Modelling uncertainty in the technologies' conversion efficiency for the design and planning of biomass supply chains

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Declaration

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

Declaração

Declaro que o presente documento é um trabalho original da minha autoria e que cumpre todos os requisitos do Código de Conduta e Boas Práticas da Universidade de Lisboa.

ABSTRACT

Bioenergy has been proven to have great potential as a substitute for fossil fuels and help reach the European Union's environmental goals. However, to be a sustainable alternative, it needs to be economically viable. Thus, an efficient and well-designed supply chain is required.

Most research works from literature assume the technologies used to convert biomass into bioenergy as stable and the process immediately productive as planned after installation. However, there is still a lot of uncertainty inherent to them and their conversion efficiency's, given they haven't reached maturity. It is of great importance that this uncertainty is considered and incorporated in the design process, so the problem becomes more realistic and results are more reliable.

The learning curve theory is the approach used to represent the technology's evolution over time due to learning and the conversion efficiency's uncertainty associated to it. It uses the accumulated production as measure of experience of the technologies and then calculates its impact on costs. Afterwards, to test the effects of this approach, it is incorporated in a Mixed-Integer Linear Programming model that supports decisions concerning biorefineries installation sites and process technologies, biomass collection sites, biomass and product's flows and transportation modes, while minimizing costs.

The model's application to the Portuguese context suggests that considering the conversion efficiency's evolution uncertainty using learning curves reduces the total production costs of the supply chain, despite increasing the total costs. This model represents reality more accurately and makes the biomass supply chain more flexible for any future scenario.

Keywords: Biomass Supply Chain, Optimisation, Technology Uncertainty, Learning Curves

RESUMO

A bioenergia tem mostrado um tremendo potencial como substituto aos combustíveis fósseis e ajudado a atingir os objetivos ambientais da União Europeia. Contudo, para ser sustentável, precisa de ser viável economicamente. Então, uma cadeia de abastecimento bem projetada é necessária.

Na literatura, a maioria assume que as tecnologias usadas para converter biomassa em bioenergia são estáveis e imediatamente produtivas após a instalação. No entanto, têm uma incerteza associada, pois ainda não atingiram um estado de maturidade. É importante que esta incerteza seja considerada no processo de planeamento das cadeias de abastecimento da biomassa para que o problema seja mais realístico e os resultados mais fiáveis.

A teoria das curvas de aprendizagem é usada para representar a evolução das tecnologias no tempo devido a ganhos de experiência e para representar a incerteza na eficiência de conversão associada a esta evolução. Esta usa a produção acumulada como medida de experiência e depois calcula o seu impacto nos custos. Para testar e avaliar os efeitos deste método, é incorporada num modelo de otimização estocástico linear que apoia decisões sobre instalação de biorrefinarias, processos tecnológicos, locais de recolha de biomassa, transporte, fluxos de biomassa e biocombustíveis, enquanto minimiza os custos.

A aplicação deste modelo ao contexto Português sugere que considerar a incerteza na evolução da eficiência de conversão reduz os custos totais de produção desta cadeia, apesar de aumentar os totais. Este é um modelo que representa melhor a realidade e torna a cadeia de abastecimento da biomassa mais flexível a qualquer cenário.

Palavras-chave: Cadeia de Abastecimento da Biomassa, Otimização, Incerteza da Tecnologia, Curvas de Aprendizagem

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EU	European Union
GHG	Green House Gas
IP	Integer Programming
LP	Linear Programming
MILFP	Mixed Integer Linear Fractional Programming
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
MIQP	Mixed Integer Quadratic Programming
NLP	Non-Linear Programming
OFLC	One-Factor Learning Curve

1– INTRODUCTION

1.1- Problem Context and Motivation

Bioenergy – the energy that results from transforming biomass (Paulo et al., 2015) - is considered a renewable source of energy, given the release of carbon dioxide during its transformation to energy is compensated by its absorption during its lifetime (Bórawski et al., 2019a). Compared to the typical energy sources, such as fossil fuels, it helps us to reduce our ecological footprint and become more environmentally friendly. Not to mention that opting for this alternative source of energy goes towards the EU objectives of increasing the consumption of energy from renewable sources and to become a low-carbon, secure and competitive economy.

Biomass has been proven to be an alternative to fossil fuel's sources with great environmental potential, however, it isn't yet a competitive one. Even with a lot of environmental benefits, the biomass resources are limited, causing debates regarding their usage, and the expansion of bioenergy systems is dependent on political and legislative issues, besides the development of the technology and processes to make the bioenergy production more efficient. Therefore, improvements in the design of the biomass supply chain are important to enhance these weaknesses.

The design of a supply chain network is a challenging process and this one is no exception. The characteristics and properties of biomass and all the processes it has to go through until it becomes bioenergy, make this a complex process with a lot of uncertainties involved (Paulo et al., 2015). Thus, improving the performance of biomass transformation into bioenergy imposes the inclusion of all these uncertainties, as accurately as possible, in the optimization models used in the design of the biomass supply chain to optimize it and reduce their impact in the decision process. Literature on this matter has been growing through the years, but it can be verified a poor consideration and underrepresentation of the uncertainty of the technological processes' developments, which is an uncertainty of great importance. This is supported by the fact that we have become more and more dependent on technology to achieve high levels of efficiency and reduce costs, and by the fact that, given it has not reached a mature stage and it is still developing, changes and improvements in the process will affect different things, with one being its conversion efficiency. Being able to predict what the conversion efficiency will be in the future will help in making more realistic decisions regarding the type and dimension of the technology used and the design of the biorefinery facilities. This will help to reduce waste, inefficient production costs and environmental implications (De Meyer et al., 2014), a development that would contribute to help bioenergy have an economically viable production and gain leverage as an alternative to fossil fuels by becoming a sustainable one.

1.2- Problem Statement

With this context, the problem being tackled in this master thesis can now be stated. Objectively, this thesis addresses the lack and inaccurate representation of the biomass technology's conversion efficiency within the biomass supply chain's optimization model. Since the choice of conversion technology is part of a design decision of the biomass SC, how the conversion efficiency is represented has influence in the whole planning of the SC, the biorefinery's process and other related decisions, not to mention on costs.

As it was said before, the technological processes have not reached maturity and are always developing, so the conversion efficiency must be handled as an uncertainty. Given it has not, the planning and process decisions have not been based on the most realistic data and the costs not accurately estimated.

1.3- Dissertation's Objectives and Research Questions

This context and problem statement motivate the present study. Ultimately, research will be done aiming to incorporate a mathematical formulation into a stochastic optimization model used to design the biomass SC. This, after finding a mathematical formulation that realistically represents the developments of the technologies used in the biomass SC through time and relates them with their conversion efficiency evolution and increase.

Secondary research goals include:

- To characterize the biomass supply chain to shed lights on some concepts and on its structure to build a solid knowledge basis on the matter and understand the whole picture;
- To review previous research on the field to understand how uncertainty has been addressed, with a focus on technology development uncertainty, and how that might be useful to support main research goal of this thesis;
- To identify potential research gaps in literature on representing the technology development uncertainty;
- To contribute to the existing literature by using the knowledge from the evolution of conversion technologies from real integrated biorefineries to propose a mathematical formulation capable to capture this evolutive process.
- To produce recommendations for the biomass supply chain's planning decisions.

In order to accomplish these objectives, we propose to answer to the following research questions:

- How can we use official information about the installation and operation of biorefineries in Europe and European Union to outline the evolution of the conversion efficiency of the installed technologies?
- How can the evolution of this conversion efficiency be quantitatively described?
- How can this evolution be mathematically incorporated into design and planning models for the biorefineries supply chain?

1.4- Dissertation's Methodology

In order to achieve the objectives stated in the previous section, the proposed methodology of the present master thesis is presented in Figure 3:

Figure 1- General Overview of Future Work

The developments of the master thesis include, generically, these 7 steps. At the end of them, a stochastic optimization SC model having incorporated an adequate and representative mathematical formulation of the technologies evolution through time will be obtained.

1. Problem Context and Background – This step seeks to introduce the context of sustainability in the EU, the biomass SC structure and its uncertainties. It is an overview that starts to introduce the possible challenges of the biomass SC design and how they might difficult the process of reaching the EU sustainable objectives.
2. Literature Review – The goal of the literature review is to demonstrate the state-of-art of biomass SC planning and design. An overview on the typical solution approaches and problems enable a theoretical foundation to present many optimization models available in literature that include uncertainty and the methods they use to represent it. It also enables to collect information focusing on the conversion efficiency uncertainty of the biorefineries conversion technologies and how literature has been modelling it. A brief overview on the learning curve theory and its applications is also made.
3. Problem Definition– After having some context and state of art on the biomass SC modelling, the problem that was found with the research done is defined and stated. Also, the case-study analysed in this thesis is here briefly presented.
4. Data Collection and Definition of Assumptions – In order to obtain relevant and substantial data to enable the conversion efficiency modelling, extensive research and collection of data is made and, when necessary, treated. In situations of shortage of data, assumptions are made.
5. Model Formulation - Considering the problem definition and the relevant models in the literature, the characteristics of the conversion efficiency's evolution mathematical representation and optimization model are selected and developed.
6. Case-study Presentation – The case study to which the model will be applied is described. The necessary data to do it is presented and the assumptions made are duly explained.
7. Model Implementation, Results and Analysis – The stochastic optimization model having included the conversion efficiency's evolution uncertainty is validated by being applied to the case-study in question. Then it is compared with the results of the corresponding deterministic optimization model and an uncertainty analysis is made. Afterwards, these results are analysed and discussed, and some conclusions are obtained.

1.5- Dissertation's Structure

To achieve these goals, the dissertation project's structure is fragmented into five key chapters:

- **Chapter 1 – Introduction:** This is the present chapter, which introduces and motivates the focus of this study, highlights the main objectives and outlines the project structure.
- **Chapter 2 – Background on Biomass Supply Chain:** Presents the European Union role on becoming a sustainable economy and provides an overview on the biomass supply chain. In this last, all its stages are specified, the planning decisions by level of decision-making are reviewed, and its related uncertainties are detailed.
- **Chapter 3 – State of Art:** The third chapter seeks to review the existing literature on approaches to incorporate uncertainty in the optimization models and, more specifically, the conversion efficiency's uncertainty of biomass conversion technologies and how it has been modelled. At last, the learning curve theory is reviewed, focusing on how it has been applied to technologies.
- **Chapter 4 – Problem Definition and Methodological Approach:** First, resumes the main findings of research so far, then states and defines the problem in question. After, explains the methodological approach of this study and then briefly describes the case-study addressed.
- **Chapter 5 – Conversion Efficiency & Learning Curves-Data Collection and Analysis:** The fifth chapter presents the process of research and all the main references used to obtain data for the construction of the conversion efficiency's evolution mathematical representation and learning curve model. Then details all the limitations and assumptions made and finally, the resultant data that will incorporate the present thesis database is treated and presented.
- **Chapter 6 – Model Formulation:** This chapter presents the learning curve and the stochastic optimization model with the conversion efficiency's uncertainty mathematically incorporated. The model is be adapted from the one by Paulo et al. 2020 and its characteristics are described.
- **Chapter 7 – Case-Study**: IN this chapter Portugal is presented in the context of biofuels and the data inputs of the optimization model are described
- **Chapter 8 – Model Implementation, Results and Analysis:** The implementation and computational experiments performed with the proposed model and solution approach are described. Also, the main conclusions and limitations of the study will be stated and recommendations will be presented.
- **Chapter 9 – Conclusion & Future Developments:** This chapter will expose the most relevant features and conclusions of this master's dissertation and mention future stages of development and opportunities for future research.

2– BACKGROUND ON BIOMASS SUPPLY CHAIN

With the development of technology and increasing worldwide industrialization, the need to use energy has been increasing over the years. Adding the clear evidence of climate change, the usage of fossil fuels stopped being a viable option and the goal has been investing in sustainable energy sources.
Measures to fight usage of non-renewable sources by the EU are presented in this section, as well as the reasons why biomass is a valid alternative. Afterwards, the biomass supply chain is explained in detail and the decisions that need to be made in each echelon are described. Finally, the uncertainties inherent to all stages of the supply chain are presented and related with the decision levels.

2.1– EU role in a bio economy

The concern of being an economy that consumes secure, safe, competitive and, most importantly, sustainable energy has been continuously present in the European Union. Even though with a slow process, the EU has been trying to transition from a fossil-input-based economy to a bio-based economy (Vandermeulen et al., 2012b).
The first European Energy Directives on the liberalisation of the energy markets were launched in 1996. Only until the late 2000s other pieces of energy market legislation were adopted, but with its focus gradually turning from energy market liberalization into energy market integration (European Parliament, 2017a). These include the three European Commission's energy packages created in order to have compatible market arrangements in (almost) all EU countries (Glachant and Ruester, 2014) and going towards the objective of establishing an internal energy market between Member States. The first and second energy packages, adopted in 1996 and 2003 respectively, had directives on the internal market for electricity and gas that have a primarily focus on liberalization and market structure. The third, and most recent package, adopted in 2009, had the goal to open up the gas and electricity markets in the EU, increase investments in infrastructure and cross-border trade. All this with the objective of achieving the 'Europe 2020 Strategy' goals (20% share of energy consumption from renewable sources and 10% minimum target for share of biofuels in transport sector by all Member States) with an energy supply that was secure, competitive and sustainable (European Parliament, 2017a). To support a single energy market in Europe, this package developed European-wide Network Codes, that are rules and obligations in respect to access and usage of the European networks. In addition, it created the European Network for Transmission Systems Operators as well, to make all transmission system operators to cooperate, develop rules for network operation, and prepare 10-year network development plans. Also, the Agency for Cooperation of Energy Regulators was established to have a central role in the development of EU-wide network and market rules. It was responsible for enhancing the coordination between National Energy Regulatory Authorities and cross-border trade (Glachant and Ruester, 2014). Besides focusing on liberalisation and market structure (the main focuses of the first and second energy packages), the third also has the focus on market access and diversified sources of energy, effective retail markets (unbundling) and wholesale market integration. In addition to these regulations on the internal energy

market, there are also EU regulations regarding energy such as infrastructure investment, energy efficiency, emission trading, market and price transparency and renewable energy (European Parliament, 2017a).

On top of the third energy package, on 25th February 2015, the Energy Union Framework Strategy to transition to a low-carbon, secure and competitive economy was published. It is composed by five relating pillars that reinforce one another: the first is supply security, the second a fully-integrated internal energy market, the third energy efficiency, the fourth is climate action and reduction of greenhouse gases and the fifth is research and innovation in low carbon technologies (European Parliament, 2017a). Moreover, in 2016, the Clean Energy Package, known as 'Winter Package', presented a set of legislative measures that would define the European energy and climate policies for the following years (Ringel and Knodt, 2018). They were constructed aiming to lead the energy transition by focusing on energy efficiency, emissions mitigation, providing fair deals for consumers and have global leadership on renewable energies, the targets of the EU's 2030 climate and energy framework (Fischer, 2014). The package uses measures of the third energy package and proposes new ones. By the time the second report of The State of Energy Union (a series of Commission reports and initiatives) was published in 2017, the conclusions were that the EU had been making good progresses relatively to the Energy Union objectives. By 2015 the greenhouse emissions were 22% below the 1990 level and 16% of the total energy consumed by the EU was renewable (European Parliament, 2017a). For instance, even though the sources of the primary energy used in the EU energy market for electricity generation are still mostly conventional (fossil and nuclear fuels, coal and oil), their share of renewables has been increasing (wind, solar and hydro energy, biomass and geothermal power). The first game changers were some large companies that have large energy generating units and that split their energy sources into fossil and renewable instead of being exclusively fossil-based companies. This was possible due to the changes in energy and climate policies.

In 2017, the countries with highest shares of electricity generated from renewable energy sources in gross electricity consumption were Austria (72.2%), Sweden (65.9%) and Denmark (60.4%) whereas Malta (6.6%), Hungary (7.5%) and Luxemburg (8.1%) were the one with the lowest shares. The highest shares of renewable energy sources in heating and cooling were in Sweden (69.1%), Finland (54.8%), and Latvia (54.6%). Netherlands (5.9%), Ireland (6.9%), and Luxemburg (8.1%) had the lowest shares. Finally, in transport, Sweden (38.6%), Finland (18.8%) and Austria (9.7%) had the highest shares of renewable energy sources used, meanwhile Estonia (0.4%), Croatia (1.2%) and Greece (1.8%) had the lowest shares (Bórawski et al., 2019b).

2.2– Biomass Supply Chain

2.2.1- Biomass

Biomass is the biodegradable fraction of agricultural material such as products, waste and residues of biological origin, forestry and related industries (fisheries and aquaculture) and the biodegradable fraction of industrial and municipal waste (European Parliament, 2009).

One can classify biomass in three categories for each of the main two characteristics – origin and quality. Regarding origin, we have natural (from natural ecosystems), residual (from all human activities), and energy crops (plants created to produce energy). Regarding quality, there is primary/high quality (from direct conversion of solar into chemical energy by photosynthesis), secondary (farming and forestry residues after primary biomass manipulation) and tertiary biomass (bio-degradable waste from human, animal, industrial and municipal origins) (Gold and Seuring, 2011).

Being a renewable resource, biomass offers opportunities to the ecological footprint of the fossil-input-based economy by being secure and environmentally friendly, besides ensuring energy diversity (Vandermeulen et al., 2012a). Also, it is very likely to be the only viable alternative to fossil sources in the production of transportation fuels and chemicals. This is supported by the fact that it is the only source with rare richness in carbon given the plant biomass used to produce biofuels and bioproducts uses carbon dioxide while growing. This compensates its release into the atmosphere in the conversion process (Naik et al., 2010).

2.2.2- Biofuels

Biofuels are biodegradable, often locally available, accessible, a reliable fuel obtained from renewable sources (Vasudevan et al., 2005). Also, besides not having negative impacts on engines (Smuga-Kogut, 2015), blending them with the conventional fuels by up to 7% does not require engine modifications (Marelli et al., 2015).

Biofuels are firstly categorized into primary and secondary biofuels. The first ones are used in an unprocessed form directly as fuels, such as fuelwood, pellets, wood chips, etc., obtained from agricultural or other recycled sources. The second ones are modified primary fuels resulting from processed biomass to power vehicles or for industrial applications (Nigam and Singh, 2011), that can be in the form of gas (biogas, syngas, hydrogen, biomethane), solid (lignin, charcoal) or liquid (bioethanol, biodiesel, FT-fuels, bio-oil) (Cherubini, 2010). Furthermore, as it is defined in the literature, biofuels from secondary sources are divided into the following generations, depending on their raw material and technological processes used in their conversion process:

1. First generation biofuels need a simple process (conventional technologies) to obtain the final fuel product (Nigam and Singh, 2011), even if with low yield (Dutta et al., 2014). They are produced from raw materials, in competition with food and feed industries, such as seeds, grains or sugars, vegetable oil or animal fats (Nigam and Singh, 2011). Also, they are characterized for being able to be blended with petroleum-based fuels, combusted in existing combustion engines and distributed by existing infrastructures or to be used in existing alternative vehicle technology or natural gas vehicles (Naik et al., 2010).

   The existing conflict with food supply for the use of biomass and agricultural land made some concerns arise: the increase of food and biofuel production cost and consequent increase of their prices. This, consequently, aggravates the food crises (Leong et al., 2018) and the lands destined to produce food are used to produce biofuel as well, making their availability to be dependent on soil fertility and availability (Cherubini, 2010). Also, concerns on environmental issues and carbon balances, due to the cost inefficient emission-abatement technology used in the production of biodiesel, limit the production of first generation biofuels (Naik et al., 2010).

2. All these concerns were the reason why the second-generation biofuels were developed. Their process of conversion can be through a biological or a thermochemical process. The first one is used only to produce a few biofuels, like butanol and bioethanol, whereas the other ones, such as methanol, biodiesel, refined Fischer-Tropsch liquids and dimethyl ether are produced thermochemically (Nigam and Singh, 2011).

   The feedstock of these biofuels is mainly lignocellulosic materials. These can be residues from agriculture, forestry or industry (Leong et al., 2018), but also dedicated feedstock, such as grasses or trees planted specifically for energy purposes. Thus, allowing a higher production per unit land area and land use efficiency than the first generation ones (Nigam and Singh, 2011). This, besides the fact that these fuels have lower feedstock prices, gives them advantage over the first-generation ones. However, even though some of the biomass plants oils have similar properties to edible oils thus making unnecessary major modifications on equipment and process flow, they might need an addition pre-treatment due to higher concentration of free fatty acid, which is costly (Dutta et al., 2014). Also, being able to grow these plants on lower quality soils does not stop the need to have regular irrigation, heavy fertilization and good management practices to obtain high conversion rates (Lam and Lee, 2012). Moreover, they will still need land to be planted on, thus competition with food production still exists, even if lower. All of these were reasons for further research on a more sustainable alternative.

3. Third generation biofuels feedstock focuses on using algae to produce biofuel. It is advantageous due to having no impact on food supply, to being a feedstock easy to cultivate and by being able to convert almost all the energy from the feedstock into different varieties useful products (Adeniyi et al., 2018). However, they have limitations regarding ecological footprint, economic performance, dependency on climate conditions (need of sunlight to develop), and geographical location (latitude). Leong et al. 2018 say that these biofuels annual productivity is really high, given microalgae would just need from 1 to 3% of total cropping area to meet 50% demand of U.S. transport fuels whereas (i.e. oil palm would need 24% of total cropping area to satisfy the same transport fuel demand). However, Dutta et al. 2014 believe they have low lipid content that makes the requirement of energy consumption to increase, thus being insufficient to replace fossil fuels. The fact that there are different opinions in the scientific community makes it difficult to conclude the reasons why fourth generation biofuels were created.

4. The fourth generation of biofuels uses genetically modified algae as a feedstock to the biofuel production, such as microalgae, macroalgae and cyanobacteria (Abdullah et al., 2019) and has great potential as a source to a sustainable and clean energy (Lu et al., 2011). The believed difference from the third generation is that the genetic modification engineering is a promising alternative to increase the lipid content and biomass yield of algae (Singh and Gu, 2010), thus

capturing more carbon dioxide and increasing the production rate. The drawback is that they require a high investment (Dutta et al., 2014).

Through the use of optimization and improvements in conversion technologies, second and third generation biofuels production can be more attractive, but, overall, the perfect biofuel might be a combination of some or all generations (Dutta et al., 2014).

By investing in the production of biofuels, the greenhouse gas emissions and pollutants from electricity generation decrease, because even though there is a carbon dioxide release when the biofuel is burnt, the same amount is absorbed while the plants are growing (Bórawski et al., 2019a). The amount of fossil fuels used decreases as well, given the usage of renewable energies reduces petroleum's importance, and also, they are responsible for energy security and have essential meaning in innovations (Bórawski et al., 2019a). Basically, conventional fuel, which affects human life, would be ideally replaced for biofuels, which contribute to climate restoration (Schmidt Rivera et al., 2018) and consequent improvement of living conditions. Not to mention their combustible potential compared with the fossil fuels besides its renewability for incessant applications (Leong et al., 2018). This replacement also helps in the improvement of the organic fuel economy and increases the sustainable development, as well as the level of employment in the green economy (Panwar et al., 2011).

2.2.3- Supply Chain's Structure

Typically, a supply chain network is formed with the supplier, manufacturer, distribution centres, and customers. Its management aims to integrate all these business functions so that the products are distributed correctly at the right place and time, according with the expected quality, quantity and service level and in a way that the total costs are minimized (Hong et al., 2016). Biomass supply chain differs from traditional supply chains, since it integrates the process of harvesting and collection, pre-treatment, integrated biorefinery, product distribution and logistics (Hong et al., 2016). A more visual structure of the biomass SC can be seen below in Figure 2. Each echelon is hereafter further explained.

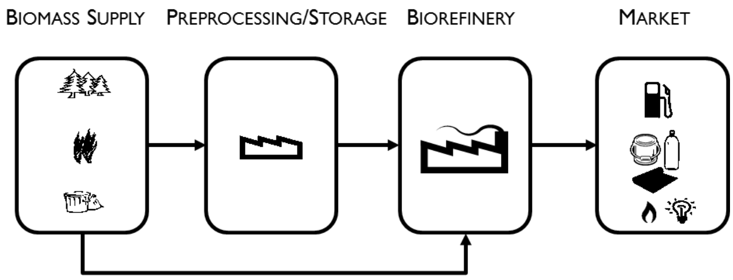

Figure 2 - *Biomass Supply Chain*

<u>Biomass Supply</u>

This stage focuses in a renewable, consistent and regular supply of feedstock from agriculture (dedicated crops and residues), forestry, industries (residues) and households (municipal waste) and aquaculture (algae and seaweeds) (Cherubini, 2010). Therefore, its main activities are the harvesting scheduling, allocation of feedstock and decentralisation of pre-treatment activities.

There are some concerns in this stage relatively to the availability and supply of raw biomass. Climate change and weather conditions can result in an inconsistent and even shortage of biomass supply, and composition of the raw material, due to the fluctuation of chemical and physical properties of biomass (Cundiff et al., 1997). Thus, supply chain efficiency, careful inventory planning and proper harvesting scheduling are extremely important. They ensure the quantity and quality of the raw biomass are within the specification limit when transported to the biorefineries (Hong et al., 2016).

Pre-Processing/Storage

This echelon focuses on converting dense biomass into less dense or more useful segments, known as platforms or precursors (Fernando et al., 2006), to reduce handling, storage and transportation costs through different types of pre-treatment (Hong et al., 2016). Also, reducing moisture content enhances the efficiency degree of combustion and gasification processes (Gold and Seuring, 2011).

Having the right raw material composition is also a concern to be dealt in this echelon of the biomass SC. Thus, by having the pre-treatment activity closer to the biomass collection site than the biorefinery, the desired raw material specification, before going to the processing facility, might be easier to maintain (Hong et al., 2016). Moreover, the right conversion technology must be chosen, since it influences decisions such as type of pre-treatment needed, choice of raw biomass material and costs (Hong et al., 2016).

Integrated Biorefinery

This echelon of the supply chain encloses the facility where the biomass is converted into valuable products (food, feed, materials and chemicals) and energy in an integrated manner (Parisi, 2020). This is done through several technological processes that can be divided into four groups: thermochemical, biochemical, mechanical/physical and chemical (Cherubini, 2010).

Some important decisions to be made in this stage are the determination of facility location, the sizing and capacity, the conversion technologies and its configuration. The fact that there are conversion technologies both in the pre-treatment and in the biorefinery, gives them a lot of importance when structuring the biomass supply chain. When selecting them to the biorefineries, it is also necessary to have in mind the type of feedstock of the pre-treated biomass, the product requirement, the capital and operational costs portion they will have in the total costs of the supply chain (Hong et al., 2016).

Products/Market

The products of a biorefinery can be divided into two main groups: material and chemical products (biomaterials), which are not used for energy generation, and energy products (bioenergy), used for their energy content to provide electricity, heat or transportation service (Cherubini, 2010).

Regarding biomaterials, the biochemicals can be used in many industry applications such as nutrition, food and beverages, pharmaceuticals, fertilizers, biodegradable plastics, fibres, adhesives, etc. Some examples are chemicals such as fine chemicals, building blocks and bulk chemicals, organic acids like succinic, lactic, itaconic and other sugar derivatives, polymers and resins and fertilizers (Cherubini, 2010). Also, they have a lot of attention in the industry, especially the high value products for pharmaceutical and cosmetics industry (Hong et al., 2016). The material products are biomaterials such as wood pallets, paper rand cellulose and food and animal feed (Cherubini, 2010), also known as primary biofuels by Nigam and Singh 2011.

Regarding bioenergy, as a renewable source of energy, holds a lot of potential to compete with fossil fuels (Hong et al., 2016) and it can be in the form of electricity and heat or secondary biofuels, such as biodiesel (produced from vegetable oils), bioethanol (derived from wastes and renewable sources of feedstock), biogas (produced from various types of agriculture substrates) (Bórawski et al., 2019a), among others mentioned above in section 2.2.2.

Relatively to product distribution, bioenergy as heat and electricity is transferred to the end user via electricity grid and as solid, liquid, or gaseous biofuels and biochemicals is distributed through the existing transportations (land, water, air).

Important decisions to be made at this stage are the products that are going to be produced and their quantities according to the demand of the customers.

Logistics

This part of the supply chain integrates all components by arranging the transportation and storage among and in each component of the supply chain. In the transportation perspective, the decisions made are regarding transportation schedule, routes, network, and mode, considering the type, characteristics, and amount of biomass materials or bioproducts. As for an inventory perspective, planning includes choosing a proper storage system (location and capacity) having in mind holding costs and storage risk of each type of biomass and bioproducts (Hong et al., 2016).

2.2.4 – Supply Chain's Decisions

Table 1 sums up the decision variables of each decision level – strategic, tactical and operational - in the biomass supply chain, that have to be made to ensure the delivery of the finished products through the supply chain effectively and efficiently (Awudu and Zhang, 2012). The strategic level consists in long-term decisions, in line with the organizations overall objectives (Sharma et al., 2013), that should be made at the beginning of planning the production and usually are investment intensive. In this case, they are relative to the design of the biomass supply chain network. It can be in terms of the sourcing and procurement of biomass, its allocation to the production facilities (De Meyer et al., 2014), type of feedstock, dimension and type of the technology used in the conversion process, capacity and location of all facilities (supply, collection, pre-treatment, processing and distribution sites) and final product type and quantity (Ghaderi et al., 2016). The tactical level is based on medium-term decisions (6 months-1 year) that go in line with the objectives of the strategic level. They concentrate on the fleet management (transportation mode, routing, scheduling, and shipment size), inventory planning decisions as location, quantity, and quality, and production decisions, such as scheduling (Awudu and Zhang, 2012) and selection of collection and pre-treatment methods (De Meyer et al., 2014). Lastly, the operational level focuses on short-term decisions (weekly/daily/hourly) that ensure a continuous operation of the supply chain processes in a timely and cost effective manner (Awudu and Zhang, 2012). Those include detailed inventory, production, and transportation management decisions (Sharma et al., 2013).

Table 1 - Main decision variables considered at each decision-making level in supply chain management, adapted from (Sharma et al., 2013), (Awudu and Zhang, 2012), (De Meyer et al., 2014), (Ghaderi et al., 2016).

Decision Level	**Strategic**	**Tactical**	**Operational**
Decision Variables	Facility: -Location -Capacity/size -Technology/Type	Inventory planning: -Location -Quantity -Quality -Safety stocks -How much to harvest -When to harvest	Inventory planning: -Daily inventory control
	Biomass: -Type -Sourcing -Allocation between facilities	Production Planning: -Production Scheduling -Collection and pre-treatment methods	Production Planning: -Detailed production scheduling
	Final product: -Product types -Products quantity	Fleet management: -Transport mode -Shipment size -Routing -Scheduling	Fleet management: -Vehicle planning -Scheduling

2.2.5 Uncertainties

Given the nature of the supply chain in question, the uncertainties are inherent to all stages of the supply chain and can be grouped in raw material supply, transportation and logistics, production and operation, demand and price, among other uncertainties (Awudu and Zhang, 2012).

- The **raw material supply** uncertainty is caused mostly by the raw material yield, type and quality, transportation lead time and harvesting delays at biomass source (Awudu and Zhang, 2012). Also, the raw material seasonal supply and widely dispersed geographic distribution cause a difficult collection, storage and transportation (Paulo et al., 2015). Their properties, such as moisture content and low energetic density, constraint storage and transportation as well and the selection of the processing technology (Paulo et al., 2015). Plus, with the unpredictable weather and natural or human disasters as well as variable acquisition cost (Espinoza Pérez et al., 2017) affecting the raw material supply, these are all reasons causing its uncertainty.
- The uncertainty in **transportation and logistics** is basically caused by everything that causes cost and time inefficiencies, such as delays, inventory levels, transportation and storage costs, delivery constrains and demand variability (Awudu and Zhang, 2012).
- The uncertainty in **production and operation** difficults the production of the planned quantity and it is caused by problems in the raw materials supply, production yields, machine breakdown,

lead time constraints, inventory decisions (Awudu and Zhang, 2012), non-mature conversion technologies, their availability and the conversion operation cost (Espinoza Pérez et al., 2017).

- Not knowing when the quantity or the timing of the demand will vary causes **demand** uncertainties. **Price** uncertainty appears with possible price changes. Both are related with raw material cost, tax subsidies and governmental polices (Awudu and Zhang, 2012).
- Other type of uncertainties are related with sustainability, taxes or governmental and regulatory policies (Awudu and Zhang, 2012).

With the uncertainties being unknown, the values of important parameters considered in the decision making of the supply chain management will influence a range of the decisions as stated in Table 1. Starting with the raw material supply uncertainty, its geographic distribution will affect strategic decisions in terms of choosing the facility locations. Its characteristics and quality will influence the type of conversion technology used in the pre-treatment facilities and biorefineries, as well as guide the sourcing activity. Therefore, the best suppliers will be chosen for the specific type of raw material, and the best type of products to offer to costumers. Regarding tactical decisions, the uncertain raw material characteristics, and seasonal supply will affect transportation modes, shipment sizes, and general scheduling of the fleet, as well as inventory decisions and safety stocks, production and collection and treatment methods. Since these are affected, operational decisions regarding short-term decisions in fleet management, inventory and production planning will also be affected. Uncertainty in the transportation and logistics will affect the tactical and operational decisions regarding the transportation mode, scheduling, and shipment sizes in fleet management. Also, inventory quantity and location in the supply chain to reduce the effects of the uncertainty. With the production and operation being uncertain, the production scheduling decisions in the tactical and operational level will be affected, as well as the levels of inventory in order to compensate failures of planned production quantities. Fleet management in the tactical and operational levels might also be affected given the varying quantities of final product produced. Lastly, uncertainties in the customer demand and product price will influence the type and amount of products to offer and their feedstock type in the strategic level. How much and when to collect it as well, inventory levels and safety stocks to respond to variations in the demand, the production scheduling and fleet management decisions, in the tactical level. The daily inventory control and fleet scheduling will have effects in the operational level. These effects of the different types of uncertainties hereabove listed in the decision levels are summarized in table 2.

Table 2- Effects of the uncertainties of the biomass supply chain, by decision level.

Decision Level/ Uncertainties	**Strategic**	**Tactical**	**Operational**
Raw Materials Supply	-Facility location -Types of Technology used in facilities -Sourcing -Product types	-Inventory quantity -Safety stocks -When to harvest -How much to harvest -Collection and pre-treatment methods -Transportation mode -Shipment size -Fleet scheduling	-Daily inventory control -Daily production scheduling -Daily fleet scheduling
Transportation and Logistics	-	-Inventory positioning -Safety stocks -Transportation mode -Shipment size -Routing -Fleet scheduling	-Daily inventory control -Daily fleet scheduling -Vehicle planning
Production and Operation	-	-Production scheduling -Levels of inventory -Safety stocks -Fleet scheduling	-Daily production scheduling -Daily inventory control -Fleet scheduling
Demand and Price	-Biomass type -Product types -Product quantity	-Inventory level -Safety stock -How much to harvest -When to harvest -Production scheduling -Shipment size -Routing -Fleet scheduling	-Daily inventory control -Daily fleet scheduling

2.3– Chapter conclusions

This chapter demonstrated that the existing uncertainties in the supply chain design have different effects in the decision process. Also, the fact that they exist through the echelons of the supply chain increases their impact across the downstream and upstream levels, being necessary to address them in order to optimize the supply chain. Since bioenergy isn't yet competitive comparing with fossil fuels (Paulo et al., 2015), aiming for it to become a sustainable competitive alternative to their production, different methods can be used to incorporate the uncertainties in the design of the supply chain of biofuels and help making more realistic decisions. Those will be discussed in the following chapter.

