121314152		
Coef. of Participant 1	Coef. of Participant 2	Coef. of Participant 3
0.200000	0.300000	0.500000

- The coefficient can be equal for all the participants: in this case 3 houses, meaning each house will get 0.333333 of the energy generated by the PV panels for every house of every year.

2.3.2 CSC and LEC

Some examples of self consumption are mentioned in [7]:

- **Apartment Building**

  Collective self-consumption installation has multiple uses, and in this case, it is in a residential building. It can be either a simple installation to cover compensation of common areas like the elevator or a more complex installation that intends to supply the needs of the apartments in the building.

  - *Individual Neighbor*: if some apartment wants to install a PV panel for their personal use, they should get the approval of more than half of the people living there. Once they have agreed, the person can apply any self-consumption modality as long as it follows what the regulations allow.
  - *Community Installation*: in case more than one apartment in a building want to share an installation, there should be an agreement, as mentioned earlier.

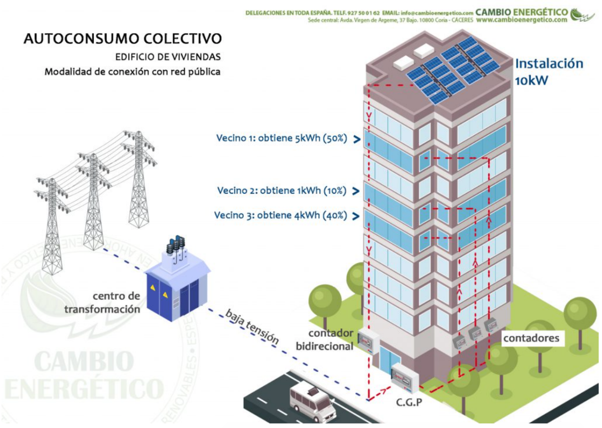


Figure 2.5: Collective self Consumption in a Residential Area [7]

The image above is an example of a community installation in a building. The PV production will be distributed through an agreement (as mentioned in section 2.2.3) between the participants that includes a distribution coefficient decided between each other. Apartment 1 has 50% of the production, apartment 2 has 10% and apartment 3 has 40%. If the neighbors are consuming it all, they will use up all their part of production, and if not, they'll get a compensation for it.

- **Industrial Estate**

  As figure 2.6 shows, an industrial collective self-consumption facility in a location such as a business park has many similar aspects with the previous case. In this example, there exist three self-consumers which are two industries and a farm and they all use PV energy.

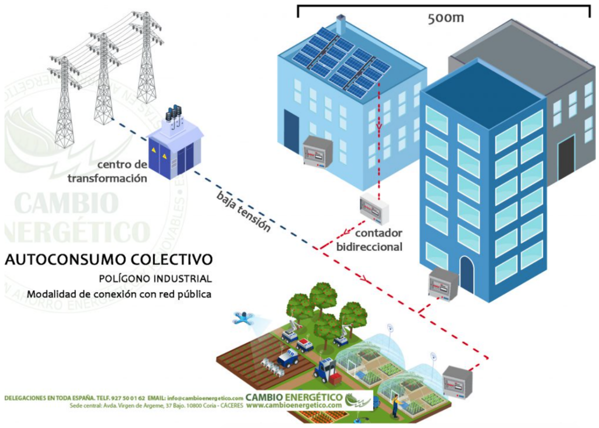


Figure 2.6: Collective self Consumption in an Industrial Estate [7]

  To install a CSC system in a certain location, a negotiation between the owners of the buildings should be done. For example, it's possible that a company has a warehouse with a large roof where they PV self-consumption installation is found but that company doesn't want to give its own surplus to the grid but instead give it to it's neighbors. If the company doesn't have enough space, they can negotiate with others to install PV panels on their roofs or other common area.

- **Residential Area**

  Residential areas, towns or places with single-family houses are in the category. As mentioned in previous sections, they should abide by the requirements: 500m of maximum distance from the user for the PV located, connected to the same low voltage distribution and located in the same cadastral area.

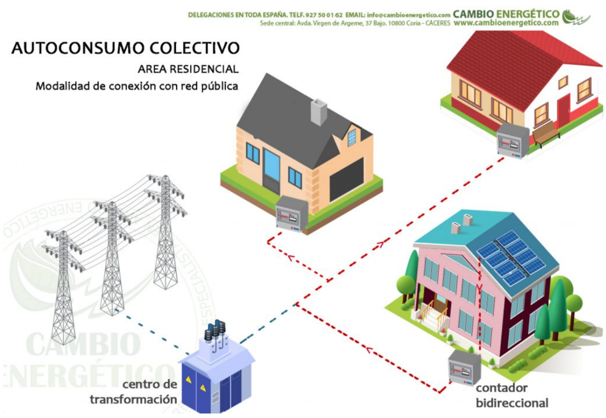


Figure 2.7: Collective self Consumption in a Residential Area [7]

  As figure 2.7 shows, one person in the neighbourhood decided to share his PV self-consumption installation with his neighbours. These three houses decided to use a standard installation and place the panels on that house's roof. Whatever the terms of the distribution, it all goes back to the contract between the distributor and the autonomous community.

2.3.3 Current Energy Community Projects

1. **Crevillent – A local energy community (LEC) in action**: Crevillent, a municipality in the province of Alicante located in southeast Spain with around 30,000 inhabitants, is said to be one of the country's driest places. The Crevillent electric cooperative, Grupo Enercoop, led and set out to make the best use of the sun which is a vital resource to make Crevillent a reference Local Energy Community in Spain and Europe and to show how the energy transition can start successfully at the local level [83]. The city council, Generalitat Valenciana, and IDAE will support the LEC project in Crevillent in which they call it Comptem is short for Comunidad para la Transición Energética Municipal. They will promote energy and electricity self-consumption through using public spaces, rooftops of buildings or industries to set up collective PV solar panels [71].
   With the future put in mind, by 2030, they forecast that the Comptem project will contain almost 5 MW installed in the urban environment of the municipality between PV plants and self-consumption services. Additionally, using its renewable generation, this capacity will cover more than half the population's energy needs, and the other part will be from sources of renewable energy already installed by the municipality[71].
   Comptem will have a mobile application where citizens can check their information in detail in real time of their consumption and bill and through which they have a personal advisor to optimize the use of the energy they have [35]. On the other hand, digital information panels will be set up with large influx where information on the production and consumption will be displayed thus introducing energy awareness and local life [35]. This pilot project is part of a bigger EU project called "Merlon".

2. **Castilfrío de la Sierra (Soria) - first rural energy community**: Under Hacendera Snolar, the motivation is to cover part of the municipality's electricity demand and help reduce carbon emissions and energy costs for the town and the people who live in it [15]. A pilot project is going to be launched centred on collective self-consumption and citizens involvement by the collaboration of The Red Eléctrica Group, the Megara Energía cooperative, the municipality of Castilfrío de la Sierra and Caja Rural de Soria [15]. Raquel Arias, from Megara Energía, mentions that the initiative responds locally to a global problem since clean energy contributes primarily to fighting climate change.
   The Solar Farm of Castilfrío de la Sierra contains two PV solar plants of 7.36 and 5.5 kWp for self-consumption that are on the two municipality buildings' rooftops (social centres) [15]. The mentioned installed, already happening, supplies electricity to a big part of the town (town hall, social centre, medical offices, some houses, water pumps, etc.), which saves around 60% of the electricity bill [15]. Additionally, it reduces the carbon footprint by 6.98 Tm of CO2 per year and reduces energy expenditure by 13.64 MWh yearly in the first phase (60.27% annual savings) [15].

2.4 The Spanish Energy Market

The Spanish energy sector was liberated in 1997. The actors' tasks have been separated from the generation to the promotion of energy to the end-user [81]. The market players of this product, energy, for Spain, the Iberian Electricity Market (MIBEL), is supervised by the National Commission of Market and Competition (CNMC). MIBEL is made up of players who produce energy and others who consume it [79]. The producers are responsible for generating electricity, either for their consumption or for third parties. They are also responsible for building, operating and maintaining their production plants. Multiple roles intervene between the source of energy production and its consumption.

PPAs or Bilateral Contracts are a commercial contract between two parties where one party undertakes placing the power in the network, and the other party receives the electricity market [36]. These contracts have to be known to the market operators, and system operators, who are responsible for verifying and validating the contracts in technical terms and the commercial relationship with the parties involved that directly affect the rest of the market [36]. A long-term contract between an energy generator and a buyer that represents demand can be directly a big consumer or a retailer that represents several consumers. There are two types of PPA: the Virtual PPA (based on financial agreement) and Physical PPA (which includes a direct physical delivery of energy from a specific renewable plant) [92].

2.4.1 Markets

There are multiple energy markets in Spain, like the day-ahead market, the intraday market.

The **day-ahead market** is the market that is more important concerning this master thesis. The day-ahead market, an essential element of the electrical energy production market, attempts to perform electrical energy transactions by submitting selling and takeover bids for electrical energy on behalf of market agents for the twenty-four hours of the next day. OMIE will be used by buying and selling agents in Spain to offer their bids to the day-ahead market [88]. The day-ahead market in Spain is hourly. Today, the retailer bids how much he thinks his clients will consume for the next day. When the next day arrives, his predictions vary from the actual consumption, and he is penalized with an imbalance cost.

Intraday means "within the day". The intraday markets are an important tool that allows market agents to adjust the day-ahead market's resulting schedule by submitting selling and takeover bids for energy, according to expected needs in real-time [88].

2.4.1.1 Free vs Regulated Market:

When people are asked if they are in the regulated or free markets, they often do not know how to answer this. It is essential to know about the two markets, as in what changes is the price that will be paid for in return for energy. It goes back to where the energy is being generated and the utility companies which sell the energy, which at the end of the month, sends a bill to the consumer [112].

Consumers can choose whom they are going to pay the electricity bill to (a company that sells electricity) [112]. The process of freeing the market is not yet complete, and the regulated market is still there. The two markets contain the following on their electricity bill [112]: **Access fees** (which are set by the government, and they are used to pay the costs of maintaining the grid and transportation of electricity) and the **taxes**. What varies between the two markets is the price charges for producing electricity.

- **Regulated Market**: the PVPC tariff (Voluntary Small Consumer Price), where the kWh price changes every hour and every day depending on the supply-demand between the person producing energy and the person selling the energy to the consumers. This means that the bill will rise if energy is consumed during expensive times of the day and down if energy is consumed at cheaper times. For example, one kWh at 1 pm is sold at 1 euro while at 1 am it is 0.3 euros. This is because demand is different at different times of the day, which makes the price vary. It is allowed to pay the PVPC rate as long as the power contract is lower than 10kW, and only certain authorized companies can do that [112]. An auction's results depend on supply and demand to set the price for the energy used in this market. The price is affected by external trends like, for example, during winter or summer in Spain, the energy is more expensive because people tend to use heaters and air conditioners; however, in spring and autumn, the energy is cheaper because the temperature is moderate.

- **The Free Market** is when the company sets the price of kWh and puts it in the contract. It would already know how much the customer is going to pay [112]. For example, the contract would say that the customer will pay 0.5 euros for every kWh, and that will be constant whether it was during peak times or not. Sometimes, these companies/retailers make discounts and supplies combined like electricity and gas, which are usually stable for the consumer.

2.4.2 Roles and Operators

- **Market Operator**: is the one who manages the auction system for the purchase and sale of energy in the daily and intraday market, and in Spain, the market operator is called **OMIE** [88]. OMIE processes purchases and sales offers, matches offers and communicates the results [88]. It settles and communicates the payments and collections in the market and sets the operation rules and regulations [88]. OMIE is responsible for performing the billing and liquidation of the energy that is purchased and sold [88]. The ones who sell make offers to sell, and the ones who buy make offers to buy. This market takes offers from both and calculates a price per kWh that is common for all. After the first match, the final price is re-adjusted according to technical constraints to obtain a viable daily program. To resolve those technical constraints comes with an extra cost added to the cleared price from the previous market clearance.

- **Transmission System Operators (TSO)**: Red Electrica de España (**REE**) is responsible for the transmission of electricity across Spain. REE is responsible for managing the system technicalities like guaranteeing security, quality and reliability of the supply and balancing the production and demand at any given time. It sets the regulations of the technical operations of the system, and it settles the payments and collections related to the guarantee of supply. It provides auxiliary services, and deviation management [100].

- **Distribution System Operator (DSO)**: is responsible for distributing the electrical energy; in other words, they expand, maintain and operate the distribution networks to transfer the energy to the end-users. In Spain, the voltage is below 220kV. Actors can use the distribution lines to distribute the electricity to the end-user by paying some tariff [94]. There are several **DSO**s across Spain, each of them is responsible for a different territory, however the big ones are: **Endesa**, **Iberdarola**, **Union Fenosa**, **HC Energia** and **Enel Viesgo**. The DSOs are responsible for expanding the network following demands for electricity supply, measuring the final consumption (to set the monthly bill), ensuring good service (to avoid blackouts and others), applying tariffs to customers, maintaining the database of supply points updated and control in real-time and present annual investment plans to the boards of the regional communities (Catalunya, Madrid, and others) [113].

- **Retailer** is the one who operates in the free market and supplies electricity to the customers [113]. The customers have an agreed signed contract with their freely chosen retailer. The retailer is the one who sends the bill to the end-user with which the price is calculated based on the signed contract [4]. With power under 10kW, small consumers can benefit from the Voluntary Price for Small Consumers (PVPC), a price calculated based on the average hourly electricity prices (this choice is slowly fading away). Their responsibilities include using the power lines from the DSO and delivering them to the end-user by paying the tariffs for the use of the network, setting electricity rates for its customers, and agreeing on certain services depending on the control. It is responsible for buying energy that is sold to its customers in the wholesale market, pay the tariffs to the DSO bills its customers for the services, and settles with the operators the purchase of energy and all the stages included [113].

2.4.3 Spanish Energy Sector Setup

- **The Spanish Electricity Sector - Today (2021) [97, 85]:**
  As of January 2021 aggregation activities are possible in Spain, with the format:

  1. Large industries that can directly offer flexibility to the ancillary markets with at least 1 MW.
  2. Retailers with aggregated flexibility of at least 1 MW can participate in the ancillary markets.

  Practically, the aggregator and retailer have joint roles. The retailer can also act as an aggregator if it can aggregate 1 MW and comply with the requisites of the ancillary markets of the TSO. Flexibility services are limited to ancillary markets (TSO). The DSO currently is not considered for flexibility services. The DSO is mainly involved when installing a self-consumption plant to provide the needed permission or possible technical changes that might be needed for the installation to be possible. Each retailer balances its portfolio, acting as its own Balancing Responsible Party (BRP). The introduction of the aggregator is a good development because, in the future, batteries will be involved in the markets; right now, they cannot, but in the future, they can.

- **The Spanish Electricity Sector - Future (2022+) [97, 85]:** According to the roadmap of REE, the aggregator will become a separate role from the retailer in June 2022. This means that a consumer can have two separate companies contracted, a retailer that represents the consumer in the wholesale market and an aggregator that manages his availability and flexibility to give services to other actors in the sector, initially only to the TSO.
  A key thing to be resolved is the compensation mechanism between the aggregator and the retailer. Since the retailer predicts the consumption of its clients, it pays for the deviation between predicted and actual consumption. However, suppose another party, such as the aggregator, modifies a client's consumption. There should be a mechanism so that the retailer is not penalized for the interference of a third party.

- **Data flow Between Sector Players [12, 10, 99]:** Currently, in Spain, a smart meter is installed at all points. Granularity is usually 1 hour and goes down to 15 minutes for industries. The DSO collects this data daily, so it is not available on a real-time basis but daily basis. The DSO usually cleans the data once a month for billing purposes and then sent to the retailer. The DSO bills a fee to the retailer who uses this monthly consumption data. The retailer receives this consumption data monthly and uses it to bill the final customer, applying its margins according to the price set between the retailer and the consumer.

Chapter 3

Literature Review

Throughout this chapter, related work that has been conducted up until this point in time will be explored. Since this thesis focuses on energy day-ahead bidding, battery operation, and two trading methods used in a CDA market, this chapter will briefly overview the work done in these areas.

3.1 Day-ahead bidding and battery operations

A battery energy storage system will probably play an essential role in the future smart grid. Applying an optimal day-ahead bid and knowing how to operate the battery is crucial in minimizing energy costs and maximize profit. Paper [33] talks about applying an optimal day-ahead bidding strategy and operation for the battery using Reinforcement Learning. Xiaolin Ayón, María Ángeles Moreno, and Julio Usaola, in paper [8], mention a similar approach where a probabilistic optimization method is proposed. It produces an optimal bidding curve to be submitted by an aggregator to the day-ahead electricity market and the intraday market, considering the flexible demand of the customers (based on batteries, for example). It also considers the possible imbalance costs and the uncertainty of forecasts (demand or market prices, for instance). Francisco Javier Eransus, in paper [38], suggests a simple methodology to be used by renewable power generators to bid in Spanish markets to minimize the cost of their imbalances. The optimal bid depends on the probability distribution function of the energy to produce, the probability distribution function of the future system imbalance, and its expected cost. Arnau Risquez Martin, paper [101], addresses modelling of bidding strategies on the day-ahead electricity market. In his master thesis, Arnau applies strategies designed with an overall objective of maximizing the power plant operator's profit. In the master thesis paper, [29], Carolina Contreras develops an optimization bidding method for a real-world case study of a Spanish energy retailer that decreases the estimated imbalance cost. It is based on a forecast of the system's imbalance quantity and past imbalance costs, with new information available after the day-ahead market gate closure for intraday market participation to affect the imbalance quantity of the agent's investment in a direction that reduces their possible imbalance cost. In paper [82], Hamed proposes an optimal supply and demand bidding, scheduling, and deployment design framework for battery systems. It considers a variety of design parameters such as day-ahead and real-time market pricing, their statistical dependence, and the location, size, efficiency, lifetime, and charge and discharge rates of the batteries. In paper [31], Saborni Das and Mousumi Basu propose an optimum bidding approach that considers the uncertainty of renewable energy resources and Demand-Response programs' outage probability. Tent chaos mapping is used to produce non-repetitive and adaptive load scenarios and all potential renewable power output scenarios within the confidence intervals. [31] proposes a bidding model optimized using mixed-integer nonlinear programming, and the 'Value of stochastic solution' is utilized to examine the efficiency of stochastic programming in incorporating uncertainty into the bidding issue. Paper [124] addresses unit commitment (UC) difficulties while considering the unpredictability of load and wind power generation. The UC issue is expressed as a two-stage stochastic programming problem with a chance constraint that limits the likelihood of load imbalance. Paper [61], proposes a two-stage stochastic optimization model to assist a prosumer aggregator in defining bids for the day-ahead energy and secondary reserve markets. The aggregator maximizes prosumers' flexibility to reduce the net cost of purchasing and selling energy and secondary reserves in both the day-ahead and real-time market stages. Scenarios are used to predict the uncertainties of renewable generation, consumption, outside temperature, and prosumer behaviours and preferences. Leon Haupt, in his master thesis [52], proposes a model that incorporates battery cycle ageing through the use of a piece-wise linear cost function. This method gives a close approximation of the battery deterioration mechanism of electrochemical batteries and may be readily integrated into current market dispatch systems with a limited time window. In paper [18], it mentions that each agent represents a user and this agent can either bid as a buyer or ask as a seller, and this happens in order to maximize the user's profit. The paper continues to say that after several rounds of bidding, the market would arrive to a state where each agent's trading price and quantity have been determined. This method is good for simulation; however, it does not mention how the process updates the bids and asks and how the market gets to equilibrium. The optimal bidding strategy for battery storage in electricity markets is investigated in paper [53]. They also use a battery life model in conjunction with a profit maximization model to calculate the best bids in the day-ahead energy, spinning reserve, and regulatory markets. A deconstructed online computation technique to determine cycle life under diverse operating methods is presented to decrease the model's complexity.

