Electricity Portfolio Optimization for Large Consumers: Iberian Electricity Market Case Study

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Abstract

Electricity markets are nowadays flooded with uncertainties that rise from renewable energy applications, technological development, fossil fuel prices fluctuation, among others, and it becomes ever so hard for any industry to contract its future energy needs in a riskless way. This results in lumpy electricity price for consumers who contract their electricity in these markets, making it necessary to come up with risk management tools to help them hedge this risk.

To cope with this behaviour, a portfolio optimization is successfully applied to electricity sector. So, based on the works of (Conejo et al., 2010), a mixed integer programming problem is solved to optimize the electricity portfolio of a decision maker by considering the pool market, forward contracts and self-generation, using the Iberian Electricity market as a market environment. The optimization is done through a multi objective approach of minimizing the expected cost and the value of the Conditional Value-at-Risk (CVaR). Scenario analysis is used to reflect the uncertainty on the price of the pool market.

Three case studies are used to explore how the portfolio evolves with different demand profiles and how to take advantage of the seasonality characteristic of the pool market. The expected cost and CVaR are optimized for each case study, and an analysis of the portfolio for each risk posture is done. It is also proven that the seasonality aforementioned can be taken advantage of.

Keywords:

Electricity Markets; Portfolio optimization; Conditional Value-at-Risk; Electricity Portfolio.

Resumo

Mercados de eletricidade são atualmente inundados com incertezas que se prendem com as aplicações de energias renováveis, desenvolvimentos tecnológicos, flutuação dos preços de energias fósseis, entre outros. Assim, é cada vez mais difícil para qualquer indústria contratar as suas futuras necessidades energéticas de uma maneira sem risco. Isto resulta em preços instáveis para os consumidores que recorrem a estes mercados, sendo necessário estratégias de gestão de risco para se poderem proteger.

Para lidar com este comportamento, uma otimização de portfólio é aplicada com sucesso ao sector da eletricidade. Assim, com base nos trabalhos de (Conejo et al., 2010), um *mixed integer programming problem* é resolvido para otimizar um portfolio de eletricidade de um tomador de decisão, onde são considerados como fontes de eletricidade o *pool market*, contractos adiantados e geração própria, usando o Mercado de Eletricidade Ibérico como meio. A otimização é feita de forma multi objetivo para minimizar o custo esperado e o valor do *Conditional Value-at-Risk (CVaR)*. Analise de cenários é feita para refletir a incerteza presente no preço do *pool market*.

Três casos de estudo são usados para explorar como o portfolio varia para diferentes perfis de procura e como tirar proveito da sazonalidade característica do *pool market*. O custo esperado e o CVaR são otimizados para cada caso de estudo e uma análise do portfolio para cada postura de risco é feita. É também comprovado que a sazonalidade referida acima pode ser aproveitada.

Palavras-chaves:

Mercados de Eletricidade; Otimização de Portfolios; Portfolios Eletricidade; Conditional Value-at-Risk.

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Glossary:

CVaR – Conditional Value at Risk

VaR – Value at Risk

MOO – Multi Objective Optimization

GenCos – Generation Companies

MIP – Mixed Integer Programming

GEP – Generation Expansion Problem

MPT – Modern Portfolio Theory

LCOE – Levelized Cost of Electricity

PV – Photovoltaics

1 | Introduction

This chapter provides an overview of the objectives of this dissertation, to better follow its scope and understand the reason behind it. It is divided in three sections: firstly, a background and contextualization of the problem is done, followed by the objectives that this project proposes to achieve and finally its structure is presented.

1.1 | Background and Contextualization

One of the main issues for any industry is to fulfil its energy needs in the smartest way possible. However, the management of an energy portfolio can prove complex and with room for optimization, reducing the cost while following a risk management method, but without ever forgetting to satisfy the demand. This is often a concern in the literature given the many opportunities and the different methods and tools that can be used. In addition, the energy sector is characterized by many risk and opportunities one can take advantage of, given the often technology and renewable energy developments, which open many doors for an energy portfolio manager to take advantage of and diversify. So, the goal is to efficiently use the energy resources available accordingly to certain objectives, such as cost, risk, renewable energy, among other, and perform an optimization in accordance to them.

To contract the energy needed the industries shall resort to electricity markets, where there are a few tools they can use and take advantage of: they can plan the long term future, with forward contracts, they can plan the short term future, by the pool market, or they could use a combination of both, finding the perfect point between the two that optimizes their objectives. In alternative, the industries can resort as well to contracting their own generation units, such as renewable technology, either to hedge risk or increase the penetration of renewables in their portfolio.

Given all the opportunities and threads present in the energy sector, serving the above as examples, it is important to for any consumer to best take advantage of them when procuring its energy needs, so an appropriate portfolio optimization would be essential. However, regarding electricity markets the main agent where research has been directed to is the generation companies, which face more sources of uncertainty and therefore more complex problems. With this is mind, the goal of this dissertation is to make a contribution directed to the less researched agent that interacts on electricity markets: the buyer. To do so a portfolio optimization for a large consumer is conducted, with the multi objective of reducing the expected cost and minimizing the risk associated with the portfolio, as well as to produce analysis tools for the decision maker.

1.2 | Purpose and objectives

The main purpose of this master dissertation is to develop a mathematical model addressing the problem of energy portfolio optimization of a large consumer by considering as objectives the total cost and risk, while integrating the problem inside the reality of the electricity markets, through data from one, and attempt to identify opportunities in it. With this in mind, a risk management and multi-objective method are needed.

The intermediate objectives needed to be accomplished in order to fulfil the purpose above are:

- A literature review on the electricity markets to understand its mechanisms, the relations among the entities involved and its issues, so that it's clear which are the trading options available for industries and what are the advantages and drawbacks of each one;
- Characterize the state-of-the-art of the methodologies and tools which can be used in the mathematical formulation:
  - Understand the methods available for multi-objective optimization and what is the trade-off each provides, so to make an informed decision when picking one;
  - Characterize portfolio optimization theory, so to understand what has been done, how is the best way to apply the theory to a large consumer and what are the results one should expect from the model;
  - Understand the risk management process and its importance, as well as its popular methods: their advantages and drawback, and their usage;
  - Characterize scenario analysis and understand what a scenario is, how can scenario building be taken advantage of and what methodologies are there;
- Problem characterization;
- Characterize the methodology for the future master thesis;
- Gathering of data from an electricity market;
- Mathematical model formulation and implementation.

As a summary, the goal is to understand electricity markets and their uncertainties, review the energy portfolios that exist, and tools previously used in their building, and apply some of this tools to a mathematical model for a large consumer which procures its energy from electricity markets.

1.3 | Project Structure

For the purpose of a better and easier read of the document, it is important to present its structure. All the following chapters are constituted by a small introduction in the beginning and a quick summary of the most important points at the end, and each is divided in sections. With this in mind, and in order to follow the objectives, this is project is structured as follows:

1. **Introduction:** introduces the problem contextualization, the objectives and the structure of the dissertation.
2. **Electricity Markets:** A brief overview of electricity markets is done, by presenting the main entities, the trading tools used by them on the electricity markets and some of the uncertainties that are typical of this business branch.
3. **Literature Review:** The literature review was focused on the topics considered relevant for the research at hand, to better understand and tackle the problem. Therefore, the following topics are reviewed: Multi-Objective Optimization techniques, portfolio optimization and downside risk, with emphasis on Conditional Value-at-Risk applications, electricity portfolios and scenario analysis.

4. **Methodology and problem characterization:** This chapter identifies gaps in the literature and with it builds the problem characterization, followed by the presentation of the methodology for the research.
5. **Mathematical formulation:** This chapter presents the mathematical formulation for the consumer’s electricity portfolio optimization.
6. **Data Collection and Parameter Estimation**: This chapters presents the data collected from an electricity market and how the parameters were estimated from it.
7. **Case Studies:** The mathematical model is run for different case studies, their results analysis is done, followed by the conclusions.
8. **Conclusions and Future work:** main conclusion from the master dissertation are taken and the grounds for the future work are set.

2 | Electricity Markets

The present chapter presents the particularities of nowadays liberalized electricity markets: the stakeholders, the instruments used for the trading, usual uncertainties and concerns, among others, so that it will be clear how electricity markets transpire.

The chapter is organized in four sections. The first section presents the players that interact in the electricity markets and that are in need of risk management tools. The second section enumerates the tools and mechanisms used by buyers and sellers of energy, characterizing it and presenting some of their advantages and drawbacks seen from the players. Thirdly, uncertainties characteristic of the energy sector are characterized, pointing out which uncertainties are mostly felt by each of the players. Lastly, a summary of the present chapter is done as well as a connection between this chapter and the next one.

2.1 | Players

In the electricity sector we have three key players, which are the main objects under study in the literature, being those the private investors, the managers commercializing energy and the planners. They all interact in the markets but face different problems and uncertainties, changing the way each of them sees and prioritizes certain tools or mechanisms of the markets (Odeh et al., 2018b). (Odeh et al., 2018a) classifies these entities as private (private investors and managers) or public perspective (planners), when classifying the applications of portfolio optimization in the electricity sector. The investors invest in technology mixes that favour them and maximize their profit, so they have the choice of selecting certain technologies or places based on their preferences, whilst the planners need to focus on every location and technology, being that social welfare is a big priority. The managers commercialize energy (buying, selling or both) for large energy holdings, large consumers, etc. (Odeh et al., 2018)

Although the private side is nowadays key in electricity markets, their risk management problems are less developed than planners, since their main goal is to seek social welfare in the short and long term, by the planning of the generation and transmission mix and their active role in policy making. However, with the current trends in power systems, it is ever so relevant to consider as well the problems of the private side: investors seek to maximize their return on the investment and can focus solely on some places or some technologies, whilst planners focus is the whole set of locations and technologies. Managers, which englobe both the sellers and buyers of energy, seek to minimize their price risks, given the potential fluctuations. Managers and Investors both seek to maximize return and minimize risk, but investors allocate energy among instruments while managers allocate energy by the different trading instruments available (Odeh et al., 2018b). Fig 2.1 summarizes the position and objectives of each player.

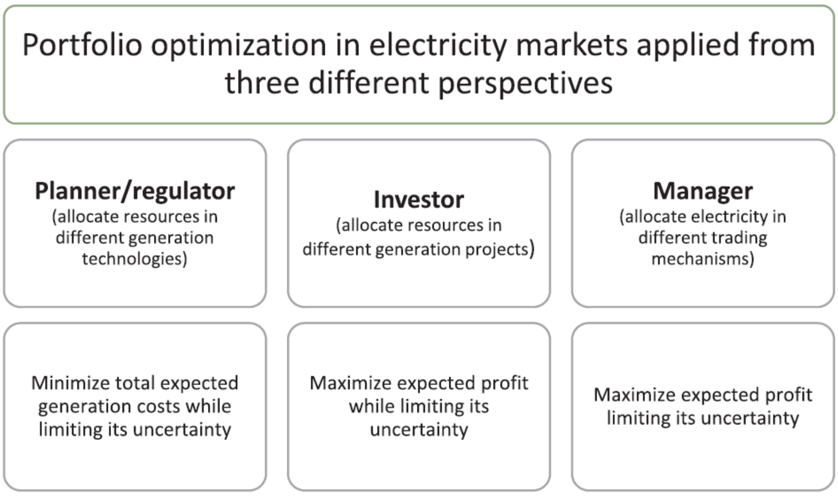

Figure 2.1 - Task and objective of each electricity market player (Odeh et al., 2018a)

The literature regarding the Investor's and Manager's side is limited and mostly focuses on the Planner's. This is due to the fact that electricity markets in most countries are relatively young, so the literature on the side of the Investors and Managers has only recently started, while the Planners' has had more time to develop. Besides, the private side dependent on the market conditions of each country, so the literature tends to focus its attention on a variety of topics, given the country's different particularities, rather than focus on a few and build upon them and improving over time. The literature from these three key agents is evolving with a special focus on renewable energy, addressing constantly more complex characteristic of it (Odeh et al., 2018a) (Odeh et al., 2018b).

2.2 | Characterization of the trading tools and mechanisms

Electricity markets are liberalized in many countries, which results in a market where large consumers and electricity retail distribution companies need to interact to contract their future electricity trading. These contracts have to be managed in order to assure delivery of electricity in the future, which, depending on the contract, can be in a long or short term with a fixed or a variable price (Huisman et al., 2009).

Electricity markets worldwide normally offer two types of market structure where energy is traded: spot (or day-ahead, or pool) market and forward (or physical) market. The spot market is the energy traded in the real time and day-ahead market, and the most popular structure is a centralized pool-base auction where the buyers and sellers submit bids, for their purchase or selling needs, to a market operator. His role is to optimize the power production schedule of the generators and load schedule of the consumers, in order to satisfy all the constraints and keep the balance between supply and demand in each period, in order to maximize social welfare. This maximization is done by maximizing an objective function that can be generally summarized as the sum of offered values by the buyers minus the sum of the offered operational costs of producers. However, sometimes buyers and sellers are not fully committed on this (for example the seller bids a higher value of cost), which implies that maximized social welfare is not truly reached, and this keeps happening since buyers or sellers won't willingly accept losses in profit if they can somehow avoid them. With this in mind some market designers establish rules that apply to the market participants, in an equity and arbitrary way, or some other define compensations to be shared evenly, or according to some criteria, between market participants, serving this as motivation as well for them to bid fairly (Toczyłowskiet and Zoltowska, 2009).

Purchasers use the electricity spot market to buy a part of their energy needs, however its price volatility is substantial, being the highest when compared to any other commodities' spot markets: daily volatilities of 29% are common (for comparison, international stock indices have, but on a yearly basis, volatilities close to 20%), which are accompanied by other factors such as electricity prices' seasonality and extreme jumps that quickly die out (Huisman and Mahieu, 2003). These variations in price can be blamed on the impossibility of storing electricity in an efficient way, on electricity's inelastic demand and steep supply curve (Odeh et al., 2018b) (Huisman et al., 2009).

The physical markets is seen as the way to avoid the risk of price variations in the spot market, where with forward contracts, consumers and suppliers commit on the trading of a specific amount of electricity, at a specific future time against a fixed price (Huisman et al., 2009).

Commonly there are three pricing mechanisms in energy markets: uniform marginal pricing, where only one energy price is used on each trading interval, zonal pricing, where a geographical perspective is put into use and there is a division into zones where, if congestion exists, each zone will define its MCP, and locational marginal pricing is the determination of prices for each location or node of the power system, also only when there is congestion (Gökgöz and Atmaca, 2012).

Literature suggests the agents involved in these markets to develop portfolios that optimally allocate the energy trading tools they provide according to each agent's goal, in order to best take advantage of the spot and physical market. The literature mostly focuses on the retailers' perspective, such as GenCos, as it was done on (Mathuria et al., 2015) or (Pindoriya et al., 2010), however, there is also some devoted to the purchaser's side, as it is example (Huisman et al., 2009).

There are several European electricity markets where the players can interact. Some of them have an open data policy, where it is possible to collect data on prices of the pool market. As examples, there is the Iberian electricity Market, which is operated by OMIE and provides electricity trading for Portugal and Spain (OMIE, 2019). SMARD provides electricity market data for Germany (SMARD, 2019). Nord Pool runs the leading power market in Europe, and operates in several countries such as France, Germany, Belgium, Netherlands, Denmark, Norway, Sweden, among others, and provides data on the day-ahead and intraday market (Nord Pool Group, 2019).

2.3 | Electricity Sector Uncertainties

The energy sector, more particularly the electricity one, is nowadays flooded by numerous sources of uncertainty that rise since the sector itself, historically, is particularly unpredictable. So, to plan in it one must think of what future conditions we might face: how will the fossil fuel prices and demand evolve, will the electricity generation still so hardly depend on fossil fuels, etc. Literature over the last two decades has majorly focused its attention on the uncertainties that come from, for example, fuel prices, demand growth and CO_2 prices. However, other factors, such as renewable resources availability, technology development, social opposition and emissions limits, also play a role.

As society shifted its mentality from a purely economic to a more sustainable one, and with the widespread of renewable energy technology, even more sources of uncertainty appeared, since these new technologies highly depend on natural resources, that can prove unpredictable, and have the potential to highly evolve throughout a short period of time, which create even more uncertainty when it's time to invest. However, renewable options also have the potential to mitigate the risk of some of the conventional uncertainties, such as fossil fuel prices, or even some that go beyond the market's scope, such as local pollution, that highly threatens society and exposes it to high levels of risk (i.e.: health problems) (Odeh et al., 2018a) (Odeh et al., 2018b).

(Soroudi and Amraee, 2013) summed up the uncertain parameters in power system studies in two different categories:

- ➢ technical parameters - they are divided in topological parameters, related to network topologies such as generators and transmissions lines, and operational parameters, which are more operating decisions related with demand and generation values;
- ➢ economical parameters - here we also make the separation between microeconomic ones (i.e.: uncertainty in fuel supply and cost, taxes, etc.) and macroeconomics ones (i.e.: environmental policies, gross domestic product, etc.).

(Odeh et al., 2018a) and (Odeh et al., 2018b) address the uncertainties in the electricity sector as dependent on the agent we are referring to (the players presented in sub chapter 2.1), as well as the way portfolio optimization is used:

- ➢ Planners are the key players on the energy sector, so they are the ones whose optimization process is the hardest, given the multiple sources of uncertainty they face:
  - ○ On the supply, with the unpredictability associated with fossil fuel prices, investments and renewable and non-conventional resources, on potential technological changes, with special importance in the renewable sector;
  - ○ On the demand side, given the non-constant electricity consumption, depending on the temporal and spatial dimension, which is somewhat limited by the level of transmission and generation expansion, thus pressuring the expansion with more uncertainty;
  - ○ With new environmental policies, with the need for new mitigation technologies, for example;
  - ○ With public opposition, which is a growing factor with sustainability being more and more a concern of society that oppose to the traditional energy;
  - ○ Supply and demand are coupled in electricity markets, which is an increase source of risk, however with developments in electricity storage technology this could turn into less of an issue.
- ➢ The Investors' scope differs from the planners' since, although they also want to maximize profit and limit risk, they generally do not seek social and environmental cost reduction, so their portfolio aims solely at financial profit, opposing itself to the planners' sustainable perspective.
- ➢ Managers, on the other hand, seek to *"choose among different financial instruments for selling and buying electricity"* in an efficient way, using them to hedge against risks that rise from the volatility of real-time prices.