3- STATE OF ART

The present chapter presents a review of the existing literature regarding biomass supply chain optimization under uncertainty and uncertainty representation methods. This information is of high importance since it enables to understand the status quo of research developments and findings through the years, as well as to acquire the knowledge necessary for proposing new research developments.

First, is presented a literature review on how the biomass's supply chain has been optimized and how the uncertainties have been incorporated in the design and optimization of the supply chain. Afterwards, a focus on the technology uncertainty is made by explaining how literature has been modelling the conversion factor of the conversion technologies used in biorefineries, followed by some conclusions for further research. Furthermore, section is dedicated to learning curves, their related concepts, and proven adequacy to model technological developments. Last, but not the least, the conclusions of the chapter will be stated.

3.1- Biomass Supply Chain Optimization under Uncertainty

The main obstacles of increasing the biomass usage in energy supply are the costs of the supply chain and the used conversion technologies (Rentizelas et al., 2009). The uncertainties inherent to each biomass SC's echelons (Awudu and Zhang, 2012) are an obstacle as well, given they affect the decision making process (Kazemzadeh and Hu, 2013). This means that deterministic assumptions about parameters used in the optimization models would lead to an infeasible supply chain design or a suboptimal solution (Bairamzadeh et al., 2018). Accordingly, uncertainty has been considered in the design phase of the biomass SC. This enables to obtain optimal solutions through models that are closer to reality and to improve its economic, environmental and social performance and efficiency (Ghaderi et al., 2016).

Table 3, inspired by the study made by Ghaderi et al. 2016 and complemented with further research on scientific publications' databases, summarizes the biomass supply chain related studies in which uncertainty is considered. All the research papers and documents found were analysed under several aspects presented in the following sections, which are: Solution Approach, Objectives, Decision Level, Uncertainties, and Uncertainty Representation Method.

3.1.1- Solution Approach

In this field of research, the optimization approach is the solution approach that is most used. Also referred as a mathematical programming model, it is used to represent real situations and obtain the optimal outcome of the decisions variables that will optimize an objective function whilst respecting some restrictions imposed by constraints (De Meyer et al., 2014). The types of mathematical programming present in research papers are linear programming (LP), used by Cundiff et al. 1997, Awudu and Zhang 2013, Bhavna Sharma et al. 2013, Azadeh et al. 2014 and Rezaei et al. 2019, integer programming (IP), mixed integer linear programming (MILP), seen in the majority of the studies presented in the Table 3, mixed integer non-linear programming (MINLP), mixed integer quadratic programming (MIQP), used by Arabi et al. 2019, non-linear programming (NLP) and mixed integer linear fractional programming (MILFP), proposed by Tong et al. 2014c.

3.1.2- Objective(s)

Some studies focus on one objective (one objective function), others in more than one, thus being multi-objective mathematical programming models (more than one objective function) (Espinoza Pérez et al., 2017). The objectives vary between economic, social, environmental, political, or technological. The majority of the articles focus on economic objectives, such as to minimize total costs of the supply chain, maximize profit, minimize the risk of investment, maximize net present value, or maximize annual income, and the minimization of maximum relative regret, as done by Ghelichi et al. 2018. The environmental focus usually is the minimization of environmental impact of Green House Gas (GHG), as by (Giarola et al., 2013), (Bairamzadeh et al., 2016), (Santibañez-Aguilar et al., 2016), (Babazadeh et al., 2017), (Osmani and Zhang, 2017), (Gao and You, 2017) and (Ghelichi et al., 2018). It can also be the maximization of carbon absorption, as in the case of Arabi et al. 2019. Focusing on social objectives, Osmani and Zhang 2017 and Bairamzadeh et al. 2016 try to maximize the number of jobs opportunities and Yılmaz Balaman and Selim 2016 the total service level.

3.1.3- Decision Level

The decisions suggested by the solution approach can be in the strategic, tactical, or operational levels of planning, as already presented in section 2.2.4. Based on research, most studies focus on strategic or/and tactical decisions, but especially on strategic decisions regarding the number of facilities, their location and capacity. Sourcing, biomass allocation and technology used are also being optimized in some studies, but not as frequently.

3.1.4- Considered Uncertainties

Bearing in mind the uncertainties exposed in section 2.2.5, Figure 3 shows the percentage of papers of Table 3 in which each of them is considered.

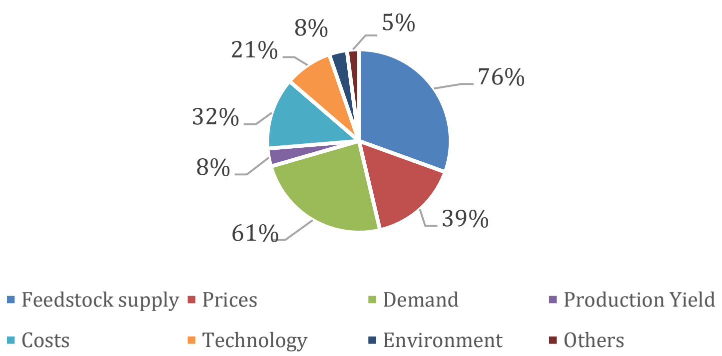

Figure 3- *Considered uncertainties in literature, in percentage.*

The most common uncertainty in the optimization models when designing the supply chain is the uncertainty in the feedstock supply, as by Gebreslassie et al., 2012, which can be regarded to biomass and raw material availability (Kazemzadeh and Hu, 2013), geographical distribution (Tong et al., 2014a), feedstock yield (Sharma et al., 2019), characteristics (moisture content) or weather conditions (Cundiff et al., 1997). This uncertainty appears in 76% of the articles listed in Table 3 and represents a continuous concern, since it is present in articles from 1997 until the present time.

Demand uncertainty is the second uncertainty most found, being considered in 61% of the articles, followed by a 39% in price uncertainty, which can be relative to feedstock (Giarola et al., 2012), product's prices (Kim et al., 2011) or both (Mas et al., 2010).

The inclusion of variations in costs (32%) incurred in terms of transportation, operation or production is done by Kazemzadeh and Hu 2013, Mohseni et al. 2016, Yılmaz Balaman and Selim 2016, Babazadeh et al. 2017, Babazadeh 2018 and Rezaei et al. 2019 and in terms of carbon costs by Giarola et al. 2012 and Giarola et al. 2013. The costs variability considered by Walther et al. 2012, Tong et al. 2014b, Tong et al. 2014a and Li and Hu, 2014 were regarding technology investment costs (main equipment, auxiliary and processing costs), an uncertainty really tied with the technology uncertainty due to its advancement and progress and included in the models of 8 articles of Table 3 (21%). Besides the capital costs, Tong et al. 2014a and Li and Hu 2014 consider the conversion rate as uncertain, defending that it is due to non-mature technologies. Sharing the same opinion, Paulo et al. 2017 and Marufuzzaman et al. 2014 also have it in consideration, as well as Gao and You 2017 and Bairamzadeh et al. 2018, who defend it is an uncertainty also caused by the fact that different technologies and different feedstocks have different conversion efficiencies, thus different production quantities.

In lower percentages (8%), we have the inclusion of the production yield uncertainty by Azadeh and Vafa Arani 2016, Awudu and Zhang 2013 and Kim et al. 2011, and environmental parameters. This last by Babazadeh et al. 2017 and Rezaei et al. 2019, such as the carbon dioxide emissions of the processes through the supply chain, and by Bairamzadeh et al. 2016, with unit environmental impact coefficient in the environmental objective function. Finally, other uncertainties (5%) were considered by (Liu et al., 2017) and (Bhavna Sharma et al., 2013). The first paper considers facility disruptions such as failures (e.g. natural disasters), man-made failures, or transportation delay as uncertain and the second the number of harvesting workdays due to weather conditions, since they also affect the production.

3.1.5- Uncertainty representation method

The most common methods used to represent the uncertainties in the design of the supply chain are stochastic programming, robust optimization, and fuzzy programming, which are briefly presented hereafter.

Stochastic programming

This method includes multi-stage approach, being the most used the two-stage. The first-stage variables represent independent decisions, made before the realization of the uncertain parameters (Tong et al., 2014b) and included at the strategic level (McLean and Li, 2013) ("here and now" decisions). However, the second-stage variables represent dependent ones, made only after the realization of the uncertain parameters (Tong et al., 2014b) and included in the tactical or operational level (McLean and Li, 2013) ("wait and see" decisions). Thus, realization is usually known only after making decisions about the supply chain network. Liu et al. 2017 proposed a three-stage stochastic programming method for the design of the biomass supply chain and Xie and Huang 2018 a multi-stage one for the biofuel supply chain. The remaining studies adopted a two-stage stochastic programming method.

Another approach is the scenario-based stochastic programming, used by Mas et al. 2010, Bhavna Sharma et al. 2013, Azadeh and Vafa Arani 2016 and Santibañez-Aguilar et al. 2016, which main idea is to tackle only a finite number of uncertain realizations, where each realization is a scenario and has its own probability assigned (Tong et al., 2014b).

Since the two-stage approach is an intractable infinite-dimensional optimization problem, is usually used along with the scenario-based approach to transform the problem into a tractable one over a finite-dimensional space while still achieving reasonable results (McLean and Li, 2013). The objective function in this cases has two parts: one regarding the impact of first-stage variables and other regarding the impact of each second-stage variables in each scenario, considering its probability (Tong et al., 2014b). This strategy is implemented by Cundiff et al. 1997, Kim et al. 2011, Dal-Mas et al. 2011, Chen and Fan 2012, Gebreslassie et al. 2012, Giarola et al. 2012, Walther et al. 2012, Kostin et al. 2012, Giarola et al. 2013, Awudu and Zhang 2013, Kazemzadeh and Hu 2013, Osmani and Zhang 2013, Tong et al. 2014b, Marufuzzaman et al. 2014, Azadeh et al. 2014, Li and Hu 2014, Gonela et al. 2015, Paulo et al. 2017, Osmani and Zhang 2017, Gao and You 2017, Ghelichi et al. 2018, Arabi et al. 2019 and Sharma et al. 2019.

Moreover, since having a large number of possible realizations of each uncertain factor in the scenario formulation increases drastically its size (McLean and Li, 2013), some solution strategies were implemented in some studies to reduce the computational complexity of the problem and difficulty in the generation of feasible solutions (Paulo et al., 2017). Those are benders decomposition used by Awudu and Zhang 2013 and Osmani and Zhang 2017, L-shaped method by Gebreslassie et al. 2012 and Gao and You 2017, Lagrangian relaxation by Chen and Fan 2012, a combination of these last two methods by (Marufuzzaman et al., 2014), or other different scenario reduction methods in Paulo et al. 2017 firstly proposed by Heitsch and Römisch 2003 and Karuppiah et al. 2010.

Robust Optimization

The idea behind this method is to choose the solution that is able to cope better with the various realizations of uncertain parameters (Tong et al., 2014c) within a specified uncertainty set (Babazadeh, 2018), to guarantee feasibility. Comparing to stochastic programming, where decisions are made anticipating that recourse actions take place with the revelation of uncertain parameters over a pre-specified scenario tree with discrete probabilities for each scenario (Grossmann et al., 2016), robust optimization addresses the "worst-case uncertainty realization" (McLean and Li, 2013). This means that, even though it doesn't face the computational complexity of the problem, the results obtained will be more conservative (Grossmann et al., 2016) and not necessarily optimal. In order to create a trade-off between conservatism and performance, the approach used by (Bertsimas and Sim 2004) was adopted by Tong et al. 2014c and Mohseni et al. 2016 to design a robust supply chain of hydrocarbon biofuel and microalgae, respectively, in which a budget parameter is used to control the degree of conservatism of the solution, since it represents the maximal number of uncertain parameters that are allowed to reach their worst case. This budget parameter is also used by Babazadeh 2018 in the model formulation used to design a biomass-to-energy supply chain system. Azadeh et al. 2014 and Azadeh and Vafa Arani 2016 not only developed a stochastic programming model, but later reformulated it into robust programming in order to make it more robust. In both of this studies and in the one made by Rezaei et al. 2019, scenario analysis is integrated in the robust optimization model, having design variables being decided before stochastic parameter's realization and control variables after its realization. Bairamzadeh et al., 2016 and Babazadeh et al., 2017 developed a possibilistic programming approach to better deal with the ambiguity of the considered uncertain parameters, given their little historical data, and Bairamzadeh et al., 2018 proposed an hybrid robust optimization model to attain multiple types of uncertainty in the design of lignocellulosic biofuel supply chain.

Fuzzy Programming

When there is unreliable or lack of information about the uncertainties and historical data, it's difficult to obtain the probability distribution for the stochastic programming approach to obtain good results and be efficient. The fuzzy programming method provides the alternative of representing the uncertainty values using fuzzy logic. This can be quite subjective and dependent on user's preferences, but reduces computational complexity and it's appropriate when there's little information about the uncertainties, once it can handle the design of the supply chain in an efficient, flexible and realistic way (Yılmaz Balaman and Selim, 2015). The most common type of fuzzy programming are flexibility programming, that treats the constraints as a fuzzy set and allows violations in them, and possibilistic programming, that deals with fuzzy constraints and uncertain coefficients on objective functions. In this last one, membership functions for each fuzzy coefficient and constraint are developed in order to be possible to transform the fuzzy model into a linear programming model and find the optimal solution (Yılmaz Balaman and Selim, 2016). Tong et al. 2014a used this approach to design the advanced hydrocarbon biofuel supply chain integrated with existing petroleum refineries. In it, the fuzzy/with uncertainty constraints are reformulated to include a possibility, necessity and credibility measure, depending on the preference of the decision maker, with an associated confidence level. If he is optimistic, possibility measure will be the most appropriate and if he is pessimistic, then necessity will give the measurement of the worst case of that event. Credibility, being defined as the average of the possibility and necessity of the fuzzy event, is the most appropriate measure when the confidence level is 0.5. Yılmaz Balaman and Selim 2015 and Yılmaz Balaman and Selim 2016 also proposed the same approach for the design and management of the biomass to energy supply chains.

Table 3- Review of biomass supply chain network design and planning considering uncertainty.

Publication	Objective	Decision Level		Solution Approach	Uncertainty Representation Method	Considered Uncertainties
		Strategic	**Tactical**			
(Cundiff et al., 1997)	Ec	CF	SS	LP	MP, 2S Stochastic programming	Feedstock supply
(Mas et al., 2010)	Ec (MO)	LF, CF		MILP	SB Stochastic Programming	Feedstock and product price
(Kim et al., 2011)	Ec	LF, NF, CF	SS	MILP	2S, SB Stochastic Programming	Production yield, product price, demand, feedstock supply
(Dal-Mas et al., 2011)	Ec (MO)	LF, CF,	R	MILP	SB Stochastic Programming	Feedstock and product price
(Chen and Fan, 2012)	Ec	LF, CF, BA	PS, R	MILP	2S, SB Stochastic Programming + SReduction	Feedstock supply, demand
(Gebreslassie et al., 2012)	Ec (MO)	LF, NF, CF, TT	PS, R	MILP	MP, 2S, SB Stochastic Programming + SReduction	Feedstock supply, demand
(Giarola et al., 2012)	Ec	CF, TT, TB		MILP	MP, 2S, SB Stochastic Programming	Feedstock price, carbon cost
(Walther et al., 2012)	Ec	LF, CF, TT		MILP	MP, 2S, SB Stochastic Programming	Feedstock supply, technology, demand
(Kostin et al., 2012)	Ec	CF	PS	MILP	2S, SB Stochastic Programming	Demand
(Giarola et al., 2013)	Ec, En (MO)	NF, CF, TT, TB	SS	MILP	MP, 2S, SB Stochastic Programming	Feedstock price, carbon cost
(Awudu and Zhang, 2013)	Ec	PQ	HQ	LP	2S, SB Stochastic Programming + SReduction	Product price and demand
(Kazemzadeh and Hu, 2013)	Ec (MO)	LF, CF	SS	MILP	2S, SB Stochastic Programming	Product price, feedstock supply, costs
(Osmani and Zhang, 2013)	Ec	LF, CF, BS	SS, HQ	MILP	2S, SB Stochastic Programming	Feedstock supply, feedstock and product price, demand
(Bhavna Sharma et al., 2013)	Ec	NF	SS, HQ, IL	LP	MP, SB Stochastic Programming	Number of harvesting workdays
(Tong et al., 2014b)	Ec	NF, CF, TT	R, HQ, SS, TM	MILP	MP, 2S, SB Stochastic Programming	Feedstock supply, demand, technology
(Tong et al., 2014a)	Ec	LF, CF, NF	HQ, HS, IL, PS, SS	MILP	MP Fuzzy Possibilistic Programming	Feedstock supply, demand, technology
(Tong et al., 2014c)	Ec	NF, CF, LF, TT	HQ, PS, SS, TM, R	MILFP	Robust Optimization	Feedstock supply, demand
(Azadeh et al., 2014)	Ec (MO)	LF, CF, BS, PQ	SS, IL	LP	MP, SB Stochastic Programming	Feedstock supply, product price and demand
(Marufuzzaman et al., 2014)	Ec, En (MO)	LF	PS, IL,TM	MILP	2S, SB Stochastic Programming	Feedstock supply, technology
(Li and Hu, 2014)	Ec	LF, CF	SS	MILP	2S, SB Stochastic Programming	Feedstock supply, technology, product's price
(Gonela et al., 2015)	Ec	CF, LF, TB	TM	MILP	2S, SB Stochastic Programming	Product price and demand, feedstock supply

(Yılmaz Balaman and Selim, 2015)	Ec (MO)	NF, LF, CF, BS	PS	MILP	Fuzzy Possibilistic Programming	Feedstock supply
(Bairamzadeh et al., 2016)	Ec, So, En (MO)	BA, LF, CF, TT	IL, SS, PS	MILP	MP Robust Optimization	Feedstock and product price, environmental factors, demand
(Azadeh and Vafa Arani, 2016)	Ec	PQ, BA, LF, CF	IL, SS	MILP	MP, SB Stochastic Programming + Robust Optimization	Production yield, feedstock supply and price, product price, demand
(Mohseni et al., 2016)	Ec	LF, CF	SS, PS, IL	MILP	Robust Optimization	Feedstock supply, costs, demand
(Santibañez-Aguilar et al., 2016)	Ec, En (MO)	BS, BA, PT, CF, TT		MILP	MP, SB Stochastic Programming	Feedstock price
(Yılmaz Balaman and Selim, 2016)	Ec, So (MO)	LF, CF	PS, R, SS, TM, IL	MILP	MP Fuzzy Possibilistic Programming	Feedstock supply, costs
(Babazadeh et al., 2017)	Ec, En (MO)	NF, LF, CF	PS, IL, SS, TM, R	MILP	Robust Optimization	Feedstock supply, demand, costs, environmental factors
(Paulo et al., 2017)	Ec	LF, CF, TT	IL, TM, R, SS, PS	MILP	2S, SB Stochastic Programming + SReduction	Feedstock supply, technology
(Osmani and Zhang, 2017)	Ec, En, So (MO)	BS, LF, CF, TT	HS, SS, PS	MILP	MP, 2S, SB Stochastic Programming + SReduction	Feedstock supply, product price and demand
(Liu et al., 2017)	Ec	LF, BS	IL, SS	MILP	MP, 3S Stochastic Programming	Feedstock supply, facility disruptions
(Gao and You, 2017)	Ec, So (MO)	BS, CF, LF, TT	TM, PS, R, TM, SS, IL	MILP	MP, 2S, SB Stochastic Programming + SReduction	Feedstock supply, demand, technology
(Ghelichi et al., 2018)	Ec, En (MO)	NF, LF, CF	SS, TM, R	MILP	MP, 2S, SB Stochastic Programming	Demand, feedstock supply
(Bairamzadeh et al., 2018)	Ec	LF, CF, TT	HQ, PS, IL, SS	MILP	MP Robust Optimization	Technology, feedstock supply, demand
(Babazadeh, 2018)	Ec	NF, LF, CF	SS, IL, PS	MILP	MP Robust Optimization	Feedstock supply, demand, costs
(Xie and Huang, 2018)	Ec	LF, CF	PS, TM	MILP	MP, SB Stochastic Programming + SReduction	Demand
(Arabi et al., 2019)	Ec, En (MO)	LF, CF, TT	IL, TM	MIQP	MP, 2S, SB Stochastic Programming	Product price and demand
(Sharma et al., 2019)	Ec	BS, LF, NF, CF		MILP	2S, SB Stochastic Programming	Feedstock supply
(Rezaei et al., 2019)	Ec	NF, LF, CF		LP	SB Robust Optimization	Demand, feedstock supply, costs, environmental factors

Ec: Economic; So: social; En: environmental; MO: multi-objective; LF: location of facility; CF: capacity of facility; NF: number of facility; TB: type of biomass; BA: biomass allocation; BS: biomass sourcing; PQ: product quantities; PT: product type; TT: type of production technology; SS: shipment size; R: routing; TM: transportation mode; PS: production scheduling; IL: inventory levels; HQ: harvesting quantities; HS: harvesting scheduling; MP: Multi-period; 2S: Two-stage; 3S: Three-stage; MS: Multi-stage; SB: Scenario-based; SReduction: Scenario reduction

From this literature review, it can be concluded that, for the optimization of the design of the biomass SC, the MILP formulation is the most used. Economic objectives are the main focus, even though environmental ones have been gaining their importance, and, when incorporating the uncertainties in the design process, stochastic programming is the most common approach. Most decisions being made in the papers are regarding the strategic level and the most common uncertainties are product demand and feedstock supply, being the last one a possible consequence of the first, since it is important to have both uncertainties in mind when making decisions at a strategic level.

3.2- Modelling the Conversion Efficiency's Uncertainty

Another important uncertainty to have in mind when making strategic level decisions is the uncertainty inherent to the conversion technologies. Its importance is sustained by the fact that, since technology has not reached a mature stage and it is still developing, changes and improvements in them will have different impacts in the supply chain (Marufuzzaman et al., 2014). However, even though in many of the papers presented in Table 3 decisions regarding the technology type were made, most fail to consider technology related uncertainties and its development stages (maturity), time to have it operating at full capacity (learning) and even adequacy to local conditions (biomass type, availability, among others).
Only 8 articles consider technology related uncertainties (21%), from which 6 do it by incorporating the technology conversion efficiency as an uncertain parameter in their stochastic modelling framework:

- In (Li and Hu, 2014), there are two uncertain conversion ratios with a probabilistic distribution: biomass to bio-oil and bio-oil to biofuel, both assumed to follow a normal distribution with an average conversion ratio of 0.63 and 0.20 on weight basis, respectively. The first one was based on the experimental results from Iowa State University and the second one on a reported conversion ratio for slurry gasification found in literature, given the lack of experimental data. For the scenario generation, the moment matching method was employed. The method generates a set of discrete probabilistic scenarios, with its distribution properties consistent with the pre-specified statistical properties, such as mean or variance, that a decision maker considered relevant (Høyland and Wallace, 2001).
- In (Marufuzzaman et al., 2014), a conversion rate of sludge to biocrude and biocrude to biodiesel are considered, but it is only investigated the impact of the technology used to transform sludge into biocrude on production and costs. Using a scenario-based approach, five different scenarios were defined with associated probabilities of occurrence, as shown in table 4: the highest probability was assigned to the scenario with the conversion rate obtained in previous studies conducted at a laboratory in a small scale (0.26), due to being the most likely rate. The other scenarios were obtained by varying the rate 0.02 points up and down and attributing this variation a probability of 10%, and by varying the rate 0.06 points up and down with a probability of 5%, since a higher variation is less likely to happen.

Table 4- Scenario definitions and probability of occurrence under technology uncertainty (Marufuzzaman et al., 2014*)*

Scenario	Explanation	Probability
1	1 ton of sludge generates 0.20 tons of biocrude	0.05
2	1 ton of sludge generates 0.24 tons of biocrude	0.10
3	1 ton of sludge generates 0.26 tons of biocrude	0.70
4	1 ton of sludge generates 0.28 tons of biocrude	0.10
5	1 ton of sludge generates 0.32 tons of biocrude	0.05

- Paulo et al. 2017 model the conversion ratios of the technology used to produce bioethanol, phenols, electricity, and heat and the technology to produce biofuels and waxes. These are modelled according to literature and inspired by the scenario definitions and probability of occurrence under technology uncertainty done by Marufuzzaman et al. 2014, presented in Table 4.
- Gao and You 2017 tackle the conversion efficiency uncertainty by considering different types of conversion ratios in their model depending on biomass feedstock type, type of technology and type of product, to account for different production yields. The type of technology used is associated with the conversion process and they have their own historical data, used to obtain the conversion factor's values of each. A scenario-based approach is also used in this study, but the technology uncertainty was not the motivation behind it. Thus, the probability of each scenario is not obtained having in consideration the probability of occurrence of each conversion factor.
- Bairamzadeh et al. 2018 express the imprecision of the conversion rates as a set of probabilistic scenarios of their possible values depending on the type of biomass feedstock and technology used and based on historical data about improvements of conversion technologies through time. The values used for the conversion rates were the ones presented below in Table 5, and the probability of selecting each scenario is equal.

Table 5- Conversion rates of biomass feedstocks through each technology type under different scenarios (gallon/tonne) (Bairamzadeh et al., 2018)

b	Biomass	Conversion rate of biomass feedstock type b through technology type q to bioethanol under scenario s ($\theta^{bel}_{b,q,s}$)			
		Low yield scenario (s=1)		**High yield scenario (s=2)**	
		Thermochemical	**Biochemical**	**Thermochemical**	**Biochemical**
1	Corn Stover	65	65	72	75
2	Wheat Straw	65	55	72	60
3	Barley Straw	75	69	82	75
4	Rice Straw	70	77	66	72

- In (Tong et al., 2014a) the conversion rate as an uncertain parameter is treated as a fuzzy member. Therefore, three values are used to characterize it: the most pessimistic, most possible and most optimistic. The most possible value is obtained by assumptions based on historical data of the upgrading facility and the general yields of crude oil, and the most pessimistic and most optimistic are set to be 10% less and 10% greater than the most possible one, respectively. These three are then included in the conversion constraints, along with the confidence level and the decision maker attitude.

These studies, with their model's results, proved the impact this uncertainty can have in the optimization of the supply chain. Even in not accurately, considering technology uncertainty at the design stage helped the models to achieve higher profit results. Plus, it is verified that this uncertainty has influence on decisions such as type of technology or dimension. Having this in mind and the fact that only 6/39 articles treat the conversion ratio/conversion efficiency as an uncertainty in their model, it is clear the little consideration it has in the literature. For the scenario generation, the method or reference used to obtain the probability of each realization of the technology's conversion efficiency it's not well defined. However, the moment matching method employed by Li and Hu 2014, by being based on statistical properties of the historical data found about technology developments, seems to have potential on describing them and interesting for further research. Moreover, even though the 6 articles try to model it, the conversion ratios' values used are only based on the past and not on the future. They were obtained by approximation from historical data, based on experimental results at a small scale in laboratories, or even inspired by the conversion ratios of the technology used in the fossil fuels conversion facilities. Even if sometimes those approximations consider technology improvements, they were the ones already achieved in the past up to the present and not the possible ones in the future. Thus, maturity and learning are still miss represented and they shouldn't so as decisions at a design stage are more realistic and accurate. This research gap is the focus of the present research.

3.3- Learning Curves

When the lack of consideration of technology maturity and learning in the optimization models is in question, a possible solution approach that can easily be remembered is the one regarding exactly technology learning and its mathematical correlation with costs. That is the learning curve approach.

3.3.1– The Learning Concept

One of the first authors to describe the learning concept was (Wright, 1936). In his paper, he explains the factors that possibly make the cost of airplane's manufacture to decrease as the quantity produced increases. One of those factors is the labour cost, which he acknowledges one of the reasons it decreases is the practice gained by the workforce as the production quantities increase, which, consequently, makes the workforce and worktime production requirements of each unit to reduce. Therefore, a negative correlation between learning and costs was empirically observed and the

graphical representation of his findings is currently referred to as *learning curve* (Weiss et al., 2010). Based on this subject, Arrow 1971 introduced the notion that technical change as a function of learning, comes from experience, gained with multiple attempts and during the activity. Over time, the concept of learning was extended from its original conception of being referred only to the productivity of labour: the modelling of the costs in function of cumulative production started to include all production costs (Conley, 1970), to be constructed for a wide range of products, technologies, and processes (Weiss et al., 2010), including learning, scale and other factors, and applied both to single companies and entire industries (Dutton and Thomas, 1984). The curves representing this broader concept of learning can be referred to as *experience curves* (Samadi, 2018). However, given the concepts of both curves come from the same idea, they are often grouped in literature under the general category of learning curves.
Independently of being a product, technology or process, improvements in performance, productivity and/or reductions in their related production costs (material costs, labour costs, technology costs or others) usually happen due to accumulation of experience gained from different processes (Wiesenthal et al., 2012). The "learning by doing", that helps obtaining the needed experience, as more units are produced, to be able to make improvements and increase efficiency in the production process (Arrow, 1971), learning by researching, which is the knowledge obtained through research and development (Cohen and Levinthal, 1989), the "learning by using" the final product/technology, on the demand side, allowing the experience obtained to make its operation more efficient (Rosenberg, 1982), and others, such as learning by scaling (Sahal, 1985) and learning by copying (Sagar and van der Zwaan, 2006).

3.3.2– Types of Learning Curves

As mentioned before, a learning curve describes the relationship between costs, the dependent variable as a measure of learning and improvement, and the experience, the independent variable usually represented by a cumulative measure of production or use (Nemet, 2006). In this relationship, the costs decline at a constant rate – learning rate - each time the cumulative production doubles (Weiss et al., 2010).
There are different types of learning curves depending on the number of cost reduction factors:

- The one-factor-learning curve (OFLC), that relates the variations of the costs over time with only one factor as the independent variable, the accumulated learning, usually represented by accumulated production (Sagar and van der Zwaan, 2006). This type of learning curve benefits from being relatively easy to access the necessary data to plot them, since volumes of production usually are well documented, and for simplifying cost dynamics. However, by aggregating the costs in its formulation, considers they are all subject to reductions when only some experience learning and in different ways (Sagar and van der Zwaan, 2006). Moreover, by having only experience as the independent variable, the OFLC doesn't consider other types of cost reduction drivers that have been found to be relevant in influencing costs developments (Samadi, 2018).
- The multi-factor-learning curve, that was constructed to compensate the OFLC's flaws and properly considers the impact of different and relevant cost reduction drivers (Samadi, 2018).

The most popular is the two-factor-learning curve and differentiates, in its formulation, two of the most important learning factors: the learning-by-doing and learning-by-searching (Wiesenthal et al., 2012). Even though the differentiation of the drivers seems appealing and more realistic, the effects of learning through research and development are difficult to quantify and are drivers of cost variations that show levels of interdependence, making it hard to distinguish the effects of each (Samadi, 2018) and consider them isolated from one another.

Independently of the type of learning curve, it's clear the difficulty that is obtaining the most appropriate learning rate, because it significantly varies across different studies and it is dependent on historical data that is often limited. Moreover, they might be different in different geographical areas due to specific factors that make the learning process to have different developments (Sagar and van der Zwaan, 2006). When applied to technology, the fact that the characteristics of different plants can vary due to different technologies used, their size and type of feedstock used, the learning rates are different as well, due to different learning processes (Samadi, 2018). Also, technology is always in development. So, even though it is important to rightly treat the historical data so the technology forecast reflects its past progress, it should be also expected for future developments to be a little bit different from past ones (Jamasb and Kohler, 2007). Therefore, it is important to be careful when treating the data in order to produce a representative learning rate.

3.3.3- Application

The learning curve approach has multiple purposes, but in the 1990s, started to treat technology dynamically and it has become a widely used method to project mostly technological changes (Nemet, 2006). Based on the concept, every time a unit of some specific technology is produced, some learning is accumulated causing a cheaper production of the next unit of the same technology. Therefore, considering the learning and experience is essential to understand and predict future costs variations of technology and how these are related to technology developments (Wiesenthal et al., 2012).

The first application of learning curves, between 1930s and 1960s, were mainly oriented for production, as in (Wright, 1936). In 1970s and 1980s, they started to be also used in business management (Towill, 1985), strategy and organization research and, since 1990, they have attracted interest for technology analysis and, particularly, for energy technologies (Jamasb and Kohler, 2007). The literature review done by Samadi 2018 proves this by presenting numerous studies with empirical observations of experience curves and corresponding learning rates for electricity generation technologies. Some of those were about renewable energy power plants (onshore wind, offshore wind, solar PV, solar thermal and biomass power plants), from which he concludes, with statistical support from literature, that most technologies using renewable energy sources have a strong negative correlation between experience and costs, nuclear power plants and fossil fuels power plants (coal and natural gas power plants). He also observed, in literature, that experience curves for this type of technology are modelled at an industry level, where the independent variable is the cumulative experience of all companies and the dependent the average cost or market price. The cumulative experience can be considered as the technology's cumulative capacity, cumulative number of plants or cumulative electricity generation built, and the type of cost considered depends on if a technology itself or just a part of it is being investigated. This is also verified by Weiss et al. 2010 that analyses the application of learning curves for energy demand technologies and by Rubin et al. 2004 for environmental technology. However, even though technology learning is widely associated with costs variations, it is important to refer that this process affects other aspects of the technology that can also benefit from learning, such as reliability, safety features, conversion efficiency, among others (Wiesenthal et al., 2012).

3.4- Chapter conclusions

This chapter demonstrated that, even if uncertainties have been considered and included in the supply chain design by the literature, there are still some of them underrepresented and continue to have a big impact on the supply chain optimization. One of those, and an important one, is the technology related uncertainty, more specifically, the conversion efficiency uncertainty, which is lacking a correct consideration of maturity and learning in its modulation. The learning curve approach was proved to be commonly used to represent technological developments due to learning and experience and, mostly regarded energy technologies. Thus, it has great potential to correctly cover this gap.

4- PROBLEM DEFINITION AND METHODOLOGICAL APPROACH

Based on the background on the research topic of biorefinery's SCs and information and findings obtained from literature review, the current chapter is destined to define the problem that will be tackled in the present master thesis. First, in section 4.1, the main findings of research will be resumed. Then section 4.2 will expose this thesis proposed solution approach, followed by section 4.3 explaining the methodology to do it. Finally, some conclusions and the next steps will be clarified in section 4.4.

4.1– Main Literature Review Findings

There are four main findings obtained through the research done so far:

First, the European Union has been trying to transition from a fossil-input-based economy to a bio-based economy and, in order to do it, created the European Commission's energy packages aiming to achieve the 'Europe 2020 Strategy' goals of increasing the share of energy consumption from renewable sources and the utilization of biofuels.

Second, even with biomass being a good renewable source to produce biofuels, the biofuel supply chain isn't yet competitive comparing with fossil fuels. Also, it is subject to several uncertainties that should be considered from scratch, this is to say, from its design process, aiming to reduce their impacts and obtain a truly optimized supply chain.

Third, one of those uncertainties, and an important one, that is lacking representation in literature is the technology development and performance uncertainty that arises with the fact that technology is still in development and hasn't reached maturity. So, despite one technology may be more attractive to install today, in a few years another may become more attractive. The few studies that considered this uncertainty incorporated the conversion efficiency uncertainty of the conversion technologies in their optimization models. However, they failed to correctly consider the effects of learning and maturity of the technology by using values based only on historical data and not on possible future developments.