In the microgrid optimum scheduling issue, paper [105] shows how to mathematically represent resources such as battery energy storage systems, solar generating systems, directly controlled loads, load shedding, programmed deliberate islanding, and generation curtailment. The suggested modelling also includes a methodology for determining the availability cost of battery and solar system assets.

3.2 Energy Trading Market, Agents and Capacity Traders

Over the many years that passed, people in some residential areas were merely considered energy consumers, where they only purchased energy from larger power plants leading to a centralized energy distribution system. Technology has been developing and multiplying in this era, leading to alternative ways to produce and generate energy. The rapid development of renewable energy generation technologies is changing the idea of "centralized distribution" of energy [76, 73]. As energy trading occurs, a market and some pricing mechanisms must exist to set the price when undergoing P2P energy trading. Some studies have been done just like in [77], where market rules of energy supply and demand have been allocated to determine a reasonable price. Actions vary from one person to another, and the same thing can be said about energy demand. Each household's demand and preferences differ from the other. Market and pricing mechanisms are usually designed to increase the economic benefits as a whole. In the paper, [68], proposed an intuitional pricing model that is directly declared based on the supply-demand ratio, as the price was calculated by the difference between the feed-in tariff and retail tariff. In paper [69], three mechanisms have been compared to determine P2P prices like bill sharing, mid-market rate and auction-based pricing strategy. Nevertheless, more and more studies still need to be done to determine which pricing mechanism is more reasonable. Agent-based methods have been introduced in the energy trading market, where multiple agents compete with each other. In paper [18], it mentions that each agent represents a user and this agent can either bid as a buyer or ask as a seller, and this happens in order to maximize the user's profit. The paper continues to say that after several rounds of bidding, the market would arrive at a state where each agent's trading price and quantity have been determined. This method is good for simulation; however, it does not mention how the process updates the bids and asks and how the market gets to equilibrium. Means of continuous double auction (CDA) market have been introduced in several papers like in [59, 121, 21].

Vytelingum, D. Cliff, and Jennings, in paper [116], describe a new bidding strategy that autonomous trading agents can use to participate in continuous double auctions. Paper [42] employs an autonomous agent model to capture the desires of both the electricity seller and buyer in terms of price and quantity of power to be exchanged at different points of the day. Paper [3] discusses Community Energy Markets (CEM), which offer trading opportunities amongst community members to make savings and profits. In his research, he offers a CEM model and runs an agent-based simulation to investigate the CEM's advantages to consumers and prosumers. Paper [78] develops a local energy market in which prosumers and consumers in a community may directly exchange electricity. This local power market promotes the integration of renewable energy sources on a local scale. The study analyzes and assesses two local market designs, a direct peer-to-peer market and a closed order book market, as well as two-agent behaviours, zero-intelligence agents, and intelligently bidding agents. Matthew Duffin and John Cartlidge, in paper [34], explore and extend Wah and Wellman's model, found in paper [119], and demonstrate that results are bid-shading parameters used for zero-intelligence (ZIC) trading agents. Following that, they introduce a more realistic minimally intelligent trading algorithm, ZIP and discusses its results.

Chapter 4

Layered Energy System Bidding

4.1 LES Framework

The Layered Energy System (LES) is a concept that tackles energy transition concerns. An open energy market model must always be in balance. The current energy system is facing imbalances due to the increased usage of renewable energy sources, and the costs to fix them are high. Several difficulties, such as congestion and high dispatch, excess and scarcity, forecasting issues, and less conventional reserves, might develop [37]. LES avoids these issues by incentivizing local customers to optimize the system by utilizing their flexibility. LES is based on near-real-time energy and flexibility auctions that favour locally produced energy over external energy. All stakeholders have roles and responsibilities to take part in order to build a system that benefits everyone [37].

With the Layered Energy System (LES), individuals can have the best of both worlds. On the one hand, it allows households and businesses to communicate and even exchange energy. LES, on the other hand, provides market participants with distributed flexibility. Because market rules drive LES, it comes at a cost. Nonetheless, overall energy will most likely become less expensive for everyone, including those who do not have solar panels on their roof. A Layered Energy System is a mechanism that organizes local communities into local marketplaces. Trading energy on this local market is free in the sense that prices for in-feed and take-off are symmetrical at the same time. Because a community is unlikely to meet all demand at all times, the local market maintains an open connection with wholesale traders who can participate in the local market. However, because this 'external' supply is subject to a premium, energy supplied elsewhere has a disadvantage compared to energy produced locally. All local trade must fit within the physical boundaries of the grid involved, which the distribution system operator maintains [37].

LES helps achieve four primary energy sector goals: lower system costs, customer empowerment, speeding transition, and scalability. At the same time, it adheres to a few essential concepts. Consumers and producers benefit from local renewable energy production and flexibility while maintaining their freedom of choice. Operators and energy suppliers continue to have access to local consumers and their smart and flexible energy production, and consumption [37]. In the Netherlands, **i.LECO** is working with **Stedin** on implementing the LES concept in the Netherlands. The work done in this thesis fits with this concept, and LES can benefit from it.

4.2 Definition

For LES day-ahead markets, there are two primary steps:

1. The first step is the day-ahead bidding, which involves coming up with committed net energy consumption for each time-step of the next day.

2. The second step is the actual consumption of energy.

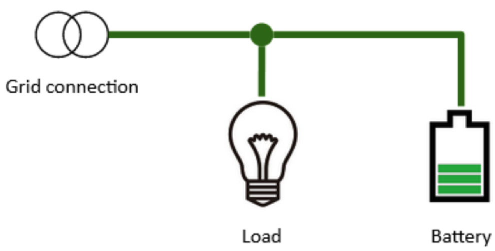
Deviations from the committed energy consumption result in imbalance fees, meaning that it is always preferable to plan energy consumption accurately in the day-ahead phase rather than pay extra imbalance fees later. A **battery**, or other flexible resources, can then be used to try and match the committed power as much as possible in order to compensate for the forecasting inaccuracy. This can be done by charging and discharging the battery such that the imbalance costs are reduced.

Currently the day-ahead bid is determined simply by taking the forecast of the grid balance of the next day, ignoring the operation of the battery or any other flexible resources. **The purpose is to explore how the day-ahead market bid could improve by considering forecasting errors and the battery operation responsible for compensating those errors.**.

The errors of day-ahead energy demand forecasts will be expected to have a mean of zero during a 24-hour period which means that the battery power used to help follow the day-ahead market commitment will also be expected to have a mean of zero; however, due to the inefficiency of the battery, the average battery power on the AC side will need to be slightly positive to compensate for losses if the state of charge is going to be maintained.

4.2.1 System, Market Information and Data Provided

Consider the following test system, which comprises simply of a grid connection, an uncontrollable electrical load, and a battery.



Energy purchased the day before is purchased at the day-ahead market price. Any deviation from the day-ahead committed energy consumption at a given time-step must be bought or sold at the imbalance price, which is equal to the day-ahead market price for that time-step + 0.02€/kWh (if buying deficit) or – 0.02€/kWh (if selling excess).
A CSV file with time-series data will be provided to describe:

- the true energy demand

- the cleared energy buy and sell prices (DAM prices)

4.2.2 Research Question

Assuming that a day-ahead forecast of energy demand is made and the probability distribution function of the forecasting errors is known, what is the optimal bidding strategy on the day-ahead market to reduce energy costs (day ahead + imbalance)? In this chapter, different strategies will be explained and after that, their results will be demonstrated.

4.3 Battery

For this paper, the basic battery is assumed to have the following characteristics:

- Initial Battery state of charge: 60%
- Total capacity: 50 kWh
- Max charging power limit: 1 kW
- Max discharging power limit: 1 kW
- Charging power efficiency: 0.95
- Discharging power efficiency: 0.95

4.3.1 Battery Model constraints:

$$B_t^e = B_t^{SoC} * B^c \tag{4.1}$$
$$0 \leq B_t^{SoC} \leq 1 \tag{4.2}$$
$$B_{t+1}^e = B_t^e + (P_t^C \eta_c - \frac{P_t^D}{\eta_d}) * \Delta t \tag{4.3}$$
$$P_t^C \leq P^{max} \tag{4.4}$$
$$P_t^D \leq P^{max} \tag{4.5}$$
$$P_t^B = P_t^C - P_t^D \tag{4.6}$$
$$P_t^C \leq P^{max} * \nu \tag{4.7}$$
$$P_t^D \leq P^{max} * (1 - \nu) \tag{4.8}$$
$$B_{t\_beg}^{SoC} = 0.6 \tag{4.9}$$

Where:

- B_t^e is the battery energy available at time t
- B_t^{SoC} is the battery state of charge at t (0 - 100%)
- B^c is the total battery capacity
- B_{t+1}^e is the battery energy availability in the next time-step $t + 1$
- P_t^C and P_t^D are the charging and discharging power respectively at t
- η_c and η_d are the charge and discharge efficiency respectively (both equal at 95%)
- P_t^B is the battery power at t
- P^{max} is the maximum power of the battery
- Δt is the time resolution (duration of time interval t)
- t_beg is the time t at the start of every day (t = 0, 96, ...)
- ν is a Boolean variable

Constraint (4.1) makes sure that the battery's energy is always between 0 and the max battery capacity.
Constraint (4.2) states that the battery SOC is always between 0 and 1.
Constraint (4.3) shows how the battery energy for the next timestep t is calculated.
Constraints (4.4, 4.5) make sure that charging and discharging power is less than or equal to the max battery power respectively.
Constraint (4.6) shows how the battery power is calculated.
Constraints (4.7, 4.8) force the battery to either charge or discharge at time-step t but never both at the same time. If $\nu = 1$, the battery charges, else it discharges.
Constraint (4.9) refers to the idea that the battery SOC at the end of the day is the same as at the start of the day. So the amount energy charged and discharged from the battery that happened are equal.

4.4 Step One: Day-Ahead Bidding Stage with Battery

For the day-ahead bidding stage, given that a forecast for the next day already exists, it is not a perfect one which means that there will be errors when comparing the forecast values to the actual load of the next day. The error (between forecast and actual data) is assumed to follow a known probability distribution which is the same across all the time-steps in a single day, and that it is not correlated, so it does not add up with time. It is also expected that the errors of the day-ahead energy demand forecasts will have a mean of zero which means that the battery power used to help follow the day-ahead market commitment will also be expected to have a mean of zero. The error is in a range roughly between -1 and 1 and will be tested in three probability distributions that are ***Gaussian distribution*** (or in other words, Normal), ***Uniform distribution***, and ***Gamma distribution***.

Gaussian distribution is a symmetric probability distribution around the mean, indicating that data closer to the mean occur more frequently than data further away from the mean [5, 106, 19]. The mean and standard deviation are the two parameters of the standard normal distribution. A normal distribution has 68% of the observations within one standard deviation of the mean, 95% within two, and 99.7% within three [106, 19]. *Uniform distribution* is a type of probability distribution in statistics in which all outcomes are equally probable. The results of a continuous uniform distribution are both continuous and infinite [20, 67]. *Gamma distribution* is a type of continuous probability distribution that is extensively used in research to describe continuous variables that are always positive and have skewed distributions. It happens naturally in systems where the time between occurrences is essential [108, 62].

Given that there is:

- A forecast of the load
- The parameters of the randomized error (load forecast error)
- The day ahead market price λ_t (given with no error)

The goal is to find an optimal day ahead market strategy for committed power, taking into consideration the availability of a battery, such that the expected cost is minimized. Note that in the Day-Ahead Market (DAM) stage, the battery operation plan is not fixed, which means a forecast has a probabilistic component, so the best that can be done is to have a general idea of what may happen. Note that in the battery constraints mentioned in section (4.3.1), there are two constraint (4.7,4.8) that ensure the battery charges or discharges but never do both at any time t.

4.4.1 Scenario Generation

Knowing what kind of data is being dealt with is crucial in anything related to optimization, machine learning techniques, and what follows. One danger is that traditional approaches lead people to view uncertainty in a binary way to assume that the world is either certain, and therefore open to precise predictions, or uncertain, and therefore wholly unpredictable. Underestimating uncertainty can lead to strategies that neither defend against the threats nor take advantage of the opportunities that higher levels of uncertainty may provide. As article [30] states, there are four levels of uncertainty:

1. A Clear-Enough Future: A precise single forecast is considered 'enough' for determining the future. Traditional prediction/forecasting strategy tools are used.

2. Alternate Futures: A few discrete possible future outcomes are defined. Decision analysis, game theory, option valuation models are used here.

3. A Range of Futures: A range of possible outcomes but nothing discrete (random variables between -1 and 1, for example). Scenario planning, forecasting, latent-demand research is applied here.

4. True Ambiguity: No basis to forecast the future. Non-linear dynamic models, analogies, and pattern recognition are used here.

In this optimization problem, the level of uncertainty is a range of futures roughly between -1 and 1.

Monte Carlo is a commonly used approach in probabilistic system analysis. It is a form of simulation in which the results are computed using repeated random sampling, and statistical analysis [98]. It is a numerical experimentation approach for obtaining the statistics of the output variables of a system computational model given the statistics of the input variables. In each experiment, the values of the random input variables are sampled based on their distributions, and the output variables are computed using the computational model. A series of experiments are carried out in this fashion, and the findings are utilized to compute the statistics of the output variables [75, 84]. This simulation approach is quite similar to random tests, in which the particular outcome is unknown in advance. In this sense, Monte Carlo simulation may be thought of as a systematic approach to what-if analysis [98].

Monte Carlo simulation is used here to generate scenarios for the forecast error, and it usually requires assuming a probability distribution for the uncertainty. However, this assumption may be unrealistic because it is difficult to accurately identify the shape of the uncertainty distribution for the day-ahead bidding stage problems. Here, probabilistic forecasting of the error is going to be tested on three different distributions which are ***Gaussian***, ***Uniform*** and ***Gamma distribution***.

In the day-ahead market (DAM), the battery plan is not fixed, so taking only one sample to represent the possible forecast deviation (between forecast and actual load) of the next day is not efficient because the actual load is not known yet, which may lead to one way of how the battery might operate and that may not be correct. For that reason, several scenarios will be generated to represent how the error in the forecast might be at every time step.

Following the scenario generation section, the strategies will be introduced.

4.4.2 Strategies

To get the day-ahead market energy commitment (p_t^{commit}), the battery (with respect to its constraints) has to be taken into consideration. Different strategies will to undergo day-ahead Bidding to eventually find the p_t^{commit} and the p_t^B at every time-step t.

A similar approach is mentioned in [8], where a probabilistic optimization method that generates optimal bidding curves for an aggregator to submit to the day-ahead electricity market and the intraday market, taking into account his customers' elastic demand (based on time-dependent resources such as batteries and shiftable need) and the potential imbalance costs as well as forecast uncertainty (market prices,...). The paper [8]'s optimization approach seeks to reduce the overall cost of traded energy over a day while taking into account inter-temporal limitations.

Following the natural temporal sequence of electricity spot markets, the suggested formulation leads to various linear optimization issues. A scheduling procedure meets inter-temporal restrictions on time-dependent resources after the day-ahead market clearing.

4.4.2.1 Strategy One

The strategy used here is called ***Two-stage chance-constrained programming*** which is a type of stochastic programming. To solve stochastic programming problems numerically, the (continuous) distributions of the data process should be discretized by generating a finite number of scenarios of the data process (as mentioned in section 4.4.1). The size of the deterministic equivalent problem is proportional to the number of generated scenarios. When the number of scenarios of the process is finite, then the problem can be written as one large (deterministic) programming problem.

Following what was mentioned in section 4.4.1, that makes this a probabilistic problem with many different scenarios explaining how the battery might operate each having a probability of happening. In a pool of infinite space, the probabilistic problem is split into X (the number of scenarios) deterministic problems and the one answer that gives the best result on average over the X problems is found. X independent worlds each with their battery and their deviation forecast (sampled from the probability distribution function) are created. Following that, the optimization problem of finding the energy bid (that is applied to all X worlds) is solved giving the highest total profit (minimum total cost).

In this strategy, the optimization problem decides on its own if the battery should charge or discharge depending on what it sees as best to minimize the energy cost. That way the battery would have the freedom to maximize profit even if it means sometimes increasing imbalance. That can be counter-intuitive but sometimes it is possible to make more money buying when the price is low and selling when the price is high than you can make from minimizing imbalance.

Now at every time-step t there exists:

- a forecast load p_t^f
- the DAM price λ_t
- the imbalance price γ_t

It's also known that:

$$p_t^f = p_t^{aL} + \xi_t \tag{4.10}$$

where:

- p_t^{aL} is the true load
- ξ_t is the error

At this stage, since as mentioned, there will be X scenarios s:

- $\delta_{s,t}$ stands for the deviation forecast for every scenario s and time-step t

In the day-ahead (DA) stage, all the battery variables and constraints, mentioned in section (4.3.1), should be indexed by the scenarios s following one single bid commitment that works for all scenarios and expecting that in each scenario, there will be a different battery operation

plan. Every scenario has a probability p_s.
The imbalance:

$$p^{imb}_{s,t} = p^{aL}_t - p^{commit}_t + p^B_{s,t}$$

leading to:

$$p^{imb}_{s,t} = p^f_t - \delta_{s,t} - p^{commit}_t + p^B_{s,t}$$

At every time-step t Energy cost (EC):

$$EC_t = \lambda_t * (p^{commit}_t + p^{imb}_{s,t}) + \gamma_t * |(p^{imb}_{s,t})| * \Delta t$$

Replacing $p^{imb}_{s,t}$ in the equation above:

$$EC_t = \lambda_t * (p^f_t - \delta_{s,t} + p^B_{s,t}) + \gamma_t * |(p^f_t - \delta_{s,t} - p^{commit}_t + p^B_{s,t})| * \Delta t$$

With all that is given above, the **objective function** would be to minimize the total energy cost for a 24-hour period (96 time-steps):

$$\text{Min} \sum_{s=1}^{S} p_s * \sum_{t=1}^{T} \lambda_t * (p^f_t - \delta_{s,t} + p^B_{s,t}) + \gamma_t * |(p^f_t - \delta_{s,t} - p^{commit}_t + p^B_{s,t})| * \Delta t \tag{4.11}$$

Subject to the constraints mentioned in section (4.3.1) indexed by s.

Remember that in the DAM stage, a fixed battery operation plan doesn't exist, there only exists a forecast which has a probabilistic component, so the best to be done is to have a general idea of what might be done. Knowing the p^f_t, λ_t, $\delta_{s,t}$, p_s, and γ_t, the result should calculate the best values for p^{commit}_t and $p^B_{s,t}$ that returns the minimal expected energy cost. It is also important to add the absolute operator. That is because, if it is not included, there could be a huge negative imbalance followed by a huge positive imbalance and eventually cancel each other out and the total imbalance would be zero (which should not happen).
Note: The absolute operator makes the problem non-linear so the problem has reformulated to a linear problem and still returns the same results and much better run-time. This procedure is explained in in Section 4.7.1.