2.4 | Summary of Chapter 2

This chapter introduces the reader to electricity markets and its general operation. First the main players that make electricity markets were presented: the planners, the investors and the managers, showing what is the goal and job of each one. Secondly, it was shown what are the tools used for electricity trading in the market, where we mainly have the pool markets, which have high price volatility and enables the possibility of almost immediate trading between buyers and sellers, or the forward market, which is characterized by the forward contracts where buyers and sellers can contract their future needs of energy at an established price. Next the uncertainties present in the electricity sector were presented: the fuel prices, technological development and demand variability. Or others that appeared when a bigger emphasis was given to sustainability and renewable sources of energy: CO2 prices, emission limits, environmental policies, etc.

The next chapter is dedicated to a review of the literature in multi-objective optimization, downside risk with a focus on the Conditional Value-at-Risk, electricity portfolios and scenario analysis, providing whenever possible examples of application related with electricity markets.

3 | Literature Review

As mentioned on the introduction chapter, the ultimate goal of this research is to build an electricity portfolio for a large consumer, while taking into consideration the risk management and the analysis needed. For that, this chapter is devoted to reviewing the tools considered fit to achieve this. By the end of it, it is expected for the reader to have a clear understanding of the key aspects of the topics.

The chapter is divided in 4 sections. The first reviews Multi Objective Optimization, enumerating some of the most popular methods and contextualizes the topic for the energy sector. Next portfolio optimization with downside risk is approached and two of the main methods are presented and compared, Value-at-Risk and Conditional Value-at-Risk, followed by some applications of the latter in the energy sector. In the third section there is a look into existing electricity portfolios from the public and private perspective. Finally, scenario analysis is review and some applications, mainly from the planner's perspective, are presented.

3.1 | Multi Objective Optimization

Multi-objective optimization (MOO) is a growing subject in the engineering world today, and problems where it can be applied arise naturally, given the conflicting nature of the multiple objectives of nowadays real-world problems. Although the ideal would be to optimize all the objectives at hand all at once, that is generally impossible due to their high number and to the fact that they can easily be in competition, so the optimization process has to search for the best compromise solution and can become consequently computational demanding (Cui et al., 2017) (Chiandussi et al., 2012). The Solution of a MOO problem is a set of Pareto Optimal alternatives (pareto frontier), and each point of this set is particular since it is impossible to find another feasible point that improves one of the objectives without worsening at least another one. The major advantage of MOO approach is to provide all efficient solutions, "optimal solutions", for the decision maker to choose from. However, it also has some drawbacks: it can become computational inefficient, since the computational time increases exponentially with the number of objectives, and it can be hard to analyse and compare "optimal solutions" when there are more than 3 objectives (Vázquez et al., 2018).

To tackle these MOO problems there are several classical techniques we can resort to:

- the weighted sum, where a multi-objective problem is solved by transforming it into a single objective function and assign relative weights to each function of the MOO problem;
- the ε-constraint method, proposed by (Chankong and Haimes, 2008), where we pick one objective to be minimized and constrain the remaining objectives to be less or equal to a target value;
- Goal Programming - it does not pose the question of maximizing multiple objectives, but it rather sets specific goals for each objective and attempts to find them,
- Etc. (Caramia and Dell'Olmo, 2008)

Our main focus in this literature review is the application of multi-objective optimization in the energy market, with a special focus on renewable energies integration. In recent years, the selection of energy projects, or other energy decision-making problems, pays some attention to sustainable development. With this in mind the balance between social, economic and environmental aspects should be kept, which opposes to the previous single-objective mentality of the energy sector based on cost minimization. Literature review shows that research on this topic is growing and MOO is the common approach (San Cristóbal, 2012) (Frini, 2014). Most of the existing literature on MOO in the energy sector resorts to intelligence algorithms based on a heuristic search approach, such as evolutionary and genetic algorithms (Cui et al., 2017), however that is not the focus of this review.

Most of the traditional algorithms tackle the MOO problem by transforming it into a single-objective function with the weighted-sum method (Pindoriya et al., 2010). Examples of this application are found in (Liu and Wu, 2007) and (Feng et al., 2007), where portfolio optimization problems are formulated for Energy Generation Companies (GenCos) to optimally allocated its energy output among multiple markets, and then it is solved using quadratic programming. More recently, (Wang et al., 2016) formulates an energy Supply-Mix Model considering the complementary and substitution possibilities between non-renewable and renewable energies, for the case of Taiwan in a target year, with the goal of developing renewable substitution, and makes use of the Weighted-sum method to deal with the Multi-objective problem.

Goal programming and its variations are popular and literature in energy portfolio is rich with examples of its applications. (Hocine et al., 2018) proposes a multi-segment fuzzy goal programming to optimize the renewable electricity generation portfolio for the Italian case, by considering solar photovoltaic, wind, biomass and tidal current renewable energy. In (Sehatpour and Kazemi, 2018) a fuzzy goal programming was developed to address the high dependence problem of the transportation sector on fossil fuel by proposing a more sustainable fuel portfolio, applying it to Iran's case. (Vázquez et al., 2018) proposes a fuzzy goal programming model to develop Oregon's renewable energy portfolio, assessing the various available future options for energy mixes, with the final goal of having renewable energy meeting 25% of the all energy demand until 2025.

A popular way to model MOO problems is to make use of Linear Programming Optimization Techniques, which consist in finding the best outcome in a model whose requisites are expressed as linear mathematical relationships (Gómez-Calvet et al., 2019). Applications to the energy sector trace back to 1957 with the works of (Masse and Gibrat, 1957). There are numerous articles where linear programming is used to optimize resources in the energy market. In (Gómez-Calvet et al., 2019) Linear programming is used to optimize the power generation mix of Spain by intensive deployment of variable renewable energies (VRES), by minimizing the fossil backup generators and the surplus (excess) energy producement. In (Koltsaklis and Dagoumas, 2018) a mixed-integer linear programming model is formulated to obtain the optimal energy and reserves mix, the market clear price and the welfares of the market participants for European electricity market. (Arnette and Zobel, 2012) proposes a multi-objective linear programming, which focuses on the regional level, specifically in a region highly dependent on fossil fuels, and intends to combine the increasing renewable energy sources with the existing electricity generating capabilities, trading off between annual generation costs and the greenhouse gas emissions.

In (Antunes et al., 2004) and (Aghaei et al., 2012) multi-objective mixed integer linear programming models are formulated, to provide decision support in the selection of power generation expansion plans, and an interactive approach was used. However, the interactive approach has been questioned to fail to provide the entire set of efficient solutions, even when applied to small scale problems (Mavrotas et al., 1999).

3.2 | Portfolio optimization with Downside Risk: Conditional Value-at-Risk

3.2.1 | Portfolio Optimization

The Modern Portfolio theory era was firstly started by (Markowitz, 1952), and has since then become the most common way for investors to deal with expected returns, costs and uncertainty for a large number of problems and industries. The portfolio optimization problem was firstly formulated through looking at the expected return and the risk, which measured the variability of the former, and has found large popularity in the field of finance, focusing the research mostly on this topic. However, it has found popularity in other fields, especially with the development of computational power, such as project selection, environmental applications, economic analysis, among others (Odeh et al., 2018b) (Mansini, 2014) (Kalayci et al., 2019).

Portfolio optimization has found popularity in the energy sector since it exploits the diversification idea through the “cancellation effect”, which is what happens when a project’s gains offsets one’s losses, this can be achieved, for example, by finding complements between renewable energy and conventional energy. Diversification is then relevant because often buying everything from the cheapest supplier can prove more expensive in the end, since this way one is more exposed to this supplier’s variability in fuel price and overall supply. So, it might be preferable to adopt a multi-fuel supply portfolio that can help reduce this variability, even if it increases the expected value in the end. This cost-risk trade-off example is one of the classic problems for energy planners, who need to opt for minimum cost, minimum risk or something in between (Odeh et al., 2018b).

3.2.2 | Downside Risk: VaR and CVaR

Portfolio theory consists in applying decision-making tools under risk to the problem of managing risky investment portfolios. Over the years there has been several techniques proposed to tackle the problem of portfolio selection, among them we have downside risk measures, which are the object under study (Nawrocki, 1999).

In economy, it is already a given fact that investors look differently to downside losses and upside gains, being this firstly recognized as early as (Roy, 1952). So, investors who are more sensitive to downside losses, rather than upside gain, will demand a compensation for holding assets highly sensitive to downside markets movements (Ang et al., 2006). The problem that arises in portfolio selection is how to optimally obtain this compensation of downside losses (Ling et al., 2019).

Modern portfolio theory, or mean variance analysis, proposed by (Markowitz, 1952), one of the most popular methods for portfolio selection, measures risks in terms of standard deviation of asset returns. This way positive and negative deviations from the expected return are both treated as risks, the positive deviations are the so called "upside risk", and the negative ones are the "downside risk". However, "upside risks" are not necessarily undesirable and in several situations are actually welcome by investors, opposite to "downside risks" which are avoidable. This asymmetric view is not reflected in this standard deviation approach, that seeks to minimize the variance penalizing "upside risk" in the same manner as the "downside risk" (Chong et al., 2013). This is an issue since according to this method an asset that experiences better results than the expected return can be labelled as risky, or even riskier, than one that experiences worse than expected return. To address this issue, downside risk measures are introduced, in our study specifically the Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) (Nguyen-Huy et al., 2018).

The VaR plays an important role in the modern financial and risk management literature. It was first proposed by the firm J.P. Morgan Chase & Co. as a "*measure of acceptability for a financial position with random return*" (Wozabal, 2012). It has become the standard method used in financial analysis for quantification of the market risk in asset or portfolio. The VaR measures the potential loss in value of a risky portfolio, for a given probability and a defined time period. It is typically used by investment banks and security houses, but it can have much broader applications (Huang et al., 2009). VaR is widely popular in the financial industry, however its "*nonlinear and non-tractable properties*" make it computationally demanding for a real-world constraint portfolio optimization problem (Lwin et al., 2017).

The vast majority of papers prefer to use the CVaR (also known as Mean Excess Loss, mean shortfall, Tail VaR or Expected Shortfall), instead of VaR as a measure of risk due to its mathematical properties. Initially introduced by (Rockafellar and Uryasev, 2000), CVaR, for a specific desired level α, refers to the *"conditional expectation of losses in the top* 100(1-α)%", whilst the VaR, for the same α value, refers to the "threshold level for losses in the top 100(1-α)%" (Lim et al., 2011). So CVaR is the average of the worst-case loss scenario for a specific level depending on the scope of the study. Common values considered for α are 0.90, 0.95 and 0.99. These two definitions ensure that, for the same confidence level the VaR never exceeds the CVaR, since for this specific case the VaR is the lower bound of the CVaR (Sarykalin et al., 2008). A low CVaR portfolio also means a low VaR portfolio, and because of this property, numerical experiments do indicate that the minimization of CVaR also leads to near optimal solutions in VaR. For a situation where the return-loss distribution can be expressed as a normal distribution, you get the same optimal portfolio using either VaR or CVaR (Krokhmal et al., 2002).

The differences between choosing VaR or CVaR have been quite popular in academic literature, and the discussion affecting the choice between the two is bound to differences in mathematical properties, stability of statistical estimation, simplicity on the optimization procedure, etc (Sarykalin et al., 2008). However, CVaR popularity has grown significantly in the literature and is mostly due to VaR's undesirable properties in certain situations. A lot of these different properties are pointed out in the literature, presenting mostly CVaR's properties as the solution of the problem. One of the most pointed out properties is that VaR measures lacks the sub-additivity property, in other words, the VaR of a portfolio that consists of two instruments might be higher than the sum of each instruments' VaR (Uryasev, 2000).

Still on the topic of CVaR's superiority over VaR, a lot of literature points out to scenario use and optimization efficiency: VaR has optimization difficulties when using scenarios in the calculation and does not control scenarios exceeding VaR (the largest loss can be increased tremendously but the VaR risk measure will not be sensitive to that), whilst CVaR contemplates losses exceeding VaR, thus preventing potential small chance high losses that would not be picked up by VaR (Sarykalin et al., 2008) (Uryasev, 2000). Risk optimization with CVaR can be done for large portfolios with a large number of scenarios with relatively small computational resources (Uryasev, 2000). When uncertainty is modeled by a finite number of scenarios, used as an approximation, and the loss function is linear, the problem at hand can be reduced to a Linear programming one (Rockafellar and Uryasev , 2000) (Krokhmal et al., 2002), therefore more easily optimized and constrained, whereas VaR is fairly difficult to optimize (Sarykalin et al., 2008). Additionally, some argue that, in a situation with a return distribution deviated from normality, particularly in periods of crisis, the usefulness of CVaR will be clear (Lim et al., 2011).

3.2.3 | Conditional Value-at-Risk applications

As mentioned above, portfolio theory is nowadays widely used in the energy sector, specifically in electricity applications, to best exploit the diversification concept. Many of these applications resort to conditional value-at-risk as a risk measure, given its properties, to deal with a wide variety of uncertainties that can arise.

Several publications focus their attention on the inherent risk on investment on weather dependent renewable energies (RES) in power markets: (Tietjen et al., 2016) compares risks of different technologies in markets with increasing penetration of RES and how they can affect the generation mix. CVaR’s confidence level is set at 95% throughout the paper and two cases are considered to evaluate the firm’s risk costs: first on a stand-alone basis and then on a portfolio risk basis. Results show that RES have a risk benefit, from a private firm perspective, since it is a protection from the volatile price fluctuation of fossil fuel, however they have the highest stand-alone risk in the model, and the previous risk benefit quickly decreases with the increase of RES share. In (Hemmati et al., 2016) there is an attempt to deal with the wind power’s uncertainty by resorting to storages devices, where CVaR is applied as measure to deal with the inherent risk related to wind power uncertainty with a risk-averse formulation. In the past 10 years, due to the subsidies offered, the number of photovoltaic and wind power plants around the world has grown rapidly, and for a more efficient power system, these plants need to be integrated in the power markets, which can happen with virtual power plants: (Gersema and Wozabal, 2018) build a model for risk-optimized pooling, where different technologies and locations are considered in order to reduce the aggregated risk of a virtual power plant portfolio, for a German market as an example, with CVaR being calculated for each individual asset and portfolio, being that its confidence level is set on 99%. In (Longoria et al., 2018) the potential of integrating renewable wind energy into electricity portfolios is assessed, taking into account the risk and cost tradeoff, from the perspective of a Load Serving entity. The wind energy and conventional generation are the two sources of energy considered. CVaR is used as a risk measure combined with another risk measure, Excess

Cost, to obtain feasible portfolios that hedge against the market's volatility and the weather uncertainty. Results show 8% to 16% of wind power should be contracted.

Another uncertainty source for investors interested in the power sector are the climate policy changes and the carbon market - place for financial transactions related with activities to reduce greenhouse gases emissions, including the trading and investment of carbon emission rights (Zhou and Li, 2019). Literature has paid attention to this for ways to mitigate the risk that these sources bring: (Nazari et al., 2015) built a decision support framework to assist investors with long-term decision-making in power generation assets under uncertain climate policy. Carbon and renewable portfolio standard certificate prices were used for modelling the climate policies interactions, and potential capacity additions to the invertor's generation mix were identified. The Portfolios' risk was based on the minimum CVaR at a range of feasible constant returns. (Chai and Zhou, 2018) pays attention to the price volatility risk for participants on carbon markets, specifically to the risk that rises from the price fluctuation of the European Union Allowance (EUA). It mainly focuses its attention on the risk measure of this carbon markets, by estimating the CVaR of EUA returns in the European Union Emission trading scheme, and compares the minimum-CVaR strategy with the Minimum-Variance Strategy.

The literature is highly devoted to the Planner's perspective, one of the most discussed topics is the long-term Generation Expansion Planning (GEP) problem, which becomes very complex when considering a wide range of features such as: economical, environmental, technical, social, operation, among others (Koltsaklis and Dagoumas, 2018). In the literature, several publications built models to best tackle this problem, and CVaR is, as expected, a very popular risk measure: (Ahmed et al., 2014) proposes a new model, which besides taking into account uncertainty in demand and fuel price, includes financial risk management. This is incorporated by minimizing the CVaR in the decision-making process, to optimally obtain the best combination of power generation assets, while meeting production and CO_2 reduction targets. (Pisciella et al., 2016) proposes a model for decision making in a mid-long time horizon, intended for a producer unable to influence electricity price, where CVaR is suitably defined in a way that guarantees time consistency in the model. Several aspects, such as risk aversion, were tested. (Seddighi and Ahmadi-Javid, 2015) suggested a socially responsible framework, with a risk-averse approach, which takes into account responsibilities towards society and environment, and accounts for the disruption risk, which results show that significantly decreases the total cost. CVaR is included on the objective function to minimize generation, disruption and socio-environmental costs. (Lu et al., 2016) proposed a model based on CVaR theory, that simulates the uncertainties that rise from fuel price, CO2 reduction technology and carbon price, and analyses their impact on investment decisions for different risk scenarios. (Munoz et al., 2017) formulates a model that minimizes a weighted average of expected transmissions and generation costs and their CVaR. The impacts of risk aversion are analysed on the levels and spatial patterns of generation and transmission investment. To investigate the effect of the risk aversion CVaR is used within 24 scenarios covering a wide range of possibilities until 2034, and the weight on the CVaR will vary to simulate risk neutrality, in one end, and extreme risk aversion, in the other. For further literature on the GEP problem, (Koltsaklis and Dagoumas, 2018) perform an extensive review on the subject.