Fourth, the concepts of maturity and learning of technology are really tied with the learning curve approach and technologies using renewable energy sources have been proven to have a strong negative correlation between experience and costs. Also, technology learning affects many aspects of a technology besides costs, including the conversion efficiency. Thus, it is difficult to obtain the respective learning curve and learning rate of energy generation technologies, because the learning process is different for each technology depending on type, feedstock, size, or others. Even so, the learning curve approach has potential as a good mathematical formulation to represent the future developments of the technologies used to generate energy from biomass in terms of their conversion efficiency ratio and its impact on costs.

4.2- Problem Statement

The studies in literature regarding optimization models that realistically include uncertainties to design the biomass SC have been increasing, but with a default. As stated before, literature review enabled to find that the technology uncertainty of the biorefinery's conversion technologies has not been modelled to correspond to reality as more accurately as possible. This uncertainty exists, because technology continues to develop as result of many important factors, such as learning with experience, research, and development, or others, that have not been rightly considered. This development can be measured in terms of the technological process's efficiency, thus, its development and evolution are dismissed when the conversion efficiency is included in the optimization models as a known, constant and in the present time period value. Instead, it should be included as a dynamic value that it is uncertain and can vary in the future. It should be included as an uncertainty.

Having this said, the research problem to be tackled in this master thesis is **the formal and mathematical representation of technology evolution and its impact using the conversion efficiency and learning curves**, as literature showed potential in these to represent technological developments. With a mathematical representation of this dynamic development of technological processes, one can prove that it affects their performance and feedstock/product conversion, while the investment costs might be uncertain as well. By doing this and then incorporating it in a biomass SC stochastic optimization model, the model becomes more accurate, and its results are more realistic. It would help planners and decision makers to take more informed design decisions regarding biomass conversion technologies and potentially reduce costs, which would help leverage biomass and reduce the fossil fuel' consumption. This is also important given the choice of the conversion technology influences the whole process and many other decisions in an integrated biorefinery that must be planned ahead. Furthermore, besides representing a research gap, this problem is highly relevant since this supply chain is evolving and expanding, while there is no maturity in the technologies used.

With the literature reviewed being from various countries, it can be said that the problem stated in this section it is general to all countries. However, the solution approach proposed will only be tested by being applied to the Portuguese case. Thus, the necessary data as an input to the model will be based on the Portugal's reality. The input data will be obtained from old studies and publications and updated with the help of the competent entities. In cases of lack of information, first, information from countries within the EU is used, given the context is similar to the Portuguese and, last case scenario, information from countries outside the EU is used.

4.3– Thesis Methodological Approach

After having stated the problem and the solution approach, the methodology on how to do it has to be clear.

- First, data collection on biorefineries is made. All their specifications are analysed with the objective of reaching conclusions on technology developments and conversion efficiency evolution. These conclusions will then help to predict the conversion efficiency of the technologies and appropriate parameters of the learning curve formulation for each technology. This is presented in chapter 5.

- Second, the mathematical formulation of the learning curves to be included in the stochastic optimization model by Paulo et al., 2020 is presented in chapter 6. The learning curves are adapted to each technology and how they incorporate the conversion efficiency evolution and represent its impact on costs is shown. In the same chapter, the Paulo et al. 2020's adapted stochastic optimization model is explained and complemented with the explanation of how the conversion efficiency uncertainty is included and the integration of the learning curve theory. The model is constructed to be **fed** by the: i) amount of available biomass, ii) biomass acquisition cost, iii) biomass conversion efficiency over time, iv) production costs of each technology, v) product's demand in each market, vi) transportation costs regarding the different transportation modes, vii) distances between the sites of the biomass collection, integrated biorefineris and markets and viii) annualized investment costs of integrated biorefineries, **and determine** the: 1) collected quantities of biomass at each production site, 2) biomass flows across each supply chain entity, 3) product's production quantities, 4) location of the installed biorefineries, 5) capacity of installed biorefineries and 6) technology to implement in each installed biorefinery, so as to **optimize** an economical objective function.
- Finally, the model is implemented to test the adequacy of the conversion efficiency's evolution representation through the use of learning curves. It will use data from the case study and then results are obtained and discussed. The case study and the remaining data necessary to run the model are presented and explained in chapter 7. The process of validation of the model is after explained and, finally, the results of the model are obtained. This can be found in chapter 8.

4.4– Conclusions

To tackle the lack of representation of technology evolution and the conversion efficiency uncertainty of the conversion technologies, learning curves for each technology will be constructed. The objective will be representing the developments of the technology through time and the consequent impacts, given it appears to be an adequate approach to do so. This approach will then be tested in a two-stage stochastic optimization model and its results will be evaluated to reach conclusions on how this will affect the design of the biomass SC. Given Portugal has great potential in the treatment of biomass and production of bioenergy, it is the chosen case study to the present thesis. Therefore, the necessary data to the models will be Portugal related.

5- CONVERSION EFFICIENCY & LEARNING CURVES - DATA COLLECTION AND ANALYSIS

This chapter introduces the data collection and data treatment procedures required to obtain valuable inputs for the representation of the conversion efficiency uncertainty and learning curve's formulation of the biomass conversion technologies.

This chapter will be organized as follows: first, the data collection process is presented and, after, is described. Since the required data is not always available, all assumptions made from the available data gathered are explained and data is treated when necessary. The chapter ends with some conclusions being stated.

5.1- Data Collection Process

The learning curve's theory will be applied to conversion technologies used in biorefineries and then used to represent the impact of their conversion efficiency uncertainty in a biomass SC optimization model. Therefore, the present chapter is focused on finding information regarding biorefineries and their used technological processes and specifications. Constructing the model and having its inputs based on real information about existent biorefineries, will make it more realistic.

The data collection process to do so is represented in Figure 4.

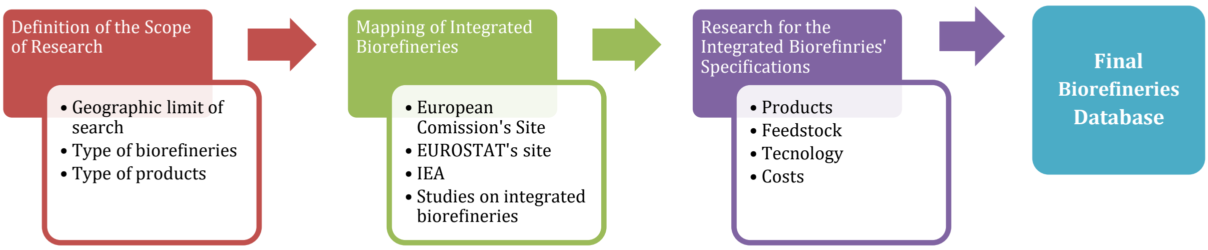

Figure 4- *Data Collection Process*

- First, the scope of research had to be defined to guide it and restrict the available data to the necessary. This was regarding the geographical limits of research for the existent biorefineries, the type of biorefineries to be considered, and the type of products they produced.
- Then, research was made only focused on mapping the biorefineries that met the scope of research. First, official sites of organizations that are concerned with a sustainable energy production were the target of research. Those were the European Commission's website and the International Energy Agency (IEA) website. To help obtaining data more objectively, the research was complemented and extended to public articles and studies on this matter in public platforms, such as Google and Google Scholar, with key words.
- Finally, once the biorefineries were mapped, their specifications needed to be collected. Considering the focus on the technology's conversion efficiency uncertainty of the present thesis and the mathematical formulation of the learning curve theory, research was done aiming to collect information, over time, mostly about production, investment and installation costs, type of biofuels

produced and their production quantities, type of biomass used and biomass feedstock quantities, type of biomass conversion technologies, their conversion efficiencies and learning rates.

The following sections will explain each of these steps in detail.

5.2- Scope of Research

This section summarizes some important definitions made to simplify the research process. To this end, several considerations must be outlined:

- The scope of data to collect is Europe/European Union since it keeps a geographical proximity with Portugal while ensuring to have a wider ground to collect data. Also, all countries are focused on goals towards a sustainable economy, which also underlines the chance to have more biorefineries to collect data from.
- It is important to have the concept of biorefinery well defined and in line with the objective of study of the present thesis. This way, from all the data available about biorefineries, research can be done objectively and focused on the relevant ones. Therefore, the definition used in this thesis is the one employed by de Jong et al., 2012 and by BIC, 2017 to define an integrated biorefinery: "a facility that does the sustainable processing of biomass into a spectrum of marketable products (food, feed, material, chemicals) and energy (fuels, power, heat), using a wide variety of conversion technologies in an integrated manner". Only facilities that corresponded to this definition were considered.
- Only integrated biorefineries that produce biofuels as one of their products were considered.
- Data should be collected from a reliable source that would help reduce the amount of information to collect on biorefineries while ensuring that standard information is obtained, guaranteeing that it would not be needed to identify and analyse different and multiple sources of highly probable unreliable information.

5.3- Mapping Integrated Biorefineries in the EU

The research for integrated biorefineries in the EU for this thesis biorefineries' database was made on Google and Google Scholar mostly using the key words "Integrated Biorefineries EU" and "Biofuels Production EU." After an extensive research was done, the following sources were found:

- **Scientific Information Systems and Databases report by Parisi 2020**: The report consists on the description of the distribution of the bio-based industry in the European Union. It also refers a link to an online interactive visualisation platform (https://datam.jrc.ec.europa.eu/datam/mashup/BIOBASED_INDUSTRY/index.html) that allows the user to navigate in the report's database by applying filters to all the available information as desired (for a visual picture of the interactive dashboard, see Figure 5). The database contains facilities using biomass that are represented with IDs of the type CuntryNumber (e.g.: Ire8). It doesn't share their names or owners, but does share, for each, its definition of biorefinery, country, coordinates, feedstock class and origin, status, range of capacity of production, product class and category, type of plant, among others. Although this is valuable information that will help to construct the integrated biorefinery's database for the present thesis, the information is still general and not quite exactly the needed. Thus, this EU's database was only used as a starting point of the existent biorefineries of the EU and to guide the rest of the research. This could be done, given it is a publication made by the Joint Research Centre (JRC), the European Commission's science and knowledge service, thus as a reliable source.

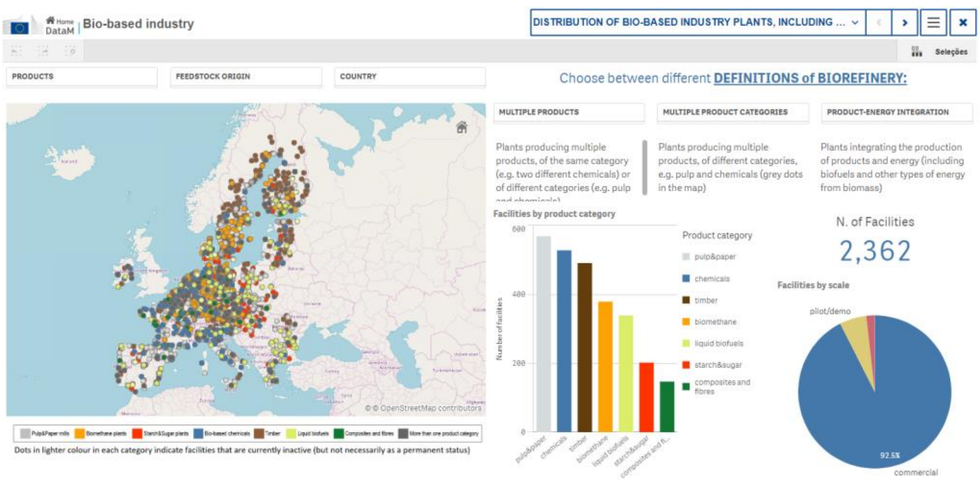

Figure 5- *Content of the interactive database of the report by (Parisi, 2020)*

- **"Mapping European Biorefineries" report by BIC, 2017**: is a list of the European commercial biorefineries in 2017 published by the Bio-based Industries Consortium and the Nova Institute of the European Biorefineries. This list has the name of 224 production plants and their respective country. This list is one of the references of the EU's report, thus it was assumed trustworthy. Also, was used to complement the lack of names of the biorefineries of the EU's database by crossing the information of the countries of the first and the coordinates (after searched in Google Maps) of the second.
- **A list of commercial biorefineries included in the BioRefineries Blog** ("EUROPEAN ADVANCED BIOREFINERIES AT COMMERCIAL SCALE," n.d.): this blog is dedicated to biorefineries and related concepts, such as advanced biofuels, events or others and was also referenced in the EU's report by Parisi, 2020. The list mentioned is a list of the advanced biorefineries at a commercial scale in Europe that was created in 2015 and deeply updated in 2018. Also, uses the same concept and definition of integrated biorefinery of this thesis. For each biorefinery, shares its location, responsible company, feedstocks, products, feedstock category, technology/technological process, production capacity, start-up date, status, and a link to a website or news. Once again, this list and this blog were used to complement the lack of names of the biorefineries of the EU's database by crossing their information of the location of the biorefineries with the coordinates (after searched in Google Maps) of the EU's database. Also, to specify the specific amount of production of each facility (the EU's database only shares

a range), the type of biofuel and the conversion technology used (also not specified by the database).

- **A list of bioenergy plants provided by the ETIP (European Technology Innovation Platform)** ("Production Facilities," n.d.): ETIP is a platform dedicated to bioenergy and the bioenergy industry that shares this list, along with a map, to provide an overview of production facilities of biofuels and intermediate bioenergy carriers. The list of the bioenergy plants shares information of the owners of each, their names, and location. Also, extra information about production quantities and processed quantities. This list was used, as well, to try to correspond its biorefineries' locations to the coordinates of the EU's database to assign a name to each biorefinery's ID. In the cases of success, the list was also used to complement the database with the specific amount of production of each facility, type of biofuels produced, the amount, and type of feedstock processed.
- **Google Maps Results:** the rest of the sources used to incorporate the database constructed by (Parisi, 2020) were also reviewed in detail. However, without success in finding more possible correspondent biorefineries. After reaching the author of that report and database for collaboration, due to confidentiality of the EU's data it was not possible to obtain additional information. So, another approach was made. It consisted in searching the coordinates available in the EU's database in Google Maps and, in the cases of success, obtaining the localization of an industrial facility with a name or site associated to it. If the information available online matched the information available in the EU's database (e.g.: the product belonged to the product category of that biorefinery in the database), that biorefinery and respective information were included in this thesis database.

5.3.1– Assumptions and Limitations in the Biorefinery's Mapping Process

The EU's database constructed by Parisi, 2020, has available information about 2362 biorefineries. However, not all of them are relevant to include in the database of this thesis. Thus, by allowing to choose filters and having in mind the scope of research previously defined, this number was reduced to 99 integrated biorefineries. The filters applied were the following:

- There are filters that can be applied to obtain only the biorefineries that go in line with the user's <u>definition of integrated biorefineries</u>. There are three definition filters options:
    1. The "Multiple Product Categories" biorefineries, that produce products of different categories (e.g. 1 chemical product and 1 biofuel),
    2. The "Multiple Products" biorefineries, facilities that produce products from different categories and/or different products from the same category (eg: 2 different chemical products),
    3. The "Product-Energy Integration" biorefineries, which integrate the production of products and energy (biofuels or other type of energy generated from biomass).

From these, the **"Product-Energy Integration"** and the **"Multiple Product Categories"** filters were chosen (see Figure 6). The "Multiple Products" filter was not used, since it incorporated biorefineries that only produce one product category. It was verified, in the database, that all facilities that produce biofuels also produce other product category. Plus, the "Multiple Product Categories" filter covers the production of products from different categories. Therefore, the "Multiple Products" filter was not relevant for the present research.

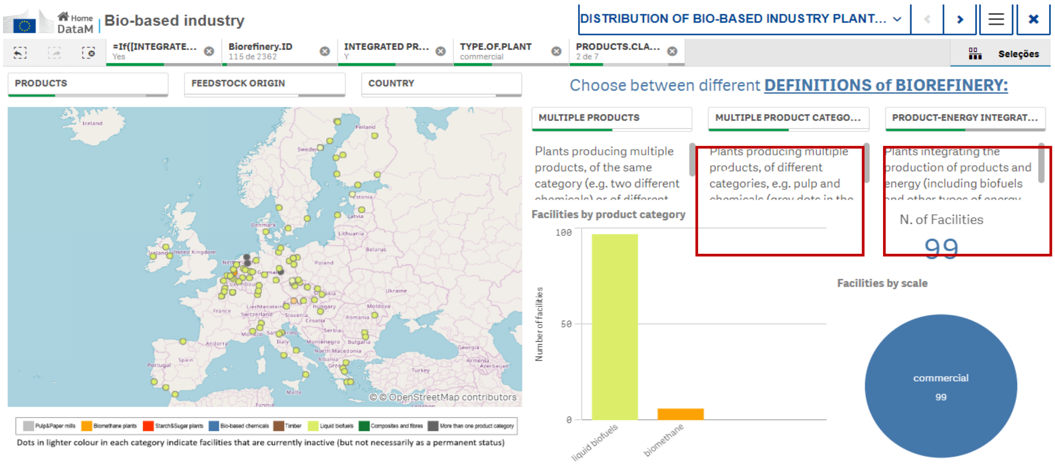

Figure 6- *Product-Energy Integration and Multiple Product Categories filters applied and the remaining number of facilities*

- The filter **"Integrated Production"** was also applied, given that it is dedicated to guarantee an integrated production in the biorefineries, which goes in line with the definition of integrated biorefinery of this thesis (see Figure 7).
- Another filter used was one regarding the scale of the biorefineries, named "Type of Plant." The pilot and R&D ones were dismissed since they were not the focus of the present research. Only the integrated biorefineries at a **commercial** scale were considered (see Figure 7), because it is in this phase that this study is considering to still be happening technology developments and efficiency increase due to gained experience.
- Last but not the least, from the product classes available, two filters were applied to guaranty that the biorefineries collected for the database produce biofuels. The two filters were "**biomethane**" and "**liquid biofuels**" as they are the only products, from the available, that are included in the scope of the present research.

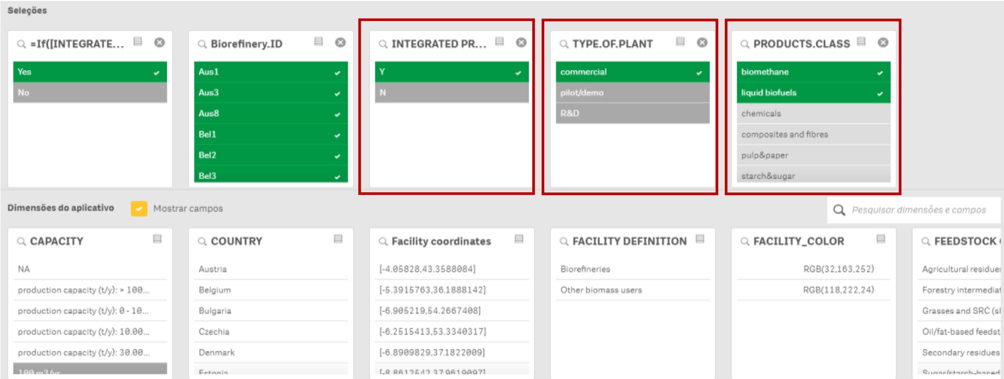

Figure 7- *Integrated Production, Commercial scale and production of Biofuels (liquid and gas) filters applied*

Furthermore, as mentioned before, the EU's biorefineries' database constructed by Parisi, 2020 had ID codes for each biorefinery. Therefore, in the attempt to find the names of the 99 integrated biorefineries of the database or the company who run them, a search for each one of them in Google Maps was made by using the available coordinates in the database. However, there were some challenges in this method:

- Sometimes, it led to random localizations. In those cases, a search for biorefineries, in that area, that matched the data from the database (feedstock class, product type, etc) was made. When this was not successful, it was assumed the coordinates in question were a localization error and that biorefinery was discarded (~36% of the biorefineries).
- Other times, the localizations were not random and the name of the biorefinery/company that owned it was found. However, there was not an official site or any information about them. Those were also considered as errors (~13% of the biorefineries).
- At last, sometimes there were similar coordinates in the EU's database and the exact biorefinery/company they were associated to was inconclusive. There were 3 integrated biorefineries in France that had the coordinates in the same industrial place. After deep analysis, it was concluded they were three different plants with an integrated production between them 3 and a fourth one that produced bioethanol with the biomass outputs of the first 3. Thus, they were considered as only one integrated biorefinery. Also, other 3 in Sweden had very close coordinates, and since it was not possible to find information about 2 of them, they were considered as one integrated biorefinery as well.

After all these assumptions were made, the 99 were reduced to 50 integrated biorefineries with known names/owner companies and available information about their activity. These biorefineries and their specifications can be found in Appendix A.

5.4- Integrated Biorefineries' Specifications and Assumptions

Once the biorefineries were mapped, the focus was on collecting all information available about them that made sense to the present study. In terms of conversion efficiency, to study its evolution in integrated biorefineries at a commercial scale, information is needed, over the time, either about the biorefinery's conversion efficiency or quantities of production and feedstock quantities. The technological processes used for the conversion of biomass into biofuels as well, and the types of biomass and biofuels. Regarding the learning curves, given they relate costs to experience, the focus was on finding any information about costs and learning rates, for each technology of conversion. Also, over the time.

Collecting all this information was an extensive process that was based on retrieving any useful information from the first 4 sources presented in sub-chapter 5.3 (EU's database and the 3 lists of biorefineries that also had their specifications). The fifth source, Google Maps, was not used to search for any of the information needed presented in the last paragraph. However, Google was. Once the coordinates of the EU's database were searched on Google Maps' and the location result was validated, the biorefinery/owner company in question was extensively searched for any websites or news that shared valuable information for this thesis. After being able to map 50 integrated biorefineries in the EU, this process was done for each of them. Moreover, Google was also used to find the remaining information mostly about costs and learning rates that could not be found in most of the cases, as will be later presented (see Table 9 in Appendix A for the 50 biorefineries mapped and section 5.4 for the final ones that are in this thesis database).

The challenges, assumptions, and the findings of research are presented in the following sub-sections and, when necessary, data is treated.

5.4.1– Product

Type of Biofuels

From the 50 biorefineries mapped, the type of biofuels produced that were found were: biodiesel, bioethanol, Naphta (biochemical), biomethanol, biomethane and biogas. The most common biofuel produced is biodiesel (60% of the biorefineries) and then bioethanol (38% of the biorefineries). The remaining 2% were biorefineries from which it could be found some information (feedstock, feedstock quantities or process), except the type of biofuel produced. Regarding the other types of biofuels, one of the biorefineries that produces biodiesel also produces biomethanol and another the biochemical Naphta. The biomethane is produced by four biorefineries that produce bioethanol, from which only one produces biogas as well. Given these are not substantial samples, the **biodiesel and bioethanol** are considered to be the main biofuels produced and thus, the focus will be on them in his study. However, the biomethane produced quantities found will still be used to help reach conclusions on the conversion efficiency of the technology used to produce it. At last, by producing biofuels, some co-products are also produced. Regarding biodiesel, the most seen co-product being produced is glycerine and regarding bioethanol, the most seen are animal feed and cellulose. However, these will not be considered in the present study, due to lack of information on their quantities for some of the biorefineries. This decision will enable to compare all biorefineries on the same basis and have the focus strictly on the biofuels, which are the main focus of the study.

Biofuel's Production Quantities

Regarding production quantities, 14% of the biorefineries only had information about the product's types and not their quantities. All these biorefineries were discarded. When the biorefineries, besides biofuels, produced some co-product or sub-product and their production quantities were not available, those sub/co-products were not considered to be produced (see subchapter 5.5 to see the final biorefineries' database). These assumptions regarding production quantities were made, because without them, the conversion efficiencies could not be obtained by dividing them by the feedstock quantities. Since the values of the conversion efficiencies off these biorefineries were also not available and the quantities could not be calculated, the biorefineries were irrelevant to the present study. Finally, when the quantities were available in litters, it was used $0.789 \mathrm{g/cm^3}$ (Muhaji and Sutjahjo, 2018), $0.88 \mathrm{g/cm^3}$ (Alptekin and Canakci, 2008), $0.00066 \mathrm{g/cm^3}$ ("Eco energia do brasil - biogas e biomethano - Biometano," n.d.) and $0.00115 \mathrm{g/cm^3}$ (:: "Portal das Energias Renováveis ::," n.d.) as the densities of bioethanol, biodiesel, biomethane and biogas, respectively, to convert them into tons. In the cases the biomethane produced was given in GWh, the equivalent tons of oil were obtained through the site ("Gigawatt hours to tons of oil equivalent (GWh to TOE) - Conversion calculator, formula, and table (chart)," n.d.)

5.4.2– Feedstock

Types of Biomass

In general, the usual types of biomass used are cereals, seeds, corn, animal fats, sugar and waste. The **cereals, corn and sugar** are the most used to produce bioethanol. The **seeds and animal fats** are mainly used to produce biodiesel, but before they are processed into vegetable oils. Only one of the biorefineries had as input not the crude biomass, but these vegetable oils. Due to the shortage of data, there won't be a differentiation between the types of feedstock of each biofuel and, for technological learning, they will be considered as only one type used to produce each. Moreover, it was verified that biorefineries that produced biochemicals, biomethanol and biomethane besides bioethanol and biodiesel, used the same respective feedstock of these last two. All this information regarding the types of biomass that are used in each biorefinery could be found in 92% of the 50 mapped.

Biomass's Collected Quantities

In terms of feedstock quantities, it could only be found information about 25 mapped biorefineries out of the 50. The cases where the quantities of feedstock were not available and it was checked there was also none information about conversion efficiencies, were discarded, since they could not be helpful in the development of the present research (see subchapter 5.5 to see the final biorefineries' database). For one integrated biorefinery (Fin13 in Table 9 in Appendix A) it could not be found the quantity of the non-biofuels products, thus the amount of feedstock known is assumed to be used entirely in the production of the biofuels. At last, when the available information was about daily processing quantities, to obtain the annual processing quantities it was considered that the biorefinery worked 5 days a week and 52 weeks per year.

5.4.3– Technological Conversion Process/Technology

Technological Conversion Process

The technological process (here also named as technology) that the biomass has to go through to transform into a biofuel has many stages. However, the mapped biorefineries were classified, similarly as how literature normally classifies, according to the stage of the process were the conversion to biofuel effectively happens. Having this said, out of the 50 biorefineries, it was only possible to find information about the conversion process used in 35 of them (~70%). From these, 18 used the fermentation process to convert the feedstock into bioethanol, from which one uses it to convert into biomethane as well. Other 9 used the transesterification process and 2 the esterification, to obtain biodiesel. Also, the processes of anaerobic digestion, to obtain biomethane, the hydrotreatment, combustion and the transesterification and esterification together, to obtain biodiesel, were used by only one biorefinery each. When information about the conversion process of a biorefinery was not available, the process assumed to be used was the most used by the others to produce the type of biofuel in question. Thus, the transesterification process as the conversion process into biodiesel and the fermentation process when bioethanol was the product.

After discarding the mapped biorefineries that had no information about feedstock or biofuel quantities, the remaining, from the initial 50, are 13 integrated biorefineries that use the fermentation process, 7 that use the transesterification process, 1 the esterification and 1 the Anaerobic Digestion (see subchapter 5.5 to see the final biorefineries' database). With only 1 biorefinery with data available, from these last two processes is impossible to reach any conclusions regarding efficiency or learning with experience. Given the **transesterification** and **fermentation** processes are the ones with more information available, even if not abundant, they will be the only ones considered for the remaining research.

Technological Process' Conversion Efficiency

When talking about efficiency, it is important to have defined what that efficiency is referring to. For instance, efficiency its commonly related to energy, thus being defined as the amount of energy required to produce a certain amount of an useful output or services (Patterson, 1996). Since in this thesis, the concept under study regards the biomass conversion process, its efficiency herein defined as the percentage of input that is turned into a useful biofuel output by an energy conversion technological process, or, as literature also refers it, by an energy conversion technology. It encompasses the whole process, the actors in it and all the stages that the biomass needs to go through until it becomes a biofuel. However, it is usually recognized only by the stage of the process where the conversion effectively happens (e.g. Fermentation, Transesterification, etc).

In terms of collected data, only 3 integrated biorefineries mapped had information about their processes' conversion efficiencies (Ger207, Ger208 and Ita10 in Table 9 in APPENDIX A) and they were used to obtain the products production or feedstock processed quantities that were not clear. The technology's conversion efficiencies of the remaining integrated biorefineries, were calculated by dividing only the biofuel quantity by the respective feedstock quantity. The co-products quantities were not considered in the calculation due to not always being available and to normalize the efficiencies amongst all biorefineries. Therefore, the conversion efficiency will be the efficiency of converting biomass into biofuel, specifically.

To reach conclusions on the evolution of the conversion efficiencies of the two technologies being considered in the present research, an analysis was made. This analysis was done per technology and, due to shortage of data, the differences in both processes when producing different biofuels from different types of biomass had to be discarded. This was only valid for the biorefineries that received crude biomass. Thus, the transesterification process, used to produce biodiesel from both animal fats and seeds, was considered as one entity, as well as the fermentation process, used to produce both bioethanol and biomethane from sugars, corn and cereals, was also considered. Also, it was not possible to have sufficient data to make an analysis on this evolution, over time, for each biorefinery. Therefore, the final integrated biorefineries of this thesis biorefineries' database had to be used together, per technology, and compared to each other. To do this, the year of the beginning of operation and the year of the information available on the conversion efficiency/feedstock/product's quantities of each bioreifnery were used. They were used to calculate the difference between the two to obtain the years of operation needed to reach their conversion efficiency found with research. Once these were calculated to every biorefinery (10 for the fermentation process and 6 for the transesterification process), Figures 8 and 9 could be obtained. These figures consist in graphics that show the trend of the conversion efficiency with the increase of the years of operation of an integrated biorefinery, for the Fermentation and Transesterification process, respectively (see subchapter 5.5 for more information on the final biorefineries of the database)

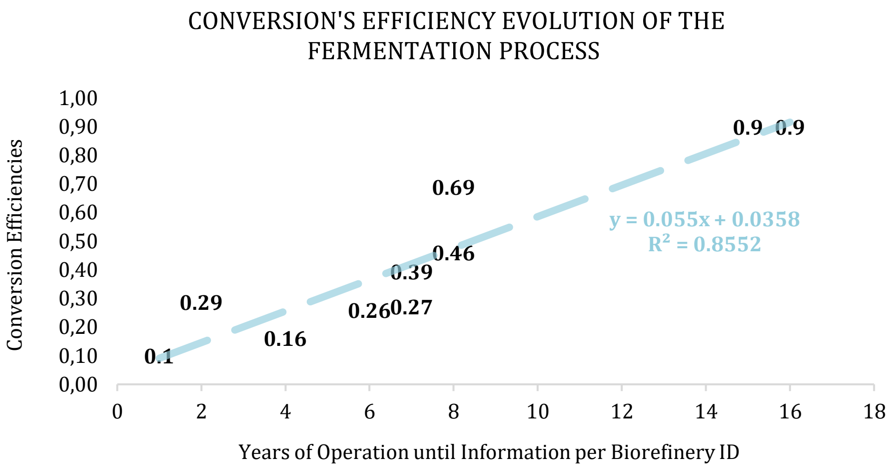

Figure 8– *Evolution of the Conversion Efficiency of the Fermentation Process*

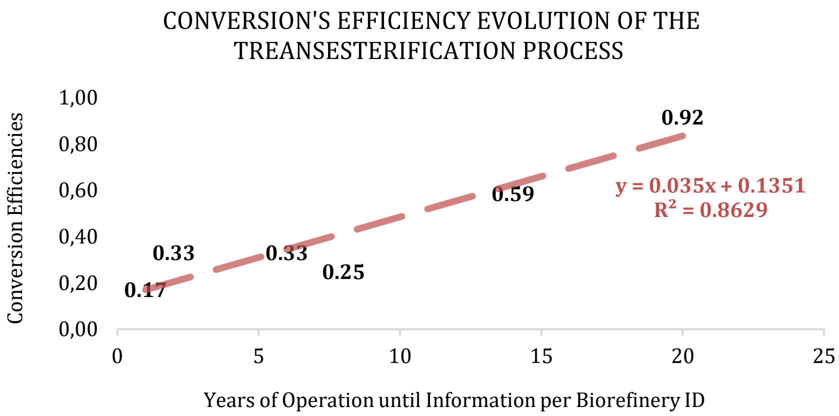

Figure 9- *Evolution of the Conversion Efficiency of the Transesterification Process*

As it can be verified for both technological processes, in Figures 8 and 9, it is clear the existent growth trend over time and, therefore, over the amount of accumulated production carried out by each biorefinery over time. By keeping producing over the years, experience is inevitably gained in the conversion process. The trends also reflects this experience and learning gained by “doing.” This is the reason why the more years pass after a biorefinery installation, the higher the conversion efficiencies reported. Moreover, from the available data, it can be concluded that the fermentation process, by having a higher slope of the tendency line, has a higher increase of the conversion efficiency with time, thus has a faster learning process. However, in the first, approximately, five years, the transesterification process shows higher values of conversion efficiency, point from which the fermentation process shows higher values (time x at which the tendency lines from both technologies cross). Lastly, it is important to refer that by not considering the production of co-products and not including them in the calculus of the conversion efficiency’s values, it is natural that their obtained values presented in the figures above are a little lower than expected.

Technological Processes’ Learning Rates

The information regarding technology’s learning rates could only be found in studies and not online about the mapped biorefineries. Also, learning rates related to the Portuguese case or the EU couldn’t be found. After a deeper research, the study by de Wit et al. 2010 was found. In this study, the learning rate considered with the increase of cumulative production for the transesterification process is 10% and for the fermentation process 20%. The estimation of the first was made for biodiesel from oil crops from seeds and used fats/oils without distinction and based on the study by Berghout 2008. The study applies the learning curve theory to the production of biodiesel in the German context, to quantify the technological learning over a period of 7 years (1993-2000). The estimation of the second learning rate was made for bioethanol from sugar and starch, also without distinction, and based on the studies by van den Wall Bake et al. 2009 and Hettinga et al. 2009. Both use the learning curve theory to determine whether it is a good method to describe the development of production costs due to experience. The first applies it to the Brazilian context over a period of 30 years (1975-2005) and the second to the United

States context over the timeframe 1980-2005. Given after extensive research it could not be found more recent studies or values, the 10% and 20% learning rates for the transesterification and fermentation process, respectively, were used in the present study for the development of the learning curves of each technological process. By using this values, this study also considers the transesterification process for biodiesel from oil crops and used fats/ oils as one entity, as well as the fermentation process from starch and sugar.

5.4.4– Costs

In general, it is difficult to find information about costs of biorefineries. Out of the 50, only the general production costs of 2 biorefineries were found. These were regarded to the total production of all the facilities of the company in question. Thus, they could not be associated to a specific biorefinery and to a specific process, ending up being irrelevant to the present study. Since the amount of costs data was not significant, an extra research was made in order to find more technology production costs. The study by de Wit et al. 2010 was the one found with more information available and regarding the two technologies. This study presented information on costs from the year 2004, thus to obtain current values, an average annual inflation rate of 1.51% was used. Also, the costs were available for the production of biodiesel and bioethanol from different types of biomass. However, as said before, since in this study the differences between the biomasses will not be considered and the technological processes will be seen as one entity, the costs from different biomasses were summed and an average cost was obtained for each technology. Therefore, for the fermentation process, the average production costs of producing bioethanol from sugars/starch obtained was 318.33€/ton of bioethanol and for a capacity of production of 100000ton. For the transesterification process, an average of 198.80€/ton was obtained for the production of biodiesel from oil seeds/fats and for a production capacity of 50000ton. These costs included operation costs, such as labour and utilities, and maintenance direct costs. Moreover, as said before, only the exact process of the transformation to bioethanol and biodiesel is being referred. However, these costs include all the other stages of the process (e.g. milling and oil extraction).