4.4.2.2 Strategy Two

This strategy is a different version of the previous strategy in section (4.4.2.1). The optimization problem in this strategy does not decide if the battery charges or discharges, but rather already predefined that when the deviation is negative, the battery discharges, and when positive, the battery charges. This limits the behavior of the battery to force it to always work to reduce the imbalance. Since the point is to minimize the energy cost for 24 hours (96 time-steps), the focus in this strategy is to limit the behaviour of the battery to force it to always work to reduce the imbalance.

$$imbalance = p^{aL}_t - p^{commit}_t$$

Knowing that the battery has a certain efficiency whether charging (c) or discharging (d) and it is being used, there will be some energy losses. For that matter, some extra energy should be assigned and added into the day-ahead bid at every time-step for those losses with respect to the battery constraints (mentioned in 4.3.1). The battery losses would be:

- for charging: $(1-c)\%$ of the expected absolute value of the deviation forecast at every time-step
- for discharging: $(1-d)\%$ of the expected absolute value of the deviation forecast at every time-step

In the battery model (section 4.3.1), the constraints (4.3) and (4.6) are very important. In constraint 4.3, the battery can either charge ($P^C > 0$ and $P^D = 0$), discharge ($P^C = 0$ and $P^D > 0$) or do none ($P^C = P^D = 0$) but it cannot do both charge and discharge. This arrives to the idea that (using constraint (4.3)):

- $B^e_{t+1} = B^e_t$
- $B^e_{t+1} = B^e_t + (P^C_t \eta_c)\Delta t = B^e_t + (P^B_t \eta_c)\Delta t \longrightarrow$ in case of charging
- $B^e_{t+1} = B^e_t + (\frac{P^D_t}{\eta_d})\Delta t = (P^B_t/\eta_d)\Delta t \longrightarrow$ in case of discharging

These battery losses will be taken into consideration when calculating the day-ahead power commitment of with respect to the battery constraints mentioned in section (4.3.1). The losses ($\varrho_{t,s}$) will be added to the objective function (same one of the previous strategy) as follows:

$$\text{Min} \sum_{s=1}^{S} p_s * \sum_{t=1}^{T} \lambda_t * (p^f_t - \delta_{s,t} + p^B_{s,t} + \varrho_{t,s}) + \gamma_t * |(p^f_t - \delta_{s,t} - p^{commit}_t + p^B_{s,t} + \varrho_{t,s})| * \Delta t \quad (4.12)$$

Subject to the constraints mentioned in section (4.3.1) indexed by s.

4.4.2.3 Strategy Three

This strategy has a similar approach to the one implemented in section **4.4.2.2**. Here, the data is re-sampled from a 15-minute interval to an hourly interval by summing the forecasted and finding the average of the DAM prices of every for time-steps (for example 0:00, 0:15, 0:30, 0:45). That done, the optimization problem is applied to the hourly data resulting in decision variables at every hour which are power committed, battery power charged, battery power discharged, overall battery power, battery energy, and battery state of charge.

After that, the data which contains the 15-minute intervals is used again but this time the battery state of charge (SOC) is taken at the state of each hour (decision variable from the hourly optimization), and then these are treated as fixed values for the 15-minute optimization knowing that the SOC refers to the actual value at a given time-step while the power refers to the average power between the two time-steps. For example, in one hour, four powers and five SOCs are needed which is to say that in the region of 0:00 to 1:00

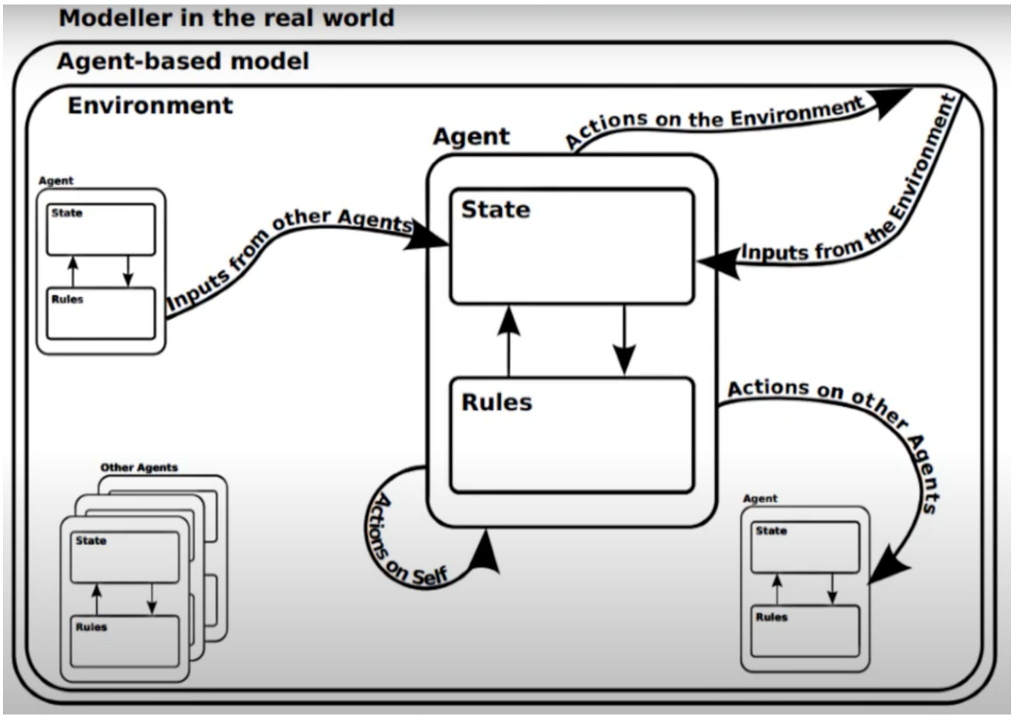
- SOC: 0:00. 0:15, 0:30, 0:45, 1:00
- POW: 0:00, 0:15, 0:30, 0:45

To be able to optimize for this hour, the SOC at 0:00 and 1:00 is fixed (obtained from the previous hourly optimization) and then the second optimization is free to choose four powers in the desired change in SOC but not necessarily the same average power. Here the same procedure and constraints have been used.

4.4.2.4 Strategy Four

Here, **Agent-based models (ABM)** are used for uncertainty for short term predictions (24-hour period).

Explaining Agent-Based Modeling:
Agent-based modelling is a type of modellings in which actions and interactions of autonomous agents, both with each other and the environment, are explicitly modeled in a computer program. As mentioned in [65], Agent-based modelling is a field that excels in its ability to simulate complex systems. Agent is a thing that does things to other things, observe the image below. It is noticed that there is an agent, an entity or thing that knows things and does things. Now this thing is situated in a model in some kind of environment, where there are other agents which sits inside a model that the modeler has chosen and drawn boundaries around. Looking at these agents, following inputs from others, from the environment and from their own behaviors, they will make decisions and they will perform actions. These actions can affect themselves, affect the environment around, or other agents (whether directly or indirectly). So it is literally the thing that does things to other things that gives rise to a pattern of interaction [47, 55, 17, 74].



The ABM components are Agents, States, Decision rules, Actions they perform, an environment they are in, and the time in which they exist. An agent can be anything, a person, idea, country, etc... The state is something that the agent has or knows, like location, technologies, etc... the decision rules are that take inputs and the conditions and convert them into some actions and overall behaviour; they can be static or dynamic. Actions are when the agent performs (or does not) something based on input: the state and internal decision rules. The agents are autonomous; they choose to act or not act considering its environment, state, and computation that it needs to do. These actions can affect agents, their own rules, their state or the environment, and it is often through the indirect interaction through the environment that the true complexity of the system arises. The environment is not an agent but is still relevant, and it provides the agents with information and structure. ABM takes place in discrete time - ticks (96 time-steps) where between two ticks, everything is assumed to happen at the same time like in the real world [47, 55, 17, 74]. What happens in ABM is parallel to what happens in the real world. Knowing that computers are sequential processing machines, things have to happen simultaneously, even if some things happen after the other. The order or sequence of agent interaction is essential because if a particular agent always goes first, for example, it is always allowed to buy first, and it will purchase the cheapest resource and always have an advantage. The agents are shuffled every time-step and enable them to form interactions, and by doing things, parallel action is simulated like in the real world. Agent-based modelling is much more flexible than other types of modelling, such as equation-based modelling. With enough rules, almost any behaviour can be modelled in any phenomenon that can be observed [74]. They present how phenomena and patterns can arise from elementary behaviours, which is a hallmark of complex systems.

It also has a downside:

- Too many rules are hard to understand. For example, if there are 20 rules affecting one agent, how is it going to know which rule is felt most strongly

Applying ABM to the problem
We want minimize the total energy cost for a 24-hour period (96 time-steps). It would be smart to buy energy at low prices and use battery at high prices. Here there is a grid, a battery (with it's constraints) and a uncontrollable load. In this model, the grid and the battery are the agents where they interact with each other to know which is better to use at a certain time-step considering the prices and the battery restrictions. The problem is stochastic because the forecast deviation of the next day is unknown and random. A threshold x will be places and x will represent the value in which the DAM price is either high or low. The decision rules would be that if the Day-ahead market (DAM) price $_t$ is below threshold x the power is bought and when the $_t$ is above the x then the battery is used first with respect to it's constraint and then the rest of the power is bought. Another rule would be to charge battery when deviation scenario we are in is positive and discharge when negative. This is applied to every one of the time-steps.

The point here is to apply some basic rules to be able to reach what is needed to reach. This may sound naive but through different researches and experiments, this has worked quite well.

4.4.2.5 Strategy Five

The strategy here is called **Distributionally Robust optimization** (DRO) which is another approach for handling uncertainty. Many real world decision problems arising in these kind of topics have uncertain parameters. This parameter uncertainty may be due to limited observability of data, noisy measurements, implementations, and prediction errors [96]. *Stochastic* and *Robust* optimization have allowed to model this uncertainty within a decision-making framework. The availability of data makes the limited hypotheses of Robust Optimization looks like the opportunity of using the available data is being missed and on the other hand, stochastic optimization makes use of the data to build a certain probability distribution but lacks the safety that Robust provides [96]. with this in mind, the idea of Distributionally Robust Optimization (DRO) comes to mind where the best of both worlds are put into one and assumed that:

1. a nominal probability distribution (distribution that is close to the real unknown distribution)

2. the protection from the worst possible distribution.

The key idea here is to find a solution vector that minimizes the worst-case expected cost. The worst case expected cost is calculated over an ambiguity set which is a family of probability distributions. DRO is a Min-Max problem where you minimize the maximum expected loss with respect to the constraints. The ambiguity set is a family of potential distributions to describe uncertainty. For example, it can be moment-based (where distributions share the same mean and covariance matrix) or metric-based (which is based on a distance function that computes the distance between the two distributions and then collects the distribution which is close in the sense of distance to an empirical distribution which is based on historical distribution for instance) [96]. The distance usually chosen is the *Wasserstein* distance. DRO is used to hedge against any misrepresentation of probabilistic forecast and may perform better than classical approaches under available information.

Here the constraints would be the battery constraints mentioned in section 4.3.1. The objective function would be the similar to the one mentioned in section 4.4.2.1

4.5 Step Two: Battery Operation Stage

When the next day arrives, there is:

- the committed power (P^{commit}) (which was bid from the day-ahead bidding stage)
- the actual power
- the difference between the two which is the power imbalance (P^{imb})

The actual power (P^{actual}) is the actual load power (P^{aL}) + the battery power (P^{B})
Given the day-ahead market price (λ) as well as what was mention, the equation for energy cost (EC) at time t is

$$EC_t = (\lambda_t * P_t^{commit} + \lambda_t * P_t^{imb} + \gamma_t * |P_t^{imb}|)\Delta t \tag{4.13}$$

Knowing that:

$$P_t^{imb} = P_t^{actual} - P_t^{commit} \tag{4.14}$$

$$P_t^{actual} = P_t^{aL} + P_t^{B} \tag{4.15}$$

Using equation (4.14), the EC equation (4.13) can be updated:

$$EC_t = (\lambda_t * P_t^{actual} + \gamma_t * |P_t^{imb}|)\Delta t$$

and using the equations (4.14) and (4.15) finally reaching the form which is the **Objective function**:

$$EC_t = (\lambda_t * P_t^{aL} + \lambda_t * P_t^{B} + \gamma_t * |P_t^{aL} + P_t^{B} - P_t^{commit}|)\Delta t \tag{4.16}$$

Where:

- t is the timestep
- γ_t is the imbalance cost (For now $\gamma_t = 0.02$)
- λ_t is the Day-Ahead Market Price at time t (€/kWh)

It is important to add the absolute operator. That is because, if it is not included, there could be a huge negative imbalance followed by a huge positive imbalance and eventually cancel each other out and the total imbalance would be zero (which should not happen). **Note:** As mentioned before (in section 4.4.2.1), the absolute operators makes the problem non-linear so it has been transformed to linear (section 4.7.1) with the same results and better run-time.

4.6 Experiments and Results

In this section, experiments have been done on the strategies 1, 2, and 3 and their results are displayed. Three strategies, mentioned in section 4.4.2, were tested on **a number of days** (10) throughout the month with three probability distributions (Gaussian, Uniform, and Gamma) giving different results in the day-ahead market procedure followed by the battery operation for the next day.

4.6.1 Results for Step One: Day-Ahead Bidding Stage with Battery

4.6.1.1 Strategies' objective function and computational time comparisons:

Since the random generation of the scenarios (using the Monte Carlo technique) that represent the possible errors for the next day (mentioned in strategies in section 4.4.2) is not the same with every run, they are still within the same range of values (roughly between -1 and 1). For stochastic processes, the optimization problem was run over **a number of days** (10), then the average of the metrics scored each day were taken that is used to analyze each strategies' effectiveness. With random processes, it is important to see the bigger picture.

The forecasted error in Table 4.1 is assumed to be of a Gaussian distribution, table 4.2 to be of a Uniform distribution and Table 4.3 to be of a gamma distribution. With the numbers of scenarios tested: **50**. The *stdev* column in each of the figures demonstrates the standard deviation of the total cost of each day in comparison to the average for each strategy.

	Computational Time (in seconds)	DA total cost (in euros/day)	Stdev
Strategy 1	24.091	**3.3736**	1.14
Strategy 2	**5.231**	3.6784	1.121
Strategy 3	21.291	3.631	**1.115**

Table 4.1: Computational Time and Objective function for every strategy during the DAM procedure when the forecasted error is of a Gaussian distribution

	Computational Time (in seconds)	DA total cost (in euros/day)	Stdev
Strategy 1	22.292	**3.6053**	1.326
Strategy 2	**5.215**	3.940	**0.924**
Strategy 3	19.892	4.172	1.286

Table 4.2: Computational Time and Objective function for every strategy during the DAM procedure when the forecasted error is of a Uniform distribution

	Computational Time (in seconds)	DA total cost (in euros/day)	Stdev
Strategy 1	22.5283	**3.0676**	1.073
Strategy 2	**4.8479**	5.3382	**0.901**
Strategy 3	24.3565	3.4798	1.031

Table 4.3: Computational Time and Objective function for every strategy during the DAM procedure when the forecasted error is of a Gamma distribution

It's relevant to note that it's unimportant what the objective function gives as a result in the day-ahead market; the key point is that the power committed sets out good results for the battery operation when the next day comes to minimize the energy cost at the end of the day.

4.6.1.2 Forecasted power vs Committed power vs DAM prices

Figures 4.1,4.3,4.5, 4.7,4.9,4.11, 4.13,4.15 and 4.17 compare the committed power, forecasted power and the *DAM* prices at every time-step t for a single day. Figures 4.2,4.4,4.6, 4.8,4.10,4.12, 4.14,4.16, and 4.18 show the residuals for each strategy, which is the difference between forecast and committed power at every time-step for a single day for every probability distribution (Gaussian, Uniform, and Gamma). The number of scenarios is **50**. The graphs below show power committed in comparison to the forecasted power and the DAM prices with every strategy. The left y-axis represents the power and the right y-axis represents the DAM prices. When the strategies are applied, different results are noticed and observed. The residual's value is the difference between the forecast and the committed power for every time step of a single day.
Note that there has been multiple runs on several days however only the graphs of one of the days was put for the results to represent the idea behind each strategy. It will be data from Sunday, March 21, 2021.

Figures 4.1 to 4.6 represent the results when the error's probability distribution is assumed to be **Gaussian**.

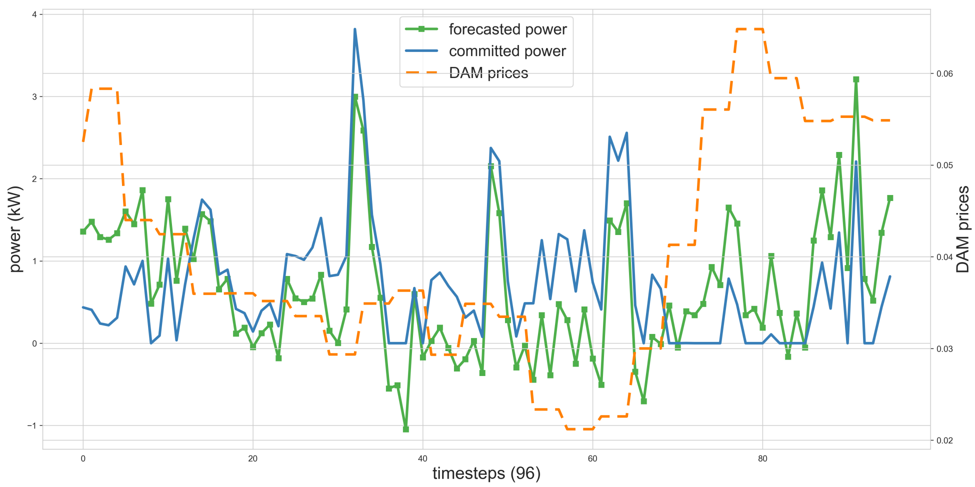


Figure 4.1: DA - Strategy One: DAM prices vs committed vs forecast power (Gaussian)

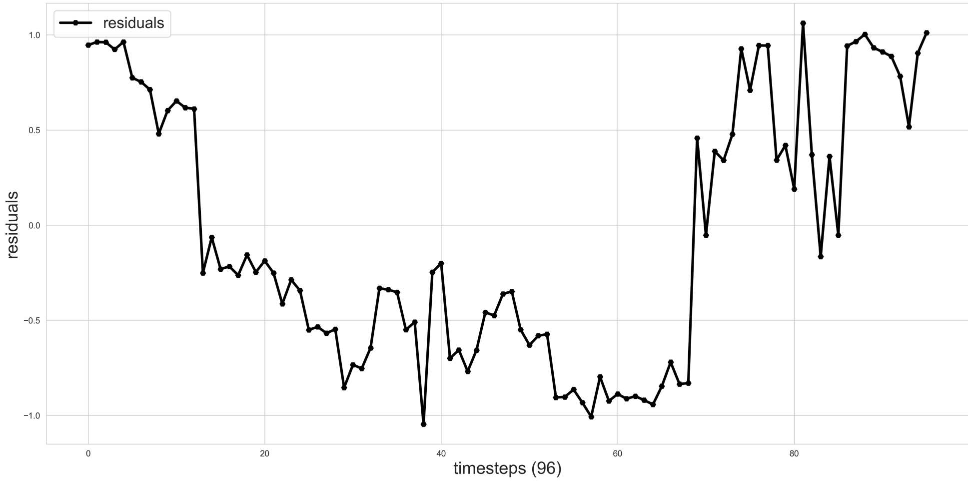


Figure 4.2: DA - Strategy One: Residuals (Gaussian)

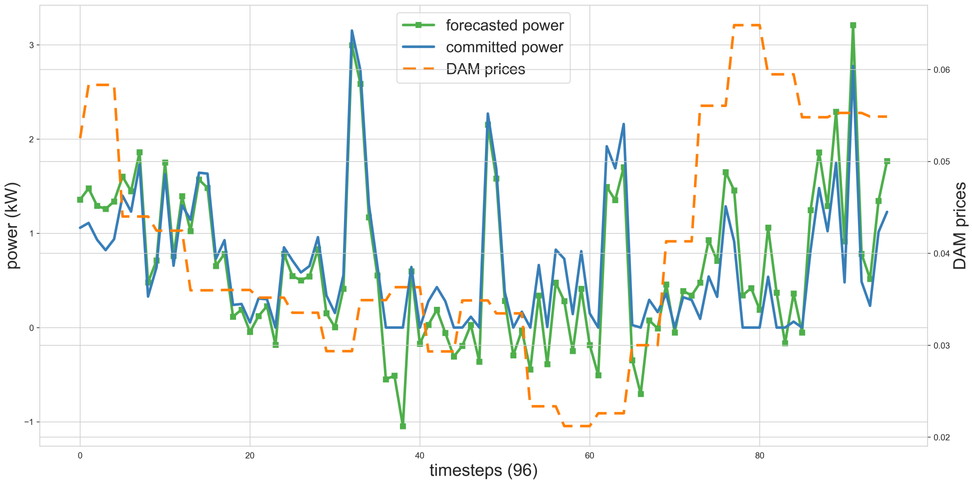


Figure 4.3: DA - Strategy Two: DAM prices vs committed vs forecast power (Gaussian)