(Suzuki and Uchiyama, 2010) built a model to estimate how the price of fossil fuels can affect the non-energy sector - sectors that produce non-energy goods or services - where the CVaR was used as a risk index. The model estimates the risk of price increase in the non-energy sector by considering the Japanese industry structure and the uncertainty in the price of imported fossil fuels. Risk reduction is obtained along the analysis by decomposing the risk index of fossil fuel (or final energy) prices based on the direct and indirect influence they can have on the non-energy products prices: direct influence by the consumption of energy products and indirect by consumption of other non-energy products.

(Lorca and Prina, 2014) takes a look at the "spatial risk" of electricity prices, since electricity supply and demand conditions can change depending on the location considered inside the same market, being this relevant for power producers that own electricity generation in several locations. So, a model is made to help this specific group to optimize their commercial decisions, in a medium term, using CVaR as a risk measurement, and applying it to a New York state electricity market case study.

3.3 | Energy Portfolios

First introduced by (Markowitz, 1952), modern portfolio theory (MPT) has seen its popularity peek achieved in the financial sector. However, its popularity has grown in the energy sector with many applications, mostly on the planner's side, standing as a widely accepted methodology to solve the long-term investment selection problem in energy planning. For this problem the most common approach used to be the least-cost alternative, which consists in picking the alternative solely based on the cost of electricity. However, this has obvious drawbacks since it does not consider, e.g., the difference between a fossil fuel and a renewable energy source besides its cost. MPT analyses technological alternatives taking into account the risk and its trade-off with cost and revenue, given that the energy planners' aim is to take advantage of diversification and construct a diversified portfolio, taking advantage of renewable and non-renewable energy in the best way they see fit (deLlano-Paz et al., 2017).

Existing literature mostly focus on portfolio applications from the planner's perspective, where a lot of emphasis was given, especially applied to Europe, to renewable options given the current priorities of CO_2 emission reduction. As an example we have the works of (Awerbuch and Yang, 2007) which aims to produce optimal generating portfolios relative to the 2020 Europe's electricity generating mix while reducing cost, market risk and CO_2 emissions through a mean-variance portfolio optimization. It arrives to the conclusion that non-fossil fuel technology, such as wind or nuclear, can help reduce the cost and risk of these portfolios. More recently we have the works of (Forouli et al., 2019) which aims to identify optimal technological portfolios for power generation in the EU-27 to reach the goal of being a competitive low-carbon economy by 2050. It considers many different kind of technologies in the portfolio such as photovoltaic, wind, nuclear, carbon capture and storage, among others, under the conclusion that photovoltaic, wind and nuclear options should be prioritized.

Still from the planner's perspective, there is some literature that adopts a country's perspective, as it's the case of (Costa et al., 2017) which aims to project a robust portfolio for Brazil's generation mix. We also have the works of (Santos-Alamillos et al., 2017) which uses portfolio optimization to specifically study the possible repowering actions to the current wind farm generation mix. Some literature focus on a more regional level, which is the case of (Fleischhacker et al., 2019) that for a large-scale energy community, covering a whole city district, quantifies the advantages of the optimization of its technology portfolio, with the bi-objective of cost and carbon emission reduction.

Despite most of the literature focusing on the planner's perspective, the private agents still play an important role on power systems in most countries, where they attempt to protect themselves from the risks of the sector. From the private agents, buyers and sellers in a liberalized market need to allocate their electricity among different instruments, such as the day-ahead or real-time markets and bilateral forward contracts. So, these agents can take advantage of portfolio optimization by diversifying throughout these instruments, as well as by choosing among generation technologies (deLlano-Paz et al., 2017).

There are many opportunities and situations where portfolio optimization can be advantageous to identify efficient electricity portfolios, e.g., the differences for a consumer between signing a bilateral contract with a conventional energy generation company or with an alternative energy one. Here factors like demand profile, carbon footprint and willingness to pay may come into play in the consumer's preference. Also, these bilateral contracts can last for several years, contradictory to the spot market which is practically instantaneous and non-binding, which poses a challenge for optimization since some decisions regarding trading instruments can be delayed in time while others need to be taken in a specific period of time. So regarding decisions we have the commonly known "here and now", which the long-term contracts are example of, or "wait and see", which can be the trades done in the spot market (deLlano-Paz et al., 2017).

The literature on electricity portfolios in liberalized markets usually adopts a specific perspective, being it normally is the buyer's or the seller's. The buyers need to contract their future electricity consumption, which they can do so by managing a hedging portfolio of contracts, which they should continuously assess. However, the problem of constructing efficient portfolios for electricity buyers has received little attention in academic literature. An example of it is (Huisman et al., 2009), which investigates how to build an optimal portfolio with forward contracts in a two-step procedure where firstly it focuses on how to optimally allocate position in peak and off-peak forward contracts, and secondly choose the exact allocations, including the day-ahead market. Another example exclusively from the buyer's side, we have a procurement model by (Conejo et al., 2010), which uses a plural of energy sources and makes used of Conditional Value-at-Risk for the optimization. Two case studies are conducted: a simple one, for the sake of validation, and one based on data from the Iberian electricity market.

From the seller's perspective the literature is richer in portfolio applications in the electricity market, for example from GenCos' perspective. GenCos have the need for portfolio optimization techniques so to come up with strategies for the allocation of their generation to different trading contracts, while managing risk to best comply with the risk taking desire and the risk-return trade-off wanted. GenCos optimization factors are a bit more complex than the ones of the buyers', since besides the electricity sale performed in forward contracts and spot market trading, there are also costs in fuel and emission permits purchase (Mathuria et al., 2015). (Mathuria et al., 2015) considered pool and bilateral contracts and concentrated on the impact external market uncertainties have on the GenCos' electricity trading portfolio. It showed that higher allocation in spot markets can hedge risk since the risk of price change in the emission market can be compensated by price changes in the spot market. (Pindoriya et al., 2010) proposed a mean-variance-skewness model for generation portfolio allocation by maximizing the expected return and skewness of portfolio return and minimizing risk. It was shown that this model performs better for assets with non-normal characteristics than classical mean-variance.

Some more restrict literature adopts the perspective of private agents, such is the case of (Algarvio et al., 2017), that focused on retailer's and presented a model to optimize their portfolio of clients, simulating the energy market with a special emphasis on the relation between retailer and end-use consumer. It concludes that the retailer can keep the portfolio optimal and stable in relation to the risk-return preference if consumers are chosen in a more realistic way. (Charwand et al., 2017) presents a methodology for a retailer in order to maximize the total expected rate of return, where sources of energy including the pool, self-production and forward contracts are considered, by using a drawdown risk measure.

3.4 | Scenarios

Scenarios have become a fundamental part of foresight science and scenario planning is recognized as the most widely used method in the futures field. However, it seems to be much confusion in the literature about the definition of scenario, and every study field seeks clarity and consensus, of course. So, many researchers have identified this confusion and point out how it should be overcome. (Spaniol and Rowland, 2019). (Spaniol and Rowland, 2019) reviewed many definitions encountered in the literature and claims that the scenario definition does not seem to suffer from confusion and provide, from the literature reviewed, a shared synthesized definition summarized in the Figure 3.1.

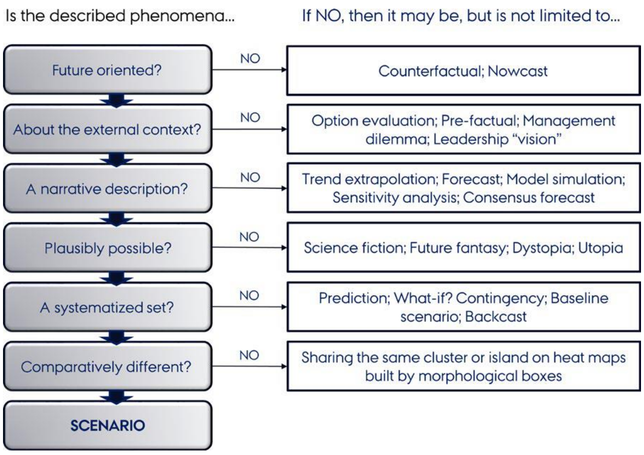

Figure 3.1 – Synthesized definition of scenario (Spanion and Rowland, 2018)

In the literature we can find the terms Scenario Analysis and Scenario Planning often used in the same matter, like in the reviews performed by (Batrouni et al., 2018) and (Amer et al., 2013). In this work Scenario Analysis is adopted. Scenario Analysis is a set of methodologies that aim to help providing insight for strategic decisions, being one of the main tools of strategic planning. One of the biggest challenges of Scenario Analysis, like any data-oriented forecast method, is dealing with Black Swans, which was a term popularized by (Taleb, 2007) and refers to rare, nonlinear and with extreme impact events, which can also be put as "*Things that we either do not know exist or do not have enough* *information to build a model, conceptual or otherwise*.". To a certain degree, and with proper knowledge, inference and intuitiveness, scenario analysis can make dealing with these events less hopeless (Batrouni et al., 2018).

In the literature of scenario analysis there are several methodologies for scenario building proposed. Some of them with common characteristics between each other, but generally these techniques "*emphasize on defining the issues, identifying key drivers, stakeholders, trends, constraints and other important issues in a systematic way and ranking of these items by importance and uncertainty*" (Amer et al., 2013). (Amer et al., 2013) reviews and exposes that there are several frameworks for scenario building and, although the classification and grouping has been performed in other ways, presents the most popular one that divides the methods into "schools":

- ➢ the intuitive logics, which gives greater control to the scenario builder that can select the tools he best seems fit, allowing him to work with intuition and gut;
- ➢ the probabilistic modified trends, which works with two-different matrix-based methodologies: Trend Impact Analysis and Cross Impact Analysis, and performs a probabilistic modification of extrapolated trends;
- ➢ The *La prospective,* which comes from the principle that future is not predetermined, and one can try to create and model it through actions.

Greater detail, explanation and comparison of each School, and particular methodologies can be found in the reviews done by (Batrouni et al., 2018) and (Amer et al., 2013).

The number of scenarios has to be higher than one in order to reflect uncertainty, and two is usually used to reflect the reaction to two extreme situations. Most of the literature recommends somewhere between 3 and 6 scenarios, since higher than that raises the cost to evaluate and draft all of those scenarios and lower cannot cover all possible alternatives (Amer et al., 2013).

The use of scenarios can be very beneficial to an organization:

- ➢ it enhances perception, with the people involved in the scenario exercises, better understanding, evaluate trend and events and become better observers of the business environment;
- ➢ it provides a structure to deal with uncertainty, helping to identify what is significant and what needs to be dealt with;
- ➢ it provides a middle ground between intuitive or informal techniques and more formal techniques;
- ➢ it is a communication tool, providing, even for people outside the organization, an adequate framework for discussion, and ultimately it contributes to organizational learning.

From this, the main objectives of the application of scenario analysis tend to be enhance the understanding, challenge the conventional way of thinking and improve the decision-making process (Wright et al., 2013).

The choice of scenarios and what criteria to use is something that has puzzled researchers (Wright et al., 2013) (Trutnevyte et al., 2016), which was often arbitrary or based on subjective perspectives of their relevance, but could also be by recurring to formal techniques. This matter is relevant since it reflects the uncertainties considered important by the scenario developers (Trutnevyte et al., 2016). (Van Der Heijden, 2011) suggested five basic principles of scenarios to serve as general rules for the scenario planner:

- ➢ Two scenarios are the minimum number to reflect uncertainty;
- ➢ Plausibility, so they should grow logically and according to current knowledge;
- ➢ Internally consistency, so events should be linked through a cause-effect relation;
- ➢ Relevance must be shown on the concerns of the client;
- ➢ An original perspective on the issue should be produced.

In the subject of energy research, energy scenarios are seen as suitable to define a strategy to the next step in an energy system, since they provide support to the strategic decision-making and are a means for discussion related with the energy future under study (Cao et al., 2016). Recently, with environmental and sustainability problems being more and more a trend topic, the development of scenarios for this purpose has seen growth given the technique's power to justify decisions and to induce learning (Guivarch et al., 2017). Given the infinite range of possibilities when it comes to energy scenarios, developers tend to pick a smaller and more relevant set of scenarios, generally picking quantitative ones. They usually use either the scenario matrix approach, picking the key factors they seem fit for that method or they identify specific desired outcomes and look for the conditions and decisions needed for that ending. To develop energy scenarios there are multiple assumptions concerning the factors that are not highlighted in the scenario choice, since those are the key factors (Trutnevyte et al., 2016). Common frameworks in energy scenarios take into account energy growth and technological advance for the future, which makes the STEEP framework (social, technological, economic, environmental and politics) popular (Dias et al., 2016), and (Van Der Heijen, 2011) adds that organizations should complement the STEEP analysis with an analysis of the structure of the industry and markets they operate in.

Scenario analysis in the energy sector has seen a large popularity in the energy sector focusing on the planner's perspective, when it comes to long-term decisions, most times from a whole country's perspective: (Park et al., 2016) applies scenario analysis to the renewable energy portfolio that large power operators have to guarantee in South Korea, building two scenarios where in first one PV and wind power are strengthen whereas in the second the bet in is other renewable energy. (Wang and Li, 2016) built three scenarios of yearly electricity consumption increase to study how that would influence the CO2 emissions of China. (Bahrami and Abbaszadeh, 2016) built a scenario based model to analyse the effect current trends might have on energy's key variables in the future, for Iran's case, by generating 4 scenarios where the political, science and technological and environmental aspects were presented. Scenarios were developed as shown in Figure 3.2.

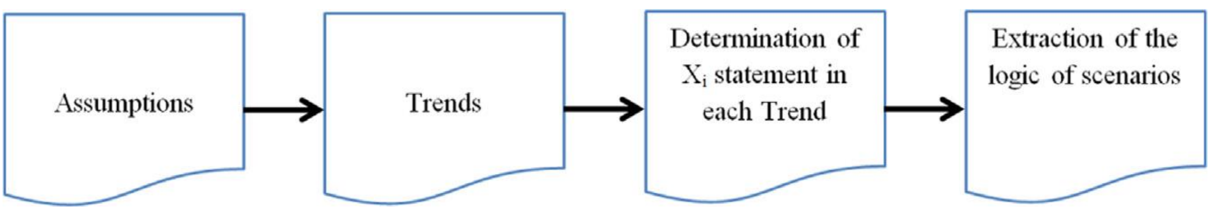

Figure 3.2: Scenario building methodology applied in (Bahrami and Abbaszadeh, 2016)

(Santo et al., 2016) aims, using scenario analysis, at identifying major uncertainties in the electricity system and their impact on the overall production mix, using Portugal as the case study. To do so it is considered a case with high renewable energy contribution and five scenarios were created by resorting to Monte Carlo Simulation. The methodology used can be summarized by Figure 3.3. (Loßner et al., 2017) performs an assessment of the economic performance of Virtual Power Plants in the German energy market and makes use of scenario analysis to illustrate the alternative energy developments by 2030 in Germany, starting in 2015. Three scenarios were developed: a reference scenario, where the development continues in a "business as usual" manner, and two extreme scenarios, where in one there is a considerable technological progress and in the other there is still a lot of dependence in fossil fuels. Some of the key factors take into account for the scenario development were Energy and climate policy, electricity demand, Fuel prices, among others.

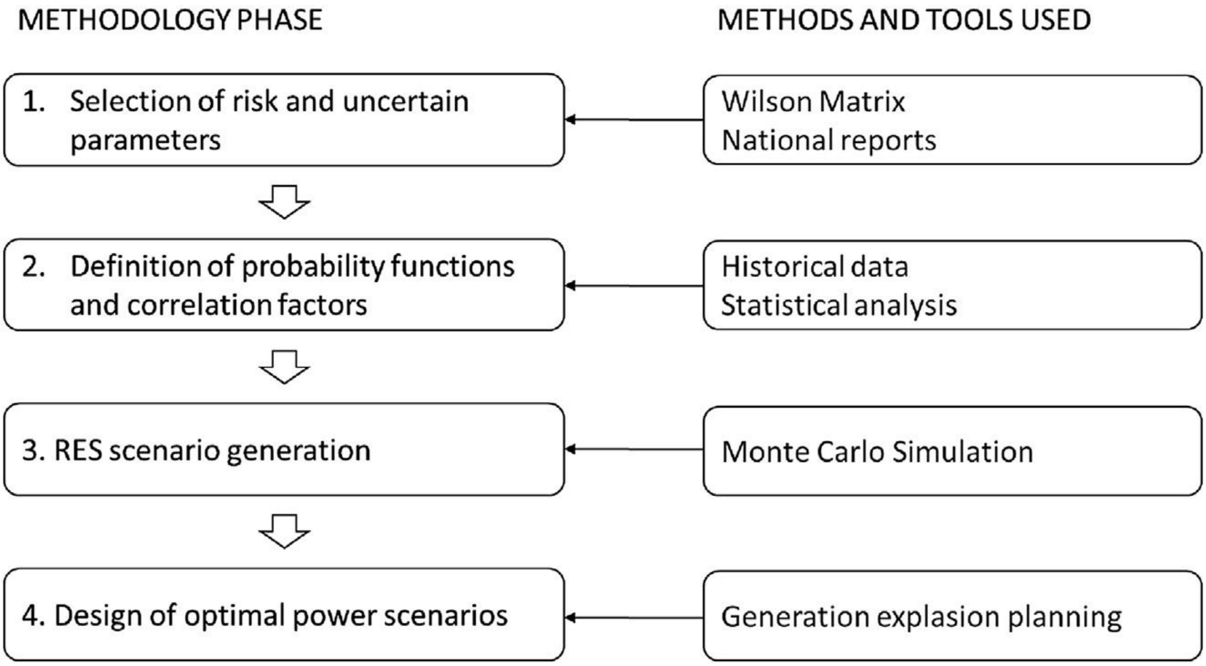

Figure 3.3 - Methodology and methods of the scenario building process in (Santo et al., 2016)

Besides the planner's perspective, scenario analysis is also popular at evaluating investments. (Cucchiella et al., 2017) performs an economic analysis to evaluate investments in renewable energy production technologies in the Italian electricity market. It makes use of scenarios in the first stage of the analysis by building three cost scenarios (high, medium and low) and identify an optimal portfolio for each, showing, as it would be evident, that the cost scenario drastically influences the optimal portfolio. (Bergen and D. Muñoz, 2018) makes uses of scenarios to model uncertainty on climate and environmental policies, by features such renewable targets, carbon taxes and demand levels, to see how these policies can affect generation and transmission investment in Chile. In this work 5 scenarios are built, exploring current policies as well as potential futures ones that have been discussed.