5.5- Data Collection Results

After all the research, data treatment, and assumptions, the data collection results on the biorefineries in the EU are presented below. Table 6 resumes the data found for the fermentation and transesterification process, both ordered by ascending order of number of years of operation of the biorefineries (Year of information – Year of start).

Table 6- Data of the final integrated biorefineries resultant from the data collection process, using the fermentation process and transesterification process.

Fermentation Technological Process							
Learning Rate		20%		**Average Production Cost**		318.33€/ton of bioethanol	
Year of start	**Year of Information**	**Biorefinery ID**	**Type of Feedstock**	**Quantity (ton)**	**Type of Biofuel**	**Quantity (ton)**	**Conversion Efficiency**
2017	2018	Fin13	Sugar/Starch	80000.00	Bioethanol	8000.00	0.10
2018	2020	Net79	Sugar/Starch	100000.00	Biomethane	28750.00	0.29
2012	2016	Hun1	Sugar/Starch	910000.00	Bioethanol	147543.00	0.16
2010	2016	Bel1	Sugar/Starch	910385.00	Bioethanol	236700.00	0.26
2008	2015	Aus1	Sugar/Starch	500000.00	Bioethanol	197250.00	0.39
2008	2015	FranTot	Sugar/Starch	580000.00	Bioethanol	157800.00	0.27
2011	2019	Ita10	Sugar/Starch	154369.57	Bioethanol	71010.00	0.46
2012	2020	Ire8	Sugar/Starch	572000.00	Bioethanol	394500.00	0.69
2005	2020	Ger207	Sugar/Starch	301882.11	Biomethane+ Bioethanol	271693.90	0.90
2004	2020	Ger208	Sugar/Starch	150941.06	Biomethane+ Bioethanol	135846.95	0.90
Transesterification Technological Process							
Learning Rate		10%		**Average Production Cost**		198.80€/ton of biodiesel	
Year of start	**Year of Information**	**Biorefinery ID**	**Type of Feedstock**	**Quantity (ton)**	**Type of Biofuel**	**Quantity (ton)**	**Conversion Efficiency**
2007	2007	Rom8	Seeds/Animal fats	144000.00	Biodiesel	25000.00	0.17
2008	2009	Lat2	Seeds/Animal fats	300000.00	Biodiesel	100000.00	0.33
2009	2015	Bul19	Seeds/Animal fats	180000.00	Biodiesel	60000.00	0.33
2010	2018	Cze20	Seeds/Animal fats	400000.00	Biodiesel	100000.00	0.25
2006	2020	Ger202	Seeds/Animal fats	170000.00	Biodiesel	100000.00	0.59
2000	2020	Ger188	Seeds/Animal fats	71100.00	Biodiesel	65300.00	0.92

5.6- Chapter conclusions

The present chapter describes the data collection process of information about the operation of integrated biorefineries in the EU to further estimate model inputs from real data. Different sources of information were used, including a database from the European Commission's science and knowledge service and public data. However, gathering all the necessary data was difficult and a lot of assumptions had to be made. This resulted in a data collection process with little information, for each biorefinery. It enabled though to, by comparing all biorefineries with each other, see a growth pattern of the conversion efficiency, as the years of operation increase. This proves that, with experience, higher values of conversion efficiency can be obtained, which will certainly result in cost reductions. Thus, with the remaining information on learning rates and unitary costs found, a learning curve that reflects the costs variation of each biorefinery as the conversion efficiency increases can still be obtained.

In the next chapter, the formulation of the learning curves and the stochastic optimization model that will use this collected data as inputs to represent the conversion efficiency's evolution with experience, will be presented, and explained.

6- MODEL FORMULATION

The goal of this chapter is to propose a mathematical formulation of a learning curve that represents the technology development and performance through time, due to learning and maturity. Also, how this formulation will be adapted and integrated in a stochastic optimization model that will be used to test it and the optimization model itself will be here explained. This should leverage the previous knowledge present in the literature regarding the evolution of the conversion efficiency of the conversion technologies used in integrated biorefineries.

In section 6.1, assumptions made to the elaboration of the curves, a description of the formulation itself and some considerations are made. Section 6.2 presents the stochastic optimization model of the biomass SC that will be used to test the adequacy of the learning curve constructed with the collected data. The chapter ends with some conclusions in section 6.3.

6.1- Learning Curve's Mathematical Formulation

6.1.1-Problem features and main assumptions

To formally and mathematically represent the technology evolution, the learning curve theory was chosen to be used and related with the conversion efficiency of the biorefineries' conversion technologies. Even though it is promising, few studies in literature apply the experience curve theory to biomass converting plants. The main reason is related to the variations in these types of plants regarding technology' type, plant size or type of feedstock used, which makes it harder to construct the learning curves (Samadi, 2018). However, from the data collection process presented in chapter 5 and resultant database for the present thesis, it is possible that another reason for the reduced amount of studies on this matter is the shortage of data necessary to the formulation process, especially about costs. Furthermore, this study focuses on studying the technology developments of integrated biorefineries after they reach a commercial level. In these, once it is installed and operational, technology evolution and optimization are most likely to happen due to learning-by-doing. The learning from research and development happened mostly when they were at a laboratory or pilot scale, given it is a phase more dedicated to investigation, research, and tests. Therefore, having all of this in mind, only the one-factor learning curve will be used and the research & development effect in learning will not be considered in the learning curve formulation of this thesis.

Regarding learning system boundaries, these only include the technological process and all of its stages. In other words, the learning is considered to occur since the moment that the biomass, after arriving to the biorefinery, starts the transformation process until it becomes biofuel. Then, it includes all the stages in between, such as the pre-processing of the biomass, conversion stage or others, but also all the handling and labour needed in the process.

At last, each technology/technological process has different characteristics and stages depending on what is being processed and what produced. Consequently, their learning rates are also different, which results in different learning curves. Therefore, the experience curves will be constructed for each technology when it produces a type of biofuel from a type of biomass.

6.1.2- Mathematical Formulation

As said before in the subchapter 3.3, a learning curve relates a technology's specific costs and its experience. It expresses that accumulating the use of a technology increases its experience, which usually translates in an optimization of the technological process involved. This optimization gives space for a technological improvement, usually of an economic nature, that ends up being reflected in cost reductions (Ferioli et al., 2009).

After research in literature of the learning curve model, this relationship and the costs development observed with a one-factor learning curve can be described by equation (1):

$$CC_{bmpt} = CC_{bmp}^{ref}\left(\frac{ACpq_{bmpt}}{X_{bmp}^{ref}}\right)^{-\varepsilon_{bmp}} \quad \text{(Ferioli et al., 2009)} \qquad (1)$$

With:

- $ACpq_{bmpt}$ as the cumulated production of biofuel p from biomass b by conversion technology m in time period t and scenario s, in tons.
- CC_{bmpt} as the unitary cost of production of biofuel p from biomass b by conversion technology m at time period t, in €/ton.
- CC_{bmp}^{ref} and X_{bmp}^{ref} as the initial conditions at an arbitrary starting point, respectively, of the cost, in €/ton, and cumulated production, in tons, of biofuel p from biomass b by technology m.
- $\left(\frac{ACpq_{bmpt}}{X_{bmp}^{ref}}\right)^{-\varepsilon_{bmp}}$ as the ratio of the current accumulated production product p from biomass b of conversion technology m in time period t to its initial accumulated production. This factor represents the reduction in cost of unit production expansion due to learning-by-doing.
- ε_{bmp} as a positive learning coefficient of conversion technology m when producing p from biomass b.

Definition of Costs

In equation (1), the costs are the dependent variable that vary with the increase of experience. Thus, they represent a measure/impact of learning and technological improvement. The choice of the type of costs being considered are related with the learning system boundary defined. Depending on what is being investigated, the costs dimension is defined. For instance, when entire power plants projects are being investigated, usually investment or electricity generation costs are analysed, given they include other relevant cost dimensions, as installation or operating and maintenance costs, or others (Samadi, 2018). Since the learning curves will be constructed by conversion technology, the technology's production costs are the chosen costs dimension for the present analysis.

Having this established, the variable CC_{bmpt} of equation (1) represents the cost per unit of biofuel p generated by technology m from biomass b in period t. Variable CC_{bmp}^{ref} refers to the initial conditions of unitary production cost of technology m.

Definition of Experience

In equation (1), the experience is the independent variable and is usually represented by a cumulative measure of production or use (Nemet, 2006). An appropriate definition of experience also depends on what is being investigated and requires some consideration of where the experience is expected to occur. For example, if significant learning is expected to occur in the installation or construction of single power plants, the cumulative measure should be in terms of number of plants (Samadi, 2018). In this thesis, the developments in the conversion process of the conversion technologies, more specifically, the evolution of their conversion efficiency as a consequence of learning-by-doing, is what is being investigated. As the concept illustrates, the learning occurs by doing and by producing. Thus, learning is expected to occur in the production process. Moreover, while using a certain technology, there are two options: there is an external technological development that enables to change some aspects of a process, making it more efficient, or experience gained by producing enables to do the process in less time. Either way, after the improvements, the amount of product obtained from the same amount of feedstock, in the same amount of time, ends up being bigger than before the improvements, which reflects on a higher conversion efficiency, in that amount of time. Since the first option is external to the process and independent of the operation in a biorefinery, the focus will be on representing the second. Thus, the cumulative production quantity is the definition of experience chosen.

In equation (1), this is represented by variable $ACpq_{bmpt}$ which is the cumulative production of biofuel p by technology t from biomass b in period t.

Learning Coefficient

The learning coefficient or elasticity of the learning-by-doing factor ε_{bmp} of equation (1) defines the slope of a power function. It is a measure of the impact the learning-by-doing factor has, in this case, on the unitary production costs of a conversion technology m producing biofuel p from biomass $b,$ in time period t. Also, it can be obtained through the learning rate (Nemet, 2006).

The learning rate (LR) expresses the experience gained, in this case, by the conversion technologies, by being the rate at which their costs decline as their experience doubles (Samadi, 2018). The higher the rate, the bigger the decrease in costs for each doubling of experience. This means the gained experience is higher and the learning process faster. On contrary, the lower the rate, the smaller the decrease, and consequent slower process of learning. However, different technologies producing different biofuels from different biomasses, as expected and confirmed with research, have different learning processes. Then, the learning rate is dependent of the technology, product and feedstock.

Therefore, the rate at which the unitary conversion technology's cost CC_{bmpt} decreases as the cumulative production quantity doubles $ACpq_{bmpt}$ for each technology m, biofuel p and biomass b, can be defined as:

$$LR_{bmp} = 1 - 2^{-\varepsilon_{bmp}} \qquad \text{(Wiesenthal et al., 2012)} \qquad (2)$$

Alternatively to the LR, the progress ratio (PR) represents the remaining costs after a doubling of experience (Samadi, 2018). Thus, the remaining conversion technology unitary costs CC_{bmpt} once the cumulative production quantity AC_{bmpt}, doubles, can be described as:

$$PR_{bmp} = 1 - LR_{bmp} \qquad \text{(Wiesenthal et al., 2012)} \qquad (3)$$

<u>Conversion Efficiency</u>

As explained before, in this thesis, the concept under study is the conversion efficiency: the percentage of input that is turned into a useful output by an energy conversion process. It is also assumed that the co-products of the biofuel production will not be considered given the lack of information on their quantities in some biorefineries. Thus, the conversion efficiency of a technology m producing a biofuel p from biomass b in a time period t in this study, is defined as the amount of the biomass feedstock bf_{bmt} that is processed and converted only into the amount of biofuel pq_{pmt} produced:

$$\mu_{conversion_{bmpt}} = \frac{pq_{bmpt}}{bf_{bmpt}} \qquad (5)$$

If the cumulative quantities over time of the biomass feedstocks $ACbf_{bmt}$ and biofuels $ACpq_{bmpt}$ are considered instead of their amount in each time period, equation (1) can then be written as:

$$C_{bmpt} = CC_{bmp}^{ref} \left(\frac{\sum_t \mu_{bmpt} . bf_{bmt}}{\mu_{bmpt_0} . bf_{bmt_0}}\right)^{-\varepsilon_{bmp}} \qquad (6)$$

From equation (5) a relationship between the conversion efficiency and the chosen measure of experience – the accumulated conversion technology's production quantity $ACpq_{bmpt}$ – can be obtained. Therefore, the higher the values of conversion efficiency, the higher the accumulated production quantities obtained. Since this last translates into a higher amount of experience, the first can too and also have impact and influence the conversion technology's cost CC_{bmpt} of producing biofuel p from biomass b in time period t, as shown with equation (6). Moreover, this influence on costs is variable, given the conversion efficiency $\mu_{conversion_{bmpt}}$ of a technology m is time dependent. This was concluded from Figures 8 and 9 of chapter 5.4.3 that show that with time passing by and experience being gained through the years, the values of the conversion efficiency tend to increase. Thus, the amount in which the accumulated production increases in consecutive time periods of equal duration is higher as the efficiency of the process increases. This will translate in increasing reductions in costs over time.

Concluding, equation (5) is the equation that represents the relationship between conversion efficiency and the experience gained and equation (6) - the expression of the learning curve - is the equation that will show, over time, the impact of gaining experience with production and, thus, of increasing the conversion efficiency in terms of costs.

6.2- Stochastic Optimization Model's Mathematical Formulation

6.2.1– Problem Features and Model Construction

To test if the learning curve formulation presented in section 6.2 is adequate to represent the evolution of the conversion technologies and the impact of their future conversion efficiencies on costs, a stochastic optimization model will be used. Since the case study, SC and uncertainty in question is the same and also, there is the opportunity to work with the authors of the study, the two-stage stochastic MILP model constructed by Paulo et al. 2020 for the design of the biomass SC considering the uncertainty in the conversion efficiency will be used and adapted to the present study (a compact version of the original model of Paulo et al. 2020 can be found in Table 10 in APPENDIX B).

Just like the original, this thesis stochastic optimization model uses a scenario tree approach, composed with nodes and arcs, to handle the uncertainty under study in the context of a two-stage stochastic programming model. Each node represents the possible outcome of the conversion efficiency with an associated probability of occurrence, the arcs represent the different evolutions it may have, and each scenario is represented by the path from the root to a leaf node. In this approach, the decision variables are divided into first-stage variables and second-stage variables. The first-stage variables are the ones related to decisions being made before the uncertainty is revealed – plant location, capacity and process technology - and the second-stage ones correspond to decisions being made after having full information on the uncertain parameters – production and processing quantities and transfer flows. Furthermore, the model of the present study contributes to the one by Paulo et al. 2020 by accounting the impact on costs of the conversion efficiency evolution due to technological developments using the learning curve theory. However, the approach to include them in the model whilst still having a linear problem was to use them to calculate the production costs of each technology for different levels of accumulated production of a certain type of product from a certain type of feedstock. This turns into a parameter that feeds the model with personalized production costs for each accumulated production level that decrease at the same time as these last increases and thus, illustrating the learning curve theory. Finally, while the model by Paulo et al. 2020 includes intermediate processing/storage facilities, the model of this study will not since its focus is the biorefineries and their processing technologies. The results of this thesis adapted stochastic optimization model will then be compared to a deterministic version of it and some conclusions will be reached.

Having this said, the next subsections are dedicated to present and explain the mention adapted version of the model developed by Paulo et al. 2020. Before presenting it, the notation is formally introduced. This includes the sets, subsets, parameters and decision variables, with respective notation and description of each symbol. Then, the objective function is presented and, finally, the constraints are introduced.

6.2.2– Sets and Subsets

The following sets are defined:

- $b, \bar{b} \in B$: Biomass type
- $p \in P$: Products
- $i \in I$: Biomass collection sites
- $k \in K$: Integrated biorefinery site
- $v \in V$: Market site
- $q \in Q$: Integrated biorefinery's conversion capacities
- $m \in M$: Integrated biorefinery's conversion technology
- $r \in R$: Biomass transportation mode
- $z \in Z$: End product's transportation mode
- $t, \bar{t} \in T$: Time periods
- $s, \bar{s} \in S$: Scenario tree nodes
- $n \in N$: Level of accumulated production in the biorefineries

Together with the following subsets:

- $W_P = \{(m,p): m \in M \wedge p \in P\}$: Available conversion technology m to produce product p.
- $W_B = \{(m,b): m \in M \wedge b \in B\}$: Available conversion technology m to process biomass b.
- $R_B = \{(b,r,t): b \in B \wedge r \in R \wedge t \in T\}$: Available transportation mode r to transport biomass b in time period t.
- $Z_P = \{(p,z,t): p \in P \wedge z \in Z \wedge t \in T\}$: Available transportation mode z to transport product p in time period t.
- $CE_{BP} = \{(b,m,p,s,t): p \in P \wedge b \in B \wedge m \in M \wedge s \in S \wedge t \in T\}$: Available technology efficiency of transforming biomass b into product p by technology m.
- $D_B = \{(i,k): i \in I \wedge k \in K\}$: Maximum distance between biomass collection site i and biorefinery k to acquire biomass.
- $S = \{(s,t): s \in S \wedge t \in T\}$: Node s of the scenario tree in each time period t.
- $H = \{(s,\bar{s}): s \in S \wedge \bar{s} \in S\}$: Predecessors $\bar{s}$ of node s in the scenario tree.

6.2.3– Parameters

The parameters are essential to the model, given they that represent input data to the model. The parameters used in this model are presented below, in groups.

<u>**Distance Parameters**</u>

- DIK_{ik} : Distance between biomass collection site i and integrated biorefinery site k (km).

- DKV_{kv} : Distance between integrated biorefinery k and market site v (km).

Cost Parameters

- CB_{bit} : Cost of biomass type $b \in B$ at biomass collection site i in time period t (€/ton).
- CIB_{mqt} : Installation cost of an integrated biorefinery facility with conversion technology m and conversion capacity q (€).
- CFB_{mqt} : Annual fixed operation costs of an integrated biorefinery facility with conversion technology m, conversion capacity q, in time period t (€).
- CC_{bmpnt}: Annual variable operation costs of a conversion technology m when producing product p from biomass b in time period t, at a given level of accumulated production n.
- CTB_{brt} : Biomass b transportation costs using transportation mode r, in time period t (€/km/ton).
- CTP_{pzt} : End product p transportation costs using transportation mode z, in time period t (€/km/ton).

Demand Parameters

- DP_{pvt} : Demand of end product p at market site v, in time period t (ton).

Production Parameters

- CAP_{mq} : Integrated biorefinery's conversion capacity q with conversion technology m (ton).
- LAC_n: Levels n of accumulated production.
- Max: Value of maximum possible production.

Resource Parameters

- BA_{bit} : Amount of available biomass $b \in B$ at biomass collection site i, in time period t (ton)

Efficiency Parameters

- μ_{bmpst} : Conversion efficiency of transforming biomass $b \in B$ into end product p by conversion technology m in scenario s and time period t.
- Ψ_s : Probability of scenario tree node s.

Conversion Parameters

- PTB_{mb} : $\begin{cases} 1, & \text{if conversion technology } m \text{ is available to process biomass b} \\ 0, & \text{otherwise} \end{cases}$
- PTP_{mp}: $\begin{cases} 1, & \text{if conversion technology } m \text{ is available to produce end product } p \\ 0, & \text{otherwise} \end{cases}$

6.2.4– Decision Variables

The model includes continuous non-negative and binary variables. Both are presented bellow:

Continuous non-negative variables

- $BF_{bikmrst}$: Flow of biomass $b \in B$ from biomass collection site i to integrated biorefinery site k with technology m using transportation mode r for scenario node s in time period t (ton).

- I^B_{bkmst} : Total flow of biomass b that goes into the integrated biorefinery's site k to technology m in time period t ad scenario s.
- PQ_{bmpkst}: Production quantity of product p by tecchnology m from biomass b on biorefinery site k, in time period t and scenario s
- $PQ^L_{bmpknst}$: Production quantity of product p from biomass b by tecchnology m on biorefinery site k, correspondent to accumulated production level n, time period t and scenario s.
- $ACPQ_{bmpkst}$: Accumulated production quantity of product p from biomass b from technology m on biorefinery's site k, in time period t and scenario s.
- $PF_{mpkvzst}$: Flow of product p, obtained by conversion technology m, from integrated biorefinery site k to market v by transportation mode z for scenario node s in time period t (Mg)

Binary Variables

- Y^B_{kmqt} : $\begin{cases} 1, \text{ if opens an integrated biorefinery on site k with converson technology m with processing capacity q, in time period t. If opens, it will not close.} \\ 0, \text{otherwise.} \end{cases}$
- O^B_{kmqt} : $\begin{cases} 1, \text{when opens an integrated biorefinery on site k with conversion technology m with processing capacity q, in time period t. If opens, it will not close.} \\ 0, \text{otherwise.} \end{cases}$
- Y^N_{kmnst} : $\begin{cases} 1, \text{ if integrated biorefinery on site k with conversion technology m with is on level n of accumulated production in time period t. and scenario s.} \\ 0, \text{otherwise or biorefinery is not installed.} \end{cases}$

6.2.5– Objective Function

This model has an economical focus and seeks to minimize the expected supply chain costs, given, as mentioned before, this is important to leverage the biofuels as a sustainable competitive alternative to fossil fuels. The expression is given by equation (8):

$$
\begin{aligned}
Min\ Cost^{SC} = \sum_s \Psi_s \Bigg(& \sum_{b:(m,b)\in W_B} \sum_{i:(i,k)\in D_B} \sum_k \sum_m \sum_{r:(b,r,t)\in Z_B} \sum_t BF_{bikmrst} CB_{bit} + && (8a) \\
& \sum_{b(m,b)\in W_B} \sum_m \sum_{p:(m,p)\in W_P} \sum_k \sum_n \sum_t CC_{bmpnt} PQ^L_{bmpknst} + && (8b) \\
& \sum_{b:(m,b)\in W_B} \sum_{i:(i,k)\in D_B} \sum_k \sum_m \sum_{r:(b,r,t)\in Z_B} \sum_t BF_{bikmrst} DIK_{ik}\ CTB_{brt} + && (8c) \\
& \sum_{b:(m,b)\in W_B} \sum_{p:(m,p)\in W_P} \sum_m \sum_k \sum_v \sum_{z:(p,z,t)\in Z_P} \sum_t PF_{bmpkvzst}\ DKV_{kv}\ CTP_{pzt} \Bigg) && (8d) \\
& + \sum_k \sum_m \sum_q \sum_t O^B_{kmqt}\ CIB_{mqt} && (8e) \\
& + \sum_k \sum_m \sum_q \sum_t Y^B_{kmqt}\ CFB_{mqt} && (8f)
\end{aligned}
$$

(8)

The costs that are being minimized include:

- The **total biomass acquisition cost** $(8a)$, which is calculated with the biomass acquisition cost CB_{bit} and the total outflow flow $BF_{bikmrst}$ in period time t, given it represents the total quantities purchased in all suppliers.
- The **total fixed operating costs** of the integrated biorefineries$(8f)$ that consider if an integrated biorefinery opens (Y^B_{kmqt}), a fixed costs CFB_{mqt} for the integrated biorefineries cannot be avoided. These are costs constant over time, in the long run, such as insurance, interests and taxes, depreciation, administration expenses, etc.
- The **total variable operating costs** of the biorefineries $(8b)$, account for utilities, direct labor, production, maintenance direct costs and all costs that vary with the operation (CC_{bmpnt}) and are multiplied by the amount of production in the facility $PQ^L_{bmpknst}$. These costs are calculated with the use of learning curves that, as defined in subchapter 6.1, use the accumulated production as the definition of experience. Thus, they are dependent on the level of accumulated production each facility has reached in each time period and scenario, and decrease each time one facility reaches a new level of accumulated production.
- The **annualized investment costs** of integrated biorefineries (8e), determined by the annualized investment cost CIB_{mqt} of a facility with a given technology and conversion capacity, multiplied by a binary variable O^B_{kmqt}. The binary enables to account this cost only in the time period the integrated biorefinery is installed.
- The **transportation costs** for biomass $(8c)$, that include all possible movements of biomass $BF_{bikmrst}$ transported from the biomass collection sites i to integrated biorefinery sites k in transportation modes r, multiplied by the distances DIK_{ik} and unitary transportation costs CTB_{brt}.
- And finally, the **transportation costs** for end products$(8d)$, that account the costs of moving the products from the integrated biorefinery site k to the market v by multiplying the unitary transportation cost CTP_{pzt} by the distance between the two DKV_{kv} and the flow of products $PF_{bmpkvzst}$.

All, but the fixed and installation costs of the integrated biorefineries facilities$(8e - 8f)$, are dependent of the scenario s of the conversion efficiency. This because, the conversion efficiency is an uncertainty that affects the amount of product produced in the integrated biorefineries and necessary amount of biomass to do it. Consequently, will also affect the biomass's and end-product's flows. Since the efficiency is dependent of the scenarios in which it is defined, the remaining variables that dependent on it, are also dependent of each scenario.

6.2.6– Constraints

Finally, the constraints of the model are presented. These are divided into the following groups:

- <u>Biomass availability</u>: this constraint guarantees that all biomass flows $BF_{bikmrst}$ that leave a biomass collection site i cannot exceed the available biomass BA_{bit} on that site.

$\sum_{m:(m,b)\in W_B} \sum_k \sum_{r:(b,r,t)\in Z_B} BF_{bikmrst} \ \leq \ BA_{bit} \quad \forall\, b \in B \ \wedge \ \forall i \in I \ \wedge \ \forall t \in T \ \wedge \ \forall s \in S$ (9)

- <u>Total inflow of integrated biroefineries:</u> this constraint ensures that the amount of biomass I^B_{bkmst} that is going to be processed by technology m in biorefinery k is equal to the amount of biomass $BF_{bikmrst}$ that arrives to that biorefinery from the various transportation modes and biomass collection sites.

$\sum_{b:(m,b)\in W_B} \sum_i \sum_{r:(b,r,t)\in Z_B} BF_{bikmrst} \ = \ \sum_{b:(m,b)\in W_B} I^B_{bkmst} \quad \forall\, k \in K \wedge \forall m \in M \wedge \forall t \in T \wedge \forall s \in S$ (10)

- <u>Mass balance between the inflow and outflow of an integrated biorefinery</u>: equation (11) states that all flows of biomass I^B_{bkmst} that arrive at the biorefinery site multiplied by the conversion efficiency of the technologies that are available to process them, must be equal to the production quantities of all products produced on that site.

$\sum_{b:(b,m,p)\in CE_{BP}} \sum_{p:(b,m,p)\in CE_{BP}} I^B_{bkmst} \mu_{bmpst} = \sum_{b:(m,b)\in W_B} \sum_{p:(m,p)\in W_P} PQ_{bmpkst} \quad \forall m \in M \wedge \forall k \in K \wedge \forall t \in T \wedge \forall s \in S$ (11)

- <u>Total outflow of integrated biorefinery</u>: this constraint illustrates that the amount of production quantity by a technology m in an integrated biorefinery site k has to be the same as the sum of all products' flows that are sent from that biorefinery's site to the markets.

$\sum_{b:(m,b)\in W_B} \sum_{p:(m,p)\in W_P} PQ_{bmpkst} = \sum_{p:(m,p)\in W_P} \sum_v \sum_{z:(p,z,t)\in Z_P} PF_{mpkvzst} \qquad \forall k \in K \ \wedge \ \forall m \in M \ \wedge \ \forall t \in T \ \wedge \ \forall s \in S$ (12)

- <u>Demand satisfaction</u>: This constraint guarantees that the demand is satisfied. Thus, the sum of each product produced must be equal or greater than the demand for that product in each market and time period.

$\sum_{m:(m,p)\in W_P} \sum_k \sum_{z:(p,z,t)\in Z_P} PF_{mpkvzst} \ \geq \ DP_{pvt} \ \forall p \in P \wedge \forall v \in V \wedge \forall s \in S \wedge \forall t \in T$ (13)

The next constraints presented, are the ones that define the installation of the integrated biorefineries. These will identify the best locations to install them, their technologies and capacities.

- <u>Number of integrated biorefineries installed:</u> this constraint defines that is only allowed to install one biorefinery facility with a given conversion technology m with capacity q, in each time period t, as shown in equation (14).

$\sum_m \sum_q Y^B_{kmqt} \ \leq \ 1 \quad \forall k \in K \wedge \ \forall t \in T$ (14)

- Production capacities of integrated biorefinery facilities: also, it is important to ensure the production of technology m cannot exceed its installed production capacity. Thus, the total production quantity of technology m in biorefinery site , in period t and scenario s , must be lower or equal to its capacity of production PBC_{mq} . This last multiplied by the binary variable Y^B_{kmqt}, that identifies if a given technology m is installed in a biorefinery on site k with capacity of production q, in time period t.

$$\sum_{b:(m,b)\in W_B} \sum_{p:(m,p)\in W_P} PQ_{bmpkst} \le \sum_q PBC_{mq}\, Y^B_{kmqt} \quad \forall k \in K \wedge \forall m \in M \wedge \forall s \in S \wedge \forall t \in T \quad (15)$$

- Installed facilities remain open: this constraint defines that if a biorefinery opens, then it will not close during the project time horizon. This is reasonable to assume, given the costs of installing a biorefinery are significant enough to difficult the decision of closing it in the following time periods.

$$Y^B_{kmqt} \ge Y^B_{kmq\bar{t}} \quad \forall k \in K \wedge \forall m \in M \wedge \forall q \in Q \wedge \forall t \in T \quad (16)$$

- When an integrated biorefinery facility opens: the following two constraints identify when a biorefinery opens for the first time period (17) and for the subsequent time periods (18). Equation (17) ensures that the first time the binary variable Y^B_{kmqt} is one, that's the time period when the biorefinery opens. Equation (18) ensures that if a biorefinery opens in the previous time period, then it will not open in the present time period.

$$O^B_{kmqt} = Y^B_{kmqt} \quad \forall k \in K \wedge \forall m \in M \wedge \forall q \in Q \wedge t = 1 \quad (17)$$

$$O^B_{kmqt} = Y^B_{kmqt} - Y^B_{kmqt-1} \quad \forall k \in K \wedge \forall m \in M \wedge \forall q \in Q \wedge t > 1 \quad (18)$$

The next constraints are this study contribution to the model developed by Paulo et al. 2020. These are constraints that enable the model to consider the impact of the experience and conversion efficiency evolution on costs using the learning curve theory. Equations (19-20) focus on the chosen definition of experience of the conversion technologies – the accumulated production. Equations (21-22) focus on defining the level of total accumulated production $ACPQ_{bmpkst}$ each technology has reached in scenario s and time period t. Finally, equations (23-24) focus on corresponding the level of accumulated production, and thus experience, a technology has reached in time period t and scenario s to its production PQ_{bmpkst} in the same scenario and time period.

- The accumulated production quantity of biofuels: the next two constraints define the accumulated production an installed technology m on a biorefinery facility site k has in scenario s for the initial time period (19) and the remaining time periods (20). In equation (19), for the first time period, the accumulated production of biofuel p from biomass b by a technology m is the same amount of the total production of that product from that biomass. In equation (20), for the remaining time periods, the accumulated production of biofuel p from biomass b by technology m is the total production of the present time period t and scenario s, plus the accumulated production of the previous time period $t-1$ and predecessor $\bar{s}$ of scenario node s.

$$ACPQ_{bmpkst} = PQ_{bmpkst} \; \forall k \in K \; \wedge \; \forall s \in S \; \wedge \; \forall m \in M \wedge \forall p \in P \wedge \forall b \in B \; \wedge (m,p) \in W_P \; \wedge (m,b) \in W_B \; \wedge \; \forall t = 1 \tag{19}$$

$$ACPQ_{bmpkst} = PQ_{bmpkst} + ACPQ_{bmpk\bar{s}(t-1)} \; \forall k \in K \; \wedge \; \forall s \in S \; \wedge \; \forall \bar{s} \in H \; \wedge \; \forall m \in M \wedge \forall p \in P \wedge \forall b \in B \; \wedge (m,p) \in W_P \; \wedge (m,b) \in W_B \; \wedge \; \forall t > 1 \tag{20}$$

- Number of levels of accumulated production: This constraint ensures that the accumulated production of conversion technology m, in each time period and scenario, belongs to at most one level of accumulated production and, consequently, has one associated unitary cost. If the binary is zero, either the level accumulated production was not reached or the biorefinery was not installed.

$$\textstyle\sum_n Y^N_{kmnst} \leq 1 \; \forall k \in K \; \wedge \; \forall s \in S \; \wedge \; \forall m \in M \wedge \forall t \in T \tag{21}$$

- Level of accumulated production: the next to constraint defines the level of accumulated production a technological process m in each biorefinery has reached. Thus, the accumulated production $ACPQ_{bmpkst}$ of technology m in scenario s and time period t, must be between two consecutive levels of accumulated production multiplied by the binary variable Y^N_{kmnst}. The binary identifies if the technology's accumulated production is between those two levels of experience. In the cases it is, it associates that accumulated production of the technology with the level that has the lower accumulated production quantity.

$$\textstyle\sum_n LAC_n \, Y^N_{kmnst} \; \leq \; ACPQ_{bmpkst} \leq \; \sum_n LAC_{n+1} \, Y^N_{kmnst} \; \forall k \in K \; \wedge \; \forall s \in S \; \wedge \; \forall m \in M \wedge \forall p \in P \wedge \forall b \in B \; \wedge (m,p) \in W_P \; \wedge (m,b) \in W_B \; \wedge \; \forall t = T \tag{22}$$

- Correspondent level of accumulated production of the total production: The two equations bellow correspond the total production of a technology in a time period t and scenario s to the level of accumulated production it enabled the technology to reach in the same time period and scenario. This is done using an auxiliary variable of production quantity $PQ^L_{bmpknst}$ that assumes the value of the production quantity PQ_{bmpkst} when the binary yN_{kmnst} is equal to 1 for a technology m in level of accumulated production n. This auxiliary variable enables the model to be maintained linear. The parameter Max is the maximum value of production that exists for any technology and it has to be higher than any possible value for PQ_{bmpkst}. This way, the parameter will guarantee that the auxiliary non-negative variable $PQ^L_{bmpknst}$ will be zero when yN_{kmnst} is zero.

$$PQ_{bmpkst} - (1 - yN_{kmnst}) * Max \leq PQ^{L}_{bmpknst} \leq PQ_{bmpkst} + (1 - yN_{kmnst}) * Max \quad \forall k \in K \ \wedge \ \forall \, n \in N \wedge \ \forall \, s \in S \ \wedge \ \forall m \in M \wedge \ \forall p \in P \wedge \ \forall \, b \in B \ \wedge (m,p) \in W_P \ \wedge (m,b) \in W_B \ \wedge \ \forall \, t = T \tag{23}$$

$$\sum_n PQ^{L}_{bmpknst} \leq \sum_n yN_{kmnst} * Max \quad \forall k \in K \ \wedge \ \forall \, s \in S \ \wedge \ \forall m \in M \wedge \ \forall p \in P \wedge \ \forall \, b \in B \ \wedge (m,p) \in W_P \ \wedge (m,b) \in W_B \ \wedge \ \forall \, t = T \tag{24}$$

6.3- Chapter Conclusions

In this chapter, the problem features are presented, and a learning curve model is developed. This model is proposed to tackle the lack of consideration of the evolution of the technology conversion factor due to the maturation of technology through time and represent the impacts it has. Thus, once the specific costs and measure of experience were defined, an equation of a curve that considers this evolution was possible to be constructed. Furthermore, an adapted two-stage stochastic MILP optimization model for the design of the biomass SC is presented. In order to maintain the problem linear, the unitary costs of production of each conversion technology are included in the optimization model as a parameter and are calculated for various levels of experience using the learning curve model. Then, to include the logic of the learning curve theory, the optimization model uses the defined measure of experience – the accumulated production - of the learning curve model as a variable and associates it to an accumulated production level that has an assigned unitary cost. This way, in the optimization model, by increasing the accumulated production of a technology and thus, its experience, the associated unitary production costs will still be decreasing.