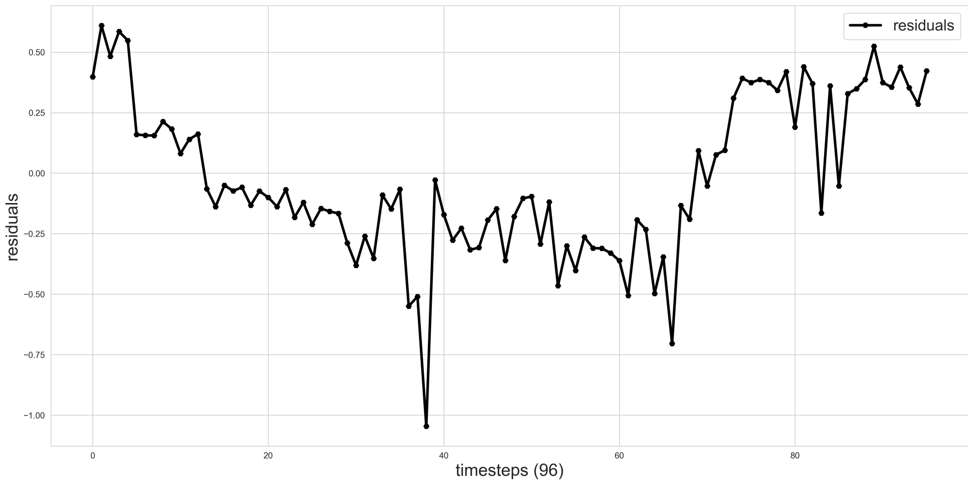


Figure 4.4: DA - Strategy Two: Residuals (Gaussian)

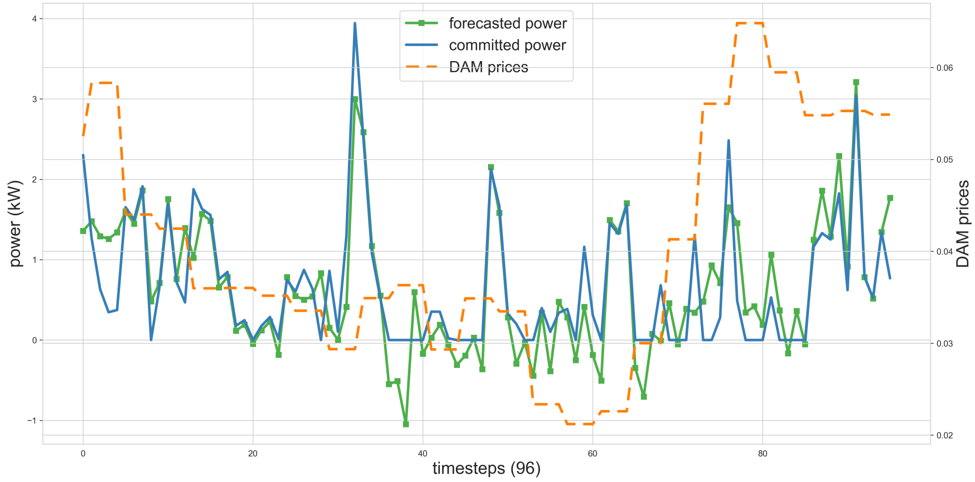


Figure 4.5: DA - Strategy Three DAM prices vs committed vs forecast power (Gaussian)

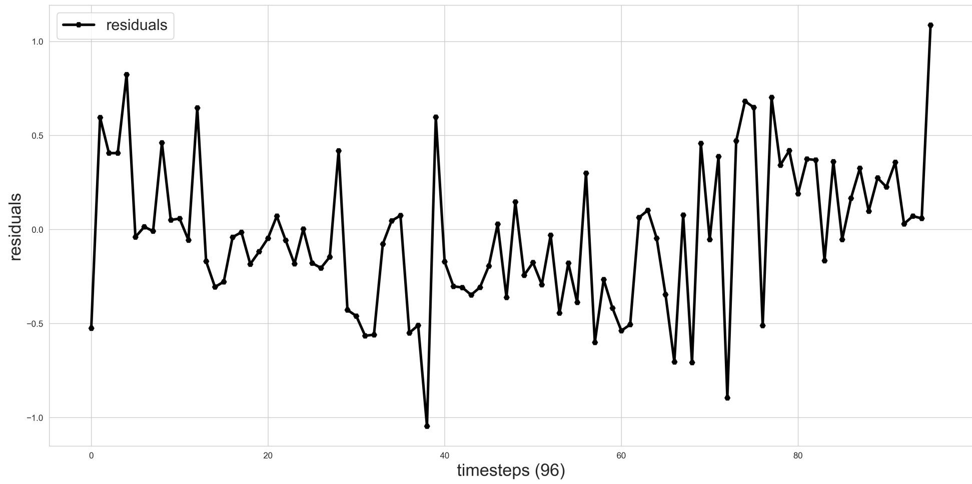


Figure 4.6: DA - Strategy Three: Residuals (Gaussian)

Figures 4.7 to 4.12 represent the results when the error's probability distribution is assumed to be **Uniform**.

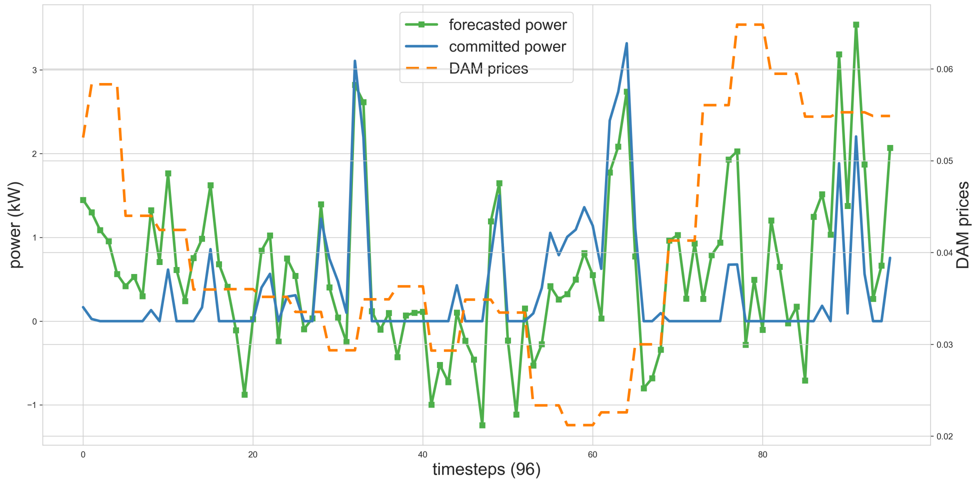


Figure 4.7: DA - Strategy One: DAM prices vs committed vs forecast power (Uniform)

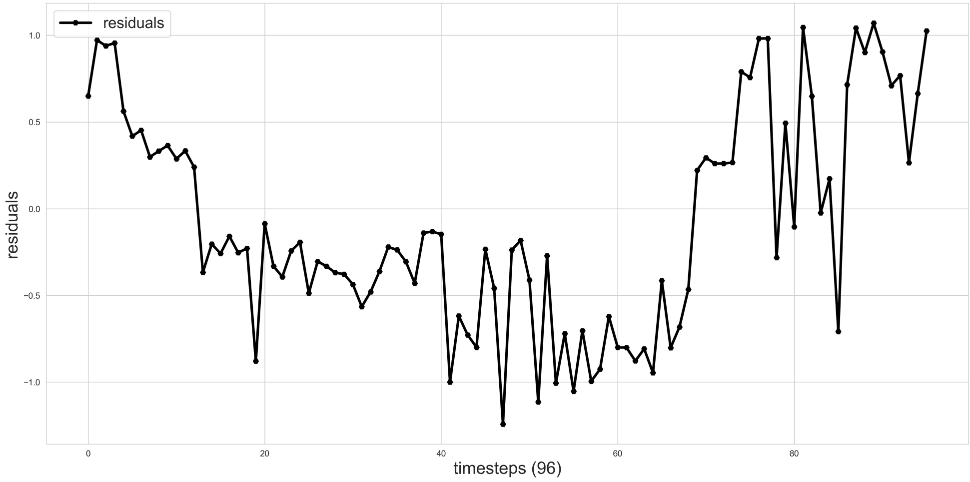


Figure 4.8: DA - Strategy One: Residuals (Uniform)

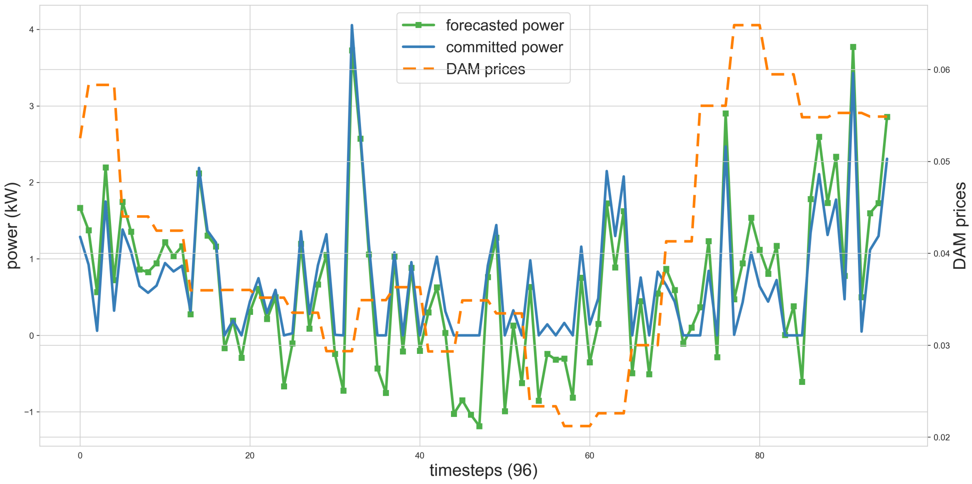


Figure 4.9: DA - Strategy Two: DAM prices vs committed vs forecast power (Uniform)

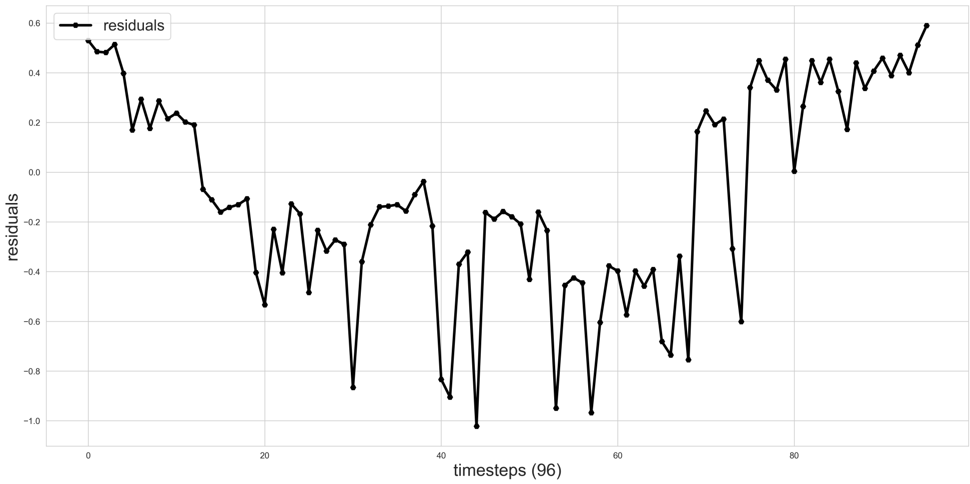


Figure 4.10: DA - Strategy Two: Residuals (Uniform)

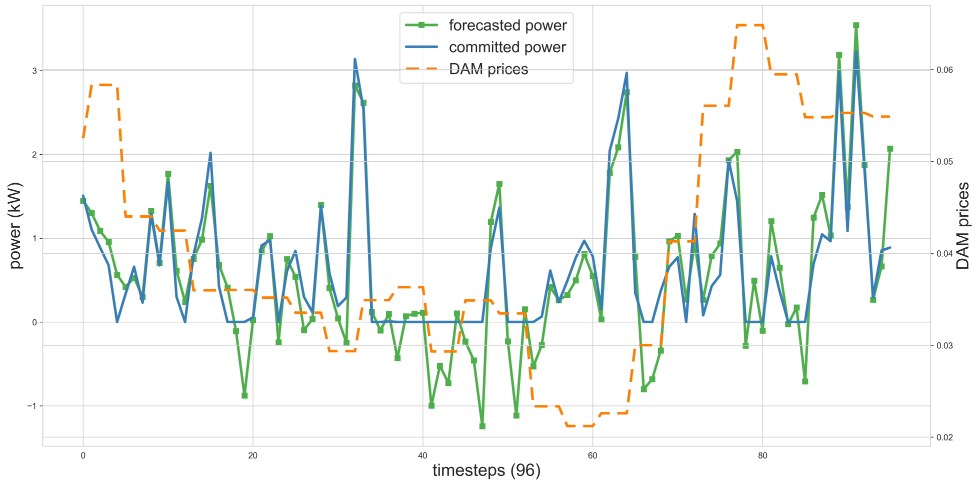


Figure 4.11: DA - Strategy Three: DAM prices vs committed vs forecast power (Uniform)

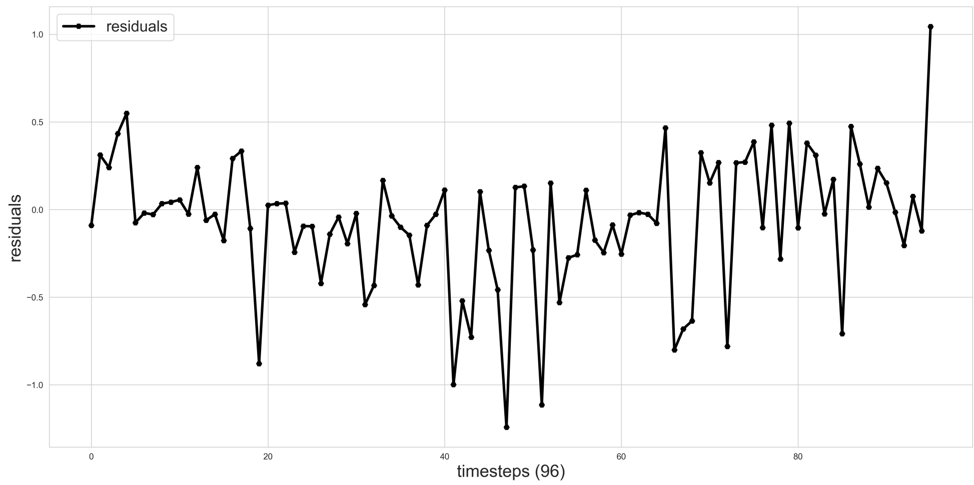


Figure 4.12: DA - Strategy Three: Residuals (Uniform)

Figures 4.13 to 4.18 represent the results when the error's probability distribution is assumed to be **Gamma**.

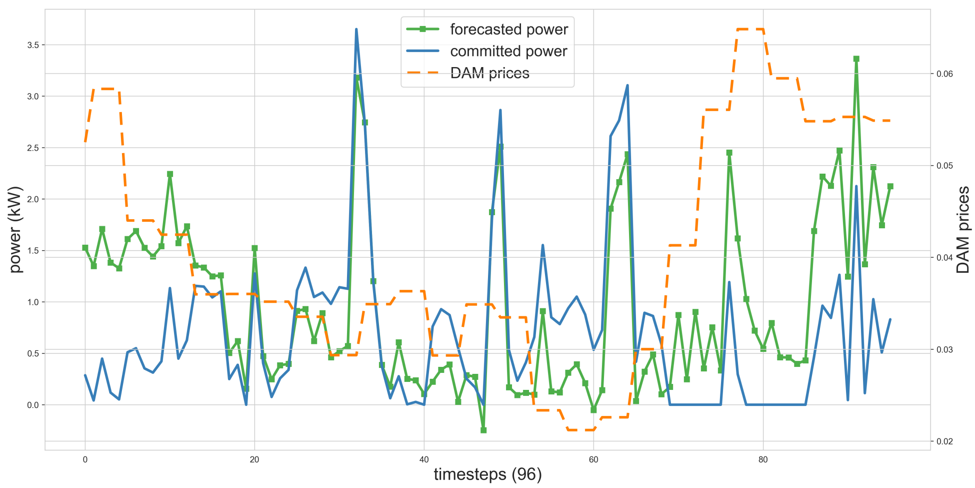


Figure 4.13: DA - Strategy One: DAM prices vs committed vs forecast power (Gamma)

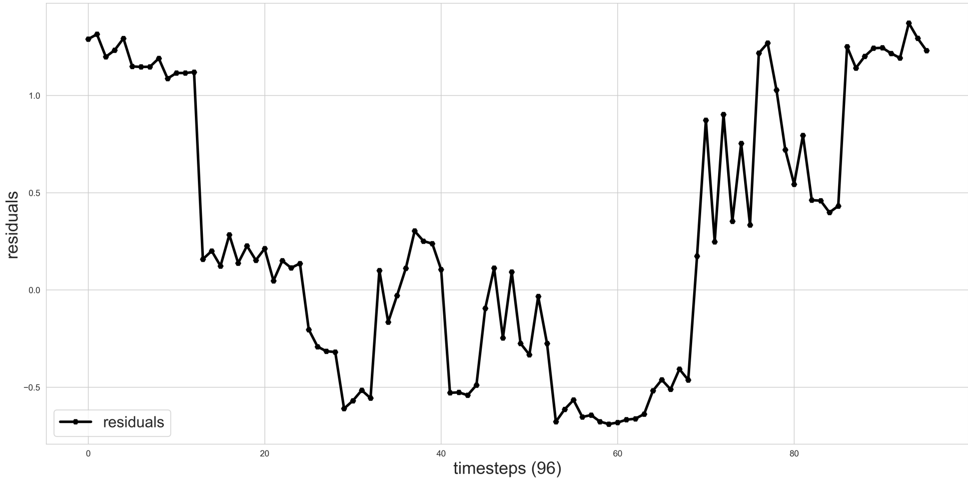


Figure 4.14: DA - Strategy One: Residuals (Gamma)

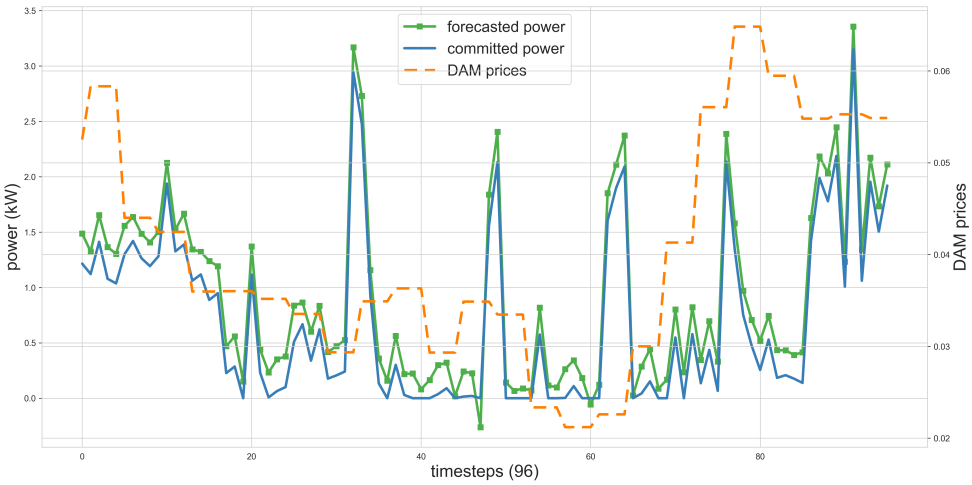


Figure 4.15: DA - Strategy Two: DAM prices vs committed vs forecast power (Gamma)