3.5 | Summary of chapter 3

The main objective of this chapter was to provide a literature review of the tools intended to be used in this research, and given the applications that were presented, it is rather obvious the importance and relevance each tool has in the energy sector.

The first section was devoted to multi objective optimization, introducing its importance in the present world and its general idea. The main families of techniques to tackle these problems were presented: weighted sums, transforms the problem into a single objective optimization, the ε-constraint method, one objective is optimized and the rest are constrained, and goal programming, goals for each objective are set and attempted to be reached. Examples of applications of each of these methods and Linear Programming Optimization Techniques were presented.

Next, portfolio optimization is presented, showing its origins and why has it found so much popularity in the energy world. Next the downside risk measure and its importance in portfolio optimization is presented, as well as two of the most popular methods: Value-at-Risk, and Conditional Value-at-Risk. Both methods are put face to face, and overall Conditional Value-at-Risk shows superiority, as it is proven by the numerous applications presented for the energy sector.

In the third section some electricity portfolios present in the literature are review. Firstly from the planner's side, some with a focus on Europe or in a single country or region, and next from the manager's side, showing the potential this tool can have for them and exemplifying it with some existing portfolios from the buyer or seller perspective.

Finally, the scenario analysis technique is review, showing the controversy and confusion there is regarding the scenario definition. Besides this, the scenario building "families" and presented, as well as the importance scenario has for organization and the basic principles they normally should follow. Next some applications are review, given emphasis to the scenario building approach each has taken.

From the literature review, we can take some very general conclusions:

- Bi-objective optimization is popular among the portfolio analysis given its easiness to present and conduct analysis to the results; as a MOO method weighted sum is the most popular and consensual;
- As a risk measure for energy portfolio, mean-variance has been preferred through time, however the more recent literature starts applying Conditional Value-at-Risk and Value-at-Risk;
- The literature in electricity portfolios focus mainly of the planner's problems and challenges, such as GenCos, and there is not a lot of work done from the private perspective, existing few articles on the retailer's side, and fewer solely on the consumer.

So, the model presented in this dissertation proposes to try to fill the gap identified in the last point, by being a tool which the consumers can take advantage of.

The following chapter presents the full problem characterization and the methodology used in the research is presented.

4 | Problem Characterization and Methodology

4.1 | Problem Characterization

The purpose for this dissertation is to build a mathematical model to optimize the energy portfolio of a large consumer with cost and risk as objectives.

So, this dissertation's goal is to partly fill that gap, by building a mixed integer programming (MIP) problem which optimizes the buyer's needs, making use of popular tools reviewed: the multi-objective problem will be a bi-objective one, with expected cost and risk as objectives. A weighted sums method will be used. Regarding risk management, there is a general consensus in the literature in favour of Conditional Value-at-Risk, so it will be adopted as the risk objective. A model from the electricity portfolio literature was selected to be the base for the new mathematical model, being that (Conejo et al., 2010) was chosen. An additional goal is to create some modelling tools for certain demand patterns, which consumers can take advantage to further enhance their electricity portfolio.

The consumer is inserted in the environment of an electricity market, being the Iberian Electricity Market (OMIE, 2019) selected for such, given its open data policies and its proximity to our reality, and so the model's definition will also be dependent of the environment on this market. Besides, opportunities are found in this market to further enhance the optimization.

Three sources of electricity are considered: forward contracts, which is when a specific amount of energy is bought for a specific price to be delivered in a specific time in advance, installation of self-generation facilities, and pool market trading, which is the trade done on the day-ahead market. Each forward contract will be set in a specific time and its potential output will be divided in 4 blocks of energy, each with a specific price. The self-generation facility will provide a constant output throughout every hour of the planning horizon, and since it implies a long-term investment, a potential long-term investment aversion from the decision maker will also be taken into account in the model. The energy from the self-generation facility will also be divided in 4 blocks, each with a different price as well.

The Pool market trading stands as the factor that brings uncertainty into the decision making. To model this uncertainty, we resort to the use of scenarios. So, inspired by (Conejo et al., 2010), the scenario tree in Figure 4.1 is built. In this scenario tree we have 3 branches leaving each node and 3 nodes, resulting in $3^3 = 27$ scenarios. Each branch represents one week, with a total planning horizon of 3 weeks.

The nodes represent decision stages, which is where the procurement decisions for the following week are made. We have 3 stages where:

- On the 1st stage decisions regarding forward contracts for the 1st week and 3-week contracts are made, the self-generation production is defined and the pool market decisions for the 1st week are decided;
- On the 2nd stage decisions regarding forward contracts and pool market for the 2nd week are made;
- On the 3rd stage decisions regarding forward contracts and pool market for the 3rd week are made.

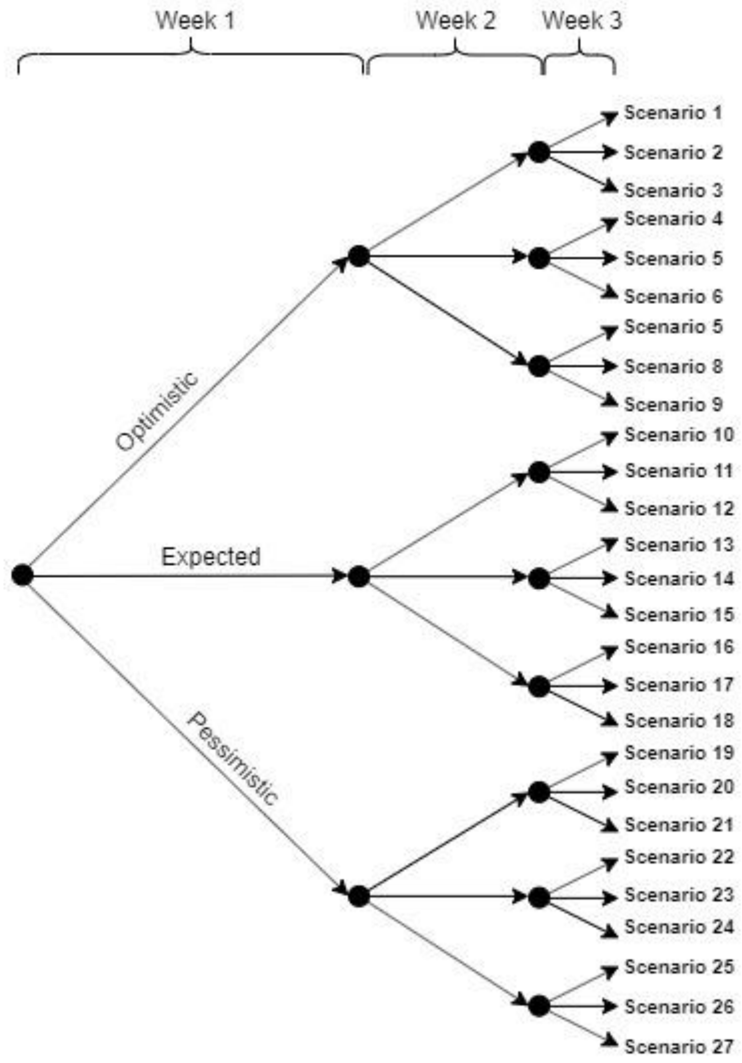

Figure 4.1 – Scenario Tree

The scenarios are done based on the data available from this market, and there will be an attempt to represent extreme scenarios, pessimistic and optimistic, as well expected ones.

So, the following problem will be solved:

Given:

- The planning horizon;
- The pool market scenarios prices and their probability;
- Forward contract details, such as electricity available, price of it and stage at which a decision has to be made;
- The price associated with the contracting of self-generation facilities and the output it can provide;
- The demand that exists in each period of the planning horizon;
- The aversion to long-term investment;
- The confidence level.

Determine:

- The procurement of electricity from the pool market;
- Whether Forward contracts were signed or not and the amount of electricity contracted in each one;
- If self-generation facilities are installed, and the output of them;
- The optimized schedule of the demand, for specific case studies;
- The pareto frontier of expected cost and CVaR for different risk postures.

Subject to the objectives of minimizing the expected cost, which is the sum of the procurement costs of the three sources of electricity, and the CVaR.

4.2 | Methodology

The mains steps taken in this master dissertation, in a general way, will be:

1. **Problem description:** contextualizes the problem and sets objectives, as well as the structure, for the rest of the work;
2. **Literature review:** attempts to give an overview of the research related fields. This step is devoted at providing a review of the literature concerning methodologies deemed important for the research at hand;
3. **Data gathering:** the aim is to collect the data necessary for the modelling part mainly through the literature available and open data websites, and then fit it to the parameters of the model;
4. **Development of a mathematical optimization model:** a combination of all the previous steps to obtain the mathematical formulation that will allow for the renewable energy portfolio optimization. In this step, the idea is to resort to the General Algebraic Modelling System (GAMS) software and obtain a mixed linear programming model;
5. **Model validation and discussion of results:** The model is validated through use of different patterns of demand, the results are discussed, and conclusions are taken;
6. **Conclusion and future work:** general conclusions from the dissertation are taken and the grounds of future work are set.

5 | Mathematical Formulation

Following the literature review, the objective settled is to build a model to optimize an electricity portfolio of a large consumer. So, a mixed integer program (MIP) was built with the multi objective of optimizing the cost and risk, excluding this way the profit factor, factor that is a key element in the retailer's perspective, which is very popular among the literature.

The chapter is divided in three sections. The following sections enumerates the sets, parameters and variables present in the model, and describes each one. The second section presents the constraints needed for the proper functioning of the model and describes each of them, explaining what the line of thought behind it was. Finally, the third section serves as a summary of the chapter and present the line of thought for the next one.

5.1 | Sets, Parameters and Variables

Index

s = Week

d = Day

t = Hour

w = Scenario

c = Contract

b = Block

g = Self-generation facility

k = Stage

Sets:

N_s = {s: set of weeks in the planning horizon}

N_d = {d: set of days in the planning horizon}

N_t = {t: set of hours in a day}

N_w = {w: set of scenarios}

N_c = {c: set of contracts available}

N_b = {b: set of blocks available in each forward contract}

N_g = {g: set of generation facilities}

N_k = {k: set of stages}

CD_s = {c: set of forward contracts available in week s}

CT_t = {c: set of forward contracts available at hour t}

Data Parameters:

H = Number of hours in the planning horizon

$E_{c,b}^{Cmax}$ = Maximum amount of energy available for contract c in block b (MWh)

$E_{c,b}^{Cmin}$ = Minimum amount of energy to be consumed from contract c in block b (MWh)

$P_{c,b}^{C}$ = Price of energy unit of contract c for block b (€/MWh)

$E_{g,b}^{Gmin}$ = Minimum energy to be generated from self-generation facility g in block b (MWh)

$E_{g,b}^{Gmax}$ = Maximum energy to be generated from self-generation facility g in block b (MWh)

$P_{g,b}^{G}$ = Levelized cost of energy unit from self-generation facility g (€/MWh)

$P_{s,d,t,w}^{P}$ = Price of energy unit in the pool market for week s, day d and hour t, in scenario w (€/MWh)

$D_{d,t}$ = Demand of energy for day d and hour t (MWh)

π_{w} = Probability of scenario w

A = Non-anticipativity matrix. $A(w,k)$ is equal to 1 if scenario w and w+1 are equal up to stage k, otherwise are equal to 0

K_{c} = Stage at which a decision for forward contract c is made

Parameters defined by the Decision Maker:

β = Risk aversion factor

λ = Aversion factor to long-term generation investment

α = Confidence level

Binary Variables:

$s_{c,w}^{C}$ = 1 if forward contract c is selected in scenario w, 0 otherwise

s_{g}^{G} = 1 if self-generation investment g is selected, 0 otherwise

Variables:

$E_{c,b,w}^{C}$ = Amount of energy contracted from contract c and block b for scenario w (MWh)

$E_{g,b}^{G}$ = Amount of energy self-generated from g in block b (MWh)

$E_{s,d,t,w}^{P}$ = Amount of energy purchased from the pool for week s, day d and hour t in scenario w (MWh)

C_{w}^{C} = Total cost of forward contracting for the whole planning horizon (€)

C^{g} = Total levelized cost of self-generation for the whole planning horizon (€)

C_{w}^{P} = Total cost of purchases in the pool for the whole planning horizon (€)

CVaR = Conditional Value-at-Risk

ζ = Value at Risk

η_{w} = Auxiliary variable needed to compute the conditional value at risk

5.2 | Buyer's portfolio optimization model

The following sub-chapter presents the constraints of the model and the consequent objective function, providing as well important clarifications regarding assumptions made, the explanation of parameters, among others.

5.2.1 | Forward contracting constraints:

The forward contracts are considered to be made for weekly intervals, so to best fit the short-medium term planning character of this model. Also, the contracts deliver the same quantity of energy for every hour of the contract horizon. The contracts can either be set for a single week or multiple ones. The formulation of the model enables a contract to be set either on consecutive weeks or not, depending on the intention. If desired, it is also possible to quickly make and adaption of the model and consider as well contracts set on specific days of the week, needed only for this to consider a parameter similar to CT_t or CD_s, defining for each forward contract c what are the days they are set on.

The energy available for each contract is divided in blocks, and each block has an associated maximum and minimum energy to be consumed, as well as a different prices per energy unit. So, for each contract, there is minimum and maximum energy that can be bought if the contract is made:

$$E_{c,b}^{Cmin} * s_{c,w}^{C} \leq E_{c,b,w}^{C} \leq E_{c,b}^{Cmax} * s_{c,w}^{C} \quad (1)$$

$\forall c \in N_c, b \in N_b, w \in N_w$

The cost of forward contracting is then given by (2), where the 7 multiplying is due to the seven days of a week.

$$C_w^C = 7 * \sum_{s}^{N_s} \sum_{t}^{N_t} \left(\sum_{c \in CD_s, CT_t} \sum_{b}^{N_b} E_{c,b,w}^{C} * P_{c,b}^{C} \right) \quad (2)$$

$\forall w \in N_w$

5.2.1.1 | Non-anticipativity constraints:

This kind of constraints are employed when it is needed to set a dependency between different scenario. These constraints are the only that establish relations and dependencies between variables of different scenarios. For our specific case, it is necessary to ensure that a decision made on forward contracts on week s is the same for multiple scenarios that follow the rule chosen. For example, the contracting for the first week has to be the same for all pool price scenarios, therefore, all scenarios. In our specific case, only the forward contract decisions are subject to these constraints.

The structure of the scenario tree highly conditions the constraints, so, as done in (Conejo et al., 2010), the structure of the scenario tree is stored in a matrix of 0s and 1s denoted by A. The size of the matrix will be (N_w- 1) x (N_k – 1), and element A(w, k) is equal to 1 if scenarios w and w + 1 are equal up to stage k, 0 otherwise. For our specific case the scenario tree is a 3 x 3 x 3, which is presented in chapter 4, so there are 3 decisions nodes and matrix A becomes a 26 x 3 matrix as follows:

$$A = \begin{pmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 0 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{pmatrix} \tag{3}$$

It is quickly grasped that A(w, 1) = 1, w=1,…, 26, since all scenarios are coincident from the first decision node, and analogously, for example, A(9, 2) is equal to 0 since scenarios 9 and 10 become different at stage 2.

By resorting to matrix A, we are now capable of formulating the non-anticipativity constraints for the forward contracts as follows:

$$E^{C}_{c,b,w} = E^{C}_{c,b,w+1} \tag{4}$$

$\forall c \in N_c, b \in N_b, w = 1, \dots, N_w - 1, \text{if } A(w, K_c) = 1$

, where K_c is the stage at which a decision on contract c is made.

5.2.2 | Self-Generation electricity constraints:

For large electricity consumers it is common to consider self-production facilities to supply in-house energy at a low risk level, and given the recent trend, renewable self-generation facilities are becoming more and more popular given the quick developments this area has seen recently. For simplicity, the self-production of energy is considered to be the same at each hour, so an approximation is made to avoid dealing with patterns of production, which are characteristic of most renewable energy technologies.