The next step involves applying this model to this thesis case study.

7- CASE STUDY

This chapter introduces the case study to which the stochastic optimization model of this thesis will be applied. After, the network at study is characterized and the data collection and analysis procedures regarding the case study are explained. Finally, some conclusions are made.

7.1- The Portuguese Case

The energy sector has huge economic and environmental impact, because besides contributing to the creation of employment, its effects are positive or negative in the environment depending on the sources. As explained in chapter 2.1, the EU is working towards becoming an economy that consumes secure, safe, competitive and, most importantly, sustainable energy. It has created regulations, energy packages, defined goals, etc., and, at the moment, it has a plan - the 2030 Climate Target Plan - to reduce greenhouse emissions to at least 55% below 1990 levels by 2030. In order to meet the targets of the plan, all EU Member States needed to submit, by the end of 2019, a 10-year integrated national energy and climate plan (NECP) for the period from 2021 to 2030. This plan had to address energy efficiency, renewables, GHG emissions reductions, interconnections and research and innovation (fernbas, 2019).

Regarding the Portuguese reality, the “Resolução do Conselho de Ministros nº53/2020” approves the National Plan of Energy and Climate 2030 (PNEC 2030) of Portugal. In this plan, besides being defined goals of GHG emissions’ reductions, the reduction of the primary energy consumption to improve the energy efficiency and increase of electricity interconnections, it was defined the incorporation of 47% energy from renewable sources in the final gross energy consumption. This doesn’t seem to be a problem given the country has been registering a good progress in its renewable energy objectives. The “Resolução do Conselho de Ministros nº53/2020” states that in 2018, around 30.3% of the final consumption of energy in Portugal was satisfied using renewable sources. This percentage goes in line with the country’s goal to be reached in the year 2020: 31% of renewable sources of energy in the final energy consumption and 10% of renewable energy sources in the final consumption of energy in transportation – the commitment done with the European Commission. Moreover, in 2017, the “Resolução do Conselho de Ministros nº163/2017” considers the existent national potential and approves the National Plan for the Promotion of Biorefineries (PNPB). The PNPB enforces the valorisation of renewable sources of energy by supporting the use of biomass as an alternative source of energy to fossil resources. Also, presents a strategy, for the next years until 2030, to promote biorefineries in the national territory, employment and energy independency, to contribute to the reduction of GHG’s emissions and to enhance biomasses that haven’t been valued, that are residual or with low energetic value. An example is the residual biomasses from forests and agriculture. These have great potential since they do not compete with the human and animal food chain and given Portugal has considerable potential on the production of those.

Even though they are not in this thesis final biorefinery database due to lack of information, Portugal has two main biofuel producers that contribute to achieving the objectives stated before: the Sovena group and the Prio group. The first has a production unit that consumes oilseeds to obtain biodiesel and glycerine and operates in a fully integrated way. Thus, ensures that everything is transformed and contribute to a greener energy. Regarding Prio, it has a biodiesel plant located in the Port of Aveiro and it was the first company in Portugal to offer biodiesel blends they consider to be reach and that enhance the lubrication, efficiency, and engine performance of their diesel.
Having now a picture of the Portuguese context, it is safe to say the model presented in this thesis is adequate and contributes to the country's objectives and future plans regarding bioenergy and biofuels. The model will then be fed with data based on the Portuguese reality, except in cases when data from Portugal is insufficient or inexistent. Either way, the model's inputs are exposed in the next section.

7.2- Case Study's Data Collection

This section focuses on the collected data for the optimization model inputs. The most uncertain parameters and the assumptions made are also here explained. Moreover, all the sources used, such as literature, public information, companies and expert's data will be identified.

7.2.1- Network Characterization

A graphical representation of the biomass SC network structure and respective flows is presented in Figure 10. The network structure used was similar to the used by Paulo et al. 2020, but without the pre-processing facilities, as they made the problem more complex and were secondary to the study's focus on biorefineries and their conversion technologies. It contains as nodes biomass collection sites, integrated biorefineries, markets and transportation mode. However, some the elements used to define the operation of each node, such as types of biomass, technology, and products were adapted according to the research done in the present study and the information collected and presented in chapter 5.

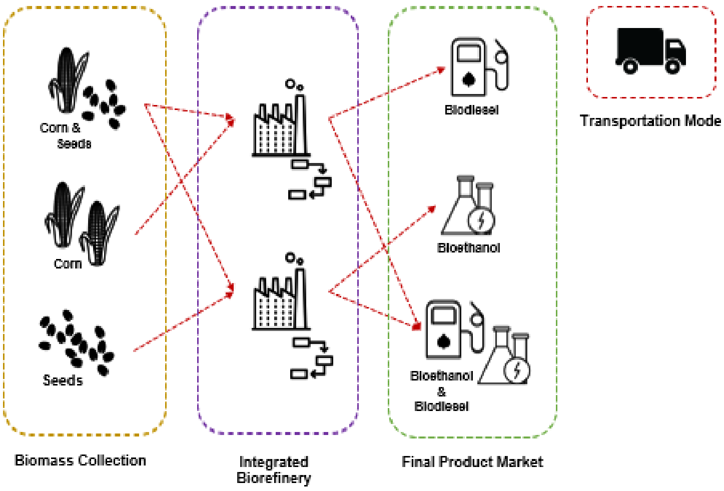

Figure 10- *Supply Chain Structure*

Regarding the considered SC network:

- **Biomass Collection Sites:** These are the geographic places, in Portugal, that are potential candidates to biomass collection. 150 out of 278 Portuguese municipalities were considered after excluding the ones with the calculated quantities relatively low to be considered as biomass production sites. Also, the collection sites are assumed to exist in the headquarters of each. Regarding the calculation of biomass availability on each, in chapter 5 it is defined the types of biomass considered in this study from the information found with research. Also, the different biomass types found for the production of each were considered together as one entity. Thus, for the considered category of sugar/starch biomass, quantities of corn/cereals production were searched and for seeds/animal fats biomass catergory, quantities of sunflower seeds production were searched for each of the considered Portuguese municipalities. From the National Statistics Institute of Portugal's website ("Portal do INE," n.d.), for each municipality could be obtained their total surfaces in acres, the percentage of starch/sugar and seeds/animal fats surface occupation from their total area dedicated to agricultural occupation and their productivity per acre for each type of biomass. These data are from 2018, however were considered updated. From the Direção-geral dos Território's website, a search made for the year 2020 on the land use and occupation in Portugal was found ("Uso e ocupação do solo em Portugal continental 1995 a 2018 | DGT," n.d.). In this report it is possible to find the percentages of agricultural occupation of each municipality and the percentage of that dedicated only to the production of crops (seeds and grains). The information from these two websites enabled to calculate both biomass types availability, in tons, for each municipality. The final biomass quantities available can be found in Table 11 in Appendix C and they are assumed to be constant over the time horizon of this study.
- **Integrated Biorefinery's Sites:** Different types of biomass can be routed to different integrated biorefineries depending on the technologies they have installed. In these, biomass goes through many stages until is transformed into biofuel. The two technological conversion processes considered are the fermentation and the transesterification processes and they can only process starch/sugar to produce bioethanol and animal fats/seeds to produce biodiesel, respectively. These conclusions were a result of the research presented in chapter 5 and the available information found with it. There are 28 potential sites considered for biorefinery's plant installation that can have either one of the technologies. Some of them are districts and others are municipalities. For both options, the installation location of the biorefineries was considered in the geographic centre of each.
- **Markets Sites:** The market sites considered are the headquarters of each one of the 18 districts of Portugal. These locations will receive biofuels from the integrated biorefineries depending on the demand of each biofuel. As stated before, the biofuels considered in this study are only biodiesel and bioethanol, thus research was done to find their demands in Portugal. Once again, the website of the National Statistics Institute of Portugal ("Portal do INE," n.d.) was consulted

and the consumption of gasoline, diesel, and biodiesel were found for each municipality, which then enabled to calculate the respective amounts of each district. With the demand of the biodiesel being known, to obtain the demand values of bioethanol, the mandatory incorporation of 10% of biofuel in the road fuels quantities was used. This percentage was stipulated for the years between 2011 and 2020 in terms of Artº 13 from the Portuguese Government's Decreto-Lei nº117/2010, of 25th of October of 2010. This percentage has been updated in Portugal, however it is the one considered given it goes in line with the mandatory objective the European Parliament approved for each member state to reach until the year of 2020 (Directive 2009/28/CE of the European Parliament). Having the total amount of consumption of fuels and biodiesel, the bioethanol consumption was calculated in order for the sum of quantities of biodiesel and bioethanol consumption to equal 10% of the fuels consumption. The final biofuels demand can be found in Table 19 in Appendix C and they are assumed to be constant over the time horizon of this study.

The distances between biomass collection sites and integrated biorefinery sites can be found in Table 12 and the distances between integrated biorefinery sites and market sites can be found in Table 13, both in Appendix C. These were the same used by Paulo et al. 2020 and are distances by road between the headquarters of each municipality or district obtained from the Portuguese organization that manages the road infrastructure.

7.2.2- Definition of Scenarios

The scenario tree approach in the model was used to study possible future situations. Each node represents a distinct conversion efficiency of each technology/technological conversion process when processing a type of biomass into a type of biofuel.

The conversion efficiencies are calculated based on the research done in chapter 5. After mapping the integrated biorefineries of the EU and finding all possible information on their specifications, it was possible to obtain the values of the conversion efficiency of transforming biomass into biofuels (and only biofuels) of each. These allowed to obtain two tendency lines: one for the fermentation process (m_1) to produce bioethanol (p_1) (equation (25)) and other for the transesterification (m_2) to produce biodiesel (p_2) (equation (26)). Also, they were constructed assuming all different types of biomass to produce bioethanol as one entity – starch/sugar (b_1)– and the same for the different types of biomass used to produce biodiesel – seeds/animal fats (b_2). Having the equations of the tendency lines for the different technologies, it is possible to calculate values of conversion efficiencies that reflect the learning-by-doing of each technology by increasing over the time horizon of this study and that are based on reality. The chosen time horizon of this study is 4 years, represented in 4 time periods, due to being a reasonable amount of time for showing a substantial evolution of the conversion efficiency.

$$\mu_{b_1 m_1 p_1 st} = 0.055t + 0.0358 \tag{25}$$
$$\mu_{b_2 m_2 p_2 st} = 0.035t + 0.1351 \tag{26}$$

Even though these equations are constructed based on reality, for the first time period they would result in efficiencies of 3.5% and 5.5%. These values are too low for a technology, even if in the first year operating and not having a lot of experience. Thus, the scenario node of the first time period for both technologies will have the value of t=4 ($\mu_{b_1 m_1 p_1 st} = 25.58\%$ and $\mu_{b_2 m_2 p_2 st}$= 27.51%) and assumed to be the normal efficiency a technology has in t=1. The remaining nodes follow the tendency normally: the fermentation technology increases its efficiency 5.5% each time period and the transesterification 3.5%. Regarding the tree structure, each node turns into two new nodes. One represents the conversion efficiency's increase with experience and following the tendency line. The other, represents the case where there is no learning or no attempt to learn, thus the efficiency remains the same. Figure 11 below, illustrates the scenario tree structure used in this study's model, up to a potential time horizon portioned in four time intervals.

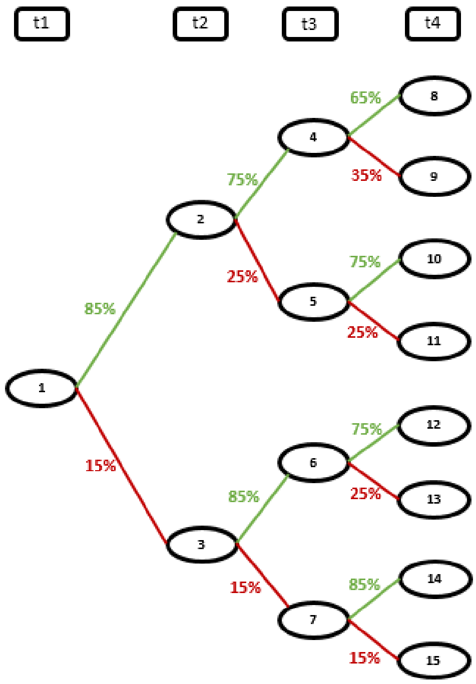

Figure 11- *Scenario Tree Structure of the Stochastic Optimization Model*

The probabilities of the nodes were chosen so as the nodes that represent an increase in the efficiency are always more likely to happen, given it is the tendency obtained with real data and the time between time periods is enough to learning something. Also, consecutive increases in conversion efficiency are less likely to happen over time. This because, it is natural that at the beginning of an operation and during the adaptation period it is easier to detect opportunities of improvement than after a few years of operation. At last, if the conversion efficiency remains the same in two consecutive time periods, in the next one, the probability that it will increase is the same as if it had increased in the previous node. This, to represent the same increasing opportunity of the conversion efficiency the technology had in the previous node. The tree was also constructed to ensure that, the probability of occurrence of the final node in the best case scenario (arch from 1 to 8) would still have a higher efficiency than the node, from the same predecessor, that represents a static conversion efficiency.

The values of conversion efficiencies used in the four time periods for the fermentation process to produce bioethanol from sugar/starch and for the transesterification process to produce biodiesel from seeds/animal fats are presented on Table 14 of Appendix C.

7.2.3- General Parameters

Capacity Parameter

The capacities of production available for each technology were chosen based on the research done on the biorefineries specifications presented in chapter 5. From table 6, for the fermentation process can be concluded that two possible production capacities that are representative of the collected data are q1= 75000 tonnes and q2 = 250000 tonnes. From table 7, for the transesterification process, two capacities that are representative of the collected data are q1= 50000 tonne and q2 = 200000 tonnes.

Cost Parameters

The costs of each parameter were obtained the following way:

- **Biomass cost:** These were obtained from the Alqueva's Agricultural Yearbook of 2019. On it, areas, market, potential and economic data for various agriculture products with agricultural potential in Alqueva are presented in detail. The costs found for the sugar/starch biomass feedstock are the costs of corn of 180 €/tonne in 2018 and actualized, with an average inflation rate of 1.51% , of 185.33 €/tonne. The costs found for the seeds/animal fats biomass feedstock are the costs of sunflower seeds of 400 €/tonne in 2018 and, with the same inflation rate, of 411.85 €/tonne. These are assumed equal in each municipality. These costs are summarized on Table 17 in Appendix C.
- **Installation Cost:** The installation costs used in this study, given lack of data, had to be costs found in studies and from outside of Portugal and from the EU. The installation costs used for a biorefinery with the fermentation process and 75000 tonnes of production capacity are 36415463 €. This value was obtained from the study by McAloon et al. 2000 using an average inflation rate of 2.17% toupdate the cost for 2020 and then an exchange rate of 0.85 from dollars to euros. For a biorefinery using the transesterification process with 50000 tonnes of capacity, the installation costs considered are 12164061.2 €. This value comes from the study by Abo El-Enin et al. 2013 after also using an average inflation rate of 2.17% and an exchange rate of 0.85 to obtain the costs in euros and for the present year. In order to obtain the costs for the other capacities of both conversion technologies, the Williams rule with a power factor of 0,6 was used (Max et al., 2003). This rule relates the fixed-capital investment of a process plant with a certain capacity to the fixed-capital investments of a similar plant with other capacity by an exponential power ratio. These costs are summarized on Table 15 of Appendix C.
- **Fixed Costs:** The fixed costs for each technology were obtained in the same studies as the installation costs. For the fermentation process with 50000tonnes of capacity, a fixed cost of 2798404,35€ (McAloon et al., 2000) and for the transesterification process, with 75000 tonnes of production capacity, a fixed cost of 1190851 € (Abo El-Enin et al., 2013) are considered. Both

were actualized to the current year with an average inflation rate of 2,17% and converted from dollars into euros with an exchange rate of 0.85. These costs consider all the costs that are fixed in the time horizon of the study, such as administration salaries, operating supplies, depreciation, maintenance, etc. These costs are summarized on Table 15 of Appendix C.

- **Variable Costs:** These are the costs that vary in the time horizon of the study, thus utilities, direct labour, operation costs and direct maintenance costs. Also, they are calculated for each level of accumulated production using the learning curve of equation (1) for each technology - one using sugar/starch to produce bioethanol (fermentation) and the other using seeds/animal fats to produce biodiesel (transesterification). Regarding the parameters of the curves, the learning rates LR_{bmp} used to calculate the learning coefficients ε_{bmp} with equation (2) are the ones presented in subchapter 5.4.3. The initial accumulated productions of reference X_{bmp}^{ref} considered are 10000 tonnes for both technologies, a quantity that is lower than any production of any technology with any capacity and conversion efficiency of t1. Their respective initial unitary costs of reference are calculated using equation (1) when replacing the unitary production costs and correspondent accumulated production quantities (values found with research and presented in subchapter 5.5.4). Therefore, the equation used to calculate the production costs for each level n of accumulated production of the fermentation process m_1 and transesterification process m_2 were, respectively, (27) and (28):

$$CC_{b_1m_1p_1nt} = 534{,}43\left(\frac{ACpq_{bmpt}}{10000}\right)^{-0{,}3219} \tag{27}$$

$$CC_{b_2m_2p_2nt} = 282{,}10\left(\frac{ACpq_{bmpt}}{10000}\right)^{-0{,}1520} \tag{28}$$

  The levels n that will be associated to the calculated costs start at 10000 tonnes - the accumulated production of reference - and then increase 25000 tonnes in each level until the accumulated production reaches 1025000 tonnes. This is one level higher than the maximum accumulated production a biorefinery with the technology that has available the biggest production capacity (in this case, m_1 with q_1 =250000 tonnes) can produce in the time horizon of this study (4 years). These costs are summarized on Table 16 of Appendix C.

- **Transportation costs:** In this study, just like in the one developed by Paulo et al. 2020, only the truck is considered as the available transportation mode for both biomasses and biofuels. Given costs couldn't be found in the Portuguese context or in studies for the biomass in question, the approach and transportation costs of the study by Hellmann and Verburg 2011 was used. The transportation costs for lingo-cellulosic crops are used and assumed to be similar for different types of biofuel crops and, the handling costs are not considered in the cost-distance analysis due to lack of reliable information. Having this said, the considered costs for both biomasses are 0.111 €/tonne/km, after being actualized using an average inflation rate of 1.50% for the pound an exchange rate of 1.11% from pounds to euros. The transportation costs of biofuels are also considered the same for the different types and are 0.44€/tonne/km, the same value used by Paulo et al. 2020. These costs are summarized on Table 18 of Appendix C.

All costs mentioned above, are assumed to remain constant in the time horizon of this study, thus are the same in each time period.

7.3- Chapter Conclusions

This chapter introduces the case study of this thesis and the necessary data in order to apply the model described in chapter 6. After, the network at study is characterized and the scenarios of the model defined, the data collection sources, and methods are described. The assumptions made are explained and the summarized data is presented in Tables 11, 12, 13, 14, 15, 16, 17, 18 and 19 in Appendix C. The next chapter presents the results of the applied model and then a general discussion and an uncertainty analysis is made.

8- MODEL IMPLEMENTATION, RESULTS AND ANALYSIS

In this chapter, the implementation of the model explained in chapter 6 and applied to the case study presented in chapter 7 is described. The objective of implementing this model is to test the adequacy of the learning curves as a representation of the conversion efficiency's evolution. Thus, the model's construction is validated for a smaller scenario tree with three time periods. The results are compared to a deterministic version to reach conclusions on the impacts of the uncertainty representation and an uncertainty analysis is done. After, the scenario tree with the four time periods presented in subsection 7.2.2 is used and both computational and case study results are analysed. Finally, after a general discussion and referring the main limitations of the model implementation, recommendations are made.

8.1- Model Implementation

In order to apply the model to the Portuguese context, the model presented in chapter 6 was implemented in GAMS (26.1.0) using CPLEX (12.8.0.0) solver. Data from the case study is initialized externally, being inputted trough excel. Also, a CPLEX Parallel MILP Optimizer was used with the intent to have increases in speed to reach a solution. All experiments are conducted on an Intel(R) Xeon(R) CPU E5-2660 v3 @ 2.60GHz 2.60 GHz (2 processors) with 64,0 GB RAM. Also, with optimality gaps of 9% and 14% as stopping criteria for the models with three and four time periods, respectively. Based on preliminary tests done with the model, these values are considered a reasonable compromise to deal with the computational complexity derived from the number of scenario nodes. Table 7 presents the computational results and statistics of each model.

Table 7 – Model statistics and computational results.

Statistics/Model	Stochastic with 3 time periods	Deterministic with 3 time periods	Stochastic with 4 time periods
# Total no. of variables	83007	11732	176783
# Binary Variables	21056	672	44476
# Equations	47209	2437	100773
# Iterations	14420590	21125	101679237
Relative Gap	0.09	0.01	0.14
CPU (s)	21279.125	12.67	189775.735

8.2- Model's Construction and Uncertainty Representation Validation

Validating the proposed model before carrying out further analysis is of high importance to ensure its accuracy in representing reality, even after having made assumptions in the modelling stages.
In order to validate the proposed model, many steps are made. First, a deterministic version of the model is analysed with a smaller quantity of biomass collection sites, integrated biorefinery sites, and markets (30, 30 and 10, respectively). Also, by varying parameters like biomass availability, to test the models response. For example, creating situations where the biomass availability increased or decreased in a further period of time. Then, the same model with the actual inputs from the case study is tested. Once

the deterministic model's results are validated, the stochastic model is then analysed, following the same logic. First with testing data and after with the complete data from the case study. However, if the values of Table 7 are compared between the stochastic model with three and four time periods, one can see a large difference in their computational dimension, given the number of variables and constraints approximately duplicates from the first model to the second. This proves that the increase of scenarios in the scenario tree has major implications on the model's performance and on providing optimality. In fact, in the first attempts to run the stochastic model with 4 periods of time and even after efforts were made to make it more efficient by using CPLEX options, one of the implications was the high amount of time it needed to find an optimized solution. This is why the model with three time periods, thus less scenario nodes, is firstly analysed and used for the ultimate validation of the model and testing of the adequacy of the learning curve theory to conversion efficiency's evolution representation. The scenario tree is the same from subsection 7.2.2, but only with the first three time periods. Thus, probabilities and conversion efficiencies remain the same for each node. The decision of the three time periods was made given the tree still has represented the relevant characteristics of the conversion technology evolution of the two technologies. These are how much each increase in the first three years of operation, the transesterification process starting with a higher efficiency in t=1 and the fermentation process ending, in general, with higher efficiencies nodes in t=3 (see Table 14 in Appendix C).

8.2.1- Case study results for stochastic model with three periods of time

In this subsection, the results of the model are analysed in order to validate the model's construction including the learning curve theory and conversion efficiency's evolution. The results of the model after being applied to the Portuguese context are shown in Figure 12.

<u>SC Network Design</u>

Regarding the supply chain network design, as Figure 12 shows, five integrated biorefineries are installed so as demand can be satisfied. Two are installed with the Fermentation technology with 75000 tonnes of capacity (the lowest capacity available) in Lisboa and Vila Real. Other two with the same technology but with 250000 tonnes of capacity (maximum capacity available), in Évora and Leiria. The fifth integrated biorefinery is installed in Montemor-o-Novo with the Transesterification technology and 50000 tonnes of capacity. These results go in line with what it was expected, given the biroefineries are strategically installed considering three factors:

- Biomass availability quantities: the biorefineries are installed near the areas where there are higher quantities of biomass available (Centre and Alentejo Regions).
- Distances to biomass collection sites: the biorefineries are installed approximately in the centre of the areas of greater density of biomass availability of each type. This happens in order to respect the maximum distances between biomass collection sites and biorefineries while taking advantage of the most biomass collection sites possible.

- Demand: given there is a higher volume of population near the capital, thus, higher volumes of demand, it is expected to have biorefineries installed near that area. The biorefinery installed in Lisboa is only dedicated to satisfy the demand in Lisboa, the district with higher demand. The integrated biorefiney in Leiria and Évora, are installed with higher capacities because, besides helping to satisfy the Lisboa's demand, they also produce to satisfy the demands of districts near them. The one in Évora focuses more on the demands in the south of Portugal and the one in Leiria on the demands of the centre region. Also, the biorefinery installed in Vila Real is dedicated to satisfy the demand of the North of Portugal. However, all of these biorefineries are dedicated to produce bioethanol. Therefore, the integrated biorefinery of Montemor-o-Novo is installed so it can produce biodiesel, as there is demand to be satisfied of this product. Since its demand is lower than the demand of bioethanol and it is greater in and around Lisboa, only one biorefinery with the smaller technology capacity available is sufficient and installed near those areas.

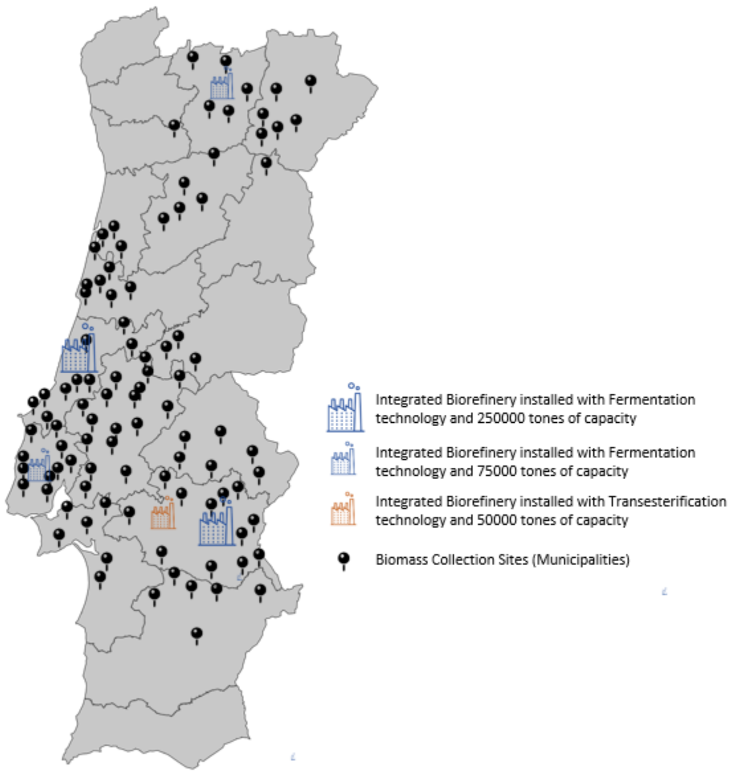

Figure 12 *– SC design results for the stochastic model with three time periods*

<u>Technology's Conversion Efficiency's Evolution</u>

In terms of conversion efficiency's evolution, the model is constructed to have a variable that saves the accumulated production of a biorefinery over the years. Then checks in which level of accumulated production it belongs to and, as that level is upgraded, the unitary costs of production decrease. This logic happens to all biorefineries installed, however the one installed in Évora with the Fermentation process technology will be used as an example to show it.

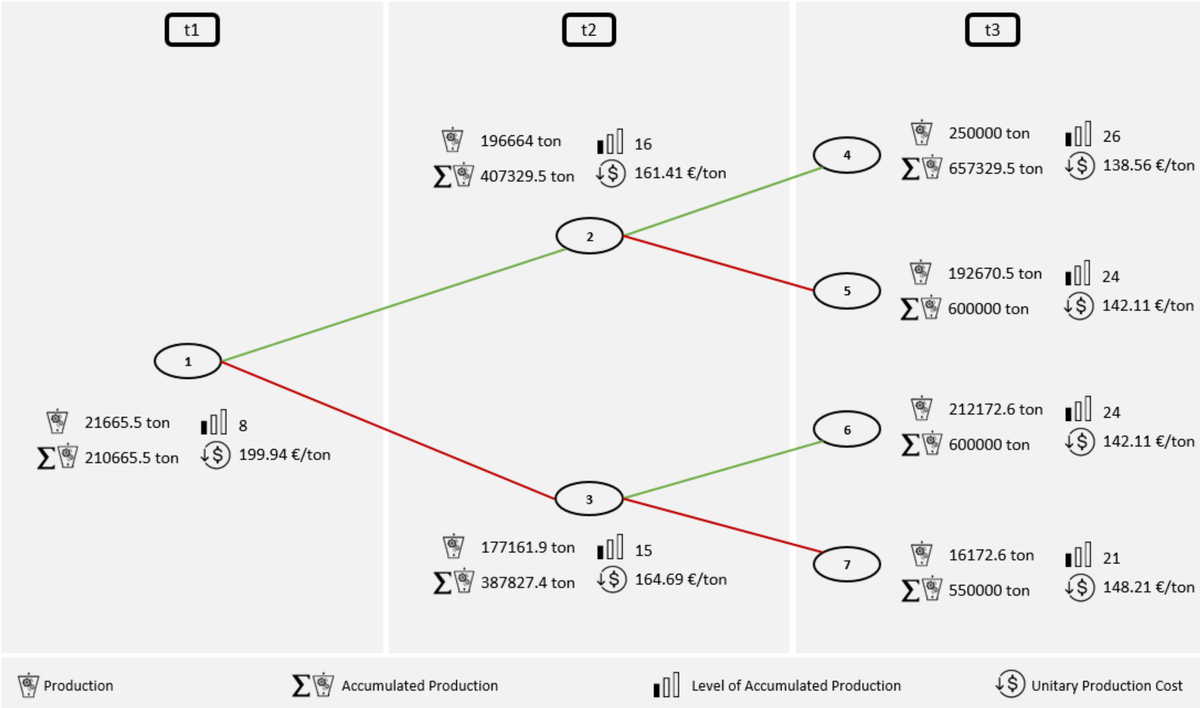

Figure 13 – *Conversion Efficiency's Evolution of Fermentation Technology of Integrated Biorefinery in Évora and its impacts on unitary costs*

As it can be seen in Figure 13, the Évora's integrated biorefinery's technology starts, in the first time period and scenario node, in the level of accumulated production 8, with a correspondent unitary cost of 199.94€/ton. By existing production over the time periods, the accumulated production of a technology on the third has already grown and, consequently, experience has been gained. Thus, independently of the scenario node of the conversion efficiency in that time period, the levels of accumulated production increased and, consequently, the unitary costs decreased. Moreover, the scenario nodes that represent an increase in the conversion efficiency, have higher accumulated production levels and lower unitary costs than the scenario nodes, of the same time period and same predecessor, that maintain the conversion efficiency (e.g. scenario node 4 vs 5). This is expected given when there is learning that is acquired by producing and that also turns into improvements in efficiency, higher quantities of product can be obtained from the same amount of feedstock. Thus, the levels of production have a higher increase than in cases where there is just learning by producing. Consequently, the unitary costs have also a higher decrease (e.g. reduce the labour required to produce a certain quantity of biofuel vs saving in utilities during operation, such as turning off lights).

Costs

Regarding the costs of SC, the solution of the stochastic model with three periods of time applied to the case study with a 0.09 relative gap, had a total cost of 1726658280.96€. Even though this is not the minimum cost associated with the optimal solution, it still is a solution and is representative of the optimal one. Thus it is possible to analyse each fraction of the total costs, their evolution over time and validate the model in terms of costs.

As it can be seen in Figure 14, the majority of the costs are regarding biomass acquisition costs and production costs, as they are the highest unitary costs considered in the case study. This is expected given the corn/cereals and the seeds/animal fats cost are expensive and cost around 200€/ton and 400€/ton, respectively. Also, even though they decrease over time, the production costs start at 466.17€/ton and 263.77€/ton of biofuel for the fermentation and the transesterification process, respectively. The transportation costs of biomass and biofuels represented a little percentage in the total costs, as their unitary costs are very low. The installation costs and the fixed costs are costs that do not vary over time and even though the first represents 14% of the total costs, it's a cost incurred only once.

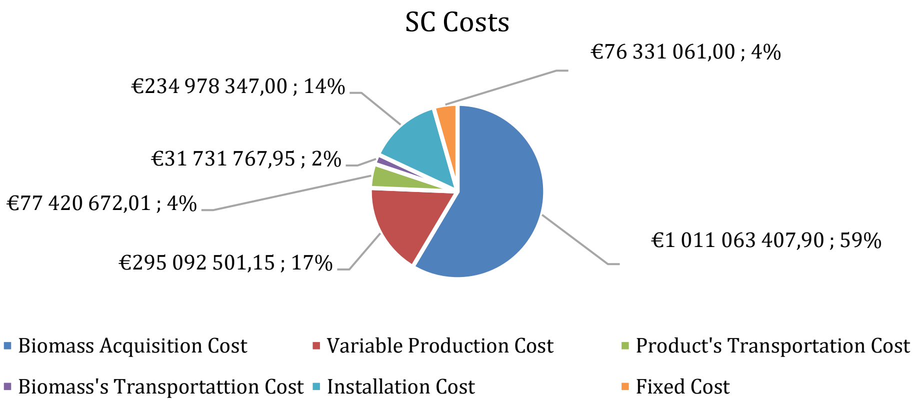

Figure 14- *Costs Distribution in the total costs of the SC*

In terms of costs evolution over the periods of time, the behaviours of the total costs of each component go in line with the expected. The total production costs decrease over time, as it can be verified in Figure 15 and graph "Production Costs Evolution Over Time", because as biorefineries are always producing, are always learning. In this graph, the costs decrease equally from one period of time to another, given the demand is constant over time. Thus, the total production quantities in each period of time are the same for every scenario. However, the production costs are different in each time period, scenario and biorefinery depending on the technology and capacity installed, its accumulated production and conversion efficiency, as it was explained before and can be seen in Figure 13. Also, having a fixed minimum demand to be satisfied, it is expected that, in scenarios where exists an increase in the conversion efficiency, less biomass needs to be acquired, as it can be seen, for example, in Scenario 1-2-4 in graph a). This traduces in lower total acquisition costs and biomass transportation costs. In the scenario where there is no improvement in the conversion efficiency – Scenario 1-3-7 in graphs a) and c) it is normal that the same amount of biomass has to be acquired, thus the transportation and acquisition costs of biomass are similar. Finally, the biofuels transportation costs (graph d)) don't have a defined pattern as they depend on distances of the biorefineries to the markets. For instance, two biorefineries that have the same conversion efficiency evolution over time and satisfy the demand of the same market. It can happen that, in one period of time, one satisfies 20% of the demand and the other 15%, and then, in the following period of time the percentages change. This will have influence on distances, thus on transportation costs.

Figure 15- *Evolutions over time and per scenario of the total costs of each component*

8.2.2- Stochastic vs Deterministic Model with three periods of time

In the last subchapter, the model's construction was validated. It was proven the results of the case study went in line with everything expected to occur when the conversion efficiency's evolution is considered, and the learning-by-doing theory is included in the model. However, one last test is made.

This study defends that literature has not been rightly considering the conversion efficiency of the conversion technologies in biorefineries, given they consider it as static instead of dynamic over time. Plus, in the cases it has, it is not in the most accurate way. The consequent problem is that decisions will not be based in the most realistic SC optimization models. Also, dynamic conversion efficiencies traduce in dynamic unitary production costs, which are most likely to decrease over time due to experience. This needs to be represented correctly in the SC optimization models that support the biomass SC designs to enhance the biomass as a substitute to fossil fuels and attract attention to the integrated biorefineries and biofuels. Having this said, the proposed stochastic optimization model of chapter 6 is compared to the deterministic version of it to reach conclusions on the effects of considering the conversion efficiency evolution over time.