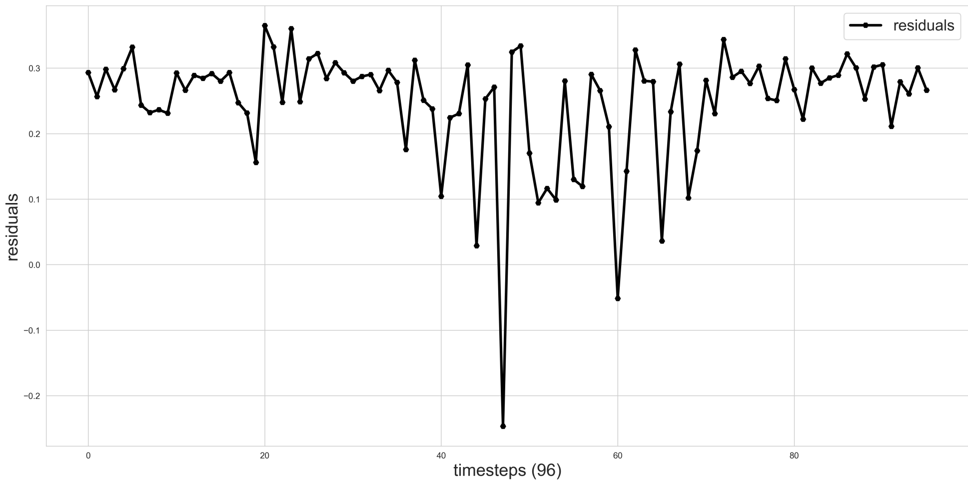


Figure 4.16: DA - Strategy Two: Residuals (Gamma)

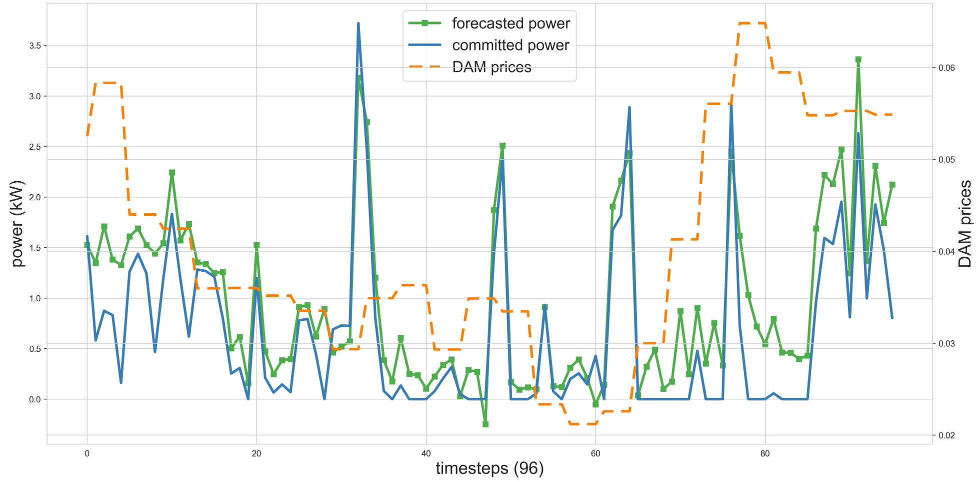


Figure 4.17: DA - Strategy Three: DAM prices vs committed vs forecast power (Gamma)

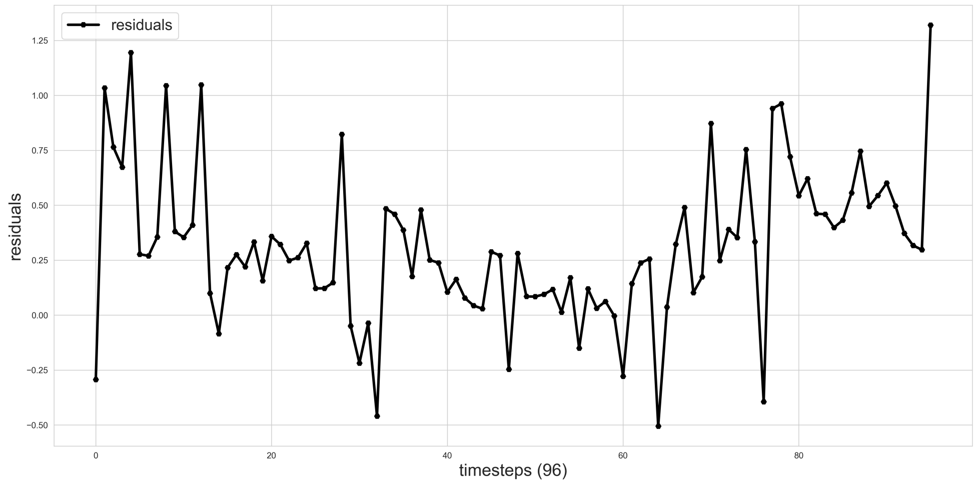


Figure 4.18: DA - Strategy Three: Residuals (Gamma)

Take figure 4.1 for instance, notice the line that represents the forecasted power and the line that represents the committed power. At times between $t = 0$ and $t = 5$, the DAM prices are high so the forecasted power during that period is much higher than the committed power. At times between $t = 55$ and $t = 65$ the DAM prices are low which shows that at every time-step during that period, the committed power is higher than the forecasted power. Figure 4.2 represents the difference between forecasted power and the committed power at every time-step of the figure above 4.1. When the DAM prices, figure 4.1, are higher, the residual value (in figure 4.2) at time-step t is positive which indicates that the forecasted power is higher than committed power and the opposite (values are negative) applies for when the DAM prices are lower. The same applies to the rest of the figures in this section (strategy [1,2,3] and probability distributions [Uniform,Gaussian,Gamma]).

Time-steps with high DAM prices contain a lower value for the committed power; meanwhile, time-steps with lower DAM prices have a higher value for the committed value. The particular reason for that is the algorithm assumes (because of the different scenarios generated in section 4.4.1) that when the next day comes, the extra energy bought when prices were low would be used to charge the battery and when prices are high, the battery is in use, with respect to its constraints, and it'll fulfill the difference between the committed power and forecast.

The optimization strategy assumes more power should bought at lower price. When the next day comes, the battery will fulfill the difference between the committed power and the actual demand power leading to a lower overall energy cost.

In the day-ahead bidding stage, it does not matter what the results are in the objective function; the critical part is the result of the objective function when the next day comes and the operation of the battery

4.6.2 Results for Step two: Battery Operation Stage

Two basic 'methods' are included, and both additional methods consider the forecast itself to be the day-ahead commitment bid but differ when it comes to the next day. The first primary method assumes a battery, but the second additional method doesn't consider a battery in the second stage. These two methods are only baselines for comparison with the strategies already mentioned in section 4.4.2.

- *Forecast with Battery*: The DA bid commitment is the forecast, and the battery is used the next day's "imbalances".
- *Forecast No Battery*: The baseline for comparison where the DA bid commitment is the forecast, and the battery is never used.

The optimization problem is applied using the power committed resulting from the day-ahead bid stage. Below, the results of the strategies (section 4.4.2 and 4.5) are illustrated.

4.6.2.1 Strategies' objective function and computational time comparisons:

The optimization problem was run over a number of days, and the average of the results was taken. Tables 4.4-4.7 compare the average computation time, the average objective function (which is the average total cost over a number of days), and the average financial savings for each strategy with the numbers of scenarios tested: **50** and the committed power obtained in the Day-ahead Market is the value used in the optimization problem. The *Stdev* column in each of the figures demonstrates the standard deviation of the total cost of each day in comparison to the average for each strategy. The *financial savings* columns are how much is being saved per strategy when compared to the baseline values of *Forecast No Battery*.

Tables 4.4-4.5 represent the results when the error's probability distribution is assumed to be **Gaussian**:

	Computation Time (in seconds)	total cost (in euros/day)	Stdev
Forecast No Battery	—	4.197532	**1.071**
Forecast with Battery	0.186813	3.80027	1.073
Strategy 1	0.17364	**3.45815**	1.103
Strategy 2	**0.12382**	3.60681	1.103
Strategy 3	0.174833	3.609142	1.084

Table 4.4: Time and Objective function for every strategy for the next day (Gaussian)

	Financial Savings (euro/day)	savings (%)
Forecast No Battery	—-	—-
Forecast with Battery	0.38003	9.464 %
Strategy 1	**0.73939**	**17.615 %**
Strategy 2	0.59072	14.073 %
Strategy 3	0.58839	14.018 %

Table 4.5: Financial Savings for every strategy for the next day (Gaussian)

Tables 4.6-4.7 represent the results when the error's probability distribution is assumed to be **Uniform**:

-	Computation Time (in seconds)	Total cost (in euros/day)	Stdev
Forecast No Battery	—-	4.719524	1.071
Forecast with Battery	0.2173	3.88407	1.064
Strategy 1	0.175	**3.56228**	1.121
Strategy 2	**0.129048**	3.66779	**1.024**
Strategy 3	0.1829	3.68974	1.12

Table 4.6: Time and Objective function for the strategies for the next day (Uniform)

-	Financial Savings (euro/day)	savings (%)
Forecast No Battery	—	—
Forecast with Battery	0.88345	17.702 %
Strategy 1	**1.15725**	**24.5205 %**
Strategy 2	1.051734	22.285 %
Strategy 3	1.2978	21.8196 %

Table 4.7: Financial Savings for every strategy for the next day (Uniform)

Tables 4.8-4.9 represent the results when the error's probability distribution is assumed to be **Gamma**:

	Computation Time (in seconds)	total cost (in euros/day)	Stdev
Forecast No Battery	—	4.10726	0.995
Forecast with Battery	0.1776	3.693	0.943
Strategy 1	0.1832	**3.0366**	**0.842**
Strategy 2	**0.12914**	3.3989	0.849
Strategy 3	0.1804	3.2612	0.949

Table 4.8: Time and Objective function for every strategy for the next day (Gamma)

	Financial Savings (euro/day)	savings (%)
Forecast No Battery	—	—
Forecast with Battery	0.41424	10.09 %
Strategy 1	**1.0707**	**26.07 %**
Strategy 2	0.70836	17.25 %
Strategy 3	0.84606	20.6 %

Table 4.9: Financial Savings for every strategy for the next day (Gamma)

It is clear that as the number of scenarios increase, the time it takes to solve the optimization problem will increase. In addition to that, the rise in the number of scenarios will most likely get you closer to the actual values for load demand of the next day (but will have take more time to compile).

4.6.2.2 Committed power vs Actual load vs battery SOC:

Figures 4.19,4.21,4.23,4.25 illustrates the comparison between the committed power, actual load power and battery SOC compared to each other at every time-step t. Figures 4.20,4.22,4.24,4.26 shows the error between actual power and committed power. The Figures are results for only one of the days, which is March 21, 2021, the number of scenarios is **50**, and the error's probability distribution is **Gaussian**. It is to set an idea of the procedure when comparing committed power, actual load, and battery SOC. Note that the left y-axis represents the power values, and the right y-axis represents the Battery SOC values.

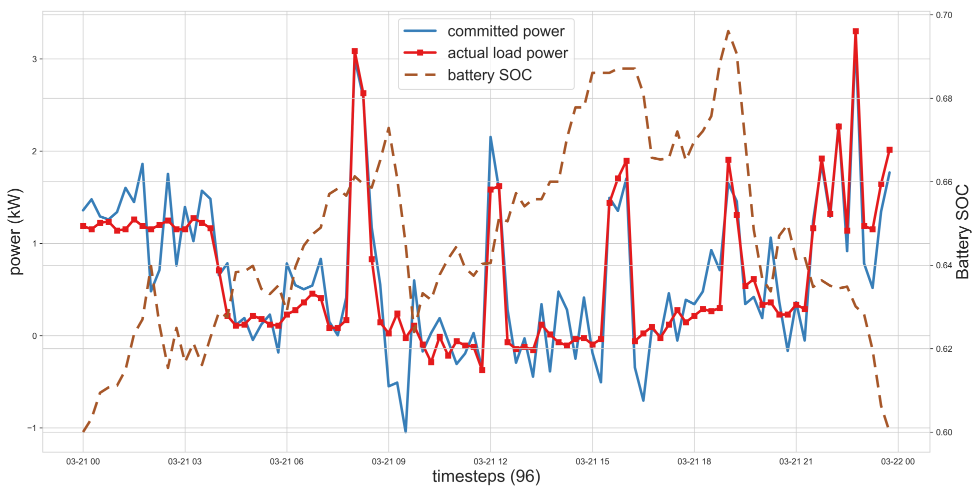


Figure 4.19: Forecast With Battery: Battery SOC vs actual vs committed power (Gaussian)

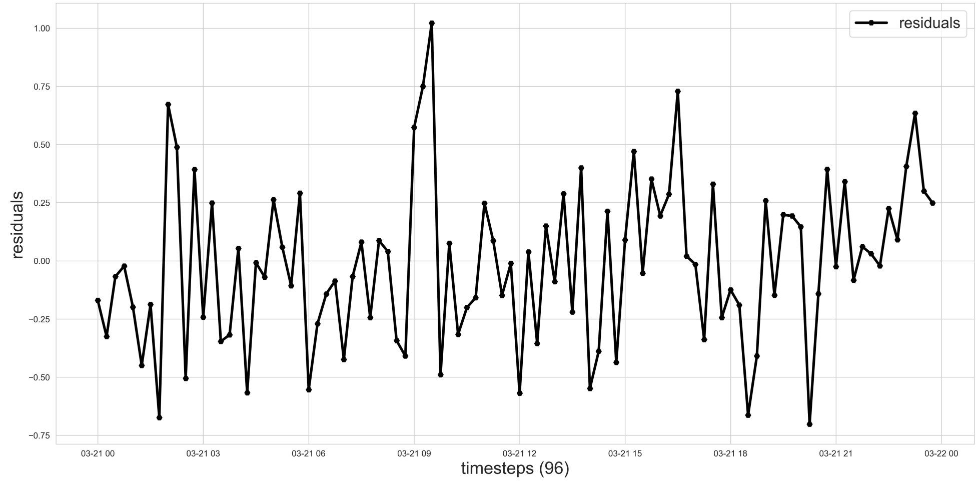


Figure 4.20: Forecast With Battery: Residuals (Gaussian)

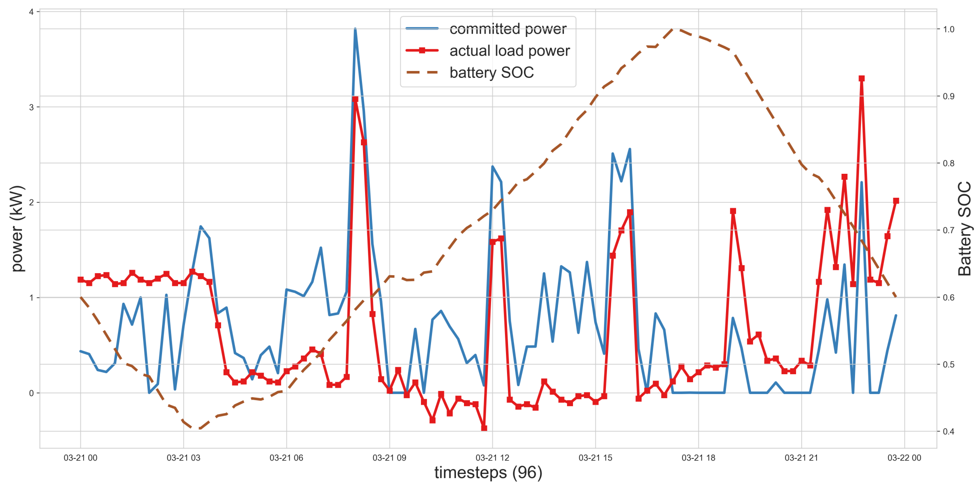


Figure 4.21: Strategy One: Battery SOC vs actual vs committed power (Gaussian)

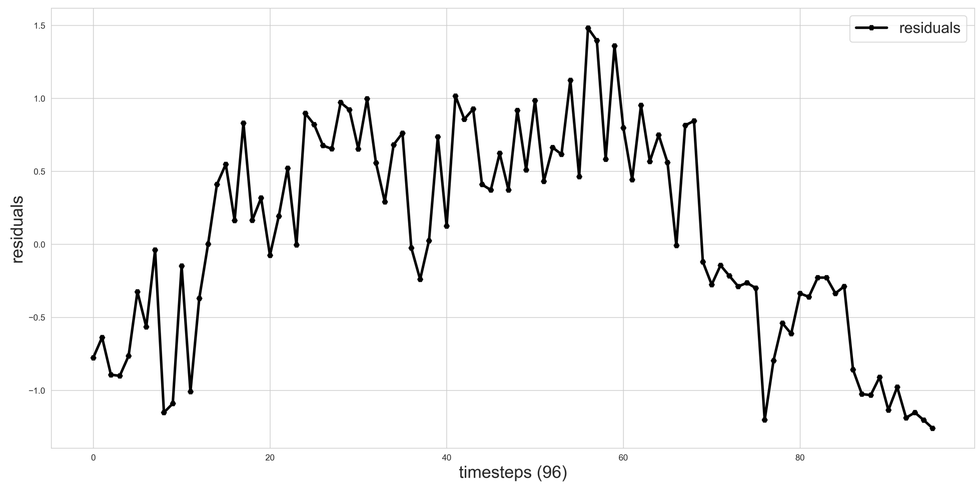


Figure 4.22: Strategy One: Residuals (Gaussian)

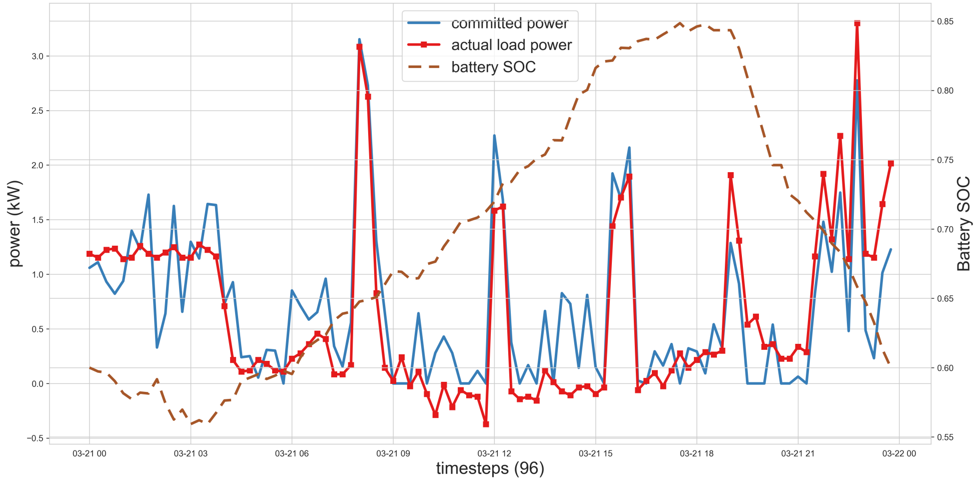


Figure 4.23: Strategy Two: Battery SOC vs actual vs committed power (Gaussian)