The energy possible to be available from this self-generation facility is divided in blocks, similarly to the forward contracts. When an investment is made on a self-generation facility g, the energy generated in each block for each scenario w for a facility g should be within certain minimum and maximum limits:

$$\mathrm{E}_{g,b}^{Gmin} * s_g^G \leq \mathrm{E}_{g,b}^G \leq \mathrm{E}_{g,b}^{Gmax} * s_g^G \tag{5}$$

$\forall g \in N_g, b \in N_b$

The total cost of the generation is done by means of a levelized generation cost, where the cost per energy unit is obtained by considering the total lifetime of the technology and the total cost associated to it (fixed and variable), which puts the cost into perspective (this long-term investment is put into review by means of the objective function later on):

$$C^g = \sum_{g}^{N_g} H * \sum_{b}^{N_b} P_{g,b}^G * E_{g,b}^G \tag{6}$$

5.2.3 | Pool Market:

For our model the consumer is considered to be a price-taker in the pool market, meaning this that its trades do not influence the market clearing price. This assumption is justified by the large market where our study is inserted (the Iberian electricity market), thus the impact of a single consumer on the price can be neglected. An example where this assumption is put into practice is in (Wozabal and Rameseder, 2020). There is no real need to constrain the trade in the pool market, so the one constraint needed is to guarantee that the consumer only interacts as a buyer, that is, that the variable which represent energy procured from the pool is positive.

$$0 \leq E_{s,d,t,w}^P \tag{7}$$

$\forall w \in N_w, t \in N_t, d \in N_d, s \in N_s$

The total cost from the pool market trading in the planning horizon is then obtained by:

$$C_w^P = \sum_{s}^{N_s} \sum_{d}^{N_d} \sum_{t}^{N_t} E_{s,d,t,w}^P * P_{s,d,t,w}^P \tag{8}$$

$\forall\ w \in N_w$

5.2.4 | Energy Balance constraints:

To meet the demand in each hour of the planning horizon, an energy balance constraint is needed:

$$\sum_{g}^{N_g} \sum_{b}^{N_b} E_{g,b}^G + \sum_{c \in CD_s, CT_t} \sum_{b}^{N_b} E_{c,b,w}^C + E_{s,d,t,w}^P \geq D_{d,t} \tag{9}$$

$\forall w \in N_w, t \in N_t, d \in N_d, s \in N_s$

This equation ensures the energy available per hour from the three different sources: self-generated, forward contracted and pool market, is equal or greater than the demand on that hour. Equal sign should not be used here because the contracts and the output of the self-generation facilities are set for more than one hour, and so in hours of low demand, it should be possible to have an energy waste.

5.2.5 | Conditional Value-at-Risk definition:

The risk of cost variability is modelled through use of Conditional Value-at-Risk. From chapter 3, we have seen that the CVaR value is approximately the expected cost of the $(1 - \alpha) * 100\%$

scenarios with greatest cost. So, from (10) we have the CVaR value to be minimized: the optimal value of ζ is the Value-at-Risk (VaR) and it is the lowest cost such that the probability of the cost being higher or equal to ζ is less or equal to $(1-\alpha)$. On the other hand, η_w is the excess of the cost over ζ in scenario w, being it always positive or qual to 0, from (12).

$$\mathrm{CVaR} = \zeta + \frac{1}{1-\alpha} * \sum_{w}^{N_w} \pi_w * \eta_w \tag{10}$$

Making use of the cost variables defined above for each electricity source (2) (6) (8), the definition of the auxiliary constraints for the CVaR definition are as follows:

$$(C_w^P + C^G + C_w^C) - \zeta \leq \eta_w \tag{11}$$

$\forall\, w \in N_w$

$$\eta_w \geq 0 \tag{12}$$

$\forall\, w \in N_w$

5.2.6 | Objective function:

The multi objective is to minimize the cost and the risk of the operation. The two objectives are considered through the use of a single objective function, (13), since a weighted sums method is considered. The way to define the weights for each objective is through the value of the risk aversion factor β, which is used to model the decision maker's propensity towards risk. So, when β = 0, the weight of the cost objective is 100%, but when it is, for example, β = 5, the weight of the cost objective is $\frac{1}{6}$ and the weight of the CVaR objective is $\frac{5}{6}$.

Here it is presented the aversion to long-term investment factor, λ, which is aimed at countering or favouring the production of self-generated energy depending on the willingness to contract technology with high fixed costs and long life span.

$$\min \sum_{w} \pi_w * \sum_{s}^{N_s} \sum_{d}^{N_d} \sum_{t}^{N_t} \left(P_{s,d,t,w}^P * E_{s,d,t,w}^P + \lambda * \sum_{g}^{N_g} \sum_{b}^{N_b} P_{g,b}^G * E_{g,b}^G + \sum_{c \in CD_s, CT_t} \sum_{b}^{N_b} E_{c,b,w}^C * P_{c,b}^C \right) + \beta * (\zeta + \frac{1}{1-\alpha} * \sum_{w}^{N_w} \pi_w * \eta_w) \tag{13}$$

5.3 | Summary of Chapter 5

This chapter serves to present to the reader the characteristics and tools offered by the model that will be used in the following chapters. First the sets, parameters and variables were presented, followed by the model constraints. It was shown how each source of electricity, self-generated, pool and forward contract, is limited, either by maximum and minimum values, or restricted in another way. The formulation of the risk management tool Conditional Value-at-Risk is also presented, and the objective function is explained.

The next chapter follows the line of this one and explains how the data needed for the parameter estimation was collected and treated, in order to fit the parameters presented in this chapter.

6 | Data Collection and Parameter Estimation

Following the model's definition, the second step is to gather data needed for the optimization. For this there was a need to resort to an open data market, so for this estimation the Iberian Electricity Market (OMIE, 2019) was preferred, given its proximity to our reality and it popularity among the literature, for example in (Wozabal and Rameseder, 2020). The portfolio options are made based on this market or on articles, whom, either from the retailer or solely from the buyer's perspective, provided options for the portfolio which could be used. And from there, the data is shaped into parameters, which ultimately influenced the way the model presented on chapter 5 is formulated.

This chapter tackles how the parameters related with the pricing of the various sources considered are estimated, specifically how the forward contract and self-generation pricing is done, the categorization done based on seasonality of the pool market's electricity price and the scenario generation.

6.1 | Electricity prices

The base of the investigation is based on the publicly available data from the Iberian electricity market from (OMIE, 2019). The prices from the Spanish region were selected as the object of study given the bigger volume of consumption it features. However, the prices from the Spanish and Portuguese regions rarely drift apart, being the same most of the times. Therefore, all the conclusions presented can be extrapolated for the Portuguese region as well.

To capture the potential statistical patterns associated with seasonality, and so not to lose any information on that regard, a whole year was considered for the studies, from September 2018 to August 2019. As it can be seen in figures 6.1, 6.2 and 6.3, seasonality is something present in electricity pool markets, therefore there is an optimization opportunity to best take advantage of this seasonality.

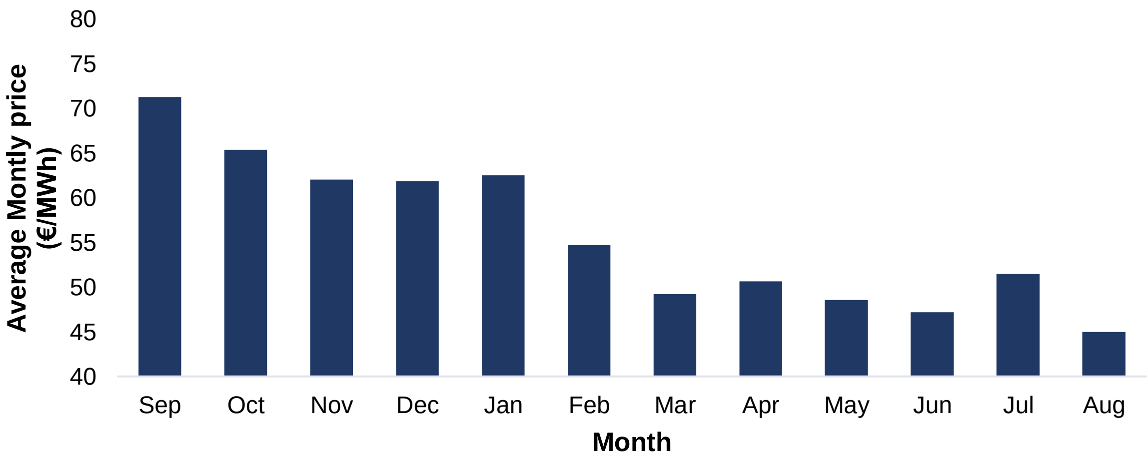

Figure 6.1 – Average Monthly price of electricity in the pool market
from September 2018 to August 2019

6.1.1 | Definition of Valley, Shoulder and Peak hours

In figure 6.2, all values from the planning horizon from each hour are averaged and displayed. We can easily see that the pool market prices follow a pattern when it comes to hours of the day and there is a tangible difference between the maximum value (61.02€ at 22h) and the minimum value (48.23€ at 5h). A popular way to categorize the hours of the day according to their average pool price, is through the definition of 3 sets of hours: valley, shoulder and peak hours, as in (Charwand et al., 2017), which have associated to them a low, medium and high price, respectively.

In order to define these sets of hours, and trying to divide the number of hours for each in a fair way, but not necessarily equal, we average the value of each hour based on the yearly data we have. From it, the maximum values were 48.66 €/MWh and 61.49 €/MWh. From the values for each hour the values 54€ and 58€ are chosen as the references to divide the interval in 3, given that this way a fair division, both in the interval of prices and number of hours, is guaranteed.

So, the valley hours are the hours with an average lower than 54€, the peak are the ones with an average higher than 58€, and the shoulder are the ones with an average between the two values. This way, we are left with the following sets:

Valley = {1, 2, 3, 4, 5, 6, 16}

Shoulder = {0, 7, 14, 15, 17, 18, 23}

Peak = {8, 9, 10, 11, 12, 13, 19, 20, 21, 22}

This division aids in the forward contract definition, being that some contracts will cover a specific time of day, as well as in the analysis of the results.

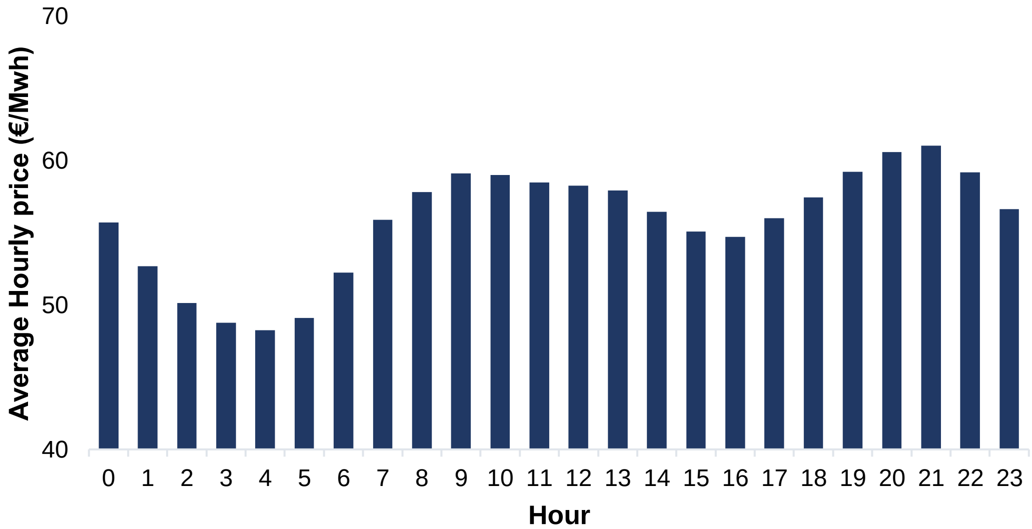

Figure 6.2 – Average hourly price of electricity in the pool market from September 2018 to August 2019

6.1.2 | Scenario generation

The uncertainty factor in this optimization problem is the electricity pool market price, given its easily noticeable volatility. So, in order to model this uncertainty, we have resorted to scenario building.

In Figure 6.3 we see the difference from the average price from each day of the week to the year average. From it we can conclude that there is indeed a statistical relation between the price of the energy and the day of the week. Therefore, for the scenario building, and given the relevance this statistical pattern can have, three different contiguous weeks were to be selected from the available data and used for the scenario tree generation. This way, we can avoid resorting to scenario generation software, popular among the literature, since that way we would lose statistical properties of the data, proven by figures 6.2 and 6.3.

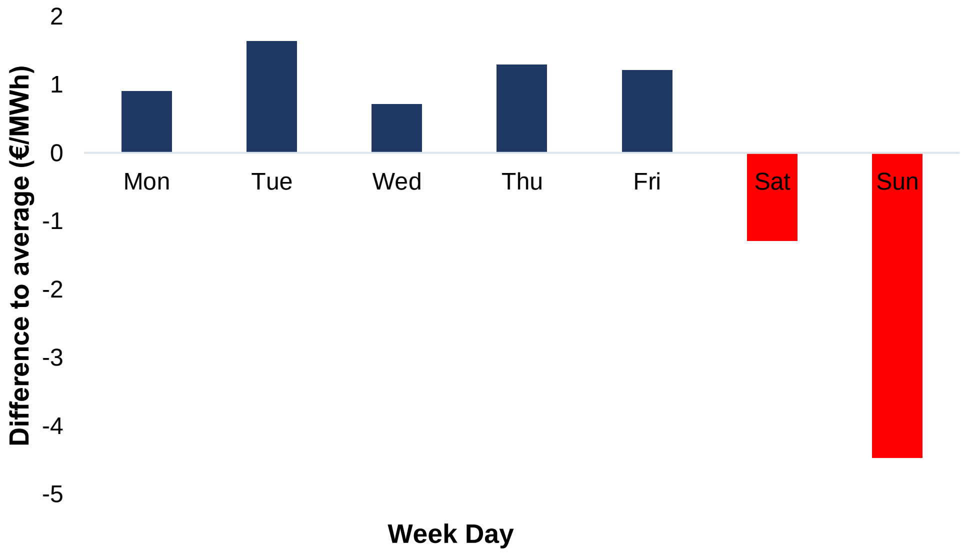

Figure 6.3 – Difference from the average of each day of the week to the year average

So, for the scenario generation 3 weeks are needed, to represent an optimistic, a pessimistic and an expected week in terms of prices. So, from the 48 weeks of the time considered, 3 weeks are sampled.

The average price value for each week is calculated, and from it the weeks with the maximum and minimum average values are chosen to be the pessimistic and optimistic weeks respectively. For the expected week, the median of the sample was considered. The statistical properties of the 3 weeks are in table 6.1.

	Pessimistic Week (week 3)	**Expected Week** (week 25)	**Optimistic Week** (week 48)
Maximum (€/MWh)	81.82	62.25	48.37
Minimum (€/MWh)	59.31	45.00	32.00
Average (€/MWh)	73.20	55.58	40.92
Standard Deviation	2.91	4.02	4.27

Table 6.1 – Details of the weeks chosen to help in the scenario generation

From here, the scenario tree in Figure 4.1 is built. The 3 branches leaving each node correspond to the time series for each of the 3 weeks selected for optimistic, expected and pessimistic. This way, the same 3 time series are used to create the 27 scenarios, simplifying this way the general process of scenario building, while still enabling the tree to be relevant for the decision making analysis.

Following the scenario determination, the need to assign probabilities to the scenarios rises, so a methodology for this is needed. Since the scenarios are composed of time series from 3 different weeks, the method thought was to first assign probabilities to each of these 3 weeks among themselves. So, for each node we consider a conditioned probability, assuming this way that the probabilities associated with each branch leaving a specific node adds to 1. In the end, for each scenario, we multiply the three probabilities, from the 3 branches leading to it, and obtain the final probability of the scenario.

Since the weeks chosen correspond to actual weeks of the year, they are technically equitable within the year, so a normalization could be done and make each scenario equitable as well. However, this would not righteously represent the truth. The way found not to underestimate neither overestimate the probability of the pessimistic and optimistic week was to consider the weeks whose average distance a standard deviation down from the maximum and up from the minimum value, respectively. This way, the extreme weeks can have a more relative importance according to the data under study, by considering a spectrum of weeks with similar average values, and therefore similar circumstances, in the probability calculation. In addition, and given the original goal to represent the extremes, we can still maintain the original worst case and best case values, rather than the median inside the worst and best spectrum, which arguably could make sense given the methodology for the probability calculation.

Finally, the probability of the expected week is determined by the rest of the cases. There are 7 occurrences for the maximum value spectrum and 13 for the minimum one, making the probability distribution the one presented in Table 6.2 (by rounding up to two decimal places).

	Pessimistic Week	**Expected Week**	**Optimistic Week**
Probability	0.15	0.58	0.27

Table 6.2 – Probabilities of each week used for the scenario generation

6.2 | Forward Contract Data

The approach chosen for forward contracting was to consider 2 types of contracts: weekly contracts and contracts for the entire time horizon (3-week contracts in this case). The former will be called weekly contracts and the latter 3-Week contracts. In addition, these 2 types will either be set on the 24 hours of the weeks they are settled on, base contracts, or on one of the 3 sets of hours of the day defined above in 6.1.1: valley, shoulder and peak contracts. These latter will be called time-of-day contracts.

Each contract is divided in 4 blocks, characterized by different prices of electricity, and have a maximum and minimum of electricity available. For simplicity, all blocks in every contract have the same maximum, 20 MWh, which means each contract can provide up to 80 MWh per hour, but obviously only in the hours they are set on. In the other hand, each contract has a minimum of 20 MWh, meaning that if a contract is chosen, its output has to been between 20 and 80 MWh.

Table 6.3 shows the map of contracts with the designation used for each contract considered, according to the weeks and hours of the day they are set on, as described above.

	Valley	Shoulder	Peak	Base
Week 1	Contract 1	Contract 2	Contract 3	Contract 4
Week 2	Contract 5	Contract 6	Contract 7	Contract 8
Week 3	Contract 9	Contract 10	Contract 11	Contract 12
3-Week	Contract 13	Contract 14	Contract 15	Contract 16

Table 6.3 – Map of contracts considered

The prices of the blocks are assigned to represent in the best way the behaviour of a price-maker, who needs to stay competitive in price and has to deal with risk. With this in mind, the blocks of the weekly contracts set on specific times of the day always have a higher price than the average value of those specific times in the week chosen as expected in 6.1.2. The price of the base contracts set is obtained through the prices of the valley, shoulder and peak contracts and the fraction of the day they represent. To achieve this, a price was assigned to the 2nd block of each contract, and from there the prices of the other blocks are obtained by subsequently increasing the price by 5% of the original value, for block 3 and block 4, and decreasing 2% for the block 1. The unit prices can be seen in table 6.4. A similar methodology was used in (Charwand et al., 2017).