Just as in the literature, the deterministic model uses a constant production cost and conversion efficiency for each technology. The production costs considered for the fermentation process technology were 198.80€/ton of bioethanol and 318.33€/ton of biodiesel for the transesterification process (de Wit et al., 2010). The conversion efficiency used for each technology was obtained by a weighted average of the possible efficiencies (Table 14 of Appendix C) of the three time periods of the scenario tree and the correspondent scenario's probabilities. For the fermentation process when producing bioethanol from cereals/corn the conversion efficiency is 0.345 and for the transesterification process when producing biodiesel from seeds/animal fats is 0.332. The cost results of the deterministic and stochastic model are presented in table 8.

Table 8- *Costs Results for the Deterministic and Stochastic Optimization Models*

	Objective Function (M €)	**Total Biomass Acquisition Cost (M €)**	**Total Production Costs (M €)**	**Total Fixed Costs (M €)**	**Total Biomass Transportation Costs (M €)**	**Total Biofuels Transportation Costs (M €)**	**Total Installation Costs (M €)**
Deterministic Model	1,721	861	502	68	32	61	199
Stochastic Model	1,727	1,011	295	76	32	77	235

After applying the deterministic model to the case study in question, four biorefineries are advised to open (Pombal, Lisboa, Santarém, Vila Real). This justifies immediately the lower fixed costs and installation costs, as the stochastic model considers these costs for 5 integrated biorefineries. All the other cost's components are dependent of the conversion efficiency.

- In the deterministic model, having a constant conversion efficiency that is an average of the dynamic conversion efficiencies of three time periods of the stochastic model, makes it higher than this last one at least in the first time period. While lower conversion efficiencies need a lot more biomass to compensate, higher conversion efficiencies do not need so much biomass to turn into product. This then gives the deterministic model advantage by saving money with biomass acquisition costs.
- On the other side, the stochastic model has scenarios, that are more likely to happen, with increasing conversion efficiencies that end up being greater than the deterministic model's over time. This behaviour compensates the lower conversion efficiency of the stochastic model in first period of time by reducing over time both biomass quantities needed for production and kilometers travelled to acquire it. All this justifies the biomass transportation costs being, approximately, the same in the two models.
- Regarding biofuel's transportation costs, they vary depending on where the biorefineries are installed and its distances to the market sites, thus they are more complex to compare.
- Last but not the least, the total production costs of the stochastic model are lower than the deterministic's given they decrease with learning, which happens in all scenario's paths. Even if this decrease doesn't traduce directly in conversion efficiency. With this not being considered in the deterministic model, the production costs component is much higher, as the unitary production costs are high for these types of products.

Finally, as expected, the value of the objective function of the deterministic model is lower than the stochastic model as it optimizes only one scenario, while this last considers the costs of 4 scenarios of possible conversion efficiency's evolution. However, it is clear the impact of considering the conversion efficiency uncertainty and using the learning curves to measure its impact, as the production costs decrease by 41% in the stochastic model.

8.2.3- Uncertainty Analysis

The efficiency's evolution tendency line was obtained from real biorefineries' data. However, the shortage of data available, besides forcing to make assumptions, only allowed to construct the tendency lines, for both technologies, based on a few biorefineries. This motivates an uncertainty analysis to assess how the solutions provided by the model are likely to change due to variations of the conversion efficiency input parameter – the uncertainty included in the model.

By varying the slopes of the tendency lines obtained with research, they automatically have impact on the conversion efficiencies used as inputs to the model. Given the tendency lines represent the evolutions over time of the technology's conversion efficiencies, increasing their slopes will result in higher conversion efficiencies over time. On the contrary, decreasing the slopes will result in lower conversion efficiencies. A $\pm$ 5% and $\pm$ 5% variation of the tendency line's slope of the fermentation and transesterification technology, respectively, is introduced. Figure 16 represents the impacts of these variations on the SC total costs, obtained by running the stochastic optimization models with three periods of time, with a relative gap of 9% and the conversion efficiency calculated with the variations.

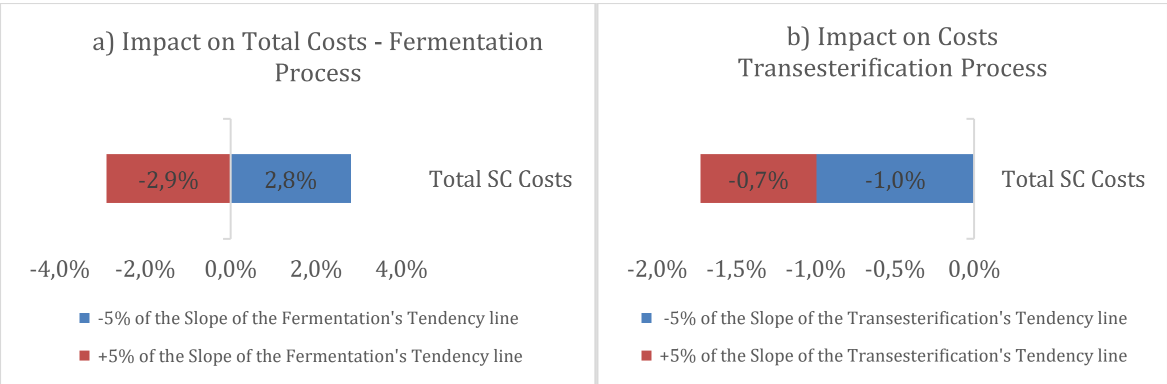

Figure 16 – *Impact on total costs of varying the slope of the tendency lines of the Fermentation and Transesterification process*

It is expected that higher conversion efficiencies over time, thus faster learning, result in greater reductions of the unitary production costs and contribute to lower total costs of the SC. From the graph a) of Figure 16, it can be seen that having a 5% increase in the increment, of each period of time, of the original inputs of the conversion efficiencies, results in a -2.9% decrease in total costs. On the other side, having a 5% reduction in the increment of the conversion efficiencies, in each time period, results in an increase in the total costs of 2.9%.

These costs behaviours are not the same for the transesterification process (graph b)), given for the two scenario variations of the tendency line's slope of this technology, the total costs decrease.

Increasing the tendency line's slope by 5% results in a cost decrease of 0.7% and reducing the tendency line's slope by 5%, results in a 1% total costs decrease. However, these reductions are not happening as consequence of the slopes variations due to the low demand of the biodiesel in Portugal. The installed biorefineries with the transesterification technology of both scenarios do not operate at its maximum capacity and they don't even upgrade their level of production in the time horizon of this study. Thus they don't reduce costs significantly to have influence in the total SC costs. These cost reductions are then associated to a possible solution given by the model as result of the 9% relative gap.

8.3- Case Study Results

After validating the stochastic model's construction, in subchapter 8.2.2, and the effects of considering the conversion efficiencies evolution of the technologies over time, in subchapter 8.2.3, the model is applied with the four time periods, to the Portuguese context. By considering four periods of time, this model helps making long term decisions given the results information are available for a larger horizon of time. The model also makes recommendations on biorefinery's installation sites and technologies, considering the biomass availability and demand, with the objective of minimizing the cost of the national supply chain of biomass. This specific model, reached a relative gap of 14% due to the mathematical complexity of solving a problem with a great number of scenarios. Thus, does not give the optimal solution. However, once the model is already validated, this a possible solution. Figure 17 represents the supply chain design of this model.

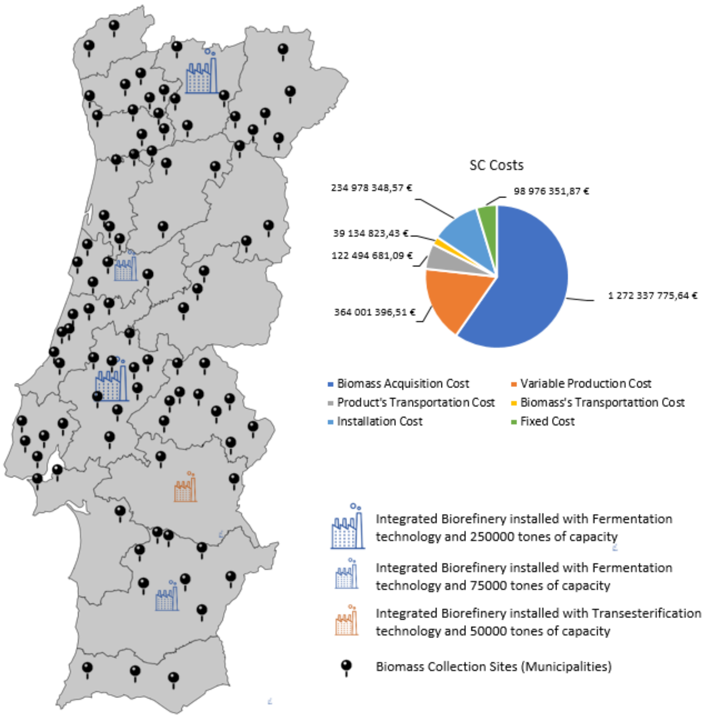

Figure 17 - *SC design results for the stochastic model with four time periods*

Four biorefineries are openned in time period 1. One in Beja with the fermentation technology with 75000 tonnes of bioethanol of capacity. One in Santarém and another in Vila Real, both installed with fermentation technologies with capacities to produce 250000 tonnes. Finally, one in Évora with the transesterification technology with production capacity of 50000 tonnes of biodiesel. Then, in the second time period, a biorefinery with the fermentation process with 75000 tonnes of capacity is installed in Coimbra.

All biorefineries are installed strategically in places near the biomass collection sites that serve them (see Figure 17), as well as near the demand focuses (Centre and then the biorefineries in the oposite points of the country to satisfy the demand in those areas – see Figure 18). The SC costs result was 2 135 217 851.58 €, with more than a half being biomass acquisition costs.

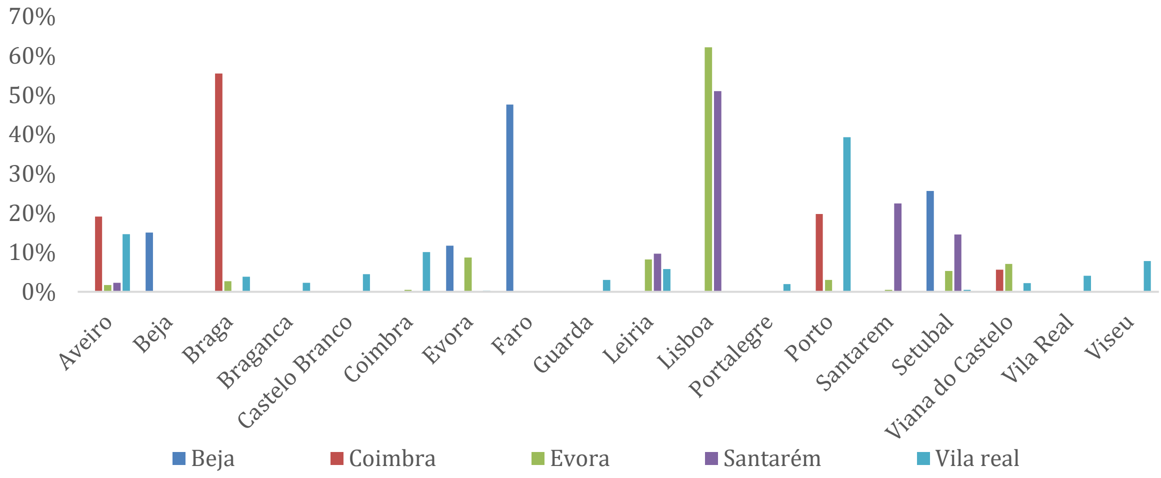

Figure 18 – *Distribution of Demand Satisfaction of the installed Integrated Biorefineries, per market site.*

8.4- General Discussion, Limitations and Recommendations

8.4.1- General Discussion

The lack of data on the technologies of the biorefineries associates a certain degree of uncertainty to the method used in this thesis to obtain the conversion efficiency's evolution over time - the tendency lines of the conversion efficiencies' of each technology that produces biofuels. However, is undeniable that, effectively, the few existent data show that this efficiency tends to increase over time, thus, as experience is gained. This, inevitably has impact on costs and the best proven method to represent the impacts of this evolution over time is in fact the learning curve theory. The implementation of the proposed model and application to the Portuguese case study proved this with favourable results, as the production costs are lower than the deterministic models that do not consider these aspects (section 8.2.2). Nevertheless, there is margin of improvement. First, it would be ideal to invest more in data collection so the tendency line can be more solid. Then, even though it was kept in mind, without it being the focus of this study, there is certainly opportunities to optimize and make the proposed model more efficient, as it takes too long to obtain results for a scenario tree with three, but specifically, with four time periods, as in this last case, the is a higher number of scenarios.

8.4.2- Limitations

Implementing this model had a certain degree of difficulty. It is a fact that increasing the number of scenario nodes allows the decision maker to obtain results regarding a larger horizon of time and make a decision with more information about the future. However, the scenario based approach increases significantly the computational complexity of the model. Thus, to obtain results and possible solutions in a reasonable amount of time, higher relative gaps have to be assumed. Validating the model with relative gaps between 9-14% wasn't a problem. Even though they don't represent the optimal solution, the solutions obtained with the model go in line with what it was expected – correctly representing the increase of conversion efficiency allows to obtain lower supply chain costs. However, this is not the most advisable when making decisions of strategic nature.
Moreover, there was a great lack of data on biorefineries, their technologies, biomass and production quantities. Thus, the data found with research in order to construct a tendency line for the evolution of the conversion efficiency, were very few and sensible to new data that might appear. Also, the only data considered was regarding the first generation biofuels, as it was the available information publicly. However, it is starting to be outdated as efforts are being made in Portugal and in the EU to increase the use of advanced biofuels from residual biomass.
Finally, due to this shortage of data, the production of by products, the competition for soils to produce biomass for human vs food, the importation of biomass and the production of biofuels to be exported were not considered. The available information did not allow to consider these aspects correctly.

8.4.3- Recommendations

From the previous discussion, it can be concluded that:

- The model is validated it enables to obtain lower values of the objective function. Thus, besides the reality being represented more accurately, the model helps the biomass and the biofuels on becoming more attractive in terms of costs.
- The higher the number of scenarios and time periods, the closer to reality the model is and the longer the planning horizon covered to make decisions. However, this requires a higher computational effort. Thus, attempts to increase the efficiency of the model or the usage of decomposition methods might help in its resolution.
- The lack of data is always a disadvantage, thus any new information that can be found and integrated it is always beneficial towards a robust solution. Therefore, more structured database would be helpful at the EU level.

9- CONCLUSION & FUTURE DEVELOPMENTS

The concern of being an economy that consumes secure, safe, competitive and, most importantly, sustainable energy has been continuously present in the European Union. It has been fully dedicated to transition from a fossil-input-based economy into a bio-based one and has been launching energy directives, goals and regulations so as the member states get as maximum as evolved possible. It is in this context that the biomass appears as a good alternative to fossil fuels in the attempted to increase the use of energy from renewable sources. However, it still needs to become a sustainable and competitive alternative. Therefore, improvements in its design of the supply chain need to be made.

In this study, the biomass SC and its design decisions, mostly regarding process technologies, are studied. A general overview on bioenergy, biomass, and its supply chain stages was is followed by a state of art on biomass supply chain optimization and uncertainty modulation. Having understood the lack of representation of the biomass technology's conversion efficiency uncertainty within the biomass SC optimization models and that researchers have been dealing with it poorly, this master thesis is introduced. After exploring the literature and finding potential on the learning curve theory to represent technological developments, this study proposes to develop a mathematical representation of technology evolution and its impacts using the conversion efficiency and learning curves. Then, it adapts the stochastic model developed by Paulo et al. 2020 to include it and test its adequacy by applying it to the Portuguese context with the objective of minimizing the cost of the national supply chain of biomass. Prior to the development of the mathematical representation of the conversion technologies evolution, an extensive research is done on integrated biorefineries of the EU in order to obtain more data and from countries similar to Portugal.

We can now provide the answers to the proposed research questions.

"How can we use official information about the installation and operation of biorefineries in Europe and European Union to outline the evolution of the conversion efficiency of the installed technologies?"

After being able to find values of efficiencies or production and biomass processing quantities, the method to use this information was to use the date of the data found as a time reference of the conversion efficiency of that moment. Then, having the installation date of the biorefinery and technology, the difference between the two dates was assumed years of experience associated with that conversion efficiency. Applying this logic for all mapped biorefineries, turns them into an increasing tendency of the conversion efficiency due to experience.

"How can the concept of learning curves be used for quantitatively describe the evolution of these conversion efficiency? What other variables can be used to outline these curves?"

The learning curve theory depends on two important parameters, the experience parameter and the costs parameter and the key is to have them well defined. In this study, the experience is expected to occur in the conversion technologies as they keep on producing. Thus, the accumulated production was the indicated experience parameter. With this last being mathematically related with the conversion efficiency, as one evolves, the other does too while also having impacts on costs.

"How can we incorporate these learning curves into design and planning models for the biorefineries supply chain"?

Implementing the learning curve theory and the conversion efficiency's evolution has its steps. First, the tendency line representing this last is of extremely importance in the creation of the scenario tree of the model. This tree dictates how the uncertainty behaves in the model. Then, with the objective of keeping the model linear, the learning curves are implemented through levels of experience that have associated costs calculated by them. These costs are in a decreasing order as experience is gained and are "activated" depending on the accumulated production quantities and thus, on the conversion efficiencies. The final proposed MILP two-stage stochastic model, used to test the incorporation of the learning curves, considers all these aspects and then from the i) amount of available biomass, ii) biomass acquisition cost, iii) biomass conversion efficiency over time, iv) production costs of each technology, v) product's demand in each market, vi) transportation costs regarding the different transportation modes, vii) distances between the sites of the biomass collection, integrated biorefineries and markets and viii) annualized investment costs of integrated biorefineries, **determines** the: 1) collected quantities of biomass at each production site, 2) biomass flows across each supply chain entity, 3) product's production quantities, 4) location of the installed biorefineries, 5) capacity of installed biorefineries and 6) technology to implement in each installed biorefinery, so as to **optimize** an economical objective function. Moreover, the model was constructed to be generalized enough so it could be applied to any case study.

Finally, the results of the model are tested for a smaller scenario tree, due to high computational complexity with a higher number of scenarios. In terms of SC network, conversion efficiency and cost evolution and comparison with an equivalent deterministic model, the results of the stochastic model are favourable and go in line with what it was expected, thus enabling to run the model for a more complete case study. Lastly, the lack of data throughout the study was overcome by several assumptions. The main one, the tendency line constructed for the conversion efficiency's evolution, it is submitted to a sensibility analysis. The others, already identified as limitations of the model, are suggested for future work, so they can be overcome.

Further suggestions can also be identified. Regarding the mathematical model, it can be interesting to dedicate in its further optimization or applying decomposition methods so its performance can be more efficient. Moreover, the proposed model assumes the demand as deterministic and does not consider importations and exportations and the production of co-product in the integrated biorefineries due to lack of data. In the future, it may be appropriate to consider the demand as stochastic and these factors in the model. Finally, the learning curves used in this study only consider one factor – the learning-by-doing factor - and it may be interesting to deepen research so as to find sufficient information on other existent factors, such as learning with research and development.

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APPENDIX A. LIST OF INTEGRATED BIOREFINERIES THAT HAD ANY AVAILABLE INFORMATION.

Table 9 - Integrated biorefinerys of the EU's database with available information about feedstock and product quantities, technology and production

BIOREFINERY'S NAME	CODE	FEEDSTOCK QUANTITY (t/y)	BIOFUEL PRODUCTION (t/y)	TECHNOLOGY	CONVERSION EFFICIENCY	PRODUCTION COSTS (€)
Pischelsdorf Biorefinery (Company-AGRANA Bioethanol GmbH)	Aus1	250000 grain (wheat), 500000 cereals (bioethanol)	185500 wheat starch, 197250 bioethanol, 175000 animal feed, 100000 biogenic CO2	Fermentation	-	-
BioWanze S.A. (CropEnergies)	Bel1	910385 grains of sugar beet and wheat	236700 bioethanol	Fermentation	-	-
Oleon	Bel2	Oilseeds, recycle vegetable oil	Petrochemicals, 100000 biodiesel	-	-	-
Bioro	Bel3	Vegetable oil	352000 Biodiesel FAME	-	-	-
Aalst Plant - SYRAL Belgium N.V (tereos)	Bel7	Cereals, sugar beat	Bioethanol, alcohol, sugars	Fermentation	-	-
Astra Bioplant	Bul19	180000 seeds, 72000VEGETABLE OIL (biofuel)	60000 Biodiesel	Transesterification	-	-
PREOL a.s.	Cze20	400000 raw rapeseed, 160000 rapeseed oil	Rapeseed oil methyl ester 100 000 (biodiesel), 10000 distilled glycerine	Transesterification	-	-
Daka ecoMotion	Den3	51282,05 animal fat	50000 biodiesel	Esterification	-	-
Biodiesel Paldiski	Est1	Rapeseed oil	100000 biodiesel	Esterification	-	-
Koskenkorva plant - altia	Fin1	210000 barley	-	-	-	-
UPM Lappeenranta Biorefinery	Fin5	Crude tall oil	Biodiesel, 130000 bionaphta (biochemical)	Hydrotreatment	-	-
Närpiö Etanolix Plant	Fin12	Waste, industrial by-products	1104,6 bioethanol	Fermentation + Dehydratation	-	-
Cellunolix Ethanol Plant (NEOT) produtor - St1 and SOK (NEB) construtor	Fin13	80000 sawdust	8000 bioethanol, animal feed	Fermentation	-	-
Cristal Union sugar beet refinery, Chamtor wheat processing, Soliance biorefinery	Fra1 Fra4 Fra60	580000 sugar beet and wheat	157800 bioethanol	Fermentation	-	-
Lestrem starch biorefinery - Roquette Frère SA unit	Fra10	7000 ton wheat, maize, potatoes	Starch, bioethanol	fermentation	-	-
Nesle Plant - tereos	Fra168	Cereals, sugar beat	Bioethanol, alcohol, sugars	Fermentation	-	-
Biopetrol Rostock GmbH	Ger17	-	200000 biodiesel	-	-	-

Akzo nobel chemicals gmbh (Oleon Emmerich)	Ger110	-	Biodiesel, 60000 fatty acids	-	-	-
KFS Biodiesel GmbH & Co. KG	Ger178	Vegetable oils, animal fats, waste	50000 biodiesel, 4500 glycerol	-	-	-
Kfs Biodiesel Kassel Gmbh & Co. Kg	Ger184	Vegetable oils, animal fats, waste	50000 biodiesel, 5000 glycerol	-	-	-
KFS Biodiesel Köln GmbH	Ger186	Vegetable oils, animal fats, waste	120000 biodiesel, 12000 glycerol, 5000 fatty acids	-	-	-
ecomotion gmbh - REMONDIS lippe plant	Ger188	vegetable oil, waste, 71100 animal fats	65300 biodiesel, bioheating oil, chemicals, 5800 glicerina	Transesterification	-	-
BKK Biodiesel GmbH	Ger198	-	4000 biodiesel, rape cake, glycerin	-	-	-
ecoMotion GmbH plant	Ger202	170000 rapeseeds	100000 biodiesel, 20000 gliceryn	Transesterification	-	-
Cargill Deutschland GmbH - Barby Plant	Ger206	Wheat	50000 bioethanol	Fermentation	-	-
Verbio Diesel Schwedt GmbH & Co. KG (NUW)	Ger200	rapeseed oil, vegetable oils	250000 biodiesel	Transesterification	-	General production costs of all products
Verbio Ethanol Schwedt GmbH & Co. KG	Ger207	Grain, corn; straw	260000 bioethanol; 11693,90 biomethane	Fermentation	0,9 for Bioethanol and Biomethane productions	General production costs of all products
Verbio Ethanol Zörbig GmbH & Co. KG	Ger208	Grain, corn, straw	130000 bioethanol; 5846,95 biomethane	Fermentation	0,9 for Bioethanol and Biomethane productions	General production costs of all products
Borregaard Deutschland GmbH	Ger228	Sugars (wood), fibers	15780 bioethanol, cellullose	Fermentation	-	General production costs of all products.
Hungrana Bioeconomy Company	Hun1	910000 sugar, corn	147543 bioethanol, 105000 glucose, 61500 starch, 305000 HFCS	Fermentation	-	-
ClonBio Group	Ire8	572000 corn	394500 bioethanol, 350000 animal feed, 15000 corn oil	Fermentation	-	-
Caviro Extra	Ita10	385000 waste grape	7920 biomethane, 17825 biogas, 71010 bioethanol	Anaerobic Digestion (biomethane) Fermentation (bioethanol)	0,46 for Bioethanol Production	-
Dp Lubrificanti S.r.l.	Ita62	Vegetable Oils	155520 biodiesel	-	-	-
Ravena biodiesel plant (Novaol)	Ita72	Vegetable oils	198000 biodiesel	Transesterification	-	-
Oil.B S.r.l.	Ita73	-	200000 biodiesel	-	-	-
Eco Fox S.r.l.	Ita74	Vegetable oils, animal fat, oil	200000 biodiesel	Transesterification	-	-
Saluzzo Plant (Tereos)	Ita80	Cereals, sugar beat	Bioethanol, alcohol, sugars	Fermentation	-	-
BioVenta	Lat2	300000 rapeseeds	100000 biodiesel	-	-	-
Sas van Gent Plant (Cargill/Royal Nedalco/bioro)	Net1	Wheat	Bioethanol	Fermentation	-	-

Biopetrol Industries AG	Net6	Rapeseed oil	400000 biodiesel, 60000 glycerine	-	-	-
Biodiesel Amesterdam	Net9	Waste oils, fats	150000 biodiesel	Esterification + Transesterification	-	-
COSUN beet company - Suiker Unie Vierverlaten	Net79	100000 sugar beet residues	28750 biomethane, bioethanol, animal feed	Fermentation	-	-
Biodiesel plant (greenline industries and ULEROm)	Rom8	144000 rapeseeds, sunflower seeds	25000 biodiesel	-	-	-
MEROCO Inc	Svk8	Vegetable oils, animal fats	100000 biodiesel, 13000 glycerine	Transesterification	-	-
Abengoa Bioenergy San Roque S.A.	Spa8	205000 vegetable oil	196517 biodiesel	Transesterification	-	-
Bio Oils - La Rabida plant	Spa23	Vegetable oils (rapeseed oil)	500000 biodiesel	Transesterification	-	-
SunPine	Swe1	Crude tall oil	100000 biodiesel	Combustion (bio-oil)	-	-
Perstorp Oxo AB	Swe3	Rapeseed	160000 biodiesel	-	-	-
SEKAB Biofuels&Chemicals AB, Domsjö Pulp Mill	Swe6 Swe15 Swe37	Wood chips	14000 bioethanol	Fermentation	-	-
Södra Cell Mönsterås	Swe43	Pine oil	6300000 biomethanol, biodiesel	-	-	-

APPENDIX B. COMPACT TWO-STAGE STOCHASTIC OPTIMIZATION MODEL FORMULATION FOR THE BIOMASS SC DESGIN BY Paulo et al. 2020

Table 10 - Compact model notation, parameters and decision variables.

Notation	Description	Notation	Description
Sets			
$b,\bar{b} \in B$	Biomass type	$q \in Q$	Integrated biorefinery's conversion capacities
$p \in P$	Products	$n \in N$	Pre-processing technologies
$i \in I$	Biomass collection site	$m \in M$	Integrated biorefinery conversion technologies
$j \in J$	Biomass pre-processing/storage site	$r \in R$	Biomass transportation mode
$k \in K$	Integrated biorefinery site	$z \in Z$	End product's transportation modes
$v \in V$	Market site	$t,\bar{t} \in T$	Time periods
$cs \in CS$	Storage capacities	$s,\bar{s} \in S$	Scenario tree nodes
$cp \in CP$	Pre-processing capacities		
Subsets			
$B = B_i \cup B_j$		The biomass is divided into collected biomass ($\bar{b} \in Bi \subseteq B$) and pre-processed biomass ($b \in Bj \subseteq B$)	
$W_S = \{(\bar{b},n,b): \bar{b} \in B_i \wedge n \in N \wedge b \in B\}$		Available pre-processing technology n to process biomass $\bar{b}$ into biomass b.	
$W_p = \{(n,b): n \in N \wedge b \in B\}$		Available pre-processing technology n to produce biomass b.	
$W_B = \{(m,p): m \in M \wedge p \in P\}$		Available conversion technology m to produce product p.	
$Z_B = \{(b,r,t): b \in B \wedge r \in R \wedge t \in T\}$		Available transportation mode r to transport biomass b in time period t.	
$Z_P = \{(p,z,t): p \in P \wedge z \in Z \wedge t \in T\}$		Available transportation mode z to transport product p in time period t.	
$S = \{(s,t): s \in S \wedge t \in T\}$		Nodes s of the scenario tree in time period t.	
$H = \{(s,\bar{s}): s \in S \wedge \bar{s} \in S\}$		Predecessor $\bar{s}$ of node s in the scenario tree.	
Parameters			
DIK_{ik}	Distance between biomass collection site i and integrated biorefinery site k (km).	CTP_{pzt}	End product p transportation costs using transportation mode z, in time period t (€/km/Mg)
DIJ_{ij}	Distance between biomass collection site i and pre-processing site j (km).	DP_{pvt}	Demand of end product p at market site v, in time period t (units of product).
DJK_{jk}	Distance between pre-processing site j and integrated biorefinery site k (km).	PPC_{nc_p}	Pre-processing capacity c_p of pre-processing technology n (Mg).
DKV_{kv}	Distance between integrated biorefinery site k and market site v (km).	PSC_{nc_s}	Storage capacity c_s of pre-processing technology n (Mg).
CB_{bit}	Cost of biomass type $\bar{b} \in B_i$ at biomass collection site i in time period t (€/Mg).	PBC_{mq}	Integrated biorefinery's conversion capacity q with conversion technology m (Mg).
$CIP_{nc_pc_s}$	Installation cost of a pre-processing/storage facility with pre-processing technology n, pre-processing capacity c_p and storage capacity c_s, (€).	BA_{bit}	Amount of biomass type $\bar{b} \in B_i$ at biomass collection site i, in time period t (Mg).
CIB_{mq}	Installation cost of an integrated biorefinery facility with conversion technology m and conversion capacity q (€).	ISL_{bnjst}	Initial stock level of biomass type $b \in B$ in pre-processing/storage facility j with pre-processing technology n, for scenario node s, in the beginning of the time period t (Mg).
$CFP_{nc_pc_st}$	Annual fixed operation costs of a pre-processing/storage facility with pre-processing technology n, pre-processing capacity c_p and storage capacity c_s, in time period t (€).	PTS_{nb}	$\begin{cases} 1, \text{if pre} - \text{processing technology } n \text{ is available to process biomass } \bar{b} \in B_i \text{ into } b \in B \\ 0, \text{otherwise.} \end{cases}$

CFB_{mqt}	Annual fixed operation costs of an integrated biorefinery facility with conversion technology m, conversion capacity q, at scenario node s, in time period t (€).	PTB_{mp}	$\begin{cases} 1, & \text{if conversion technology } m \text{ is available to convert biomass } b \in B \text{ into end product } p \\ 0, & \text{otherwise.} \end{cases}$
CVP_{bnt}	Variable operation costs of pre-processing biomass $\bar{b} \in B_i$ with pre-processing technology n, in time period t (€/Mg).	$FCP_{\bar{b}nb}$	Conversion factor of biomass $\bar{b} \in B_i$ into biomass $b \in B$ with pre-processing technology n.
CVB_{bmt}	Variable operation costs of converting biomass $b \in B$ with conversion technology m, in time period t (€/Mg).	FCB_{bmp}	Conversion factor of biomass $b \in B$ into end product p with conversion technology m.
CHP_{bnt}	Storage costs for biomass $b \in B$ on a pre-processing/storage facility with pre-processing technology n, in time period t (€/Mg)	Ψ_s	Probability of scenario tree node s
CHP_{bnt}	Biomass b transportation costs using transportation mode r, in time period t (€/km/Mg).		
Decision Variables			
B^c_{bist}	Collected biomass $\bar{b} \in B_i$ on biomass collection site i for scenario node s in time period t (Mg).	U^B_{bmkst}	Amount of biomass $b \in B$ that arrives to integrated biorefinery k to be processed by conversion technology m for scenario node s in time period t (Mg).
$X^A_{binjrst}$	Flow of biomass $\bar{b} \in B_i$ from biomass collection site i to pre-processing facility j by transportation mode r that is processed by pre-processing technology n in scenario s in time period t (Mg).	$Y^S_{jnc_pc_st}$	$\begin{cases} 1, & \text{if opens a pre} - \text{processing facility on site j with pre} - \text{processing technology n with pre} - \text{processing capacity cp and storage capacity cs in time period t. If opens, it will not close.} \\ 0, & \text{otherwise.} \end{cases}$
X^B_{bikrst}	Flow of biomass $\bar{b} \in B_i$ from biomass collection site i to integrated biorefinery site k using transportation mode r for scenario node s in time period t (Mg).	Y^B_{kmqt}	$\begin{cases} 1, & \text{if opens an integrated biorefinery on site k with conversion technology m with pre} - \text{processing capacity q, in time period t. If opens, it wil not close.} \\ 0, & \text{otherwise.} \end{cases}$
$X^C_{jnkbrst}$	Flow of biomass $b \in B$, obtained with pre-processing technology n, from pre-processing site j to integrated biorefinery site k using transportation mode r for scenario s in time period t (Mg).	$O^S_{jnc_pc_st}$	$\begin{cases} 1, & \text{when opens an pre} - \text{processing facility on site j with pre} - \text{processing technology n, pre} - \text{processing capacity cp and storage capacity cs in time period t. If opes, it will not close} \\ 0, & \text{otherwise.} \end{cases}$
$X^P_{kmpvzst}$	Flow of product p, obtained by conversion technology m, from integrated biorefinery site k to market v by transporation mode z for scenario node s in time period t (Mg).	O^B_{kmqt}	$\begin{cases} 1, & \text{when opens an integrated biorefinery on site k with conversion technology m with pre} - \text{processing capacity q, in time period t. If opens, it will not close.} \\ 0, & \text{otherwise.} \end{cases}$
H_{bnjst}	Stock of biomass $b \in B$ obtained by pre-processing technology n in intermediate facility site j for scenario node s in time period t (Mg).		