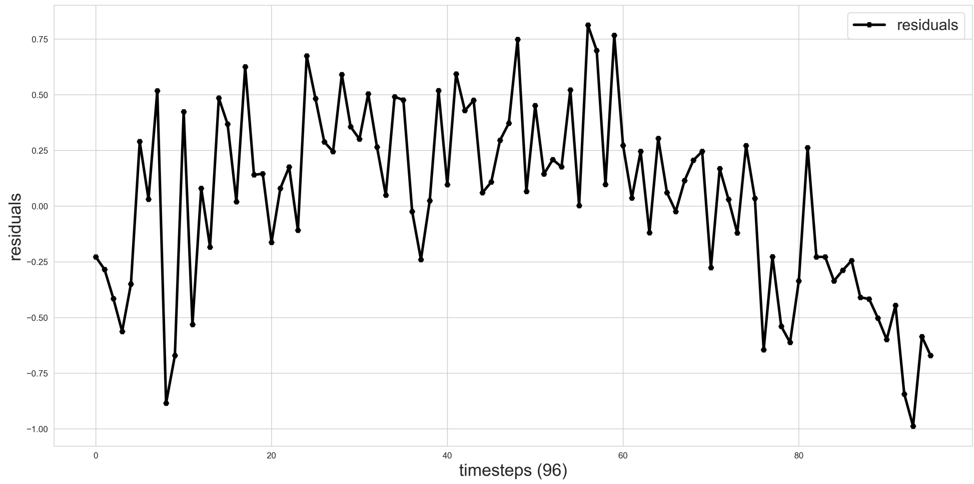


Figure 4.24: Strategy Two: Residuals (Gaussian)

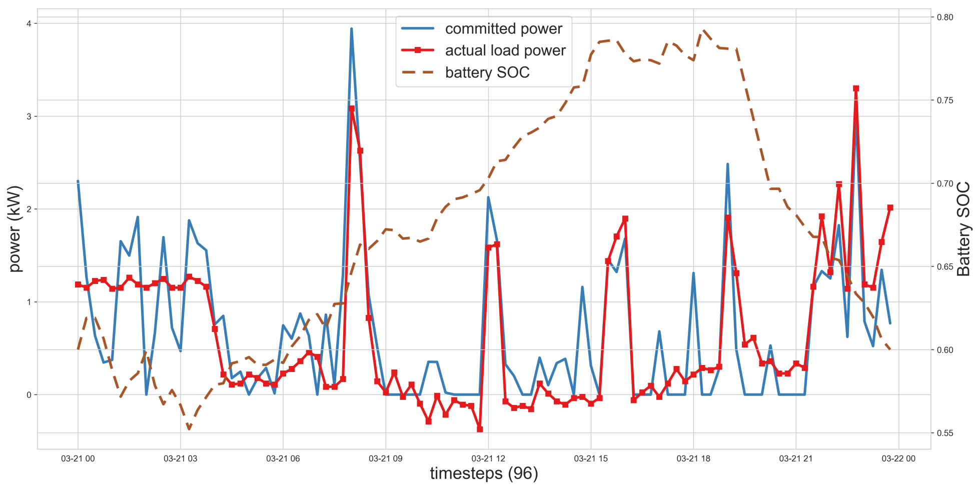


Figure 4.25: Strategy Three: Battery SOC vs actual vs committed power (Gaussian)

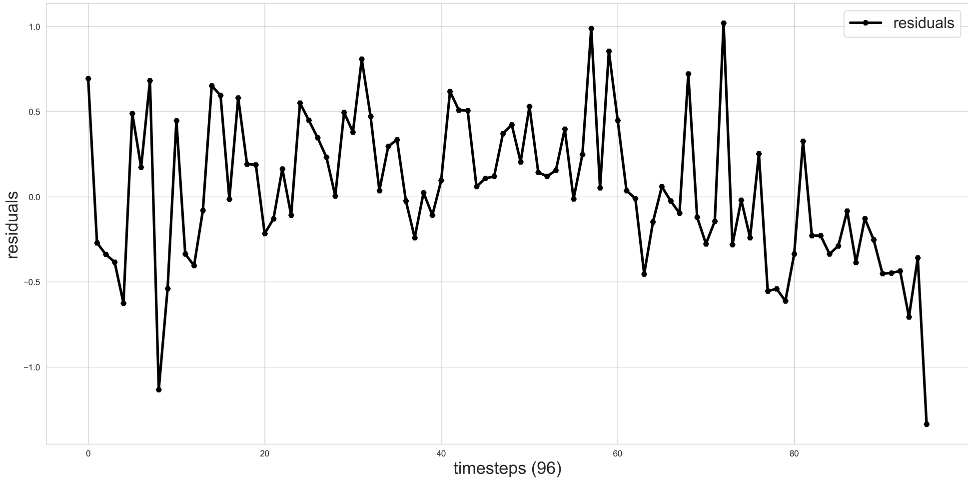


Figure 4.26: Strategy Three: Residuals (Gaussian)

Figures 4.19, 4.21, 4.23, and 4.25 shows how the battery is functioning with respect to the difference found in between the committed power and the actual demand power (Figures 4.20, 4.22, 4.24, and 4.26) for every strategy respectively, considering the battery's constraints. Remember that in the day-ahead bidding stage, the idea is to buy power at every time step based on the DAM prices. Figures 4.19 to 4.26 represents the results of the different strategies. The battery state of charge (SOC) varies from one strategy to another (because of the different values of the committed power for every strategy) at every time-step t.

Let's take Figures 4.21-4.22 for instance. Between time-steps $t = 0$ and $t = 12$ in figure 4.22, most of the values of the error (which is the difference between actual and committed power in figure 4.21) are below zero which means that the battery will discharge as seen figure 4.21 between time-steps $t = 0$ and $t = 12$. Between time-steps $t = 13$ and $t = 70$, the battery is charging most of the time because the error values were above zero. And finally the last part of the figure, the errors are below zero again, so the battery is discharging back to 60% SOC (because of one of the battery's constraints in 4.9).

4.6.2.3 Total Bidding Cost and Total Imbalance Cost comparison

In this section, the total bidding cost, total imbalance cost and the total overall cost for each strategy are demonstrated. For Tables 4.10-4.12 and Figures 4.27 to 4.31 below:

- Total bidding cost is the DAM prices multiplied by the power committed at all time-steps $(\lambda_t * P_t^{commit})$
- Total imbalance cost is the imbalance cost (0.02) multiplied by the absolute value of the result of the true power added to the battery power and subtracted from the committed power
$(\gamma_t * |P_t^{aL} + P_t^B - P_t^{commit}|))$
- Total overall cost is the same as the objective function of every strategy (section 4.4.2).

Bidding cost vs Imbalance cost at every time t:

Figures 4.27 to 4.31 represent the results of the optimization for every strategy during a single day which is 21 March 2021, and the number of scenarios is **50** knowing that the error's probability distribution is **Gaussian**. The following figures show how the imbalances and bidding costs behave at every time-step for every strategy. Note that the left y-axis represents the bidding cost values, and the right y-axis represents the imbalance cost values at every time-step t.

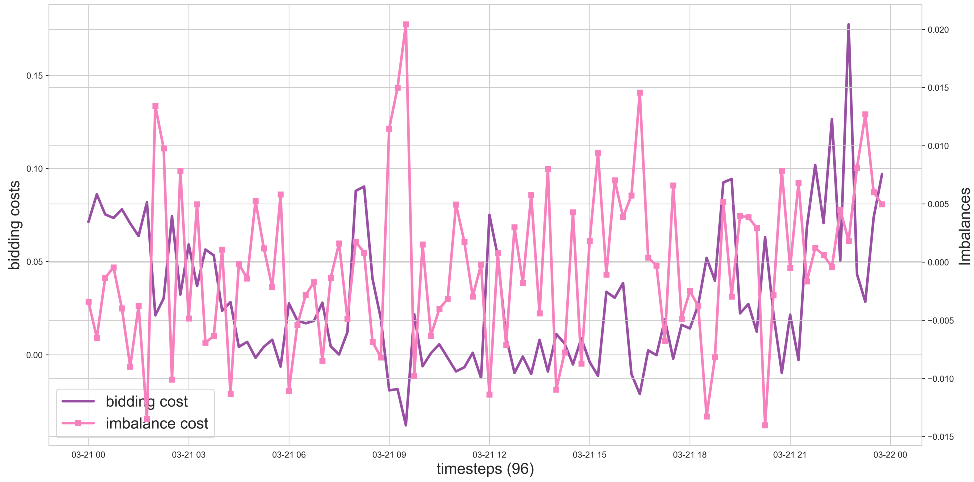


Figure 4.27: Forecast With No Battery: Bidding cost vs imbalance cost at every time-step (Gaussian)

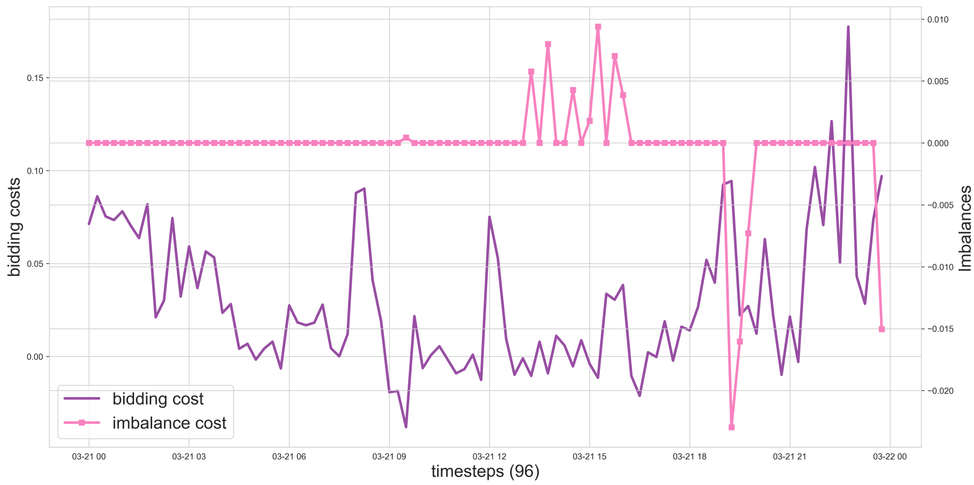


Figure 4.28: Forecast With Battery: Bidding cost vs imbalance cost at every time-step (Gaussian)

Figure 4.29: Strategy One: Bidding cost vs imbalance cost at every time-step (Gaussian)

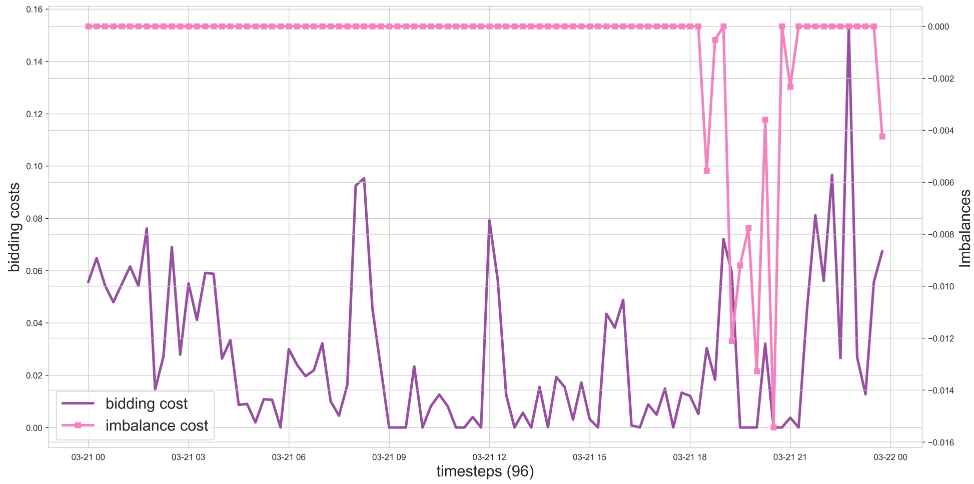


Figure 4.30: Strategy Two: Bidding cost vs imbalance cost at every time-step (Gaussian)

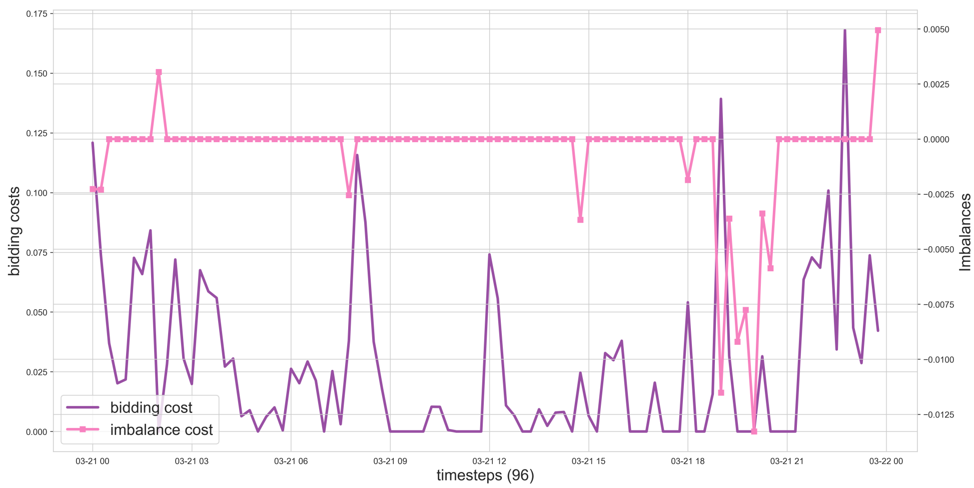


Figure 4.31: Strategy Three: Bidding cost vs imbalance cost at every time-step (Gaussian)

The figure 4.27, shows how a lot of imbalances exist at every time-step when no battery is involved knowing that for every imbalance power, there is an extra charge. Figures 4.28

to 4.31 have a much smaller range of imbalances at every time-step. Some strategies have more imbalances than others, but the overall total cost is what matters at the end of the day.

Total overall cost vs Total bidding cost vs Total imbalance cost:

The following tables 4.10-4.11 compares the strategies' objective function, total bidding cost and total imbalance cost across all time-steps and figures 4.32-4.33 is the representation of the tables using a horizontal stacked bar chart respectively.

Table 4.10 and Figure 4.32 represent the results when the error is assumed to be **Gaussian**:

	Total Overall Cost	Total Bidding Cost	Total Imbalance Cost
Forecast No Battery	4.197532	3.79617	0.52246
Forecast with Battery	3.8003	3.70302	0.09989
Strategy 1	**3.45825**	**3.37971**	0.13235
Strategy 2	3.60681	3.69293	**0.05816**
Strategy 3	3.60914	3.62354	0.08280

Table 4.10: Total cost, total bidding cost and total imbalance cost for every strategy (Gaussian)

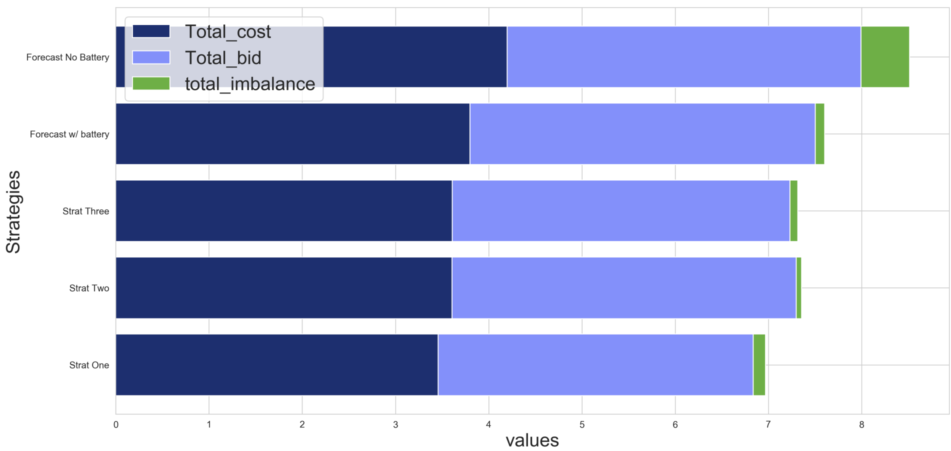


Figure 4.32: Total cost vs bidding vs imbalance (Gaussian)

Table 4.11 and Figure 4.33 represent the results when the error is assumed to be **Uniform**:

	Total Overall Cost	Total Bidding Cost	Total Imbalance Cost
Forecast No Battery	4.71952	3.76623	0.951303
Forecast with Battery	3.88407	3.76623	0.15041
Strategy 1	**3.56228**	**3.69503**	0.20685
Strategy 2	3.66779	4.00769	0.195754
Strategy 3	3.68974	3.99119	**0.15039**

Table 4.11: Total cost, total bidding cost and total imbalance cost for every strategy (Uniform)

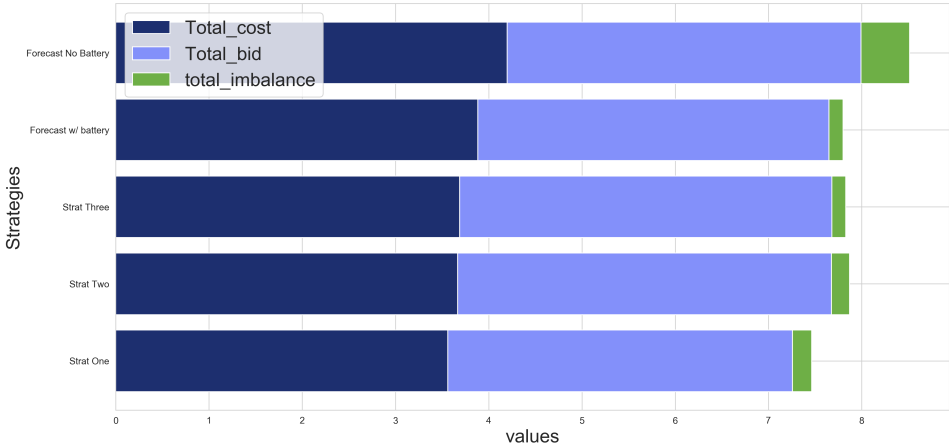


Figure 4.33: Total cost vs bidding vs imbalance (Uniform)

Table 4.12 and Figure 4.34 represent the results when the error is assumed to be **Gamma**:

	Total Overall Cost	Total Bidding Cost	Total Imbalance Cost
Forecast No Battery	4.10726	5.0081	0.6651
Forecast with Battery	3.693	5.0081	0.6368
Strategy 1	**3.036598**	**3.15119**	0.11383
Strategy 2	3.3989	3.9041	0.202
Strategy 3	3.2612	3.4365	**0.0832**

Table 4.12: Total cost, total bidding cost and total imbalance cost for every strategy (Gamma)

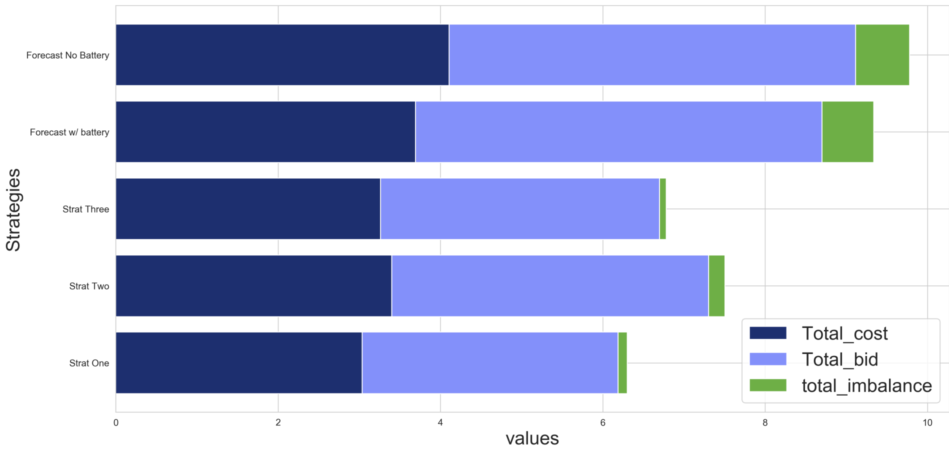


Figure 4.34: Total cost vs bidding vs imbalance (Gamma)

4.6.3 Different Range of Values for the Error

A minor recap:

- The day-ahead bidding stage was involved in coming up with committed net energy consumption for each time-step of the next day, considering that a battery exists within the process.