Type of weekly Contract	Block 1	Block 2	Block 3	Block 4
Valley (€/MWh)	56.84	58.00	60.90	63.80
Shoulder (€/MWh)	58.80	60.00	63.00	66.00
Peak (€/MWh)	60.76	62.00	65.10	68.20
Base (€/MWh)	59.05	60.25	63.26	66.28

Table 6.4 – Forward Contract unit price

The price of the second block for the 3-week contracts is determined by decreasing the values of the corresponding weekly contract in 2%. The price for the other blocks is calculated following the same methodology as the one used in the weekly contracts.

6.3 | Self-Generation Facility

As options for the self-generation facility, only a single renewable electricity source is considered. A renewable option is considered since it can be seen as a risk-free electricity option (disregarding long-term investment risk), since weather profiles are assumed to be stable and constant.

Instead of considering fixed and variable costs separately, the model considers instead a merge of the two, a levelized electricity price. This is an estimation of the price per energy unit produced throughout the entire expected lifetime of the equipment. This is obtained by considering the total expected cost throughout the entire lifetime, fixed and variable, and dividing it by the total output expected in that time. This way it is possible to put the long-term investment, the fixed cost needed initially, into perspective, enabling this for a comparison with the electricity pool market prices, which allows for an analysis to the trade-off of the two.

The data used was taken from a study conducted by Fraunhofer Institute for Solar Energy Systems, where an analysis was made to the levelized cost of electricity (LCOE) of renewable energy technologies in the first quarter of 2018. The main focus of the study is the LCOE of photovoltaic (PV), wind turbines and biogas. For further information on the methodology used for the calculus of the LCOE consult (Kost et al., 2018).

We will consider the installation of PV technology, given the popularity and the favourable weather conditions of the Iberian Peninsula. The study presents different values of LCOE for different locations which are characterized by distinct global horizontal irradiance values. For a value of global horizontal irradiance of 1800 KWh/m^2a, characteristic of the South of Spain, the values of LCOE range from 3.1€cent/KWh and 4€cent/KWh, that is, 31 €/MWh and 40 €/MWh, respectively. The mid value of the interval made by those two values, 35.5 €/MWh, will be used as the price of the first block. The price of the other blocks, similarly to the methodology for the forward contract, will be calculated by raising the price 10% of the original value. The price and energy available for each block can be seen in Table 6.5. This methodology of increasing the levelized cost with the increasement of the self-generation unit's output is intended to represent other costs that can arise as the investment grows, such as, for example, the cost of space for the PV panels.

	Block 1	**Block 2**	**Block 3**	**Block 4**
Unit Price (€/MWh)	35.5	39.5	42.6	63.8
Energy available (MWh)	15	15	15	15

Table 6.5 – Price and energy available in each block of the self-generation unit

A minimum value of energy to be generated was defined for the case when a self-generation investment is made, so to be realistic and not to have absurdly small values, since in reality an investment would not exist for a very small scale. The minimum value considered was the 15 MWh of the first block.

6.4 | Summary of Chapter 6

On this chapter the parameters estimation was explained: what were the sources, what were the methodologies used and what were the final value. On the first section we looked at the prices of the electricity in the pool market and how this is seasonal depending on the hour, day of the week and month. The hours of the day were sorted in 3 categories: valley, shoulder and peak hours, which represent a low, medium and high price of electricity, respectively. Finally, the scenario generation method was explained, originating 27 scenarios, based on the time series of 3 weeks chosen as examples of optimistic, pessimistic and expected scenarios.

On the next two sections, the parameters which define the options to the pool market are explained: the forward contracting was explained: how the contracts are spanned either for a week or the 3-Week period and cover the 24h or are time-of-day contracts. The cost per unit and the maximum and minimums of energy for each contract are also settled. Next, the self-generation unit is tackled, and the unit energy price is defined for each block as well as maximum and minimum energy to be produced hourly.

The next chapter is devoted to results analysis. Different case studies are elaborated to evaluate different aspects, and the model presented in chapter 5 and the parameters defined in this chapter are used to enable the results analysis.

7 | Case studies

To best demonstrate the model's applicability to different situations three case studies are elaborated. For each case study, the electricity demand profile is changed, so to analyse different portfolios. The value of the other parameters needed to run the model is presented in chapter 6, so the only change is in the Demand.

The three cases of demand profiles used are: case a) a constant demand throughout the planning horizon; case b) a cyclic demand with different values for the 24h which is repeated every day; case c) a week profile composed of 7 independent days which can take place in any order. On case a the more general aspects of the portfolio options are analysed, while on case b and c the focus is put into evaluating the impact of the specific optimization done. The portfolios in each case are the expected portfolios over all scenarios, meaning this that there is not a single specific scenario considered.

For the Conditional Value-at-Risk the same confidence value of 95% will be used throughout all the cases explored.

This chapter is divided in 4 subchapters. On the first chapter case a is analysed and we look at the aversion factor to long-term generation investment value definition, the trade-off between expected cost and CVaR for different risk postures, as well as how the procurement changes with these postures, regarding shares on the portfolio, first week decisions and forward contracts. On sub chapter 7.2 the case b is considered: we start by explaining the modelling of the starting-time optimization followed by the results, where there is a comparison between the case with and without this optimization, regarding the Expected cost and CVaR trade-off and procurement changes for Valley, Shoulder and Peak hours Thirdly, the case C is tackled, where firstly the modelling of the order optimization is explained, followed by comparison of the trade-off between expected cost and CVaR with and without optimization, and the results regarding the order chosen. Lastly a summary of the results of the chapter is done.

The General Algebraic Modelling System (GAMS) is used, and the problem was solved with an Intel Core i7 processor.

7.1 | Case a): Constant Demand profile

As aforementioned, in this first case study there is a constant value of demand for each hour. The value assumed was 200 MWh since it is considered a big enough value considering the amount of energy available hourly from the electricity options, which enables the results to alternate in a relevant way between the more risk free options and risky ones, always depending on the risk aversion from the decision maker.

For this case, an alteration is done to the energy balance equation (9), since the demand is only dependent on the hour, being the same for every day, the parameter $\mathrm{D}_{\mathrm{d,t}}$ is substituted by the parameter D_{t}. So (9) gets replaced by (14).

$$\sum_{g}^{N_g}\sum_{b}^{N_b} E^{G}_{g,b} + \sum_{c\in CD_s, CT_t}\sum_{b}^{N_b} E^{C}_{c,b,w} + E^{P}_{s,d,t,w} \geq D_t \tag{14}$$

$\forall w \in N_w, t \in N_t, d \in N_d, s \in N_s$

From here, an analysis of the portfolio chosen for different values of the risk aversion factor is made and aspects like the different sources of electricity chosen or the cost and CVaR values are presented.

7.1.1 | Aversion factor to long-term generation investment Value Definition

In this first step of the analysis we will tackle the issue of the definition of a value for the aversion factor to long-term generation investment (λ). Like previously explained, it is considered an option for the customer to contract a Self-Generation facility. However, this facility will imply a big initial financial effort from the customer. So, to diminish the impact this could have, and since we are considering a short-term decision-making-model, we consider a levelized electricity price per unit. As a way to somewhat penalize or favour this self-generation facilities on the eyes of the decision-maker, this factor is multiplied by the cost obtained from the levelized electricity price. Thus, a static value for this factor should be chosen to be used in the rest of the analysis, in order to fully focus on the impact the risk measurement tool has. In the absence of a specific decision maker's intention, the value of the factor will be in a way that makes the contracting of this self-generation facility competitive in comparison with the other options, which means, do this in a way that the value contracted changes for different risk postures.

To achieve this, the model is run for different values of the risk aversion factor and for different values of long-term generation investment aversion, with the intention of comparing the contract of self-generation facilities among these different postures by means of the value of self-generated electricity per hour. The result obtained are presented in table 7.1.

Table 7.1 – Self-Generated Electricity for different values of β and λ (MWh)

$\boldsymbol{\lambda}$	$\boldsymbol{\beta}$				
	0	1	1.5	2	5
1	60.00	60.00	60.00	60.00	60.00
1.3	30.00	45.00	52.65	60.00	60.00
1.6	0	0	0	15.00	15.00
2	0	0	0	0	0

From table 7.1 we can easily notice that the amount of electricity contracted from the Self-Generation is sensitive to the value of these two factors. The cases where the long-term generation investment factor was 1 and 2, represent the two extremes: on the former the electricity contracted from this source is at the maximum available value for all the different values of risk aversion, which means it makes it very attractive compared to the other sources. On the latter however no self-generation investment is made for any risk posture, meaning this that the price is not competitive at all. For the cases where the factor was 1.3 and 1.6, we can note that the electricity generation reacts to different values of risk aversion, however it is more noticeable in the case where λ is 1.3, since the range of the maximum and minimum values is higher and the amount changes for almost every value of risk aversion.

Finally, from Table 7.1, and following the above-mentioned goal of choosing a value for the long-term generation investment factor which makes the self-generated electricity source competitive, the value chosen for λ was 1.3, and it will be the value considered for all the cases going forward from here on out. By considering this factor, the cost function of the self-generation facility, and therefore the total cost function at the end, will not be a truly cost function that only takes into account the real cost of the electricity, since this way it will also incorporate the aversion the decision maker feels towards big initial investments.

7.1.2 | Expected Cost vs Conditional Value-at-Risk trade-off

The goal of any analysis where there is an optimization through means of a risk measure, being it either a mean-variance analysis or, in our case, a Conditional Value-at-Risk one, is to observe how the risk aversion factor (β) changes the ratio between the total cost and the CVaR value, and what are the tradeoffs happening from one value to another.

To achieve the aforementioned goal, trials are done for different values of β, and the optimal solutions in terms of expected cost and CVaR are provided in table 7.2. The solution reached for β = 0 is the one with the lowest expected cost and highest CVaR, because when β = 0 the term of the objective function regarding risk is not taken into account, making it the solo objective to minimize the expected cost. This means that when β = 0 the decision maker is prone to risk. Through the increase of the risk aversion factor, the expected cost increases and the value of the CVaR decreases, which is expected since the risk term of the objective function gains more and more relevance in the optimization as the risk aversion factor increases. So, with the increment of β, the decision maker becomes more risk averse. For β = 5, and comparing with the values from the case where risk is not considered, β = 0, the expected cost saw an increase of 7.4% whereas the CVaR value suffered considerable reduction of 17.42%. However, these two cases represent two extremes: not consider risk at all and over consider risk. So, it can be more interesting looking at the trade-offs happening in the interval made by these two extreme cases, since most decision-making postures will be in between these two.

Table 7.2 – Expect Cost and CVaR trade-off for different risk postures

$\boldsymbol{\beta}$	Expected Cost (million €)	CVaR (million €)
0	5.386	7.009
1	5.649	5.874
1.5	5.702	5.831
2	5.732	5.812
5	5.787	5.788

For a more visual way to see the data above, the efficient frontier in terms of expected cost and CVaR is plotted in Figure 7.1. This representation is particularly interesting to quickly notice the size of the trades-off happening between the cost and the CVaR with the increase of β, by means of the slop of the line connecting each dot. For example, from β = 0 to β = 1, which is the line with the best CVaR/Cost ratio, for an increase of 4.88% in the expected cost, the CVaR value drops 16.2%, which is very close to the total drop value of 17.42% mentioned before. Continuing the increase of β, the value differences become smaller and smaller percentage wise, since from β = 1 to β = 5 we see an increase of the cost in 2.4% and a decrease in the value of CVaR in 1.46%, so, a decision on this interval of values would massively depend on how much risk aversion the decision-maker has.

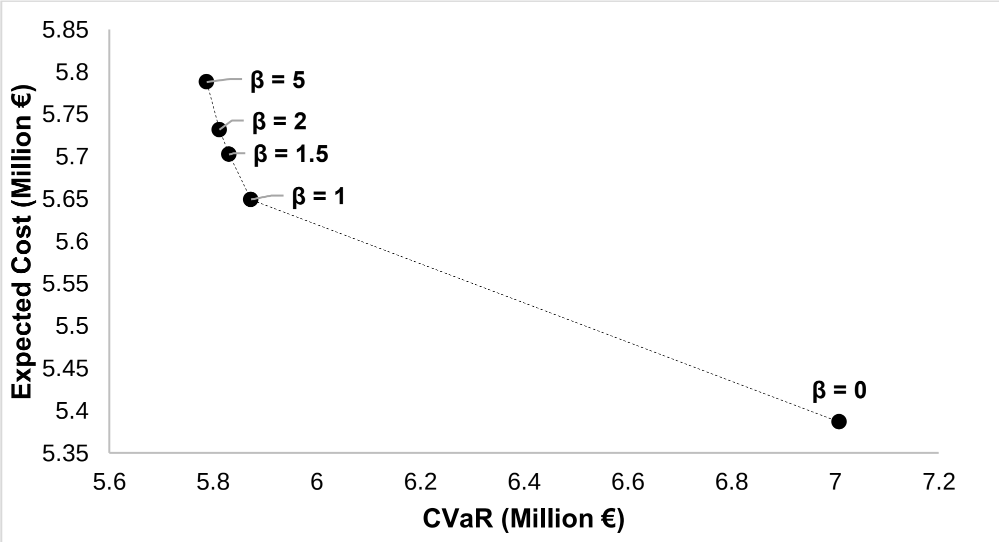

Figure 7.1 – Efficient Frontier of the expected cost and CVaR for different risk postures

7.1.3 | Portfolio evolution

While building the portfolio, the model is presented with sources with different prices and, through the value of the Conditional Value-at-Risk, different risk levels associated to them. So, the sources chosen for the portfolio while varying the risk aversion factor will change accordingly. With this in mind, it would be of interest to see which of these sources, and how much electricity from each, is chosen for different levels of risk aversion. In that line of thought, Figure 7.2 shows the expected portfolio of sources of electricity for both the first week of the planning horizon and the total of the 3 weeks for different levels of β. The pie charts are made by resorting to the expected value of procurement over all the scenarios. These show four types of sources: pool market, self-production, weekly contracts and 3-Week contracts. These former are the ones that are settled in every week of the study.

One of the most noticeable result is how the share of the Weekly and 3-Week Contracts grows as the value of β increases, as well as the self-generated electricity, which also grows. This is an expected result since these sources represent more risk-free options. This growth is particularly impressive in the case of the contracts: when β = 0 the combined share of the two typologies of contracts is equal to zero for both the first week and the 3 weeks, and it increases in a proportional way to the increase of the value of β, reaching a 70% share when β = 5. It is important mentioning that the share of 3-Week contracts is always higher than the share of weekly contracts. The self-production also sees an increase, however a bit more modest, from 15%, when β = 0, to 30% when it equals to 5. In the opposite direction, the electricity procured from the pool drops massively as the risk aversion increases, going from a respectable 85% share, when CVaR was not accounted for, to 0% when β = 5.

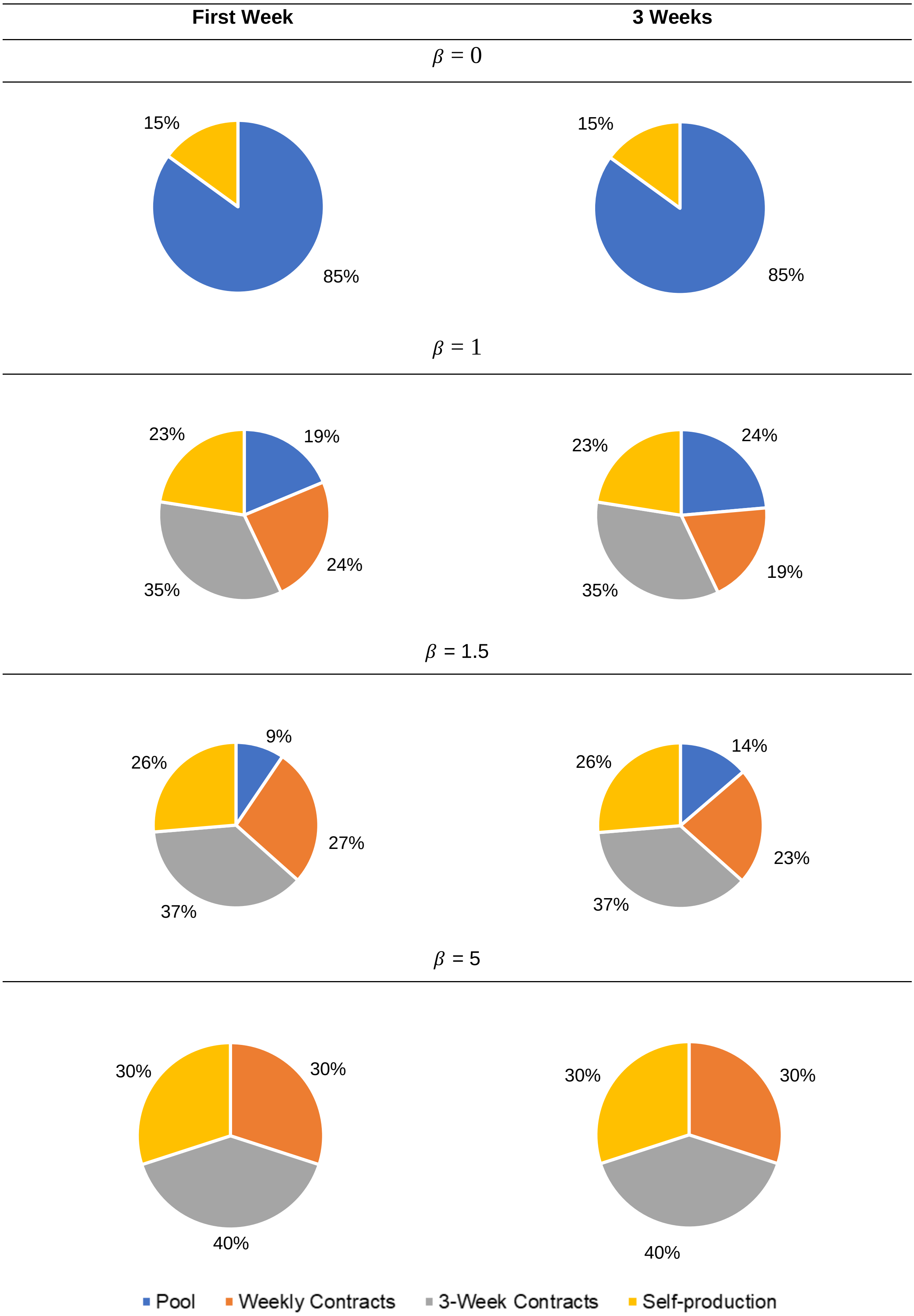

Figure 7.2 – Portfolio evolution for different risk aversions

For β = 1, the pool share of electricity sees its biggest drop, dropping around 75% from the original value, the contracts in the other hand see their biggest growth, from a 0% share to have a combined share of 54% in the total of the 3 weeks, which stands to reason being the pool the main source of risk and the contracts the biggest risk-free source of electricity. Finally, the self-generated share goes up from 15% to 23%. To the β values of 1.5 and 5, the same trend continues, however in a more modest way.