Objective Function

$$Min\ Cost^S = \sum_s \Psi_s \begin{pmatrix} \sum_{\bar{b}\in B_i}\sum_i\sum_t B^C_{bist}\ CB_{bit}\ + \\ \sum_{\bar{b}\in B_i}\sum_i\sum_n\sum_j\sum_{r:(b,r,t)\in Z_B}\sum_t X^A_{binjrst}\ CVP_{bnt}\ + \\ \sum_{b\in B}\sum_{n:(n,b)\in W_p}\sum_j\sum_t H_{bnjst}\ CHP_{bnt}\ + \\ \sum_{b\in B}\sum_m\sum_k\sum_t U^B_{bmkst}\ CVB_{bmt}\ + \\ \sum_{\bar{b}\in B_i}\sum_i\sum_n\sum_j\sum_{r:(\bar{b},r,t)\in Z_B}\sum_t X^A_{binjrst}\ DIJ_{ij}\ CTB_{brt}\ + \\ \sum_{\bar{b}\in B_i}\sum_i\sum_k\sum_{r:(b,r,t)\in Z_B}\sum_t X^B_{bikrst}\ DIK_{ik}\ CTB_{brt}\ + \\ \sum_j\sum_{n:(n,b)\in W_p}\sum_k\sum_{b\in B}\sum_{r:(b,r,t)\in Z_B}\sum_t X^C_{jnkbrst}\ DJK_{jk}\ CTB_{brt} + \\ \sum_k\sum_{m:(m,p)\in W_B}\sum_p\sum_v\sum_{z:(p,z,t)\in Z_P}\sum_t X^P_{kmpvzst}\ DKV_{kv}\ CTP_{pzt} \end{pmatrix} + \sum_j\sum_n\sum_{cp}\sum_{cs}\sum_t Y^S_{jnc_pc_st}\ CIP_{nc_pc_st}\ +$$

$$\sum_k\sum_m\sum_q\sum_t Y^B_{kmqt}\ CIB_{mqt}\ +\ \sum_j\sum_n\sum_{cp}\sum_{cs}\sum_t Y^S_{jnc_pc_st}\ CFP_{nc_pc_st}\ +\ \sum_k\sum_m\sum_q\sum_t Y^B_{kmqt}\ CFB_{mqt}$$

Constraints

- $B^C_{bist} \le BA_{bit} \quad \forall\ \bar{b}\in B_i\ \wedge\ \forall i\in I\ \wedge\ \forall t\in T\ \wedge\ \forall s\in S$
- $B^C_{bist} = \sum_n\sum_j\sum_{r:(b,r,t)\in Z_B} X^A_{binjrst} + \sum_k\sum_{r:(b,r,t)\in Z_B} X^B_{bikrst}\ \forall\bar{b}\in B_i\ \wedge\ \forall i\in I\ \wedge\ \forall t\in T\ \wedge\ \forall s\in S$
- $\sum_{b\in B} ISL_{bnjst} + \sum_{\substack{b\in \boldsymbol{B}\\ b:(n,b)\in W_P}}\sum_i\sum_{r:(b,r,t)\in Z_B} X^A_{binjrst}\ FCP_{\bar{b}nb} = \sum_{\substack{b\in B\\ b:(\bar{b},n,b)\in W_S}} H_{bnjst}\ +$

  $\sum_k\sum_{\substack{b\in B\\ b:(\bar{b},n,b):W_S}}\sum_{r:(b,r,t)\in Z_B} X^C_{jnkbrst}\ \ \forall\bar{b}\in B_i\wedge\forall n\in N\wedge\forall j\in J\wedge\ \forall s\in S\wedge t=1$
- $\sum_{\substack{b\in B\\ b:(\bar{b},n,b)\in W_S}} H_{bnjst-1} + \sum_{\substack{b\in B\\ b:(n,b)\in W_P}}\sum_i\sum_{r:(b,r,t)\in Z_B} X^A_{binjrst}\ FCP_{\bar{b}nb} = \sum_{\substack{b\in B\\ b:(\bar{b},n,b)\in W_S}} H_{bnjst}\ +$

  $\sum_k\sum_{\substack{b\in B\\ b:(\bar{b},n,b)\in W_S}}\sum_{r:(b,r,t)\in Z_B} X^C_{jnkbrst}\ \forall\ \bar{b}\in B_i\ \wedge\ \forall n\in N\ \wedge\ \forall j\in J\ \wedge\ \forall s\in S\ \wedge\ t>1$
- $\sum_i\sum_{r:(b,r,t)\in Z_B} X^B_{bikrst} + \sum_j\sum_{n:(n,b)\in W_p}\sum_{r:(b,r,t)\in Z_B} X^C_{jnkbrst} = \sum_m U^B_{bmkst}\,\forall\bar{b}\in B_i\wedge\forall k\in K\wedge\forall t\in\ \ T\wedge\ \forall s\in S$
- $\sum_j\sum_{n:(n,b)\in W_p}\sum_{r:(b,r,t)\in Z_B} X^C_{jnkbrst} = \sum_m U^B_{bmkst} \quad \forall b\in B_j\ \wedge\ \forall k\in K\ \wedge\ \forall t\in T\wedge\ \forall s\in S$
- $\sum_{b\in B} FCB_{bmp}\, U^B_{bmkst} = \sum_v\sum_{z:(p,z,t)\in Z_P} X^P_{kmpvzst}\ \forall m\in M\ \wedge\ \forall k\in K\ \wedge\ \forall p\in P\ \wedge\ \forall t\in T\ \wedge\ \forall s\in S\ \wedge(m,p)\in W_P$
- $\sum_k\sum_{m:(m,p)\in W_B}\sum_{z:(p,z,t)\in Z_P} X^P_{kmpvzst} \ge DP_{pvt} \quad \forall p\in P\ \wedge\ \forall v\in V\ \wedge\ \forall s\in S\ \wedge\ \forall t\in T$
- $\sum_n\sum_{c_p}\sum_{c_s} Y^S_{jnc_pc_st} \le 1 \quad \forall j\in J\wedge\ \forall t\in T$
- $\sum_m\sum_q Y^B_{kmqt} \le 1 \quad \forall k\in K\wedge\ \forall t\in T$
- $\sum_{\bar{b}\in B_i}\sum_i\sum_{r:(b,r,t)\in Z_B} X^A_{binjrst} \le \sum_{c_p}\sum_{c_s} PPC_{nc_p}\ Y^S_{jnc_pc_st} \quad \forall j\in J\wedge\ \forall n\in N\ \wedge\ \forall s\in S\wedge\forall t$
- $\sum_{\substack{b\in B\\ b:(n,b)\in W_P}} H_{bnjst} \le \sum_{c_p}\sum_{c_s} PSC_{nc_s}\ Y^S_{jnc_pc_st} \quad \forall j\in J\wedge\ \forall n\in N\ \wedge\forall s\in S\wedge\forall t\in T$
- $\sum_{b\in B} U^B_{bmkst} \le \sum_q PBC_{mq}\, Y^B_{kmqt} \quad \forall k\in K\wedge\ \forall m\in M\ \wedge\ \forall s\in S\ \wedge\ \forall t\in T$
- $Y^S_{jnc_pc_st} \ge Y^S_{jnc_pc_s\bar{t}} \quad \forall j\in J\wedge\ \forall n\in N\wedge\ \forall c_p\in CP\wedge\ \forall c_s\in CS\wedge\ \forall t\in T$
- $Y^B_{kmqt} \ge Y^B_{kmq\bar{t}} \quad \forall k\in K\ \wedge\ \forall m\in M\wedge\ \forall q\in Q\wedge\ \forall t\in T$
- $O^S_{jnc_pc_st} = Y^S_{jnc_pc_st} \quad \forall j\in J\wedge\ \forall n\in N\wedge\ \forall c_p\in CP\wedge\ \forall c_s\in CS\wedge\ t=1$
- $O^S_{jnc_pc_st} = Y^S_{jnc_pc_st} - Y^S_{jnc_pc_st-1} \quad \forall j\in J\wedge\ \forall n\in N\wedge\ \forall c_p\in CP\wedge\ \forall c_s\in CS\wedge\ t>1$
- $O^B_{kmqt} = Y^B_{kmqt} \quad \forall k\in K\ \wedge\ \forall m\in M\wedge\ \forall q\in Q\wedge\ t=1$
- $O^B_{kmqt} = Y^B_{kmqt} - Y^B_{kmqt-1} \quad \forall k\in K\wedge\ \forall m\in M\wedge\ \forall q\in Q\wedge\ t>1$

APPENDIX C. CASE STUDY

Table 11 – *Seeds and Corn/Cereals availability per Portuguese Municipality, in tonnes (Parameter BA_{bit}).*

Municipalities	Seeds production (tonnes)	Corn/Cereals Production (tonne)
Abrantes	78,32	22548,098
Águeda	36,74	10577,594
Alandroal	613,94	17063,904
Albergaria-a-Velha	31,91	9186,262
Alcácer do Sal	1696,81	47161,564
Alcanena	39,54	11382,053
Alcobaça	82,00	23607,109
Alcochete	450,62	9826,838
Alenquer	94,46	27194,285
Alfândega da Fé	0,00	14233,287
Alijó	0,00	13156,783
Aljustrel	2247,57	62469,439
Almeida	104,07	29960,333
Almeirim	711,98	19788,821
Almodôvar	469,34	13045,055
Alpiarça	467,49	12993,403
Alter do Chão	750,96	20872,216
Alvaiázere	32,24	9282,278
Alvito	549,32	15267,784
Amarante	0,00	8619,914
Anadia	43,52	12530,034
Ansião	35,38	10185,171
Armamar	0,00	7927,149
Arraiolos	773,53	21499,676
Arronches	355,97	9893,782
Arruda dos Vinhos	37,02	10658,256
Aveiro	39,70	11428,168
Avis	1256,82	34932,297
Azambuja	841,92	23400,557
Barcelos	0,00	16751,025
Barrancos	349,31	9708,892
Beja	5620,42	156215,155
Belmonte	36,88	10615,979
Benavente	1081,37	30055,945
Bombarral	43,35	12480,659
Borba	711,77	19783,056
Bragança	0,00	51883,084
Cadaval	54,30	15633,451
Caldas da Rainha	79,39	22856,179
Campo Maior	1211,86	33682,564
Cantanhede	78,53	22608,778
Carrazeda de Ansiães	0,00	7988,002
Cartaxo	775,40	21551,663
Castelo Branco	157,61	45374,147
Castelo de Vide	299,69	8329,769
Castro Daire	41,54	11958,515
Castro Verde	2791,58	77589,803
Celorico da Beira	49,67	14299,381
Chamusca	843,97	23457,365
Chaves	0,00	16912,858
Coimbra	64,17	18474,324
Condeixa-a-Nova	27,86	8020,772
Coruche	1262,22	35082,441

Covilhã	111,63	32136,300
Crato	450,34	12516,821
Cuba	551,61	15331,614
Elvas	2023,52	56242,053
Estarreja	33,59	9669,337
Estremoz	1065,65	29618,981
Évora	4189,67	116448,641
Ferreira do Alentejo	3177,74	88322,714
Ferreira do Zêzere	38,25	11011,715
Figueira da Foz	76,16	21924,522
Figueira de Castelo Rodrigo	157,91	45461,171
Fronteira	796,85	22147,942
Fundão	140,68	40500,068
Golegã	413,36	11489,134
Gouveia	60,40	17387,497
Grândola	498,34	13851,022
Guarda	143,07	41188,372
Idanha-a-Nova	284,56	81922,116
Leiria	113,53	32685,209
Loulé	0,00	18193,041
Loures	587,11	12803,368
Lourinhã	69,89	20120,260
Mação	43,83	12619,161
Macedo de Cavaleiros	0,00	30908,714
Mafra	1582,33	34506,610
Mangualde	44,05	12682,155
Mêda	88,82	25570,065
Mértola	2681,49	74529,958
Miranda do Douro	0,00	21538,043
Mirandela	0,00	29132,371
Mogadouro	0,00	33628,048
Monforte	871,62	24226,113
Montalegre	0,00	12567,911
Montemor-o-Novo	1394,87	38769,223
Montemor-o-Velho	71,09	20466,779
Montijo	1223,86	26689,251
Mora	502,24	13959,461
Moura	3072,22	85389,849
Mourão	577,90	16062,158
Nisa	651,27	18101,548
Óbidos	43,95	12653,182
Odemira	1946,53	54102,147
Oleiros	27,53	7926,744
Oliveira do Hospital	47,12	13564,804
Ourém	83,72	24101,069
Ourique	750,41	20856,966
Palmela	2523,49	55030,737
Penamacor	61,78	17784,757
Pinhel	97,35	28024,983
Pombal	125,77	36208,287
Ponte de Lima	0,00	9161,144
Ponte de Sor	506,65	14081,945
Portalegre	505,85	14059,766
Portel	679,93	18898,019
Porto de Mós	52,61	15144,434
Proença-a-Nova	43,33	12474,664
Redondo	766,39	21301,109
Reguengos de Monsaraz	962,37	26748,165
Rio Maior	565,72	15723,771

Sabugal	90,16	25955,757
Salvaterra de Magos	781,89	21731,889
Santarém	2708,73	75287,071
Santiago do Cacém	1198,83	33320,646
São João da Pesqueira	0,00	17992,951
São Pedro do Sul	38,24	11009,191
Sátão	40,57	11680,354
Seia	47,75	13745,793
Serpa	3543,95	98501,324
Sertã	48,96	14094,099
Setúbal	441,05	9618,186
Silves	0,00	16201,185
Sines	421,66	11719,616
Sintra	1120,68	24439,245
Soure	53,25	15331,260
Sousel	1369,32	38059,118
Tábua	40,14	11555,996
Tavira	0,00	14459,950
Tomar	70,56	20313,659
Tondela	74,58	21471,630
Torre de Moncorvo	0,00	15205,925
Torres Novas	128,22	36912,892
Torres Vedras	126,42	36395,217
Trancoso	72,63	20910,575
Vagos	33,13	9539,090
Valpaços	0,00	24259,587
Viana do Alentejo	816,50	22693,858
Viana do Castelo	0,00	9125,958
Vidigueira	1014,85	28206,999
Vila Flor	0,00	11751,359
Vila Franca de Xira	1726,32	37646,694
Vila Nova de Foz Côa	0,00	17602,060
Vila Real	0,00	10836,038
Vila Velha de Ródão	36,15	10408,489
Vila Viçosa	404,15	11233,076
Vimioso	0,00	13776,472
Vinhais	0,00	19874,175
Viseu	101,88	29331,026

Table 12 – *Distances between Biomass Collection Site and Integrated Biorefinery Site, in km. (Parameter DIK_{ik})*

Integrated Biorefiney Site / Biomass Collection Site	Aveiro	Beja	Braga	Braganca	Castelo Branco	Chaves	Coimbra	Evora	Faro	Fundao	Guarda	Leiria	Lisboa	Mertola	Montemor-o-Novo	Pombal	Ponte de Sor	Portalegre	Porto	Santarem	Serta	Setubal	Sines	Viana do Castelo	Vila Nova de Foz Coa	Vila Real	Vila Velha de Rodão	Viseu
Abrantes	170,1	202,8	281,4	364,0	86,1	349,9	115,0	126,8	331,8	125,4	178,2	82,0	141,9	254,8	115,0	90,0	33,2	83,7	227,8	64,8	54,0	153,4	229,5	300,9	258,00	288,30	59,20	195,70
Águeda	22,6	352,3	126	260,2	183,7	207,9	45,1	283,2	473	164,9	147,9	110,1	240,3	404,3	256,1	84,7	189,6	219,2	72,4	177,8	120,2	268,3	356,6	145,6	181,8	146,3	167,6	74,9
Alandroal	294,2	112,7	405,4	434,4	156,5	441,4	239,1	51,8	251,7	195,8	248,6	206	178,3	164,6	81,5	214,1	91,6	78,1	351,8	155,1	178	148,3	187,6	425	328,3	393,1	128,8	303,2
Albergaria-a-Velha	19,7	367,5	112,5	250,5	198,9	198,2	60,3	298,4	488,2	174,9	138,2	125,4	255,5	419,5	271,4	100	204,8	234,4	59	193	135,5	283,6	371,8	132,1	172,1	136,6	182,8	65,2
Alcácer do Sal	297,6	85,2	412,1	505,2	227,2	481	246,1	67,9	194,9	266,5	319,4	186,4	88,7	137,2	45,9	212,3	132,2	165,2	358,5	117,1	214,6	50,7	69,5	431,7	399,1	419,4	199,6	326,7
Alcanena	157,2	213	267,6	396,2	130,3	348,5	109,6	147	333,7	169,6	222,5	46,9	105,7	265	116,8	69,8	84,4	131,3	214,1	31,2	91,5	130,6	217,3	287,2	290,1	287	103,5	194,3
Alcobaça	142,1	243,7	261	386	166,4	338,3	99,4	177,7	351,4	205,7	245	30,9	106,9	295,6	147,5	56,8	120,4	167,4	207,5	61,9	121,4	135	232,7	280,6	279,9	276,8	139,5	184,1
Alcochete	246,1	151,1	365	482,1	215,7	439,6	203,4	101,3	255,1	255	307,8	134,9	34,5	203	71,2	160,8	127,2	185,8	311,4	75,7	177,2	30	134,8	384,6	376	378	188,8	285,4
Alenquer	198,5	186	317,5	442,4	190,2	394,7	155,8	126,5	288,5	229,5	282,4	87,3	44	237,9	96,3	113,2	128,7	189,7	263,9	43	151,8	72	169,7	337	336,3	333,2	163,3	240,5
Alfândega da Fé	230,8	462,5	193,6	72,8	215,8	90,4	225	387,2	596,9	178,7	123,8	291,2	421,4	514,5	395,2	265,8	310,5	293,2	191,9	349,7	263,3	441,8	509,8	241,4	42,2	98,6	242,4	149,9
Alijó	170,1	469,5	131,3	110,9	222,7	73	196,9	394,1	603,9	185,6	130,8	263,1	393,3	521,4	402,2	237,7	317,5	300,1	129,5	326,7	254,8	418,8	505,5	179	79,3	35,3	249,4	109,8
Aljustrel	365,5	36,6	480,2	543,5	265,5	548,8	314	93	119,2	304,8	357,6	254,3	162,2	66,2	99,4	280,2	185,7	193	426,6	185	268,1	124,6	76,8	499,8	437,4	487,3	237,8	394,6
Almeida	191	381,9	233,5	165,7	133,9	172,7	184,4	306,6	516,3	98,7	46,3	250,5	357,8	433,8	314,6	225,1	229,9	212,6	231,2	281	197,1	372,9	429,2	281,3	59,7	154,2	161,8	109,2
Almeirim	187,4	175,1	302,1	413,1	146,7	370,6	135,8	109,1	295,8	186	238,9	76,2	83,9	227,1	78,9	102,1	81,7	142,7	248,5	6,9	108,3	92,7	179,4	321,6	307	309,1	119,8	216,4
Almodôvar	409,1	65,7	523,8	587	309	592,4	357,5	136,5	74,5	348,3	401,2	297,9	206	41,5	142,9	323,8	229,2	236,5	470,2	228,5	311,6	168,3	100,6	543,3	480,9	530,8	281,4	438,2
Alpiarça	184,1	182,1	295,3	406,3	139,9	363,8	128,9	116	302,7	179,2	232	80,4	88,1	234	85,9	100,8	74,9	135,9	241,7	11	101,4	99,6	186,3	314,8	300,2	302,2	113	209,6
Alter do Chão	237,2	164,7	348,4	362,1	84,1	369	182,1	89,3	299,1	123,4	176,2	149	178,2	216,6	97,4	157,1	34,6	34	294,8	119	106	162,9	212	368	256	320,8	56,4	230,9
Alvaiázere	110	259,4	221,2	332,3	115,4	289,8	54,9	190,3	380,1	145,6	190,5	56	161,6	311,4	163,2	36,8	96,7	143,9	167,6	84,9	50	177	263,7	240,8	226,2	228,2	99,4	135,5
Alvito	327,2	35,8	441,9	491,7	213,7	498,7	275,6	41,2	170,5	253	305,9	216	147,5	87,8	61	241,9	135,3	141,2	388,3	146,6	221,7	109,4	103,6	461,4	385,6	448,9	186,1	356,3
Amarante	124,7	480,3	56,8	158,7	253,5	101,9	173,2	411,2	601	216,4	161,6	233,7	363,9	532,3	384,2	208,3	317,6	331	58,8	299,3	248,3	391,9	484,6	104,6	121,1	39,3	280,2	107,8
Anadia	31	337,6	143,5	277,7	168,9	225,3	30,4	268,4	458,2	147,4	143,2	95,4	225,6	389,5	241,4	70	174,8	204,5	89,9	163	105,5	253,6	341,8	163	178,1	163,8	152,9	77,4
Ansião	94	276,3	204,4	326,1	109,7	281,7	42,8	207,2	397	139,4	184,3	45,2	175,4	328,3	180,1	19,5	113,6	145,2	150,9	101,8	46,3	193,9	280,6	224	220	220,2	93,6	127,5
Armamar	140,4	444,9	112,4	154,7	198,1	102,4	167,2	369,5	579,3	161	106,2	233,4	363,6	496,8	375,4	208	292,9	275,6	110,8	297	225,1	389,1	475,8	160,1	90,5	40,8	224,8	80,1
Arraiolos	274,2	100	385,4	436,8	158,8	443,8	219,1	24	234,4	198,1	251	175,3	119,4	152	22,7	191,9	71,5	97,9	331,8	105,9	158	88,2	137,2	404,9	330,7	392,3	131,2	299,7
Arronches	257,2	166,6	368,4	381,5	103,5	388,5	202,1	91,3	301	142,8	195,7	188,5	205,1	218,6	109,9	188,9	79,7	24,7	314,8	164,1	125,4	175,4	224,4	388	275,4	340,2	75,9	250,3
Arruda dos Vinhos	214,7	186,8	333,7	458,6	197,5	411	172	127,3	289,2	236,8	289,6	103,5	35,8	238,7	97,1	129,4	135,9	197	280,1	50,3	159,1	69,3	170,5	353,2	352,5	349,4	170,6	256,7
Aveiro	4	362,2	121,4	267,5	197,1	215,2	58,5	296,2	482,9	178,2	155,2	111,6	241,3	414,2	266	94,4	203	232,6	67,8	180,4	133,6	269,3	366,5	140,2	189,1	153,6	181	82,2
Avis	230,9	142,1	342,1	393,5	115,5	400,5	175,8	66,1	276,5	154,8	207,7	142,7	146,8	194,1	66	150,7	28,2	65,4	288,5	112,6	114,7	131,5	180,5	361,6	287,4	349	87,9	256,4
Azambuja	199,6	192,4	318,6	440,5	174,1	395,9	157	132,9	294,8	213,4	266,2	88,4	50,4	244,3	102,7	114,3	112,5	173,6	265	26,9	135,7	78,4	176,1	338,1	334,4	334,3	147,2	241,7
Barcelos	120,6	476,2	23,8	233,6	307,6	142,5	169	407,1	596,9	284,6	236,4	229,5	359,7	528,2	380	204,1	313,5	343,1	52,9	295,1	244,1	387,7	480,5	31,3	195,9	114,1	291,5	174,9
Barrancos	391,8	96,1	503	532,1	254,1	539,1	336,7	107,4	210,8	293,4	346,2	292,2	234	109,5	137,2	311,7	189,2	180,6	449,4	222,8	275,6	203,9	192,8	522,6	426	490,8	226,5	400,9
Beja	362,6	9,6	477,2	526,6	248,7	533,6	311	76,1	139,5	288	340,8	251,4	173,9	52,4	96,4	277,3	170,2	176,1	423,6	182	256,7	135,9	98,5	496,8	420,5	484,3	221	391,6
Belmonte	178,8	316,4	242,1	211,7	69,6	218,7	148,6	241	450,8	33,3	24,9	214,7	292,3	368,3	249,1	189,4	164,4	147	219,1	215,5	131,5	307,3	363,7	289,9	105,6	170,4	96,2	97,1
Benavente	219,8	166,3	334,3	445,6	179,2	403,1	168,3	108,2	268,8	218,5	271,3	108,6	51,9	218,3	78	134,5	111,6	170,2	280,7	39,3	140,8	60,3	150	353,8	339,5	341,5	152,3	248,9
Bombarral	181,7	223	302,2	427,1	197,2	379,5	140,6	163,6	325,5	236,5	286,1	72,1	71,7	275	133,4	97,9	146,8	198,1	248,6	61,2	158,3	107,4	206,8	321,7	321	317,9	170,3	225,2
Borba	281,6	121,3	392,8	419,4	141,4	426,4	226,5	55,8	260,3	180,7	233,6	193,4	172,8	173,3	76	201,5	79	63,1	339,2	142,5	163,3	141,5	190,2	412,4	313,3	378,1	113,8	288,2
Bragança	267,7	527,3	215,6	9,7	280,6	100,3	289,8	452	661,7	243,5	188,6	356	486,2	579,3	460,1	330,6	375,3	358	214,4	414,5	328,1	506,6	574,6	263,9	107	121,2	307,2	207,4
Cadaval	188,9	216,7	309,4	434,3	190,2	386,7	147,8	157,2	319,1	229,5	282,3	79,3	74,5	268,6	127	105,2	138,7	191,2	255,8	53	151,4	102,7	200,4	329	328,3	325,1	163,3	232,5
Caldas da Rainha	163,7	232,3	284,2	409,2	185,7	361,5	122,6	167,5	334,8	225	268,2	54,1	89,6	284,3	137,3	80	137,3	186,7	230,6	51,7	145,3	118,3	216	303,8	303,1	300	158,8	207,3
Campo Maior	280	165,4	391,2	404,2	126,3	411,2	224,9	100,6	304,4	165,6	218,4	210,3	219,2	217,3	122,5	211,7	95,8	47,5	337,6	180,2	148,2	188	235	410,7	298,2	363	98,6	273,1
Cantanhede	34,8	332,3	155,4	290,4	163,7	238,1	25,1	263,2	453	158,4	154,2	87,9	218	384,3	236,1	62,5	169,6	199,2	101,8	153,4	100,2	246,1	336,6	174,3	189,1	176,5	147,6	88,5
Carrazeda de Ansiães	196,7	459,4	163,3	94,2	212,6	91,5	207,6	384,1	593,8	175,5	120,7	273,8	404	511,4	392,1	248,4	307,4	290,1	161,7	337,4	260,2	429,5	506,7	211	53,1	68,5	239,3	123,9
Cartaxo	194,6	195,3	308,8	427,8	161,4	385,3	150,4	129,3	308	200,7	253,5	83,4	63,6	247,3	99,1	109,3	99,8	160,9	255,2	14,2	122,9	91,6	189,3	328,4	321,7	323,7	134,5	231,1
Castelo Branco	197,3	248,8	308,5	279,6	10,7	286,6	142,2	173,4	383,2	41	93,8	154,7	224,7	300,7	181,5	129	96,8	79,5	255	147,9	65,5	239,8	296,1	328,1	173,6	238,4	28,7	148,5
Castelo de Vide	226,4	194,4	337,6	350,6	72,7	357,6	171,3	119,1	328,8	112	164,8	158,4	218,7	246,4	137,7	158	74,9	19,4	284	141,6	94,5	203,2	252,2	357,1	244,5	309,3	45	219,4
Castro Daire	93,5	427,4	133	175,2	184	122,9	123,1	355,5	548,1	145,7	108,3	189,3	319,5	479,4	331,2	163,9	264,7	261,5	111,5	252,9	180,9	345	431,7	179,2	108	61,3	210,7	36
Castro Verde	387,7	44,3	502,4	565,7	287,7	571	336,2	115,2	95,9	327	379,8	276,5	184,6	42,9	121,6	302,5	207,9	215,2	448,8	207,2	290,3	147	91,4	522	459,6	509,5	260	416,8
Celorico da Beira	130,3	364,2	195,9	165,5	117,4	172,5	123,7	288,8	498,6	80,3	25,5	189,8	320	416,1	296,9	164,4	212,2	194,8	170,5	248,3	162	340,4	411,5	243,7	59,4	124,2	144	48,5
Chamusca	167,6	198,5	278,9	389,9	123,5	347,4	112,5	130,3	319,1	162,8	215,6	67,9	104,5	250,4	102,3	84,4	64	119,5	225,3	27,4	85	116	202,7	298,4	283,8	285,8	96,6	193,2
Chaves	214,5	533,6	119,3	99,8	286,8	6,9	241,4	458,2	666,3	249,7	194,9	307,5	437,7	585,5	449,5	282,1	381,6	364,3	156,7	371,2	299,2	463,2	549,9	172,5	113,2	63,4	313,5	154,3
Coimbra	58,8	310,9	170	289,1	142,3	241,5	5	241,8	431,6	147,5	148,1	68,7	198,9	362,8	214,7	43,3	148,2	177,8	116,4	136,4	78,8	226,9	315,2	189,6	183	179,9	126,2	87,2
Condeixa-a-Nova	68,5	299,5	179	303,9	130,9	256,2	17,3	230,4	420,2	151,9	162,9	52,6	182,8	351,5	203,4	27,2	136,8	166,4	125,4	122	67,5	210,8	303,8	198,5	197,8	194,7	114,8	102
Coruche	219,6	144,2	334,3	445,4	178,2	402,9	168,1	78,2	264,9	217,5	270,3	108,4	80	196,1	48	134,3	81,6	140,2	280,7	39,1	140,6	73,6	151,3	353,8	339,3	341,4	151,3	248,7
Covilhã	169,2	303,7	255,6	229	56,9	236	138,7	228,3	438,1	18,6	42,2	198,4	279,6	355,6	236,4	172,6	151,7	134,3	213,3	202,8	118,8	294,7	351	286,4	122,9	184	83,6	91,9
Crato	225,4	177,1	336,6	349,7	71,7	356,6	170,3	101,7	311,5	111	163,8	156,3	190,6	229	109,8	157,1	47	21,6	283	131,4	93,6	175,3	224,4	356,2	243,6	308,4	44	218,5
Cuba	344,4	19,1	459	508,8	230,9	515,8	292,8	58,4	158,1	270,2	323	233,2	164,6	71,1	78,2	259,1	152,4	158,4	405,4	163,8	238,9	126,6	99,1	478,6	402,8	466,1	203,2	373,4