- In the stage where the next day arrives, the battery with respect to certain constraints (section 4.3), is being optimized and used to compensate for the imbalances (between the committed and actual power) and helping in reducing the total energy cost.

All the results found in section 4.6 are based on an error that is part of a known probability distribution (ones tested here are (*Uniform Gaussian and Gamma*) that is roughly within a range of -1 and 1. However, a question can arise, and that question is: What would happen if the range changed to a smaller or large one? Having a smaller range for the probability distribution of the error leads to smaller values for the imbalances (difference between committed and actual power). With smaller imbalances and since the battery compensates for the imbalances, therefore the overall total cost would be smaller. And if the range of errors was larger than the one tested, it will lead to larger values for the imbalances and eventually a larger total energy cost.

A minor test was applied to show the idea mentioned in this section. A single day (March 21, 2021), three distributions (Uniform, Gaussian and Gamma) and strategy 1 (mentioned in section 4.4.2.1) were be applied and the result is found in the following tables 4.13,4.14,4.15.

If the range of errors is [-0.5,0.5], table will show present the results:

Error Distribution	DA objective	Total Overall Cost	Total Bidding Cost	Total Imbalance Cost
Uniform	2.1951	2.25704	2.2353	0.10511
Gaussian	2.2169	2.20965	2.3042	0.10467
Gamma	2.1005	2.1764	2.2027	0.0565

Table 4.13: DA objective function, Total cost, total bidding cost and total imbalance cost for strategy One with a range of errors [-0.5,0.5]

If the range of errors is [-1,1] (the one used in this paper), table will show present the results:

Error Distribution	DA objective	Total Overall Cost	Total Bidding Cost	Total Imbalance Cost
Uniform	2.34616	2.41653	2.2822	0.139127
Gaussian	2.3539	2.26623	2.354	0.15288
Gamma	2.2073	2.2388	2.32005	0.1214

Table 4.14: DA objective function, Total cost, total bidding cost and total imbalance cost for strategy One with a range of errors [-1,1]

If the range of errors is [-2,2], table will show present the results:

Error Distribution	DA objective	Total Overall Cost	Total Bidding Cost	Total Imbalance Cost
Uniform	2.956	2.73	2.823	0.402
Gaussian	2.4714	2.48734	2.5903	0.3167
Gamma	2.2534	2.3049	2.35078	0.1326

Table 4.15: DA objective function, Total cost, total bidding cost and total imbalance cost for strategy One with a range of errors [-2,2]

The second column of tables 4.13, 4.14, and 4.15 defines the Day-ahead objective function value at every error distribution mentioned during the day-ahead bidding stage. The last three columns represent the total overall cost, bidding cost, and imbalance cost for every distribution during the battery operation stage. The mentioned table can indicate that if the error range is smaller and closer to zero, the imbalances will be smaller, making the total energy cost smaller, and the opposite applies when the range of errors is larger.

4.6.4 Discussions and Analysis

The purpose is to explore how the day-ahead market bid could improve by considering forecasting errors and the battery operation responsible for compensating those errors. The objective is to maximize profit and minimize energy costs at the day/week/month. Three strategies were applied and their results were compared amongst each other and amongst two extra baseline methods which are *forecast no battery* and *forecast with battery* (mentioned in section 4.6.2). The need to choose which strategy is best depends on several aspects which are:

1. Computation time in the day-ahead bidding stage
2. Total overall cost (objective) in the battery operation stage
3. Battery behavior during the day
4. Total bidding cost
5. Total imbalance cost
6. Financial Savings

Tables 4.1,4.2 and 4.3 demonstrate the computational time and objective function of each strategy for a Gaussian, Uniform and Gamma distribution respectively in the day-ahead bidding stage. In this stage, what matters is the computational time and in both tables 4.1, 4.2 and 4.3. *strategy 2* has the best values with *strategy 1* being the slowest one. In addition, the objective function in these tables is not of big importance because if it's good in the day-ahead stage and bad in the battery operation stage then it's of no use. So, according to tables 4.1, 4.2 and 4.3, strategy 2 is best because it is the fastest in terms of computation time.

Stepping into the next day, tables 4.4-4.7 represent the computation time, total cost (objective function) and financial savings and compare every strategy. Observing these tables, the computation time is fairly similar between all of them but the objective function in *strategy 1* stands out with a value of 3.445815 (for table 4.4) and 3.56228 (for table 4.6) in comparison to the others. The same applied to the tables 4.5, 4.7 and 4.9 where *strategy 1* has the best values in the **Financial Savings** column with 17.615%, 24.52095% and 26.07% respectively.

Figures 4.19 to 4.25 show battery operation, committed power and actual load power being compared to each other for every strategy. Figure 4.19 shows the battery continuously charging and discharging continuously at every time-step. Figures 4.21 to 4.25 have a much smoother battery behavior; however, Figure 4.21 has the smoothest battery operation in comparison to the rest of the strategies. The first strategy uses the battery more often than the other two as it is noticed through the values on the right y-axis which are between 0.4 and 1. Strategy two, where the battery focuses strictly on reducing imbalances, has battery SOC values between 0.55 and 0.85. Strategy three's battery SOC values are between 0.6 and 0.8. Note that the battery's SOC is always between 0 and 1.

Figures 4.32 to 4.34 and Tables 4.10-4.12 compare the total overall cost, total bidding cost and total imbalance cost of every strategy for when the error's probability distribution is either **Gaussian**, **Uniform** or **Gamma** respectively. In figures 4.32, 4.33 and 4.34, the first bar from the top represents the *forecast with no battery* and noticed that in comparison to the rest, it is the worst with a big total cost, bid cost and imbalance cost. Comparing the strategies, Strategy one has the lowest total cost and bidding cost, and Strategy two has the lowest imbalance cost. Strategy three is the worst in comparison to the other two strategies; however, in terms of computation time, it is better than strategy one (mentioned in earlier section 4.6.1). Strategy one has a better total cost than strategy two because sometimes it is possible to make more money buying power when the price is low and selling when the price is high than what is made from minimizing imbalance values.

Following that, **strategy one** is the best option because it gives the best results. In strategy one, when the prices are low, more power is bought, and the extra power is used to charge the battery when the price is high and less committed power is bought.

Strategy one was tested on three different distributions (Uniform, Gaussian, and Gamma). What is also important is to see which distribution seems to be preferred when applying this strategy. Figure 4.35 compares the committed power at every time-step t across the different distributions and to the DAM prices, and figure 4.36 compares the Battery SOC at every time-step t across the different distributions for a single day which is March 21, 2021. Figure 4.37 shows the average of the financial savings over a number of several days for the three probability distributions applied in this experiment. The values in the figure 4.37 were taken from tables 4.5,4.7, and 4.9 with the selected strategy being strategy one.

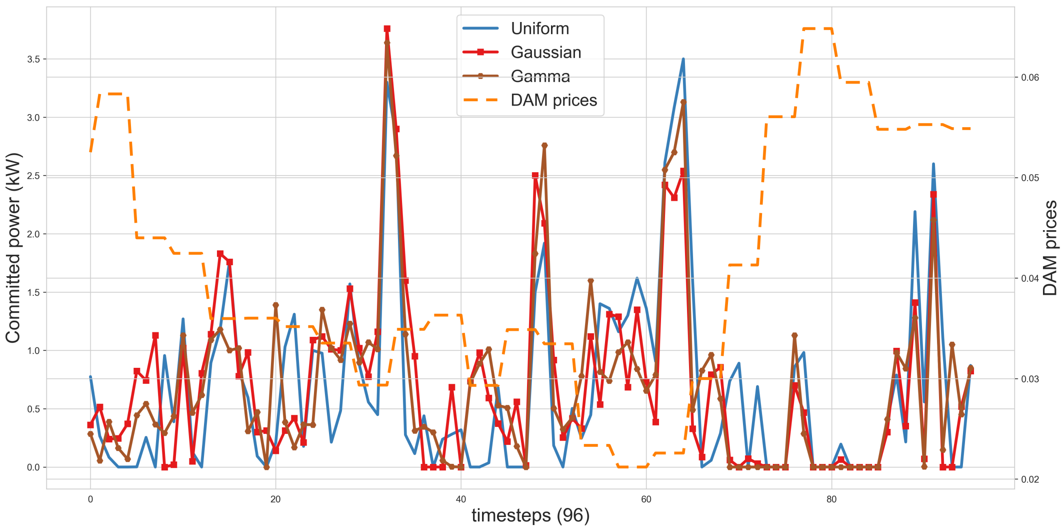


Figure 4.35: committed power across the different distributions of the error and to the DAM prices for a single day

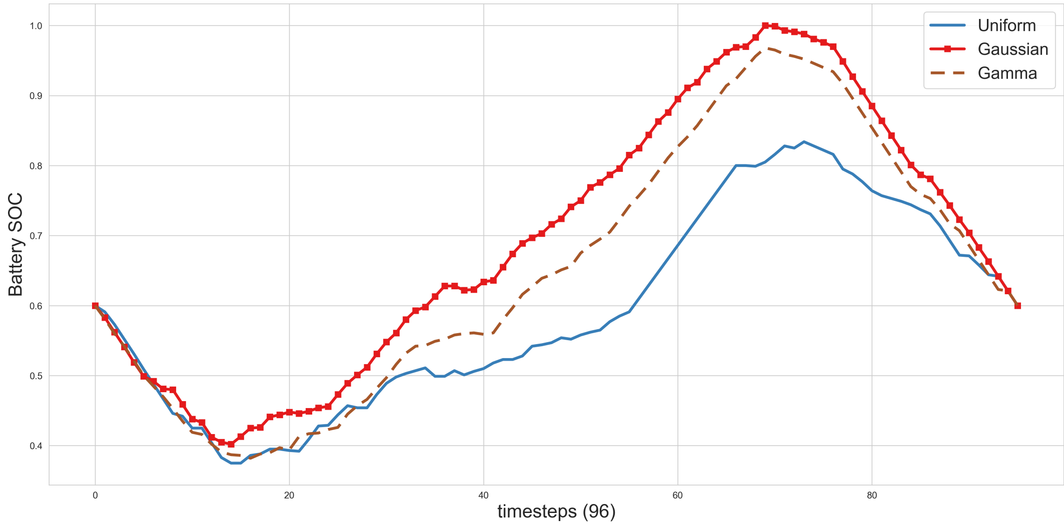


Figure 4.36: Battery SOC across 3 different distribution of the error for a single day

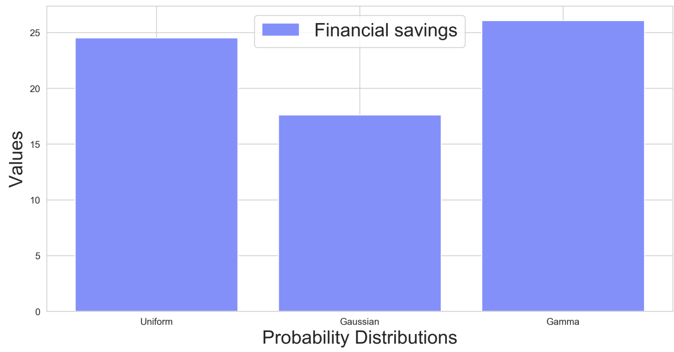


Figure 4.37: Average financial saving (in %) across 3 different probability distributions of the error

In figure 4.35, in most of the time-steps, the results coming from the committed power for the 'Gaussian distribution' contain the better results when comparing against the DAM prices. In most cases, the Gaussian distribution is a more realistic distribution where the probability grows higher as the values get closer to the center (the mean), which is zero.
In figure 4.36, when the error probability distribution is Gaussian, the battery is used more often, and around time-step $t = 70$, the battery's SOC reaches 100% which can be in some cases problematic because there is no wiggle room for the system to change its mind in case something happens. When the error probability distribution is Gamma, the battery shows a smoother line in the figure 4.36 and does not reach 100% battery SOC, which leaves some room for any sudden changes.
In figure 4.37, the gamma distribution shows the best financial savings (in %) with a 26.07% savings in comparison to the Gaussian with 17.615 % and Uniform with 24.5205 %.
For the purpose is to maximize profit and minimize total energy cost, **strategy 1** produces the best results across all tested error probability distributions, and the preferred error probability distribution is **Gamma** since it contains the best financial savings and battery operation.

4.7 Solvers Used

Different solvers were used and tested through this optimization problem that range from non-linear solvers **couenne** to linear solvers like **gurobi**, **cplex**, **ipopt** and **cbc**.

Initially, the *couenne* solver was used because the problem was non-linear due to the absolute value in the optimization problem. When the couenne solver ran, much time was spent trying to find an optimal solution. For example, during the day-ahead bidding stage in section 4.4, the more scenarios added to the strategies, the more time it required to find a solution which could go up to 5 hours (depending on the strategy). For that reason, the non-linear problem was transformed into a linear problem as mentioned in section 4.7.1. When the problem became linear, *gurobi*, *cplex*, *ipopt* and *cbc* solvers were applied to indicate which one gives the best result across all strategies. Gurobi and Clpex were unable to find a solution; however, ipopt and CBC could find one. The solution *cbc* solver gave was better than the one of the *ipopt* solver, not to mention that it was also faster in terms of computational time. Therefore the ***cbc*** was the one to used for this optimization problem.

4.7.1 From Non-Linear to Linear

In the sections 4.4.2 (in day-ahead bidding stage) and 4.5 (in the battery operation stage), an absolute absolute operator and it's importance were mentioned in the optimization problems. Optimization with absolute values makes a linear problem a non-linear one. Absolute value functions are complicated to perform standard optimization procedures on since they are not continuously differentiable functions and are non-linear [50, 70]. It is possible to manipulate the absolute value expression found in the problem and to be able to avoid these difficulties and change the problem into a linear one [50, 70]. Let's take an example:

$$min f(x) = g(x) + b * |x - a|$$

subject to: other constraints

can be switched into:

$$min f(x) = g(x) + b * p + b * q$$

subject to:
other constraints
$x - a + p - q = 0$
$p, q >= 0$

4.8 Summary

It is not easy to predict people's behavior and especially when it comes to energy usage. A forecast can be made, but there will always be an error compared to the actual energy demand, knowing that every error, or deviation/imbalance, adds an extra cost. In order to avoid the extra costs and errors, a battery can be used to compensate for those imbalances and maybe minimize the total bidding cost knowing that a battery has certain constraints.

This chapter aims to find an optimal bidding strategy of the BESS to maximize profit and minimize total energy cost. Three strategies (section 4.4.2) have been applied and studied. These strategies were compared amongst each other well as two other extra methods (section

4.6.2) were used as baselines for comparison. It is challenging to predict people's energy demand for the day-ahead bidding stage, so errors still happen. For that reason, a number of scenarios (of how possibly the error might be) were made assuming that the probability distribution of the error is known. Three probability distributions of the error were considered, which are *Uniform*, *Gaussian* and *Gamma* and that is to see how the strategies would perform with different probability distributions of the error. Decisions on which strategy is best were based on computational time in the day-ahead bidding stage (section 4.4), the total cost, and financial savings in the battery operation stage (section 4.5). With the results (section 4.6), it can be concluded that **strategy 1** is the most successful strategy in comparison to the rest of the strategies. **Strategy 1** uses *two-stage chance-constraint* programming, and the financial saving reaches almost an average of 25% of the energy cost.

It can be concluded that using a battery, with respect to its constraints, can be beneficial in reducing the error in the forecast, leading to minimizing the energy cost at the end of the day and the month. However, it is essential to know how to use the battery to minimize the energy cost. With **strategy 1**(since it said to be the best strategy), when the prices are low, more power is bought, and the battery charged, and when prices are high, the battery is used, with respect to its constraints, and less power is bought. Moreover, the preferred probability distribution of the error is a Gamma distribution.

Optimization Technique	Uncertainty Modeling
Deterministic	Single-value forecast
Chance-constraint programming	Probability distribution or scenarios (Probability)
Agent-based Modeling	Apply a set of rules
Robust Optimization	Worst-case among scenarios or continuous set

Technique	Chance-constraint	Distributionally Robust	ABM
Uncertainty	Probability distribution or scenarios	Worst-case among Scenarios or continuous set	follow set of decision rules
Goal	Optimize objective & be feasible within a level of confidence	Optimize the worst-case value of uncertainty	find values that satisfy the decision rules
Risk	Controllable	Risk-averse	Controllable
Computation	Easy (reformulation)	Easy (reformulation)	Easy
Critique	Assumption on the shape of the distribution	Too conservative	Too many rules are hard to understand & complex

4.8.1 Future Work

After that, consider how the bidding strategy would change if the following were considered:

- the battery power limit
- the battery energy capacity
- the grid power limit

That is to see how they effect the efficiency of different optimization techniques. To see if there are preferable parameters for optimizing a customer's energy usage costs.

Chapter 5

Trading Markets, Agents and Capacity Traders

This chapter will explore Continuous Double Auctions (CDA) and trading agents limited to Zero-Intelligence Constraint (ZIC) and Zero-Intelligence Plus (ZIP) techniques. A table with a summary of this section will be provided at the end of this chapter. It will then introduce capacity traders and some metrics for market performance.

5.1 Auctions

Before delving into CDA and the trading agents, let us introduce the notion of an auction.

For many years, buyers and sellers have gathered in markets and bargained in various human societies. When bargaining, the sellers declare the offer price they wish to sell, and the buyers answer with a lower bid price than the offer. The seller may lower the offer slightly, and the buyer may slightly raise the bid. These price adjustments are repeated until a bargain is reached or one party walks away.

The term "auction" is used in economics to describe the process through which buyers and sellers together agree on a transaction price, exchanging money for goods or services. A bargain is a type of auction [24]. There are several different sorts of auctions. Auctions are commonly used to allocate particular commodities, almost always in short supply, to participating merchants who want to buy them [2, 122]. This is made feasible by the participation of the hereinafter roles in any auction:

- **Auctioneer**: who selects who will get the product and at what price.
- **Trader**: might be either a *bidder* trying to acquire products, or a *seller* aiming to sell things or a mix of the two.

An example of an auction is the *English Auction* [22, 24]. Items are always appointed to the top bidder in this auction, who purchases them at a price provided by the highest bid. If a seller of items i receives bids from A, B, and C with values $b(A) > b(B) > b(C)$, the auctioneer will assign the items to A, who will then pay $b(A)$. This method is also known as a *first-price* auction. A **shout** can either be a bid submitted by a buyer or an offer submitted by a seller.

Differentiating different variants of an auction is not limited to only identifying the transaction price. Paper [89] discusses over 30 auction types depending on a given number of properties. Paper [2] offers a quick summary of the properties stated. The summary of the properties can be found in paper [2] and they include: *open-cry or sealed-bid*, *single or multi-dimensional*, *one or two sided*, *first or kth price*, *single or multi- unit*, and *single or multi-item*. According to paper [2], the design and implementation of the auction mechanism allow individuals to reason about other characteristics inherent in the method used. Papers [63, 2] provide a detailed overview as going deeper into this topic is not part of this thesis. The brief overview mentions: *allocative efficiency*, *budget balance*, *individual rationality*, *incentive compatibility*, and *tractability*.

5.2 Continuous Double Auction

Following what has been mentioned in section 5.1, any auction includes an auctioneering process, which according to paper [116], is defined by a market protocol that defines the following auction aspects:

> ... the nature of bids and asks allowed in the market, the clearing rule that indicates when a transaction occurs, the pricing rule that indicates the price at which a transaction occurs and the information published to the buyers and sellers in the market.
>
> *Vytelingum, D. Cliff, and Jennings* [116]

A trading mechanism was introduced by [107] which triggered and formed the basis of a widely used market, called the Continuous Double Auction (CDA) [23, 49, 111]. In CDA, there are multiple buyers and sellers that participate through submitting shouts, generated from their individual *limit prices*. To formulate the CDA mechanism, basic notions have to explored first:

- Definition 1: *limit price* l_s is the maximum price the buyers are willing to pay and the minimum price the sellers will ask [107, 104].
- Definition 2: *transaction price* t_p is the price the goods are going to be bought at.
- Definition 3: *trading round* is the period during which asks and bids are submitted until there is a match and a transaction occurs. There are typically several trading rounds in a trading day. At the beginning of the trading round, $O_{bid} = 0$ and $O_{bid} =$ max ask [116, 104].
- Definition 4: The outstanding bid, O_{bid}, is the current best bid (highest unmatched bid). The outstanding ask, O_{ask}, is current best ask (lowest unmatched ask) [104].