7.1.4 | First Week Decisions

Through the definition of the non-anticipativity constraint and the scenario tree, both presented in the chapter 5 and 4 respectively, the decisions made for the first week contracts, 3-Week contracts and self-production is done for every scenario. As a result, this is a step which influences a great deal the final portfolio of electricity, especially since the 3-Week contracts and the self-production decisions influence all of the planning horizon, since they are long term decisions.

On Table 7.3, it is possible to see the way these decisions are impacted by the value of β. With the increment of it, the number of contracts and quantities contracted grows, as expected, since contracts are a risk-hedging tool. As it could be deducted from Figure 7.2, given the shares of each source, for β = 0 no 1st week decisions are made, and for β = 5, all the contracts are signed and, specifically, the maximum amount of Self-production unit is contracted. On the specific time-of-day contracts, for β values of 1, 1.5 and 2, we can observe that the contracts defined on valley hours, contract 1 and 13, generally have a lower amount of electricity contracted than the ones defined for shoulder and peak hours, contracts 2, 3, 14 and 15. Specifically, contract 1 is only contracted when β = 2, whilst contracts 2 and 3 already had 40 MWh contracted for a lower risk aversion factor of β = 1. The contracts that relate to the shoulder and peak hours are chosen straightaway from β = 1, and the value contracted for these hours increases very little with the increment of the risk aversion factor, being that the biggest difference is how the trade-off between time-of-day contracts and base contracts changes.

Table 7.3 – First Week decisions

First week Decisions	β				
	0	1	1.5	2	5
1	0	0	0	20.00	20.00
2	0	40.00	40.00	39.88	20.00
3	0	40.00	40.00	39.88	20.00
4	0	20.06	25.90	20.12	40.00
13	0	20.00	20.00	20.00	40.00
14	0	40.00	40.00	40.00	40.00
15	0	40.00	40.00	40.00	40.00
16	0	35.00	40.00	40.00	40.00
Self-Production	30	45.00	52.65	60.00	60.00

It is also noticeable that there is a preference of 3-Week Contracts rather than weekly ones, a situation which is further verified for every week in table 7.4. Additionally, the self-production unit is also preferable as a source than the contracts in general.

7.1.5 | Forward Contract: Valley, Shoulder and Peak hours

The concept of valley, shoulder and peak hours, explained in sub-chapter 6.1.1, is employed for the definition of the forward contracts, and, as a consequence, the decisions on them can be analysed by looking at these three sets of hours. Table 7.4 presents different analysis done for the valley, shoulder and peak hours for different values of risk aversion.

Table 7.4 – Forward contract: Valley, Shoulder and Peak hour statistics

β	Hours	Forward Contracted Energy per week (MWh)			Energy per source of type of Forward Contract (MWh)			
		Week 1	Week 2	Week 3	Time-of-day Contract	Base Contracts	Weekly Contracts	3-Week Contracts
0	Valley	0	0	0	0	0	0	0
	Shoulder	0	0	0	0	0	0	0
	Peak	0	0	0	0	0	0	0
1	Valley	75.1	75.6	85.9	25.6	53.3	23.9	55.0
	Shoulder	135.1	119.3	109.9	68.1	53.3	46.5	75.0
	Peak	135.1	110.2	110.1	65.1	53.3	43.5	75.0
1.5	Valley	85.9	87.0	87.6	25.7	61.2	26.85	60.0
	Shoulder	145.9	135.7	124.6	74.2	61.2	55.4	80.0
	Peak	145.9	135.7	115.3	71.1	61.2	52.3	80.0
2	Valley	100.1	97.7	93.0	35.6	61.3	26.9	60.0
	Shoulder	140.0	138.8	129.5	74.8	61.3	56.0	80.0
	Peak	140.0	130.8	126.5	71.0	61.3	52.3	80.0
5	Valley	140.0	140.0	140.0	70.3	69.7	60.0	80.0
	Shoulder	140.0	140.0	140.0	70.3	69.7	60.0	80.0
	Peak	140.0	140.0	140.0	70.3	69.7	60.0	80.0

On the section of the table entitled “Forward Contract Energy per week”, we have the electricity contracted for each hour of each week, from each of the three sets (Valley, Shoulder and Peak). Again, we see the values for β = 0 and 5 are the two extremes, with no and maximum forward contracting, respectively, as well as the forward contracting growing with the increment of the risk aversion factor. However, it is interesting to see the values in between: the shoulder and peak hours decrease their forward contracting along the weeks, for the same β value, while the valley hours experience increasement and decreasement over the weeks depending on the risk aversion factor. It is also worth mention that the shoulder hours have either an equal amount of energy contracted or higher than the peak hours, which can be found unusual since peak hours have higher pool prices, and therefore, should be tackled more quickly than the shoulder ones when considering risk management. This can be due to the fact that peak contracts span for more hours than the shoulder ones, 10 against 7, representing then a bigger commitment, or also that the price parameter of the peak hour contracts was not estimated in the best way. However, it is important to acknowledge that this difference is not that vast, and that shoulder and peak hours still have much more contracted energy per hour than the valley ones, thus still being an indicative of how these hours have a lower price associated.

The section of Table 7.4 entitled "Energy source per type of Forward Contract" conducts an analysis of the electricity procured from different types of contracts. Contracts can be categorized in two different ways, based on two different criteria: time-of-day Contracts or Base Contracts, and, Weekly Contracts or 3-Week Contracts, as explained in the sub-chapter 6.2. This is relevant since it shows how much of the electricity from forward contracts is procured from each typology and gives insight on preferences that may exist. For both, the values are averaged from the total of the 3 weeks. For example: for the valley hours when β = 1, most of the electricity contracted comes from base contracts rather than time-of-day contracts, moreover, the electricity procured from 3-Week Contracts is also significantly greater than the one from weekly contracts. So, for these specific hours, base and 3-Week Contracts are preferred.

Firstly, a comparison between time-of-day contracts and base contracts is made. It is noticeable that the amount of electricity contracted for valley hours is higher from the base contract source than from the specific time-of-day one, and for the shoulder and peak hours the opposite scenario presents itself. We can state this for every β value, although, as β increases, the contracted values do as well but the rule is kept. This happens since the pricing of the base contract is done based on the prices of the 3 times of day, and although it might be advantageous since it can represent a cheaper option in peak and shoulder hours, it makes the decision maker overpay in valley hours, so a trade-off is done in that regard. It is also worth mentioning that for shoulder and peak hours the time-of-day contract source sees an increase throughout the increment of the risk aversion value, except from β = 2 to β = 5, where an increase in the base contracts and a decrease in the time-of-day contracts were preferred.

Secondly, a comparison between weekly and 3-week contracts is made. The biggest point to take here is that the energy contracted comes primarily from the 3-Week contracts, which makes sense since they present a cheaper price per unit and the demand is constant throughout the planning horizon. This way the commitment these 3-week contracts imply, since they contract a specific amount of electricity to be deliver every hour for the 3 weeks, is not penalized in any way because there are no hours without demand, because if they were, contracting these contracts would necessarily mean an electricity waste. Exemplifying: if the demand was constant in the first 2 weeks and then zero in the 3rd, weekly contracts for the week 1 and 2 would be preferred rather than a 3-week contract, since this former would result in the waste of one third of the electricity, so a slightly cheaper energy per unit price would not enough of a factor as it is in this case. Besides this, all the patterns found before are repeated: the procurement increases with the increment of the risk aversion factor, there is more procurement for shoulder plus peak hours than for valley hours, and shoulder hours have sometimes more procurement than peak hours, although in this case it is only noticeable in the weekly contracts.

7.1.6 | Summary of Case a) for operational decisions

This first case study main purpose was to explore how the several aspects of the portfolio evolve with the decision maker's risk aversion for a constant demand. So, from it we can say:

- From the trade-off analysis of the expected cost and CVaR, we can say that it can be beneficial for a risk prone decision maker, β = 0, to increase its risk aversion slightly, since that from Figure 7.1 we see that slightly increasing the expected cost leads to a significant decrease in the CVaR value. On the other hand, for a very risk averse decision maker, β = 5, it can be beneficial to increase its risk proneness, since slightly decreasing the expected cost does not increase significantly the value of CVaR.
- From the portfolio evolution we can advise decision makers who are more risk averse to avoid procure their electricity from the pool market, and rather prioritize the self-production and the forward contracts. For risk prone decision makers, the pool market should be preferred.
- From the first week decisions, it is advisable for a risk averse decision maker to think about hedging the risk since the first decision staged, by signing forward contracts and deciding on the output of the self-generation facility.
- For forward contracts: the electricity procured for valley hours should be mainly from base contracts, and the one for shoulder and peak should come mainly from weekly contracts. In addition, the 3-week contracts should be preferred, within some extend, over the weekly ones.

7.2 | Case b): Cyclic Demand profile

The second case study is of a cyclic daily demand profile. This case study is inspired by the situation described in (Pinto-Varela et al., 2009), where the problem of design of multipurpose batch plant is tackled and tasks are scheduled to fit a 24-hour cycle which repeats itself continuously. For these cases there is an optimization opportunity: optimize the starting time of this 24-hour cycle so to best achieve the objective of the problem: minimize cost and risk. In this study we will only conduct the cost optimization of a pre-defined demand profile, but this philosophy could be integrated in the design and scheduling of these plants, enabling the optimization of these taking into account the expected cost and Conditional Value-at-Risk of the energy procurement. The values used for the energy demand are presented in Table 7.5.

Table 7.5 – Cyclic Demand profile

Time	**0h**	**1h**	**2h**	**3h**	**4h**	**5h**	**6h**	**7h**	**8h**	**9h**	**10h**	**11h**
Demand (MWh)	200	180	170	170	170	170	180	190	200	200	200	180
Time	**12h**	**13h**	**14h**	**15h**	**16h**	**17h**	**18h**	**19h**	**20**	**21h**	**22h**	**23h**
Demand (MWh)	190	200	210	220	200	190	200	220	230	250	250	230

This case study serves the purpose of exploring the seasonality that the pool market prices suffer depending on the hour of the day, which leads to the definition of valley, shoulder and peak hours in chapter 6. Having a mixed profile of demand such as the one in table 7.5, allows us to analyse how the model will react according to this aforementioned seasonality and allows us to explore the consequences of it.

7.2.1 | Modelling the starting time

To model this we need to define:

- a new index, which represents the possible starting times, θ;
- a new parameter for the demand, where the demand profile along the hours t is shifted for all the possible starting times θ, $ND_{t,\theta}$;
- a binary variable, s_θ, which is used to select the demand profile of $D_{t,\theta}$ that corresponds to the starting time chosen by the optimization. This binary variable equal to 1 for the value of θ chosen as ideal, and 0 for all other options. This modelled by (15).

$$\sum_{\theta}^{N_\theta} s_\theta^s = 1 \tag{15}$$

Now we need to define the D_t for equation (14), which is kept for this case. However, D_t now is a variable. So, from (16) D_t is defined by the product of the binary variable s_θ^s and the parameter $ND_{t,\theta}$.

$$\sum_{\theta}^{N_\theta}(s_\theta^s * ND_{t,\theta}) = D_t \tag{16}$$

$\forall t \in N_t$

So, equations (15) and (16) are added to the model for case b).

7.2.2 | Expected Cost vs CVaR

Again, and for the same reasons stated for case a), it is critical to look at how the expected cost and the CVaR value react, their trade-off, to the increment in the aversion factor β. However, for this particular optimization, it is also interesting to analyse what are the practical impacts in this area when an optimization on the starting time is done.

In order to do this analysis, the model is run for different values of β for two situations: one where the starting time was optimized and one where there was no optimization, being that in the latter the way to consider no optimization was to define the starting as hour 0. The results are presented in Table 7.6.

Table 7.6 – Expect Cost and CVaR trade-off and starting time for different risk postures with and without optimization

$\boldsymbol{\beta}$	**Starting-time optimization**			**No Starting-time optimization**	
	Expected Cost (million €)	CVaR (million €)	Starting time	Expected Cost (million €)	CVaR (million €)
0	5.364	6.994	7h	5.414	7.025
1	5.576	5.925	6h	5.644	5.940
1.5	5.643	5.878	8h	5.703	5.893
2	5.689	5.851	8h	5.720	5.884
5	5.705	5.846	8h	5.746	5.873

The solutions reached are in line with the expected: the expected cost grows in both scenarios with the increment of the risk aversion factor and the CVaR decreases. From the table we can see that the values of the expected cost and CVaR on the starting-time optimization are always lower than the ones without optimization, for the same β value, which demonstrates the relevance this optimization has. So, with optimization we can reach the lowest levels of expected cost and CVaR, and without it the highest. Besides, the starting time changes from different values of β, which is particularly interesting, making the starting time dependent on the decision maker's level of risk aversion.

The results from Table 7.6 are represented in Figure 7.3, showing the positive impact this optimization brings, since for the same value of expected cost, the value of CVaR is significantly lower when there is starting-time optimization, rather than when there is not.

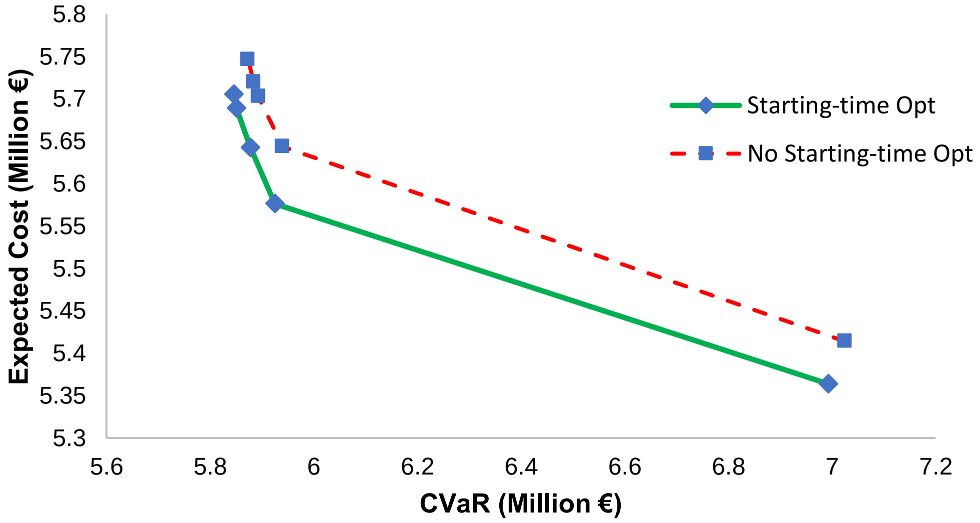

Figure 7.3 – Efficient frontier between the expected cost and CVaR for the situations with and without starting-time optimization

7.2.3 | Procurement differences on Valley, Shoulder and Peak hours

Again, and since it is intrinsic to the whole price definition, the categorization of the hours of the day in Valley, Shoulder and Peak will be used and we will be looking at how the shares of electricity from each source changed for each of these categories, given that by changing the starting time, and therefore shifting the demand profile, these shares can variate. This analysis is represented in table 7.7.

For starters, the totals for the first case, the one without starting-time optimization, and for the second case, the one with it, remain practical the same for each time of day as the value of the risk aversion factor rises. This is expected since the demand stays the same in each hour independently of the risk, being that the only thing that should change is the energy from each source. The small variations can be justified since a fixed value is contracted in forward contracts and in the self-generation unit and so, in certain hours with low demand, it can go over the demand and produce an energy waste.

Another easily noticeable difference is that, for the same β value, the energy procured in the first case for peak hours and valley hours was, respectively, higher and lower when compared to what happened in the second case, seeing very little difference for the shoulder hours. This conclusion is justified by how the optimization on the starting time avoided matching the hours with higher demanded to the peak hours, and rather matched them with the valley hours. This resulted on a drop of 12.24% in the electricity procured in peak hours, on average from every value of β, and on an increase of 26.5% in the valley hours, from the first case to the second one. A point that could be raised is that in the second case the sum of electricity consumed in the peak hours is still higher than the one in valley hours, however this is misleading since there are 10 peak hours and only 7 valley ones, so relativizing these values by number of hours, each Valley hour has 4687.06 MWh electricity procured and each peak has instead 3908.26 MWh, thus a significant difference.

As a final point between the comparison between these two cases, let us look at the sourcing in the valley hours. From case 1 to case 2 the valley hours demand of energy increased considerable, as seen, and so an increasement in the share of each source of electricity followed the trend, however the share that suffered the biggest was the one from the pool. This is particularly noticeable when β = 1.5, where the share of contracts stayed exactly the same and the pool share saw an increase of 115.27%, or when β = 5 that the increase was of 229%. This last one is mostly because there is a cap of forward contract and self-generated energy available, and so if the demand is increased over this cap the only source available would be the pool. Also, the pool presents its lowest values in valley hours, and valley contracts usually have a higher average value, so since we are looking at the worst 5% cases, it's normal that they do not influence much here and the pool is preferred.

