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

The Portuguese Case-Study

Mafalda Carvalhaes de Alte da Veiga e Seabra

Industrial Engineering and Management

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

1. Background on Biorefineries Supply Chain

1.1 – EU's role in a bio economy

With the development of technology and increasing worldwide industrialization, the need to use energy has been increasing over the years. Adding the climate change, the usage of fossil fuels stopped being a viable option and the goal has been investing in sustainable energy sources. 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). It has created three European Commission's energy packages 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 third, and most recent package, adopted in 2009, was created 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).

It is in this context that the biomass is introduced. 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. Being a renewable resource, it 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 which compensates its release in the conversion process (Naik et al., 2010).

1.2 – Biomass Supply Chain

The biomass supply chain differs from traditional supply chains given it integrates the process of harvesting and collection of the biomass and the pre-treatment into less dense biomass. Then, a step dedicated to the conversion process in integrated biorefineries where biomass is transformed into valuable products and energy (biofuels, bioenergy, biochemical, biomaterials) in an integrated manner (Parisi, 2020). Finally, it has product distribution and logistics (Hong et al., 2016). To ensure the delivery of the finished products through the supply chain effectively and efficiently, there are decisions that have to be made at a strategic, tactical and operational level (Awudu and Zhang, 2012). The strategic level decisions should be made at the beginning of planning and in line with the organizations overall objectives. They are relative to the design of the biomass supply chain network in terms of the sourcing of biomass, type of feedstock, dimension and type of the technology installed, capacity and location of all facilities and final product type and quantity (Ghaderi et al., 2016). The tactical level is based on medium-term decisions (6 months-1 year) that concentrate on the fleet management, inventory planning decisions and production decisions, such as scheduling (Awudu and Zhang, 2012). 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).

Given the nature of the supply chain in question, there are uncertainties inherent to all stages of the supply chain. However, uncertainties existing in important parameters considered in the decision making of the supply chain design influence the decision process. Plus, the fact that they exist through the echelons of the supply chain increases their impact across the supply chain 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.

2. – State Of Art

Before diving into the research problem, several theoretical concepts regarding biomass supply chain optimization under uncertainty and uncertainty representation methods are covered to understand the status quo of research developments and findings over the years.

2.1 – Biomass Supply Chain 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). Also, the uncertainties inherent to its stages (Awudu and Zhang, 2012) are an obstacle as well, given their implications, as it was explained before, affect the decision making process (Kazemzadeh and Hu, 2013). Accordingly, uncertainty has been considered in the design phase of the biomass SC in order to obtain optimal solutions through models that are closer to reality (Ghaderi et al., 2016).

From the literature review, it can be concluded that, for the optimization of the design of the biomass supply chain, the mixed integer linear programming (MILP) is the most seen in literature (Bairamzadeh et al., 2016), (Paulo et al., 2017). Other types of mathematical programming presented in research papers are linear programming (LP) (Cundiff et al., 1997), (Bhavna Sharma et al., 2013), integer programming (IP), mixed integer non-linear programming (MINLP), mixed integer quadratic programming (MIQP) (Arabi et al., 2019), non-linear programming (NLP) and mixed integer linear fractional programming (MILFP) (Tong et al. 2014c). In these the uncertainty representation can be done by using different methods. The first is the stochastic programming. This method includes the multi-stage approach, which usually considers two-stages. The first-stage variables represent decisions made before the realization of the uncertain parameters (Tong et al., 2014b) and the second-stage represent decisions made only after the realization of the uncertain parameters (Tong et al., 2014b). Another approach is the scenario-based stochastic programming, used by Mas et al. 2010, among others, 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). Robust optimization and fuzzy programming are also used, although not as often. The first chooses 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. The second is most used 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.

Regarding uncertainties, the most common uncertainty considered in the optimization models when designing the supply chain is in the feedstock supply (Kazemzadeh and Hu, 2013). Demand uncertainty is the second, followed by price uncertainty. The inclusion of variations in cost incurred in terms of transportation, operation or production (Kazemzadeh and Hu, 2013), and in terms of carbon costs (Giarola et al., 2012). 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, an uncertainty really tied with the technology uncertainty due to its advancement and progress. 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, Gao and You 2017, Bairamzadeh et al. 2018 and Marufuzzaman et al. 2014 also have it in consideration and defend it is an uncertainty also caused by the fact that different technologies and different feedstocks have different conversion efficiencies, thus different production quantities.