Paper [107]'s protocol is characterized as an open-cry, single-dimensional, one-sided, single-item auction with matching shouts being cleared at the average of the bid and the ask [116]. Two more rules are imposed:

- Any new bid should be higher than O_{bid} while all new asks should be lower than O_{ask}. This is called the **NYSE spread improvement** rule.
- Shouts only entail a single unit, are not queued and upon receiving an improving shut, removed from the auction. This is called **No-order queuing**.

Any CDA operates for a specified amount of time, *trading period*, generally across several *trading days*, with each day containing training rounds [116].

Each round comprises of the following steps:

1. Participating traders submitting their shouts until a trade is possible or maybe till a certain number of failed trades occur.
2. If a match between a bid and an ask occurs, a transaction is made, the round is over, and the auction moves to the next round.

It's called **continuous** double auction because of participants can continuously submit their shouts while the auction mechanism each time a new shout enters. In case some transaction happens, the surplus generated is updated. For sellers, l_s is subtracted from the t_s and for the buyers it's a similar formula:

$$surplus_{seller} = units * (t_p - l_s) \tag{5.1}$$
$$surplus_{buyer} = units * (l_s - t_p) \tag{5.2}$$

The overall surplus generated by a trader is the sum across all rounds acquired. The market surplus is the sum across all traders after a trading period has ended.

5.2.1 CDA different Versions

CDA has no "standard" definition or implementation; it varies depending on how each author defines it. The authors of paper [49] only accept single-unit shouts and define the transaction price t_p as the price of the transaction's first submitted shout. The NYSE spread-improvement mechanism is not employed in this case, and shouts are not withdrawn from the auction when an improved shout is provided. When a transaction is completed successfully, any shouts that did not find a match are removed from the auction, resulting in a clean state for the following round. Cliff and Bruten employed a version of CDA that is NYSE open-cry auction with shouts being removed from auction when a better shout is submitted. Miller, Rust, and Palmer in Paper [103] use discrete period for submitting bids and asks. Authors of paper [48] employ a version that is quite similar with the entire transaction history being publicly available. There are many more versions of CDA.

5.3 Trading Agents

There are many other trading agent strategies. For example, Zero-intelligence Plus, Adaptive Attitude (AA) [72], Adaptive Aggressiveness (AAg) [116], Fuzzy logic [54], Chris Priest [93], Gjerstad and Dickhaut (GD) [48] and many more.

However, in this section, the focus will be on introducing *Zero-intelligence* and *Zero-intelligence Plus* trading agents which are CDA traders. An analysis of these two strategies is provided with a minor example of how they function in the market.

5.3.1 Zero-Intelligence

Zero-intelligence (ZI) was developed by Gode and Sunder in paper [49] and they explored CDA's performance. They decided to replace human traders with ZI computer program traders to isolate different human behavioural impacts on market performance. In addition to that, some more changes have been applied:

> Each bid, ask, and transaction was valid for a single unit. A transaction canceled any unaccepted bids and offers. Finally, when a bid and ask crossed, the transaction price was equal to the earlier of the two.
>
> *Gode and Sunder* [49]

The ZI agents generates random asks (if its role is a seller) and bids (if its role is a buyer). Following that, they're distributed uniformly over the entire range of trading prices [49]. **ZI buyer** is given a price range and during every round a uniformly random bid is made where every price in the range has an equal probability. **ZI seller** the same is applied for the seller with a price range of its own.

Realistic pricing ranges must be supplied for these agents to operate at all. If the upper bound of buyers is lower than the lower bound of sellers, the market will fail to perform since bids and asks would never match.

There are two versions of ZI [49] and they are: $[b_i, b_{i+n}]$ $[s_i, s_{i+n}]$

- **Zero-Intelligence Constraint (ZI-C)**: This is subject to a budget limit that prevents it from buying or selling at a loss.
- **Zero-Intelligence Unconstrained (ZI-U)**: This has no budget limit.

ZI is given price ranges for both buyers and sellers, resulting in *four parameters*. The price ranges for the ZI buyer is $[b_i, b_{i+n}]$ and the one for ZI seller is $[s_i, s_{i+n}]$. Because there are just four parameters, tuning ZI is a simple task. Digging deeper into ZI agent design reveals that it does not require market information, such as previous transaction prices or the latest bid/ask prices, to function. ZI cannot adjust to changing markets because of its random nature, and no information is used in calculating the price. Lastly, no agent desires may be included in a ZI trader.

5.3.2 Zero-Intelligence Plus

Following the Zero-Intelligence agent type, Dave cliff and Bruten introduced an improved version called *Zero-intelligence Plus* (ZIP) in [27, 23]. But why did they want to improve ZI? The ZI agents are supplied with certain price ranges as a prior information. Cliff and Bruten could not see how ZI-C traders might be employed in scenarios like Smith's experiment [27, 23], which convinced Gode and Sunder.

After doing analysis and experiments, Cliff and Bruten did not agree with the following statement:

> the convergence of transaction price [to the theoretical equilibrium price] in zi-c markets is a consequence of the market discipline; trader's attempts to maximize their profits, or even their ability to remember or learn about events of the market, are not necessary for such convergence
>
> *Cliff and Bruten*[23]

ZIP was introduced shortly after and held on to the idea that minimal machine learning techniques would result in a performance similar to the human compared to the ZI agent. In ZIP, agents can have only one role, either a seller or buyer. Each ZIP agent keeps tracks of a profit margin which determines the difference between the limit price and the shout price that are going to be submitted [123].

For sellers, the limit price is the least amount the agent requires get for a unit to consider a transaction. For bidders, the limit price is the most the agent is willing to pay for a unit. It is prohibited for both ZI-C and ZIP agents to take a loss in a trade. If an agent had a successful trade in the prior round, its profit margin grows [56]. The behaviour of ZIP agents in Cliff and Bruten's paper is as follows.

ZIP sellers agent[27, 23]:

- If the last shout was accepted at price q
  - Any seller who asks a price less than or equal to q increases their profit margin.
  - If the previous shout was a bid, any seller who demanded a price more than or equal to q reduces its profit margin.
- Else
  - If the previous shout was an ask, any seller who asked a price more than or equal to q reduces its profit margin.

For buyers agent [27, 23]:

- If the last shout was accepted at price q
  - Any buyer who bids a price more than or equal to q increases the its profit margin.
  - If the previous shout was an ask, any buyer who requested for a price less than or equal to q reduced its profit margin.
- Else
  - If the last shout was a bid, each buyer who requested for a price less than or equal to q reduces the its profit margin.

ZIP agent contains *eight* parameters according to [25, 56, 114], and they are:

1. Each agent has a different learning rate (β_i), which specifies how quickly the profit margin should change. It is obtained at random from a parameterized uniform distribution (β_b, $\beta_b + \beta_\Delta$).

2. Each agent has a momentum (γ_i) which refers to the *Widrow-Hoff with momentum* [122] machine learning rule. The momentum is obtained at random from a uniform distribution with parameters (γ_b, $\gamma_b + \gamma_\Delta$).

3. Each agent has an initial profit margins of ZIP agents ($\mu_i(0)$), that is obtained at random from a uniform distribution. This distribution differs for sellers and buyers. For sellers the parameters are (μ_b, $\mu_b + \mu_\Delta$).

4. Cliff's two parameters, c_r and c_a, determine the distribution of stochastic perturbations used to calculate each trader's target price.

As noticed, ZIP requires certain market information, which is anything linked to an agent's last shout Q. Things like its type (whether it is a bid or an ask), whether it's accepted or not, and the price of Q. Zip is also able to adapt to the market as it changes, and in addition to that, the agent's preferences are possible to pinch through its parameters [27, 56].

How does the ZIP agent work?

ZIP applies the Widrow-Hoff with the momemtum learning rule [27, 122, 56]:

$$\Delta_i(t) = \beta * (\tau_i(t) - p_i(t)) \tag{5.3}$$

Knowing that β_i represents the learning rate, p_i represents the price at which the trader submitted its shout and τ_i represents the *target price* determined based on the most recently submitted shout. After that, it updates its profit margin μ_i at time $t+1$ [14, 56]:

$$\mu_i(t+1) = \frac{p_i(t) + \Gamma_i(t+1)}{l_i - 1} \tag{5.4}$$

where l_i is the trader's limit price and

$$\Gamma_i(t+1) = \gamma_i(t) + (1 - \gamma_i(t)) * \Delta_i(t) \tag{5.5}$$

where, as mentioned earlier, γ_i is the momentum. After the traders submits the shout at time t, the shout price is calculated [56]:

$$p_i(t) = l_i * (1 + \mu_i(t)) \tag{5.6}$$

There is an improved version with 60 parameters instead 8 called ZIP60 in paper [26] but it won't be discussed because it's out of the scope of this thesis.

5.4 Summary on Trading Markets and Agents

Two tables (5.1, 5.2) will be present in order to summarize the main points of CDA market and ZI and ZIP trading agents.

-	CDA
Round	finishes when transaction is possible
Price	Calculated per transaction
Liquidity	Best suited for high-volume trading
Frequency	Best suited for high frequency trading
Mechanism runs	Every time a shout is submitted

Table 5.1: CDA Summary [118, 64]

Trader	Params	Market Info	Adapt to market	changes to agent preferences
ZI	None	None	No	trades below/above the limit
ZIP	8	Last shout data	Yes	Learning rate and momentum

Table 5.2: ZI and ZIP trading agents summary

5.5 Capacity traders and Market Performance

Capacity trading in the context of business parks is related to capacity (peak) charges. A business within a business park will have a peak amount that they should not exceed. Their energy bill is calculated firstly by applying the standard tariffs but then adding an additional *capaciteit* or peak charge (in Belgium, it is called capaciteit). The peak power is set at, say, 50kW because a company suspects they will rarely exceed this power over a set time period (PTU, in the context of the business park that is working on a PTU, is 15 minutes). Their bill is charged by multiplying their peak power limit by a pricing co-efficient regardless of whether they use their peak or are way below it. Obviously, for this reason, businesses will choose a peak power limit that is a low as possible. However, if they exceed their peak power, the peak power they reached becomes their new peak power limit, which remains in place for however long their energy contract is fulfilled.

Now, if several businesses in a park use power at different times, they can forecast their likely usage. Then if they expect to have an excess capacity that they will not use over some time (i.e. the day-ahead gets split up into 15 min blocks or PTU), they can sell it to another business through a capacity auction and the other way around if a business needs more capacity they buy but just for that specifically selected time slot. This kind of action also benefits the electrical services infrastructure, as peak loads come with risks of damage to hardware. If a business park can spread out, it is capacity by strongly incentivising some users to not use up to their peak limit during a period while other businesses have to use a lot, as opposed to everybody just using power independently of each other and at times perhaps exceeding a safe amount of power for the park and damaging a nearby transformer.

The market performance in the context of capacity trading also needs to take into account how well the buildings can reach their desired capacity through bidding and selling. Furthermore, this feature is still being worked on, but it will not be available through the primary continuous double auction by Dave Cliff **due to the time limit**.

5.5.1 Market Performance Measurement

This section will go through several market performance metrics that have been offered for the purpose of:

- Measuring how well the auction is.
- Interest of the traders participating.
- The performance throughout a run.

The *theoretical market equilibrium* will be introduced first. A perfect auction is often distinguished by the fact that supply equals demand (the items being sold equals the items being bought). When auction prices rise, more sellers will enter the auction, since everyone wants a share of the profit, as the traditional economics recommend. Similarly, a drop in auction prices would stimulate demand as more purchasers want to purchase items at a reduced cost.

Stotter, Cartlidge, and Dave Cliff in paper [109] say that "*At some point, the quantity demanded will equal the quantity supplied. This is the theoretical market equilibrium*"

1. A first performance metric is to observe the amount of profit generated by participating traders in the auction, called *market surplus*. Equations 5.2 and 5.1 are used to calculate the surplus of a single trader leading to the actual market surplus S_{actual}:

$$S_{actual} = \sum_j P_{actual}^{(j)} \tag{5.7}$$

Where j is the number of participants and $p_{actual}^{(j)}$ is the surplus generated by trader j. Following the definition of the theoretical market equilibrium P_0, the surplus is calculated with the condition for each trader if all trades occurred at the optimal price-point (also known as the theoretical surplus $P_{theoretical}$).

- **For buyers** with limited price l_b:

$$p_{theoretical}^{buyer} = \sum_{i=1}^{n} u^i * (l_p - p_0) \tag{5.8}$$

- **For sellers** with limited price l_s:

$$p_{theoretical}^{seller} = \sum_{i=1}^{n} u^i * (p_0 - l_s) \tag{5.9}$$

Where n is the amount of transactions where that particular buyer was involved in and u is the amount of units sold during transaction i. Therefore the theoretical market surplus $S_{theoretical}$ will be:

$$S_{theoretical} = \sum_j p_{theoretical}^{(j)} \tag{5.10}$$

With $p_{theoretical}^{(j)}$ is the theoretical surplus generated by trader j.

Using the S_{actual} and $S_{theoretical}$, the allocative efficiency metric e is defined. **Allocative efficiency** [91] is when the auction mechanism implements a solution that maximizes the total valuation across all agents (the total profit earned by all traders divided by the maximum total profit that could have been earned by all the traders).

$$e = \frac{S_{actual}}{S_{theoretical}} \tag{5.11}$$

When e<1, it says that this surplus ceiling was not reached for some transactions. When e>1 demonstrates that some traders were exploited as more surplus was generated than calculated theoretically. When e=1, this results that all traders have the max amount of surplus available for every single transaction. The scenario where e>1 only occurs if the price limit is ignored.

2. The second performance metric is the one that measures the **profit dispersion** that occurs during an auction. The profit/price dispersion metric [86, 91] assesses the significance of the gap between generated and theoretical surplus (the extent to which values of a variable differ from a fixed value such as the mean). Smaller values imply that traders' surpluses are close to theoretical surpluses, but larger values suggest generated surpluses.

$$p_d = \sqrt{\frac{1}{n} * \sum_{i=1}^{n} (p_t^{(a)} - p_t^{(i)})^2} \tag{5.12}$$

   Where $p_t^{(a)}$ and $p_t^{(i)}$ are the actual surplus and theoretical surplus of trader i respectively, and n is the amount of traders participating.

3. The third performance metric is **Smith's alpha**. Smith's alpha metric α captures the equilibrium finding capabilities of a particular auction through the following equation [109, 107]:

$$\alpha = \frac{1}{p_0} \sqrt{\frac{1}{n} * \sum_{i=1}^{n} (p_i - p_0)^2} \tag{5.13}$$

   It is calculated as the root mean square deviation of trade prices from the equilibrium price (EP) (i.e., the standard deviation of trade prices around EP rather than the mean). A low value of α is a desirable property (describes a stable market trading close to equilibrium.). A low α value means the generated clearing prices lie very close to p_0 while a higher value denotes clearing prices were generated that differ significantly from p_0.

Chapter 6

Conclusions

This thesis is part of a more significant project (Layered Energy System (LES) model [37]) that is yet to be piloted in Spain. This field is essential to address, and much work is currently being done on batteries in the day-ahead markets in the context of energy communities in Spain. In order to pilot this project in Spain (the technical work), the Spanish rules and regulations need to be understood and analyzed. Firstly, the rules and regulations concerning Local Energy Communities were defined. It provided a clear understanding of what is and is not possible in Spain. It explained local energy communities and collective self-consumption as well as the markets, operators and roles. Examples were also provided to make the understanding more clear. Research demonstrated how the market works and the status of these technologies in Spain. The literature review chapter then presented similar research papers for both the day-ahead bidding chapter and the trading markets chapter. It provided an anchor point for readers looking to start their journey into the field.

Once familiar with the topic's surroundings, the technical task is what came next. This technical task explores how using the battery allows for better and cheaper bidding strategies in the day-ahead energy market in Spain. It explores how the day-ahead market could improve through the use of batteries for better planning and error compensation. Firstly several error scenarios were generated to represent the deviation between the power committed (the power forecasted in the day-ahead market) and the actual data (when the next day comes) that will possibly happen. Three distributions of the errors were tested, which are Gaussian, Uniform and Gamma. After that, five different algorithms were introduced as different ways of how the battery can operate and how to optimize it. A subset (three) of the studied strategies was selected and implemented, comparing their performance on actual electricity data and choose the one that best fits various scenarios and requirements in real-world commercial pilots. They opted to find an optimal day-ahead strategy for committed power, considering the availability of the battery so that the expected total energy cost is minimized. They opted to solve the problem from a mathematical programming perspective. A particular objective function (total cost euro/day) was minimized with respect to constraints involving certain variables. A linear program was applied to find the values that best fit those variables at every time-step t. After those variables were determined, the best strategy was chosen based on the results obtained, such as the total cost (euro/day) and the financial savings (in %). After the best strategy was chosen, the preferred error distribution was chosen based on their performances. **Strategy One** (from section 4.4.2.1) is the best strategy since it gives the best results across all mentioned error distributions (Uniform, Gaussian and Gamma). The preferred error distribution is the **Gamma distribution** because it gives the best results (highest financial savings and smoothness of the battery operation) in comparison to the other two distributions. Using a battery to offset imbalances can help minimise total energy cost for a whole day (up to 26%).

After obtaining an algorithm that allows the battery to optimize interaction with the day-ahead energy market, ways to use this algorithm in the context of energy trading have been explored. The domain of auctions was first introduced, then continuing with an investigation of Continuous Double Auction (CDA) characteristics providing a definition and ensuring all auction aspects were clear. CDA variants were discussed and compared in terms of well-established auction properties. An extensive review of existing CDA strategies was then mentioned but focused on two strategies were are Zero-intelligence (ZI) and Zero-intelligence Plus (ZIP). Assumptions made by the authors were mentioned, as were the parameters required by each trader. **Capacity (energy) traders** were explained in the context of business parks, and **different performance metrics** aimed to quantify how well an auction performed. The market performance in the context of capacity trading takes into account how well the buildings in business parks are able to reach their desired capacity through bidding and selling, but this is a feature that is being worked on in using Python and will not available through the basic continuous double auction simulation by Dave Cliff [25] due to time limit. The performance metrics that were described are:

1. Allocative efficiency [91] which is when the auction mechanism implements a solution that maximizes the total valuation across all agents (the total profit earned by all traders divided by the maximum total profit that could have been earned by all the traders)
2. A metric that measures the profit/price dispersion that occurs during an auction. This metric assesses the significance of the gap between generated and theoretical surplus [86, 91].
3. Smith's alpha which captures the equilibrium finding capabilities of a particular auction [109, 107].

The whole point of this is to make energy cheaper for the consumers and prosumers, minimize energy cost and maximize profit.

6.1 Future work:

6.1.1 LES bidding

Consider how the bidding strategy would change if the following were considered:

- the battery power limit
- the battery energy capacity
- the grid power limit

That is to see how they will effect the efficiency of different optimization techniques to see if there are preferable parameters for optimizing a customer's energy usage costs.

6.1.2 Capacity Traders

There is an research in exploring how the work could be expanded in relation to i.Leco's ongoing work in capacity trading. It is also to study how market performance can be measured in capacity trading between buildings in a business park. For capacity traders, the future work is to apply the feature which undergoes trading of energy. This feature is modified version of the basic continuous double auction simulation by Dave Cliff. It takes into account how well the buildings are able to reach their desired capacity through bidding and selling.

Chapter 7

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Code

The code is available in this link