Table 7.7 – Source of procurement from Valley, Shoulder and Peak hours for different risk aversion factors with and without starting-time optimization

$\boldsymbol{\beta}$	**Hours**	**No Starting-time Optimization (MWh)**			**Starting-time Optimization (MWh)**		
		Valley	Shoulder	Peak	Valley	Shoulder	Peak
0	Contracts	0	0	0	0	0	0
	Pool	21630	25830	38220	28770	24150	32760
	Self-Gen	4410	4410	6300	4410	4410	6300
	Total	26040	30240	44520	33180	28560	39060
1	Contracts	9730	16158	22162	9283	14724	20298
	Pool	9695	7467	12920	17282	6801	9732
	Self-Gen	6615	6615	9450	6615	6615	9450
	Total	26040	30240	44532	33180	28140	39480
1.5	Contracts	13977	19131	26082	13997	18247	23748
	Pool	5448	4494	9000	11728	4958	5442
	Self-Gen	6615	6615	9450	6615	6615	9450
	Total	26040	30240	44532	32340	29820	38640
2	Contracts	15184	20188	26767	18956	19345	25771
	Pool	4241	3437	8318	6769	3872	3419
	Self-Gen	6615	6615	9450	6615	6615	9450
	Total	26040	30240	44535	32340	29832	38640
5	Contracts	16501	19416	25938	19978	19035	25200
	Pool	1522	2807	7145	5012	3453	2940
	Self-Gen	7350	7350	10500	8017	8017	11453
	Total	25373	29573	43583	33007	30505	39593

7.2.4 | Summary of Case b) for operational decisions

This second case study purpose was to explore how important factors, inherent to the portfolio decision, change if we optimize the starting time of a 24 hour demand cycle, with different demand values for each hour. So, a decision maker whose demand fits this profile should set its starting time according to optimized starting time for his risk posture. By doing this:

- Independently of being risk prone or averted, the decision maker will have a lower expected cost for the same value of CVaR, and for the same expected cost a lower CVaR. However, a decision maker prone to risk will probably be more thrilled to have a lower expected cost for the same CVaR, whilst a risk averted one will prefer to see the situation as a lower CVaR for the same expected cost.
- The procurement on Valley hours will increase and decrease for Peak hours.

7.3 | Case C: Weekly optimization

This third case study is a weekly optimization. Similar to case b, the scheduling of activities is optimized according to the objectives of minimizing risk and cost. However, for this case we consider a set of 7 different day demand profiles that have to all be scheduled within the week. The schedule chosen is repeated for the 3 weeks under study.

Each of these 7 day demand profiles is defined by a set of 24 values, which define the demand for the 24 hours of a day. To generate each set, 24 values were randomly sampled from a normal distribution. The mean value and standard deviation were changed for each of these 7 sampling procedures, so that we could have different ranges of values for each set, and therefore enable a more diverse analysis. The mean and standard deviation for each set, along with the maximum and minimum value, are shown in Table 7.8.

This cases study explores the seasonality that the pool market prices suffer depending of the day of the week, proven by figure 6.2. Having different profiles of demand for each day with different mean values, such as the ones in table 7.8, allows us to see which days of the week will be preferred and see how this seasonality affects the procurement.

Table 7.8 – Statistics on the 7 day demand profiles

Day time series	**1st**	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**
Mean	180	220	250	270	250	220	250
Standard Deviation	10	20	20	20	30	40	40
Maximum	193	256	296	318	324	305	334
Minimum	263	181	211	228	130	136	185

7.3.1 | Modelling the order optimization

In order to perform the optimization explained above, firstly we need a strategy to model the situation. So the 7 time series are inserted in the model, through means of a parameter, in the order presented on table 7.8, and the goal is to have a variable where during the run of the model the days are sorted accordingly. So, to model this new situation we need:

- A new index γ, serving this new index as an alias of d;
- The parameter where the 7 time series will be inserted in, $\mathrm{EED}_{t,\gamma}$;
- A new binary variable $s^{s}_{d,\gamma}$.

Now, as a thinking tool, imagine a matrix of 1s and 0s and the lines represent the index d and the columns represent the index γ : for the first real day d, the position of the 1 in the first line would denote which time series would fit the first day, and so on. To make this happen it is necessary that the sum of each element of each line sums 1, since only a time series should be assigned to each day, and the sum of each element of each column should, as well, sum 1, since each time series should be assigned only to a single day. To make this happen a binary variable $s_{d,\gamma}^{s}$ is considered with the following constraints guaranteeing the rules explained above:

$$\sum_{\gamma} s_{d,\gamma}^{s} = 1 \tag{17}$$

$\forall d \in N_d$

$$\sum_{d} s_{d,\gamma}^{s} = 1 \tag{18}$$

$\forall \gamma \in N_\gamma$

Finally, and using both the binary variable and the parameter containing the time series, the parameter $D_{d,t}$ from chapter 5 is considered here as a variable and its definition is done through the following equation:

$$D_{d,t} = \sum_{\gamma} s_{d,\gamma}^{s} * EED_{t,\gamma} \tag{19}$$

$\forall d \in N_d, t \in N_t$

The model stays the same as presented in chapter 5, with addition of the equations (17), (18) and (19).

7.3.2 | Expected Cost vs CVaR

As previously done in case study b), it is important to see how the expected cost and CVaR values change on the 2 different cases when there is an order optimization and when there is not. For the case of no order optimization, the order from Table 7.8 was used.

On the table 7.9 we can see the values for the expected cost and CVaR for different values of the risk aversion factor for the two cases. Again, as expected in both cases the expected costs rises and the CVaR drops with the increment of β, besides the order optimization produces more favourable trade-offs between the two variables for every β and both the expected cost and CVaR see their lowest value when there is an order optimization and their highest where the is not. However, for β = 5 the expected cost is lower in the case when there is no order optimization, on the other hand the CVaR is lower when there is, so it is understandable that the cost was a bit more penalized since the priority in this case is mostly put on reducing the CVaR rather than the cost, by reason of the high risk aversion, β = 5, and that was achieved best in the case with order optimization.

Table 7.9 – Expect Cost and CVaR trade-off for different risk postures with and without order optimization

β	With order Optimization		Without order Optimization	
	Expected Cost (million €)	CVaR (million €)	Expected Cost (million €)	CVaR (million €)
0	6.249	8.176	6.266	8.205
1	6.459	7.026	6.476	7.048
1.5	6.501	6.992	6.517	7.018
2	6.523	6.991	6.528	7.011
5	6.602	6.979	6.591	6.990

On Figure 7.4 we can see the efficient frontier built from the data from Table 7.9. Something very noticeable still is that both lines start to converge for high values of β, however the order optimization still reaches a better CVaR value. Something we can also tell from table 7.9 but it is clearer from the efficient frontier is that, for the case with order optimization, the value of CVaR does not change significantly from the increment of β above the value 1.5, being that from β = 1.5 to β = 5 the expected cost increases 1.55% and the CVaR drops only 0.27%.This could be significantly important for a decision maker, since for most risk aversion postures this would not be a favourable trade-off.

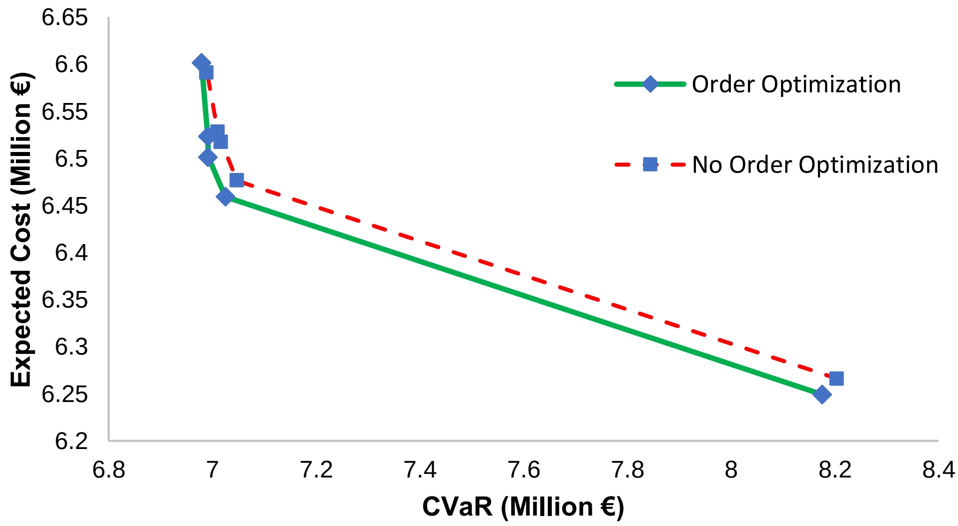

Figure 7.4 – Efficient frontier between the expected cost and CVaR for the situations with and without order optimization

7.3.3 | Day-order analysis

As aforementioned on the beginning of this chapter, there is an optimization on the order of the 7 day-time series happening, so, as already predictable from the two different cases from 7.3.2, the order optimization is done and has a positive impact.

The result of this optimization is presented in Table 7.10. On the table we have, for each risk aversion factor value, which day-time series from Table 7.8 was assigned to each weekday. The results generally change with the increment of β, even if just one or two days.

One of the objectives for this order optimization was to analyse how the price seasonality of the day of the week, which is under analysis in Figure 6.3, could come into consideration in the model when choosing the optimized order of the day-time series from Table 7.8, which have different mean and maximum values. With that in mind, let's look carefully at Table 7.10: from Figure 6.3, generally, the days with cheaper electricity are Sunday and Saturday, in that order, and from table 7.10 we see that for almost all risk aversion values, except β = 5, the day-series assigned to each are the 7th and 4th, respectively, which significantly proves the impact seasonality has. This because the 4th series is the one with the highest mean value and is assigned to the day with cheaper electricity, in general, and the 7th time series is the one with the second highest mean value, tied with the 3rd and 5th. However, it is the one with the highest standard deviation, and therefore highest maximum, making it the least favourable among the 3, making sense then that it was assigned to the second cheapest day. This pattern only breaks for β = 5, since, as we saw for example from Figure 7.2, the pool market's procurement share drops with β, so for the extreme case of β = 5 it is normal that the pool price is not as big as a factor in the objective optimization, although it is important to notice that the pool market share is decreasing already for β = 0 until β = 2, but still the results do not change for these two days, which shows the relevance of this price seasonality.

For the remaining days of the week, Monday to Friday, the pattern of price difference is not as relevant, seen from the figure 6.3, where the days' difference to average was very similar. However, it is interesting to see that the series with the lowest mean value, the 1st, was assigned, for β = 0, to Tuesday, which is the week day with the biggest difference to average, situation that changed when risk aversion was taken into account, which is not a surprise given the relatively small difference to average pointed out.

Table 7.10 – Result of the assignment of the day-time series to the days of the week from the order optimization

β	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
0	2nd	1st	6th	5th	3rd	7th	4th
1	3rd	6th	1st	2nd	5th	7th	4th
1.5	2nd	6th	1st	3rd	5th	7th	4th
2	6th	5th	1st	3rd	2nd	7th	4th
5	4th	5th	1st	7th	2nd	6th	3rd

It is worth mentioning how important the results pointed out in this sub chapter are, since they are aligned with the expected from the seasonality presented in figure 6.3 and it would be easy for them not be. This because the results from figure 6.3 were obtained through the average of every week of the year under study, and the sample done for the scenario generation was only 3 weeks of the year, so it could be expected that this pattern would not be seen in these 3 weeks.

7.3.4 | Summary of Case c) for operational decisions

This third case study purpose is to explore how the portfolio decisions change with the optimization of the scheduling of 7 different day demand profiles within each week of the planning horizon. So, a decision maker whose demand fits this profile should set its scheduling according to the obtained for his risk posture. With this:

- Regarding the trade-off between the expected cost and CVaR, the decision maker will face similar benefits to the ones pointed out in the operational decisions from case b).
- The procurement over the weekend increases and decreases throughout the days of the week, since the price of electricity is lower and higher respectively.

7.4 | Summary of Chapter 7

The main objective of this chapter was to conduct an analysis of the results from the model presented in chapter 5 with the parameters estimated in chapter 6. Three case studies with different demand patters, and therefore different objectives, are conducted and conclusions for each one are taken. The number of equations, number of discrete and binary variables, resource usage and relative gap are presented for each case study in table 7.11.

Table 7.11 – Execution summary of the case studies

	Case a)	Case b)	Case c)
Resource usage (s)	3.234	8.484	10.250
Relative gap	0.0	0.0	0.0
Equations	18,716	18,741	18,898
Discrete Variables	15,887	15,935	16,104
Binary Variables	433	457	482

Firstly, after the introduction to the chapter the analysis to the case study a) begins. This case study with constant demand is considered as a more general one to analyse in depth the portfolio results and analysis tools. The impact of different values for the aversion factor to long-term investment is analysed and the value of λ = 1.3 is chosen as the most competitive, being it used all the time the model is run in this chapter. Afterwards, the Expected cost CVaR trade-off is analysed for different risk postures: it was seen that the expected cost grows and the CVaR drops with the increment of the risk aversion factor, and that the CVaR value drop becomes less significate as the β value grows. Latterly, the portfolio evolution with risk aversion increment is analysed for the first week and the total of the 3 weeks, where it is noticed that the pool market share is heavily penalized by β and the forward contracts are the ones most favoured, with a preference for 3-week contracts rather than weekly ones. Subsequently, the first week decisions are evaluated: it is perceived how more and more electricity is contracted with the increment of β, given that these contracts are a risk-hedging tool, and how the peak contracts are preferred in favour of the valley ones. Lastly, there is a deeper analysis made on the contracts signed for each set of hours: Valley, Shoulder and Peak, where it was shown that there is higher procurement for the 3-week contracts rather than weekly ones, and there is higher procurement from Base contracts rather than valley contracts, but more from shoulder and peak contracts rather than base.9

Secondly, case study b analysis is done, where the starting time of a 24h cycle with a mixed demand profile is optimized with the intention of analysing how the hour seasonality of pool market price, seen from Figure 6.2, influences this time. Firstly, the way to reach this starting-time is modelled. Next, a comparison of the trade-off of the expected cost and CVaR is conducted for both the cases with and without this starting-time optimization, where it is clear that this optimization brought considerably better results. Besides, the starting time changed for different risk aversion factors, which proves the starting time will depend on the decision maker. Lastly, we look separately at valley, shoulder and peak hours, where an increase in the demand on valley hours and a decrease in peak ones is clear in the case with starting time optimization, showing this that the model avoids matching the hours with higher demanded to the peak hours, and rather matched them with the valley hours, proving this the impact the hour seasonality has.

Thirdly and lastly, case study c) is analysed, where a set of 7 day-time series is ordered and assigned to the days of the week in order to study the effect of the pool market price seasonality in the days of the week expressed in Figure 6.3. On a first instance the modelling alterations needed are explained, followed by a comparison of the trade-off of the expected cost and CVaR with and without order optimization, where as expected the run with it presented better results. As a last point in this chapter, the assignment of the day series to the days of the week for different risk aversion factors is analysed and it is shown that there is some correspondence between the least favourable series, in terms of demand, to the days with the lowest pool market price, and vice versa. So, it proves that the price seasonality from Figure 6.3 is impactful.

In the following and last chapter, the final conclusions and remarks are taken and the grounds for future work are set.

8 | Conclusions and Future Work

This dissertation proposes to come up with a mathematical framework to fill the gap identified in the literature: the lack of tools for buyers to interact in electricity markets. So, this framework's goal is to help large consumers to procure their energy needs through means of an electricity portfolio, with risk and cost minimization as objectives. The trading environment chosen was the Iberian Electricity Market.

With that in mind a detailed mathematical model for portfolio optimization is developed and tested. From it the portfolio is obtained with specific values for the electricity contracted from the pool market for each time period, forward contracts signed and the amount of energy contracted in each, energy contracted from self-production facilities, the expected cost and Conditional Value-at-Risk. For case studies b) and c), the model also provides information of the optimized schedule of Demand. The output of the model is subject to different values of the risk aversion factor and demand. The problem is formulated as a mixed integer programming where binary variables define procurement decisions that influence more than one time period, and continuous variables define the electricity procured and cost from each source, as well as the value of the CVaR.

A first case study, case a), was studied to explore the more general aspects of portfolio building: pool market procurement is more suitable for decision makers prone to risk, whilst risk averted decision makers would prefer forward contracting and self-generated energy. These different postures lead to a higher CVaR and lower expected cost for the risk prone decision maker, and lower CVaR and higher expected cost for the risk averted decision maker.

Given the Iberian electricity market as the instrument of trade, price data is studied and it is proven that price is seasonal, possibly varying on the hour and day of the week. To explore the effect of this seasonality, two case studies were built, b) and c). On case b) the hour seasonality is studied, and it was concluded that if possible, the model will avoid the typical high price hours and favour the low-price ones. In case c), the week seasonality was put into perspective and a tendency towards favouring low price days rather than high price ones was noticeable. Taking advantage of the hour price seasonality, case b) obtained significantly better results in terms of objective than case c). So, allocating demand taking into account hours of the day is more effective in price reduction than solely paying attention to the day of the week. Further favourable results can be obtained by optimizing based on both components of the seasonality.

Further work can be developed by building models that take more stages of decision into consideration, rather than only weekly decisions, and with this build a more complex scenario tree with more decision stages and uncertainties (more nodes and branches), therefore having a more descriptive and complete number of scenarios. For this a shorter-term model could be made, where instead of weekly decisions there are hourly decisions. With this, besides the pool market considered, which is day-ahead market, the intra-day market could be considered, enabling the possibility of analysing its patterns and exploring ways of taking advantage of them.

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