Elvas	289,2	145,9	400,4	413,5	135,5	420,5	234,1	83,4	284,9	174,8	227,7	211,9	200,4	197,8	103,6	220	97,5	56,7	346,8	170,1	157,4	169,1	217,8	420	307,4	372,2	107,9	282,3
Estarreja	19,5	380,9	102,3	261,4	212,3	204,6	73,7	311,8	501,6	188,3	151,6	131	260,7	432,9	284,8	110,5	218,2	247,8	48,7	199,9	148,9	288,7	385,2	121,1	185,5	141,9	196,2	78,6
Estremoz	269,4	121,4	380,6	409,6	131,7	416,6	214,3	46	255,8	171	223,8	181,2	161,4	173,3	64,6	189,2	66,7	55,8	327	131,1	153,2	130,1	179,2	400,1	303,5	368,3	104	278,4
Évora	296,5	76,2	408,1	451,3	173,3	458,3	241,8	10,2	210,6	212,6	265,5	185,3	127	128,1	30,3	211,2	94,2	100,8	354,5	115,9	180,7	97	136,7	427,6	345,2	410	145,7	320,1
Ferreira do Alentejo	340,9	24	455,6	518,9	240,9	524,2	289,4	68,4	142,3	280,2	333	229,7	151,5	75,9	74,8	255,7	161,1	168,4	402	160,4	243,5	113,9	75,3	475,2	412,8	462,7	213,2	370
Ferreira do Zêzere	126,5	250,9	237,7	348,8	101,1	306,3	71,4	181,8	371,6	136,4	191,7	64,5	153,1	302,9	154,7	57,4	88,2	135,4	184,1	76,4	35,7	168,5	255,2	257,3	242,7	244,7	85,1	152
Figueira da Foz	60,9	305,1	182,2	327,8	168,5	275,9	44,3	239,1	425,8	186,2	186,8	54,4	184,1	357	208,9	41,4	163,9	204,1	128,6	123,3	105,1	212,1	309,4	201	221,7	214,4	152,5	125,9
Figueira de Castelo Rodrigo	202,1	396,4	211,2	143,5	149,6	150,5	195,5	321	530,8	113,2	59,9	261,6	372,3	448,3	329,1	236,3	244,4	227,1	209,7	295,5	211,5	387,4	443,7	259	37,4	131,9	176,3	120,4
Fronteira	253	147,7	364,2	379,1	101,1	386,1	197,8	72,3	282,1	140,4	193,3	164,8	169,7	199,6	81,1	172,8	50,3	49,4	310,6	134,7	123	146,6	195,7	383,7	273	337,8	73,5	247,9
Fundão	178,3	288,2	272,9	242,5	41,5	249,5	147,8	212,9	422,6	7,5	55,7	184,5	264,2	340,2	221	158,7	136,2	118,9	231,7	187,4	102,4	279,2	335,5	304,9	136,4	201,2	68,1	110,4
Golegã	159,8	208	271	382	115,6	339,5	104,7	139,8	328,7	154,9	207,8	59,9	108,8	259,9	111,8	76,5	69,4	116,6	217,4	31,7	77,2	125,6	212,3	290,5	275,9	278	88,7	185,3
Gouveia	123,3	358,3	203,6	192,2	111,5	193,5	106,5	282,9	492,7	73,2	50,5	172,7	302,8	410,2	291	147,3	206,3	189	163,6	226,5	140,2	318,6	405,3	236,8	86,1	131,9	138,2	41,6
Grândola	321,6	68,8	436,2	529,1	251,2	505	270,2	91,9	172,9	290,5	343,3	210,4	112,8	120,7	69,9	236,3	156,2	189,2	382,6	141,2	238,6	74,8	45,9	455,8	423,1	443,5	223,5	350,8
Guarda	154,8	340,8	218,1	187,7	94	194,7	148,2	265,5	475,2	55,7	7,5	214,4	316,7	392,7	273,5	189	188,8	171,5	195,1	239,9	156	331,8	388,1	265,8	81,6	146,4	120,7	73,1
Idanha-a-Nova	223,3	283,3	307,2	276,8	34,6	283,8	176,7	207,9	417,7	45,5	92,2	189,2	259,2	335,2	216	163,5	131,3	113,9	276,8	182,4	100	274,2	330,6	349,9	170,7	235,5	63,2	155,4
Leiria	111,5	251,3	230,3	355,3	154,8	307,6	68,7	185,3	372	184,5	214,3	6,7	130,4	303,3	155,1	26,1	115,1	162,3	176,7	69,5	91,3	158,4	255,6	249,9	249,2	246	134,4	153,4
Loulé	471,1	127,7	585,8	649	371,1	654,4	419,5	198,5	17,3	410,4	463,2	359,9	264	89,3	204,9	385,8	291,2	298,5	532,2	290,5	373,6	226,4	154,2	605,3	542,9	592,8	343,4	500,2
Loures	237,9	171,5	356,9	481,8	220,5	434,2	195,3	124,7	275,5	259,8	312,6	126,7	14,5	223,4	94,5	152,7	151,8	210,4	303,3	73,5	181,7	50	155,2	376,5	375,8	372,6	193,6	280
Lourinhã	198,8	225,1	319,3	444,3	214,3	396,6	157,7	168,7	329,1	253,6	303,3	89,2	67,9	277,1	138,5	115,1	164	215,3	265,7	78,3	175,5	103,6	208,8	338,9	338,2	335,1	187,4	242,4
Mação	177,2	215,7	288,4	342,1	64,2	342,5	122,1	139,7	348,8	103,5	156,3	102,7	166,4	267,7	131,9	108,8	45,6	68	234,8	89,6	43,7	181,3	246,5	307,9	236	280,9	37,3	188,3
Macedo de Cavaleiros	232,6	485	181,1	41,8	238,2	78,9	247,5	409,6	619,4	201,1	146,3	313,6	443,8	536,9	417,7	288,3	333	315,7	179,3	372,2	285,8	464,2	532,3	228,9	64,7	86,1	264,9	172,3
Mafra	231,9	196	352,4	477,3	233,7	429,7	190,8	149,2	300	273	325,8	122,3	38,8	247,9	119	148,2	171,4	230	298,8	86,4	195,2	74,5	179,7	372	371,3	368,1	206,8	275,5
Mangualde	98,1	383,6	178,4	200,7	136,8	168,3	88,5	308,2	513,5	98,5	59,7	154,7	284,9	435,5	296,7	129,3	229	214,2	138,4	218,3	142,4	310,4	397,1	211,5	94,6	106,7	163,5	16,4
Mêda	171,4	405,6	175,1	128,3	158,9	135,3	168,1	330,3	540	121,8	66,9	234,3	364,5	457,6	338,3	208,9	253,6	236,3	173,6	292,8	206,4	384,9	452,9	222,9	22,2	98,2	185,5	91,8
Mértola	414,6	52,7	529,2	578,6	300,6	585,6	363	128,1	101,4	339,9	392,8	303,4	225,9	10,1	148,4	329,3	222,2	228,1	475,6	234	308,7	187,9	133,8	548,8	472,5	536,3	273	443,6
Miranda do Douro	308,2	529,3	268,4	76,1	282,5	167,2	302,4	454	663,7	246,1	192,8	368,6	498,7	581,3	462	343,2	377,3	360	266,6	427,1	340,7	519,1	576,6	316,1	119,6	173,4	309,2	227,3
Mirandela	207,4	481	155,9	62,2	234,2	52,6	234,3	405,6	615,4	197,1	142,3	300,4	430,6	532,9	413,7	275	329	311,6	154,2	364,1	281,8	456,1	528,3	203,7	60,6	60,9	260,9	147,2
Mogadouro	261,2	482,3	230,9	83,4	235,5	128,7	255,4	407	616,7	199,1	145,8	321,6	451,7	534,3	415	296,2	330,3	313	229,1	380,1	293,7	472,1	529,6	278,7	72,6	135,9	262,2	180,3
Monforte	260,6	148,3	371,8	384,9	106,9	391,9	205,5	72,9	282,7	146,2	199	175,8	186,7	200,2	91,5	183,9	61,4	28,6	318,2	145,8	128,8	157	206,1	391,4	278,8	343,6	79,2	253,7
Montalegre	210,1	565,7	89,7	142,8	326,9	43,3	258,6	496,6	686,4	289,8	235	319,1	449,3	617,7	469,6	293,7	403	404,4	142,5	384,7	326,1	477,3	570	142,9	156,3	90,3	353,6	181,2
Montemor-o-Novo	266,3	96,3	380,9	459,4	181,4	449,6	214,7	30,3	217	220,7	273,5	155,1	96,8	148,2	9,9	181	86,4	119,4	327,4	85,7	168,8	66,8	114,7	400,5	353,3	388	153,8	295,3
Montemor-o-Velho	58,6	318,1	179,3	311,3	150,8	261,7	27,7	250,3	438,7	169,7	170,3	66,9	197,1	370	221,9	41,5	156,7	186,3	125,7	136,3	87,3	225,1	322,3	198,1	205,2	200,1	134,7	109,4
Montijo	250,6	145,7	369,5	486,6	220,2	444,1	207,9	99,5	249,8	259,5	312,3	139,4	33,2	197,7	69,4	165,3	131,7	188,7	316	80,2	181,7	24,3	129,5	389,1	380,5	382,5	193,3	289,9
Mora	243,2	136,4	354,4	419,4	141,4	422,9	188,1	60,4	261,3	180,7	233,5	143,4	108,8	188,4	44,4	160	44,8	105,2	300,8	74,6	127,2	102,4	159	373,9	313,3	361,4	114,5	268,7
Moura	371,9	51,3	483,9	518,3	240,4	525,3	317,6	76	184,2	279,7	332,5	260,8	202,5	82,9	105,8	286,7	170,1	166,9	430,3	191,4	256,5	165,9	144,2	503,5	412,2	477	212,7	387,1
Mourão	342,1	87	453,3	482,3	204,4	489,3	287	57,7	220,7	243,7	296,5	242,5	184,2	119,4	87,5	261,9	139,5	130,9	399,7	173,1	225,9	154,2	179,9	472,9	376,3	441,1	176,7	351,1
Nisa	199,5	203,6	310,7	323,7	45,7	330,7	144,3	128,2	338	85	137,9	135,3	197,8	255,5	136,3	131,1	54	34,3	257,1	120,8	67,6	199,2	250,9	330,2	217,6	282,4	18,1	192,5
Óbidos	169,4	233,1	289,9	414,9	187,3	367,2	128,3	167,1	336,6	226,6	273,9	59,8	83,2	285,1	136,9	85,7	137	188,3	236,3	51,3	148,5	118,9	217,9	309,5	308,8	305,7	160,4	213
Odemira	401,6	93,8	516,2	600,5	322,6	585	350,1	150,1	136,6	361,9	414,7	290,4	192,7	105,1	149,8	316,3	236,2	250,1	462,6	221,1	318,5	154,7	56,7	535,7	494,5	523,4	294,9	430,8
Oleiros	154,9	270,8	266,8	315,9	61,2	300,5	100,5	195,5	405,2	73,5	129,2	113	212,9	322,8	191,4	87,2	105,1	101,5	213,2	136,2	29	228,3	306	286,4	209,9	238,9	49,9	146,3
Oliveira do Hospital	103,1	365,4	215,5	223,8	125,5	211,9	75,5	289,4	490,8	87,2	82	141,7	271,9	417,3	273,9	116,3	195,8	203	161,9	195,6	109,2	287,7	374,4	235,1	117,7	150,3	152,2	58,2
Ourém	133,5	241	243,9	365,6	136,1	321,2	82,3	172,8	361,7	172,5	223,8	25,3	137,3	292,9	144,8	42,9	89,9	137,1	190,3	66,4	71,7	158,6	245,3	263,5	259,5	259,6	109,2	167
Ourique	395	58,8	509,5	580,2	302,3	578,4	343,5	129,8	98,9	341,6	394,4	283,8	187,4	57,5	136,1	309,7	222,5	229,8	456	214,5	304,8	149,7	76,1	529,1	474,2	516,8	274,6	424,1
Palmela	264,9	138	383,9	500,9	234,5	458,4	222,3	95,6	242	273,8	326,7	153,7	40,8	190	65,4	179,6	145,6	183,5	330,3	94,6	196,1	8,2	121,7	403,4	394,8	396,9	207,6	304,2
Penamacor	208,8	300,5	276,2	245,8	51,8	252,8	178,2	225,1	434,9	36,1	61,2	206,4	276,4	352,4	233,2	180,7	148,5	131,1	253,2	199,6	117,2	291,4	347,8	324	139,7	204,5	80,3	131,2
Pinhel	177,9	372,2	211,4	167,6	125,5	174,6	171,3	296,9	506,6	89	35,7	237,5	348,2	424,2	304,9	212,1	220,2	202,9	209,8	271,4	187,4	363,2	419,5	259,2	61,5	139,7	152,1	96,2
Pombal	94,2	277,2	204,6	329,6	129,1	281,9	43	211,2	397,9	158,7	188,6	26,1	156,3	329,2	181	7,1	123,1	164,6	151	95,4	65,6	184,3	281,5	224,2	223,5	220,4	113	127,7
Ponte de Lima	149,7	505,3	33,5	247,5	336,7	151	198,1	436,2	626	305,2	250,4	258,6	388,8	557,2	409,1	233,2	342,6	372,2	82	324,2	273,2	416,8	509,6	26,6	209,9	128,1	320,6	196,6
Ponte de Sor	203,3	170,2	314,5	374,7	96,7	381,7	148,2	94,2	303,3	136	188,9	115,1	153,5	222,2	86,4	123,1	8,2	68,5	260,9	85,7	87,1	145,3	201	334	268,6	321,5	69,8	228,8
Portalegre	233,1	176,1	344,3	357,3	79,3	364,3	177,9	100,8	310,5	118,6	171,5	164,3	212,1	228,1	119,4	164,7	68,5	6	290,7	147,5	101,2	184,9	234	363,8	251,2	316	51,7	226,1
Portel	337,5	38,5	449,5	492,1	214,1	499,1	283,2	41,6	177,5	253,4	306,2	226,3	168,1	90,5	71,4	252,2	135,6	141,6	395,9	157	222,1	133,8	124,3	469	386	450,8	186,4	360,9
Porto de Mós	145,1	225,3	260,9	389,1	134,1	341,4	102,5	159,3	346	173,4	226,2	33,9	115,2	277,3	129,1	59,9	88,1	135,1	207,3	44,2	95,2	142,9	229,6	280,5	283	279,8	107,2	187,2
Proença-a-Nova	149,4	248,3	260,6	324,5	48,2	314,8	94,3	172,3	381,4	85,9	138,7	106,8	195,7	300,2	164,5	81,1	78,2	84,7	207	118,8	17,6	210,7	279,1	280,2	218,5	253,2	33,1	160,5
Redondo	294,9	97,2	406,1	435,2	157,2	442,1	239,8	36,4	236,2	196,5	249,3	206,7	162,8	149,2	66,1	214,8	92,3	83,7	352,5	151,7	178,7	132,8	172,2	425,7	329,1	393,9	129,5	304
Reguengos de Monsaraz	322,7	83	433,9	462,9	184,9	469,9	267,6	38,3	222	224,2	277,1	223	164,8	135	68	242,5	120	111,4	380,3	153,7	206,5	134,8	168,8	453,4	356,8	421,6	157,3	331,7
Rio Maior	170,7	212,6	289,6	414,6	163,2	366,9	128	146,6	330,3	202,5	255,3	59,4	85,9	264,5	116,4	85,4	116,5	164,2	236	30,8	124,4	113,9	211,6	309,2	308,5	305,3	136,3	212,7
Sabugal	182	332,3	245,2	214,8	83,6	221,8	175,4	257	466,7	53,9	30,2	238	308,2	384,2	265	212,3	180,3	163	222,3	231,4	149	323,3	379,6	293	108,7	173,5	112,2	100,3
Salvaterra de Magos	214,4	168,8	328,9	440,2	173,8	397,7	162,9	102,8	274,2	213,1	265,9	103,2	57,3	220,7	72,6	129,1	106,2	164,8	275,3	33,9	135,4	65,7	155,4	348,4	334,1	336,1	146,9	243,5
Santarém	180,7	181,9	295,3	413,7	147,3	371,2	136,4	115,9	302,6	186,6	239,5	69,5	77,2	233,8	85,7	95,4	85,8	146,8	241,8	5,4	108,9	99,5	186,2	314,9	307,6	309,7	120,4	217
Santiago do Cacém	346,3	77,9	460,9	553,8	275,9	529,7	294,9	116,6	164,9	315,2	368	235,1	137,5	121,7	94,6	261,1	180,9	213,9	407,3	165,9	263,3	99,5	21,3	480,5	447,8	468,2	248,2	375,5
São João da Pesqueira	169	432,4	135,6	121,9	185,7	110,1	180,7	357,1	566,8	148,6	93,7	246,8	377	484,4	365,2	221,4	280,4	263,1	134	310,5	233,2	402,5	479,7	183,4	42,3	56,2	212,3	96,9
São Pedro do Sul	67,1	410,3	153,7	200,2	170,8	147,8	105,4	341,1	531	132,5	95	170,4	300,6	462,2	314,1	145	247,6	248,3	100,2	235,8	163,8	327,8	414,6	173,4	127,4	86,3	197,5	22,8
Sátão	100,9	406,4	155,5	194,6	159,6	145,4	108,5	331	533,5	121,3	79,9	174,7	304,8	458,3	316,6	149,3	250,1	237,1	139,8	238,3	165,2	330,4	417,1	203,3	88,5	83,8	186,3	21,4
Seia	122,4	350,5	208,8	206,9	103,8	198,7	91,9	275,2	484,9	65,4	65,2	158	288,2	402,5	283,2	132,7	198,5	181,2	166,4	211,9	125,6	304	390,7	239,6	100,9	137,1	130,4	45
Serpa	389,7	28	504,4	548,9	271	555,9	338,1	103,3	156,2	310,3	363,1	278,5	201	54,9	123,5	304,4	197,4	197,5	450,8	209,1	283,8	163	125,6	523,9	442,8	507,6	243,3	417,7
Sertã	133,9	256,7	245,1	327,4	65,6	299,3	78,8	180,7	385,7	102,4	156,1	91,3	185,6	308,6	168,8	65,6	87,1	101,1	191,6	108,9	3,3	201	283,4	264,7	221,3	237,7	49,5	145,1
Setúbal	269,8	135,8	388,7	505,8	239,4	463,3	227,1	97	239,8	278,7	331,5	158,6	45,3	187,8	66,9	184,5	145,3	185	335,2	99,4	200,9	0,8	119,6	408,3	399,7	401,7	212,5	309,1
Silves	459,6	122,1	574,2	643,5	365,5	643	408,1	193	56,7	404,8	457,7	348,4	252	107,2	199,4	374,3	285,7	293	520,6	279,1	368,1	214,3	138,9	593,7	537,4	581,4	337,9	488,7
Sines	366,4	98,4	481	573,9	295,9	549,8	314,9	136,6	166,3	335,2	388,1	255,2	157,5	133,5	114,6	281,1	201	233,9	427,4	185,9	283,3	119,5	4,4	500,5	467,8	488,2	268,3	395,6
Sintra	253,3	195,5	373,8	498,7	245,8	451,1	212,2	148,7	299,5	285,1	338	143,7	25,8	247,5	118,5	169,5	175,8	234,4	320,2	98,9	207	67,9	179,3	393,3	392,6	389,5	218,9	296,9

Soure	77,3	299,3	191,2	316,1	138,2	268,5	29,6	233,3	420	164,7	175,1	48,2	178,4	351,3	203,2	22,8	142,1	173,7	137,6	117,6	74,7	206,4	303,6	210,7	210	206,9	122,1	114,2
Sousel	255,2	135,2	366,4	392,2	114,3	399,2	200	59,8	269,6	153,6	206,4	167	157,4	187,1	68	175	52,5	57,4	312,8	123,2	136,1	133,5	182,5	385,9	286,1	351	86,6	261
Tábua	81,6	351,6	194	242,7	137,6	203,9	55,6	275,6	477	96,8	101	121,8	252	403,6	260,2	96,4	182	194,4	140,5	181,8	95,5	273,9	360,6	213,6	136,6	142,4	142,8	49,7
Tavira	488,1	138,3	602,8	664,3	386,3	671,3	436,5	213,8	30,1	425,6	478,5	376,9	285	85,8	221,9	402,8	307,9	313,8	549,2	307,5	390,6	247,3	179,9	622,3	558,2	609,8	358,7	517,2
Tomar	134,1	232	245,3	356,3	115,5	313,8	79	162,9	352,7	152,2	207,5	45,9	134,2	284	135,8	53,9	69,3	116,5	191,7	57,5	51,5	149,6	236,3	264,8	250,2	252,3	88,6	159,6
Tondela	76,7	370,1	179,3	230,2	158,9	177,9	65,8	301	490,8	120,6	96,5	131,9	262,1	422	273,9	106,6	207,4	222,6	125,8	195,6	123,6	287,7	374,4	198,9	131,4	116,3	171	23,7
Torre de Moncorvo	205,3	437,1	194,4	97,5	190,3	104,5	199,6	361,7	571,5	153,2	98,4	265,7	395,9	489	369,8	240,3	285,1	267,7	192,9	324,2	237,9	416,3	484,4	242,2	16,7	102,1	216,9	124,4
Torres Novas	158,9	217,3	269,3	381,6	115,5	339,1	104,2	149,1	338	154,8	207,7	51,3	110,5	269,2	121,1	70,6	69,6	116,5	215,7	38,4	76,7	134,9	221,6	288,9	275,5	277,5	88,6	184,8
Torres Vedras	205,8	207,3	326,3	451,2	216,3	403,6	164,7	151,7	311,3	255,6	308,5	96,2	50,1	259,3	121,5	122,1	158,2	217,3	272,7	72,5	177,5	85,8	191	345,9	345,2	342	189,4	249,4
Trancoso	147,7	381,4	175,6	151	134,6	158	143,9	306	515,8	97,5	42,7	210	340,2	433,3	314,1	184,7	229,4	212,1	174,1	268,5	182,2	360,6	428,7	223,4	44,9	104	161,3	68,2
Vagos	8,9	353,4	130,2	276,3	193,1	224	54,5	287,4	474,1	175,9	164	102,7	232,4	405,3	257,2	89,7	199	228,6	76,6	171,6	129,6	260,5	357,7	149,1	197,9	162,4	177	91
Valpaços	220,3	505,2	140,5	74,6	258,4	28,5	247,2	429,8	639,6	221,3	166,5	313,4	443,5	557,1	437,9	288	353,2	335,8	162,5	377	305	469,1	552,5	190,7	84,8	69,2	285	160,1
Viana do Alentejo	316,6	47,2	431,3	481,7	203,7	488,7	265	31,2	179,5	243	295,8	205,4	143,2	99,1	50,4	231,3	125,2	131,2	377,7	136	211,7	105,2	112,5	450,8	375,6	438,3	176	345,7
Viana do Castelo	139,8	496,3	53,8	263,5	327,7	172,5	189,1	427,2	617	304,7	266,3	249,7	379,8	548,3	400,1	224,3	333,6	363,2	73,6	315,2	264,2	407,9	500,6	4,6	225,8	144	311,6	195
Vidigueira	348,2	23,6	460,7	503,3	225,3	510,3	294,4	52,8	162,6	264,6	317,5	237	168,5	75,5	82,1	262,9	146,9	152,8	407,1	167,7	233,3	130,5	110,1	480,3	397,2	462	197,7	372,1
Vila Flor	214,6	455,6	170,6	80,8	208,8	78,1	218,1	380,2	590	171,7	116,9	284,2	414,4	507,5	388,3	258,8	303,6	286,2	168,9	342,7	256,4	434,8	502,9	218,4	35,2	75,6	235,5	141,8
Vila Franca de Xira	210,7	174,7	329,6	454,6	193,5	406,9	168	115,2	277,2	232,8	285,6	99,5	31	226,7	85,1	125,4	129,9	188,5	276,1	46,3	155,1	60,7	158,4	349,2	348,5	345,4	166,6	252,7
Vila Nova de Foz Côa	147,7	381,4	175,6	151	134,6	158	143,9	306	515,8	97,5	42,7	210	340,2	433,3	314,1	184,7	229,4	212,1	174,1	268,5	182,2	360,6	428,7	223,4	44,9	104	161,3	68,2
Vila Real	153	484,2	96	120,3	238,5	63,5	179,9	409,9	604,9	201,4	146,6	246	376,2	536,1	388	220,6	321,5	315,9	94,3	309,7	237,7	401,7	488,5	143,8	98,4	3,4	265,1	92,8
Vila Velha de Ródão	181,5	221	292,7	306,5	28,6	313,5	126,4	145,7	355,4	67,9	120,7	134,9	197,7	273	153,7	113,1	69,8	51,7	239,1	120,9	49,6	212,8	268,3	312,2	200,4	265,2	5	175,3
Vila Viçosa	287,3	116,6	398,5	424,4	146,4	431,4	232,2	55,8	255,6	185,7	238,6	199,1	178,4	168,6	81,7	207,1	84,6	68,1	344,9	148,2	168,3	147,2	191,6	418	318,3	383,1	118,8	293,2
Vimioso	289,5	518,6	238	47,6	271,8	136,8	291,7	443,3	653	235,4	182,1	357,9	488	570,6	451,3	332,5	366,6	349,3	236,2	416,4	330	508,4	565,9	285,8	108,9	143	298,5	216,6
Vinhais	264,3	532,5	186,4	32,6	285,8	67,2	291,2	457,2	666,9	248,7	193,8	357,4	487,6	584,5	465,3	332	380,5	363,2	211,1	419,7	333,3	511,8	579,8	239,7	112,2	117,8	312,4	204,1
Viseu	81,8	391,5	164,5	206,7	148,7	154,4	87,2	320,1	512,2	110,4	73,1	153,4	283,6	443,5	295,3	128	228,8	226,1	122,1	217	145	309,1	395,8	195,3	108	92,8	175,3	3,7

Table 13- *Distances between Integrated Biorefinery's sites and Market's Sites, km. (Parameter DKV_{kv})*

Integrated Biorefinery's Sites \ Market Sites	Aveiro	Beja	Braga	Bragança	Castelo Branco	Coimbra	Évora	Faro	Guarda	Leiria	Lisboa	Portalegre	Porto	Santarém	Setúbal	Viana do Castelo	Vila Real	Viseu
Aveiro	3,964	362,6	121	267,7	197,3	58,82	296,5	483,1	154,8	111,5	241,9	233,1	67,75	180,7	269,8	139,8	153	81,82
Beja	362,2	9,554	476,6	527,3	248,8	310,9	76,16	139,7	340,8	251,3	173,6	176,1	423,4	181,9	135,8	496,3	484,2	391,5
Braga	121,4	477,2	3,82	215,6	308,5	170	408,1	597,8	218,1	230,3	360,8	344,3	54,15	295,3	388,7	53,83	96,04	164,5
Braganca	267,5	526,6	215	9,664	279,6	289,1	451,3	661,1	187,7	355,3	485,8	357,3	213,3	413,7	505,8	263,5	120,3	206,7
Castelo Branco	197,1	248,7	308	280,6	10,7	142,3	173,3	383,1	94,03	154,8	224,4	79,34	254,8	147,3	239,4	327,7	238,5	148,7
Chaves	215,2	533,6	119,3	100,3	286,6	241,5	458,3	666,4	194,7	307,6	438,1	364,3	156,5	371,2	463,3	172,5	63,46	154,4
Coimbra	58,49	311	169,4	289,8	142,2	5,042	241,8	431,6	148,2	68,71	199,2	177,9	116,2	136,4	227,1	189,1	179,9	87,19
Évora	296,2	76,14	407,5	452	173,4	241,8	10,2	210,6	265,5	185,3	126,8	100,8	354,2	115,9	97,04	427,2	409,9	320,1
Faro	482,9	139,5	597,3	661,7	383,2	431,6	210,6	4,005	475,2	372	277,5	310,5	544	302,6	239,8	617	604,9	512,2
Fundão	178,2	288	273,5	243,5	40,97	147,5	212,6	422,4	55,72	184,5	263,7	118,6	231,7	186,6	278,7	304,7	201,4	110,4
Guarda	155,2	340,8	218,7	188,6	93,81	148,1	265,5	475,2	7,528	214,3	316,5	171,5	195,1	239,5	331,5	266,3	146,6	73,1
Leiria	111,6	251,4	229,9	356	154,7	68,71	185,3	371,9	214,4	6,706	130,7	164,3	176,7	69,48	158,6	249,7	246	153,4
Lisboa	241,3	173,9	360,1	486,2	224,7	198,9	127	277,5	316,7	130,4	2,599	212,1	306,9	77,16	45,31	379,8	376,2	283,6
Mértola	414,2	52,41	528,5	579,3	300,7	362,8	128,1	101,4	392,7	303,3	225,6	228,1	475,3	233,8	187,8	548,3	536,1	443,5
Montemor_o_Novo	266	96,39	380,4	460,1	181,5	214,7	30,27	217	273,5	155,1	96,61	119,4	327,2	85,71	66,87	400,1	388	295,3
Pombal	94,41	277,3	204,5	330,6	129	43,32	211,2	397,8	189	26,07	156,6	164,7	151,3	95,39	184,5	224,3	220,6	128
Ponte de Sor	203	170,2	313,9	375,3	96,78	148,2	94,22	303,3	188,8	115,1	153,9	68,49	260,6	85,76	145,3	333,6	321,5	228,8
Portalegre	232,6	176,1	343,5	358	79,46	177,8	100,8	310,6	171,5	162,3	212,5	5,965	290,3	146,8	185	363,2	315,9	226,1
Porto	67,79	423,6	53,33	214,4	255	116,4	354,5	544,2	195,1	176,7	307,2	290,7	1,812	241,8	335,2	73,56	94,29	122,1
Santarém	180,4	182	295,5	414,5	147,9	136,4	115,9	302,6	239,9	69,52	77,45	147,5	242,3	5,422	99,44	315,2	309,7	217
Serta	133,6	256,7	244,5	328,1	65,5	78,82	180,7	385,7	156	91,34	185,6	101,2	191,3	108,9	200,9	264,2	237,7	145
Setúbal	269,3	135,9	388,1	506,6	239,8	226,9	97	239,8	331,8	158,4	45,51	184,9	334,9	99,46	0,795	407,9	401,7	309,1
Sines	366,5	98,49	480,9	574,6	296,1	315,2	136,7	166,3	388,1	255,6	157,3	234	427,6	186,2	119,6	500,6	488,5	395,8
Viana do Castelo	140,2	496,8	53,52	263,9	328,1	189,6	427,6	617,4	265,8	249,9	380,4	363,8	73,25	314,9	408,3	4,635	143,8	195,3
Vila Nova de Foz Côa	189,1	420,5	178,2	107	173,6	183	345,2	555	81,59	249,2	379,7	251,2	175,8	307,6	399,7	225,8	98,43	108
Vila Real	153,6	484,3	96,34	121,2	238,4	179,9	410	604,9	146,4	246	376,5	316	93,84	309,7	401,7	144	3,443	92,83
Vila Velha de Rodao	181	221	291,9	307,2	28,67	126,2	145,7	355,4	120,7	134,4	197,5	51,69	238,7	120,4	212,5	311,6	265,1	175,3
Viseu	82,2	391,6	164,9	207,4	148,5	87,21	320,1	512,2	73,11	153,4	283,9	226,1	122,1	217	309,1	195	92,77	3,661

Table 14- *Conversion efficiencies of conversion technologies for a type of biomass and product, per scenario and time period.(Parameter μ_{bmpst})*

Biomass	Technology	Product	Scenario	t1	t2	t3	t4
Sugar/Starch	Fermentation	Bioethanol	s1	0,2558			
Sugar/Starch	Fermentation	BIoethanol	s2		0,3108		
Sugar/Starch	Fermentation	BIoethanol	s3		0,2558		
Sugar/Starch	Fermentation	Bioethanol	s4			0,3658	
Sugar/Starch	Fermentation	Bioethanol	s5			0,3108	
Sugar/Starch	Fermentation	Bioethanol	s6			0,3108	
Sugar/Starch	Fermentation	BIoethanol	s7			0,2558	
Sugar/Starch	Fermentation	BIoethanol	s8				0,4208
Sugar/Starch	Fermentation	Bioethanol	s9				0,3658
Sugar/Starch	Fermentation	Bioethanol	s10				0,3658
Sugar/Starch	Fermentation	Bioethanol	s11				0,3108
Sugar/Starch	Fermentation	BIoethanol	s12				0,3658
Sugar/Starch	Fermentation	BIoethanol	s13				0,3108
Sugar/Starch	Fermentation	Bioethanol	s14				0,3108
Sugar/Starch	Fermentation	Bioethanol	s15				0,2558
Sugar/Starch	Transesterification	Biodiesel	s1	0,2751			
Seeds/Animal fats	Transesterification	Biodiesel	s2		0,3101		
Seeds/Animal fats	Transesterification	Biodiesel	s3		0,2751		
Seeds/Animal fats	Transesterification	Biodiesel	s4			0,3451	
Seeds/Animal fats	Transesterification	Biodiesel	s5			0,3101	
Seeds/Animal fats	Transesterification	Biodiesel	s6			0,3101	
Seeds/Animal fats	Transesterification	Biodiesel	s7			0,2751	
Seeds/Animal fats	Transesterification	Biodiesel	s8				0,3801
Seeds/Animal fats	Transesterification	Biodiesel	s9				0,3451
Seeds/Animal fats	Transesterification	Biodiesel	s10				0,3451
Seeds/Animal fats	Transesterification	Biodiesel	s11				0,3101
Seeds/Animal fats	Transesterification	Biodiesel	s12				0,3451
Seeds/Animal fats	Transesterification	Biodiesel	s13				0,3101
Seeds/Animal fats	Transesterification	Biodiesel	s14				0,3101
Seeds/Animal fats	Transesterification	Biodiesel	s15				0,2751

Table 15- *Capacities of each conversion technology and respective installation and fixed costs, in year 2020. (Parameters $CAP_{B_{mq}}, CIB_{mqt}, CFB_{mqt}$*

Technology	Capacity (tonne)	Installation Costs	Fixed Costs
Fermentation	75000	36415463€	2798404€
	250000	74991680€	9328014€
Transesterification	50000	12164061€	1190851€
	200000	27945674€	4763405€

Table 16- *Production Costs for each technology, biomass and biofuel and level of accumulated production, in €.(Parameter CC_{bmpnt})*

Type of Biomass	Technological Process	Type of Biofuel	Level of Accumulated Production (tonne)	Cost over the time horizon of the study (€,2020)
Sugar/Starch	Fermentation	Bioethanol	10000	466,17
Sugar/Starch	Fermentation	Bioethanol	25000	358,12
Sugar/Starch	Fermentation	Bioethanol	50000	298,85
Sugar/Starch	Fermentation	Bioethanol	75000	267,02
Sugar/Starch	Fermentation	Bioethanol	100000	245,84
Sugar/Starch	Fermentation	Bioethanol	125000	230,25
Sugar/Starch	Fermentation	Bioethanol	150000	218,09

Sugar/Starch	Fermentation	Bioethanol	175000	208,20
Sugar/Starch	Fermentation	Bioethanol	200000	199,94
Sugar/Starch	Fermentation	Bioethanol	225000	192,88
Sugar/Starch	Fermentation	Bioethanol	250000	186,74
Sugar/Starch	Fermentation	Bioethanol	275000	181,34
Sugar/Starch	Fermentation	Bioethanol	300000	176,53
Sugar/Starch	Fermentation	Bioethanol	325000	172,20
Sugar/Starch	Fermentation	Bioethanol	350000	168,27
Sugar/Starch	Fermentation	Bioethanol	375000	164,69
Sugar/Starch	Fermentation	Bioethanol	400000	161,41
Sugar/Starch	Fermentation	Bioethanol	425000	158,38
Sugar/Starch	Fermentation	Bioethanol	450000	155,57
Sugar/Starch	Fermentation	Bioethanol	475000	152,95
Sugar/Starch	Fermentation	Bioethanol	500000	150,50
Sugar/Starch	Fermentation	Bioethanol	525000	148,21
Sugar/Starch	Fermentation	Bioethanol	550000	146,06
Sugar/Starch	Fermentation	Bioethanol	575000	144,03
Sugar/Starch	Fermentation	Bioethanol	600000	142,11
Sugar/Starch	Fermentation	Bioethanol	625000	140,29
Sugar/Starch	Fermentation	Bioethanol	650000	138,56
Sugar/Starch	Fermentation	Bioethanol	675000	136,92
Sugar/Starch	Fermentation	Bioethanol	700000	135,35
Sugar/Starch	Fermentation	Bioethanol	725000	133,85
Sugar/Starch	Fermentation	Bioethanol	750000	132,43
Sugar/Starch	Fermentation	Bioethanol	775000	131,06
Sugar/Starch	Fermentation	Bioethanol	800000	129,74
Sugar/Starch	Fermentation	Bioethanol	825000	128,48
Sugar/Starch	Fermentation	Bioethanol	850000	127,27
Sugar/Starch	Fermentation	Bioethanol	875000	126,11
Sugar/Starch	Fermentation	Bioethanol	900000	124,98
Sugar/Starch	Fermentation	Bioethanol	925000	123,90
Sugar/Starch	Fermentation	Bioethanol	950000	122,86
Sugar/Starch	Fermentation	Bioethanol	975000	121,85
Sugar/Starch	Fermentation	Bioethanol	1000000	120,87
Sugar/Starch	Fermentation	Bioethanol	1025000	119,92
Seeds/Animal Fats	Transesterification	Biodiesel	10000	263,77
Seeds/Animal Fats	Transesterification	Biodiesel	25000	233,16
Seeds/Animal Fats	Transesterification	Biodiesel	50000	214,28
Seeds/Animal Fats	Transesterification	Biodiesel	75000	203,24
Seeds/Animal Fats	Transesterification	Biodiesel	100000	195,48
Seeds/Animal Fats	Transesterification	Biodiesel	125000	189,54
Seeds/Animal Fats	Transesterification	Biodiesel	150000	184,75
Seeds/Animal Fats	Transesterification	Biodiesel	175000	180,75
Seeds/Animal Fats	Transesterification	Biodiesel	200000	177,33
Seeds/Animal Fats	Transesterification	Biodiesel	225000	174,35
Seeds/Animal Fats	Transesterification	Biodiesel	250000	171,71
Seeds/Animal Fats	Transesterification	Biodiesel	275000	169,34
Seeds/Animal Fats	Transesterification	Biodiesel	300000	167,21
Seeds/Animal Fats	Transesterification	Biodiesel	325000	165,26
Seeds/Animal Fats	Transesterification	Biodiesel	350000	163,47
Seeds/Animal Fats	Transesterification	Biodiesel	375000	161,82
Seeds/Animal Fats	Transesterification	Biodiesel	400000	160,29
Seeds/Animal Fats	Transesterification	Biodiesel	425000	158,86
Seeds/Animal Fats	Transesterification	Biodiesel	450000	157,52
Seeds/Animal Fats	Transesterification	Biodiesel	475000	156,26
Seeds/Animal Fats	Transesterification	Biodiesel	500000	155,08
Seeds/Animal Fats	Transesterification	Biodiesel	525000	153,96
Seeds/Animal Fats	Transesterification	Biodiesel	550000	152,90
Seeds/Animal Fats	Transesterification	Biodiesel	575000	151,89

Seeds/Animal Fats	Transesterification	Biodiesel	600000	150,93
Seeds/Animal Fats	Transesterification	Biodiesel	625000	150,02
Seeds/Animal Fats	Transesterification	Biodiesel	650000	149,14
Seeds/Animal Fats	Transesterification	Biodiesel	675000	148,30
Seeds/Animal Fats	Transesterification	Biodiesel	700000	147,50
Seeds/Animal Fats	Transesterification	Biodiesel	725000	146,73
Seeds/Animal Fats	Transesterification	Biodiesel	750000	145,99
Seeds/Animal Fats	Transesterification	Biodiesel	775000	145,27
Seeds/Animal Fats	Transesterification	Biodiesel	800000	144,58
Seeds/Animal Fats	Transesterification	Biodiesel	825000	143,92
Seeds/Animal Fats	Transesterification	Biodiesel	850000	143,28
Seeds/Animal Fats	Transesterification	Biodiesel	875000	142,66
Seeds/Animal Fats	Transesterification	Biodiesel	900000	142,05
Seeds/Animal Fats	Transesterification	Biodiesel	925000	141,47
Seeds/Animal Fats	Transesterification	Biodiesel	950000	140,91
Seeds/Animal Fats	Transesterification	Biodiesel	975000	140,36
Seeds/Animal Fats	Transesterification	Biodiesel	1000000	139,83
Seeds/Animal Fats	Transesterification	Biodiesel	1025000	139,31

Table 17 - *Biomass Acquisition Costs, in € (Parameter CB_{bit})*

Type of Biomass	Cost in every Municipality, €
Sugar/Starch	185,33
Seeds/Animal Fats	411,85

Table 18- *Transportation costs for biomass and biofuels, €/ton/km (Parameters CTB_{brt}, CTP_{pzt})*

Biomass/Biofuel	Transportation Mode	Cost (€/ton/km)
Starch/Sugar	Truck	0,111
Seeds/Animal Fats	Truck	0,111
Bioethanol	Truck	0,44
Biodiesel	Truck	0,44

Table 19- *Bioethanol and Biodiesel Demand for each Portuguese District, in tonnes. (Parameter D_{pvt})*

District	Total Bioethanol (ton)	Total Biodiesel (ton)
Aveiro	44734,8	89
Beja	9014,7	0
Braga	37002,6	136
Bragança	4716,1	0
Castelo Branco	9128	0
Coimbra	20824,7	27
Évora	7479	99
Faro	28430,5	0
Guarda	6133,1	0
Leiria	31735,6	422
Lisboa	104406,1	3180
Portalegre	3968,6	0
Porto	91174,8	156
Santarém	46052,1	24
Setúbal	46053,4	269
Viana do Castelo	7409,9	363
Vila Real	8374	4
Viseu	16027	1