This uncertainty inherent to the conversion technologies is of great importance given the impacts it has in the supply chain for not having reached maturity and still being in development. However, only a few studies consider it and 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, since decisions at a design stage are regarding the future, they shouldn't in order to make them more realistic.

2.2 – The Learning Curves

One of the first authors to describe the learning concept was (Wright, 1936). In his paper, he explains that one of the factors that possibly make the cost of airplane's manufacture to decrease as the quantity produced increases is the labor cost. 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*. 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) relates the variations of the costs over time with only one factor as the independent variable - the accumulated learning (Sagar and van der Zwaan, 2006). The multi-factor-learning curve considers the impact of different and relevant cost reduction drivers (Samadi, 2018). The most popular is the two-factor-learning curve and differentiates that considers two learning factors: the learning-by-doing and learning-by-searching (Wiesenthal et al., 2012). However, the effects of learning through research and development are difficult to quantify.

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. Since 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 learning curve theory has great potential to cover the gap in literature and correctly represent the technology's conversion efficiency uncertainty, which is lacking a correct consideration of maturity and learning in its modulation.

3 – Problem Statement and Main Contributions

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. 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. 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.

4. 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. These technologies are used in biorefineries to produce bioenergy, therefore, information regarding biorefineries and their used technological processes and specifications are searched.

4.1. Scope of Research

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, due to the same focus on goals towards a sustainable economy, which also underlines the chance to have more biorefineries to collect data from. Moreover, the definition of integrated biorefinery 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. Also, only integrated biorefineries that produce biofuels as one of their products were considered. Finally, 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 analyze different and multiple sources of highly probable unreliable information.

4.2. Mapping Integrated Biorefineries in the EU

Research aiming to find the existent biorefineries in the EU was made in many sources. The report and associated database developed by Parisi 2020 was used as a starting point and to guide the rest of the research. The report consists on the description of the distribution of the bio-based industry in the European Union and the database allows the user have access on the facilities using biomass. These are represented with IDs and, for each, can be found 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. A report by BIC 2017, the *Biorefineries Blog* and the European Technology Innovation Platform were consulted to complement the information of the work by Parisi 2020**.** These sources have available lists of biorefineries and respective specifications. The remaining cases where a match between the database by Parisi 2020 the other sources couldn't be made, Google Maps was used to search the coordinates the database has available and find the information about each biorefinery.

The database by Parisi 2020 includes 2362 biorefineries. From these, only 50 are mapped in this study. This number was obtained by reducing the biorefineries to the relevant ones for this study. First, only biorefineries with product-energy integration and that produced biofuels were considered. This ensures that the facilities obtained produce energy and products in an integrated manner. Also, only biorefineries at a commercial scale were considered, given it is in this phase that this study is considering to be happening technology developments and efficiency increase with experience. Finally, random locations were assumed as errors and similar coordinates that resulted in facilities in the same industrial place, were considered as only one integrated biorefinery.

4.3. Integrated Biorefineries Specifications

Once the biorefineries were mapped, the focus was on collecting all information available about them that made sense to the present study. To do this, the same sources used for mapping the biorefineries were consulted, plus Google to extensively search for information on the biorefineries that the other sources didn't have available.

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 are biodiesel and bioethanol, and given the others don't have substantial of information, the biodiesel and bioethanol are assumed to be the focus of this study. Also, co-products are not being considering due to lack of information on some of the biorefineries and so as to compare them all on the same basis. All biorefineries that didn't have available information on production quantities were discarded as they couldn't contribute to this study.

Regarding quantities and type of **feedstock**, the first follows the same logic of the product in cases of inexistent information. The most used biomass to produce bioethanol is cereals, corn and sugar and to produce biodiesel is seeds and animal fats. Due to shortage of data, the different types of feedstock of each biofuel are considered only as one.

In terms of the **technological conversion processes** used in the biorefineries mapped, the most popular and the ones who have more information available are the fermentation and the transesterification processes. The other found are esterification, anaerobic digestion and hydrotreatment. Since these last don't have a considerable amount of information, they will not be considered in this study. On another matter, the conversion efficiencies of the two technologies considered were estimated from biofuels and feedstock data or their exact values were found with research. In this study, this concept is 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. In order to make an analysis on the conversion efficiency evolution over time, all biorefineries found were 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 found (10 for the fermentation process and 6 for the transesterification process), the tendency lines from Figure 1 were 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. As it can be verified for both technological processes, 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. It also 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. Finally, regarding the learning rates of the

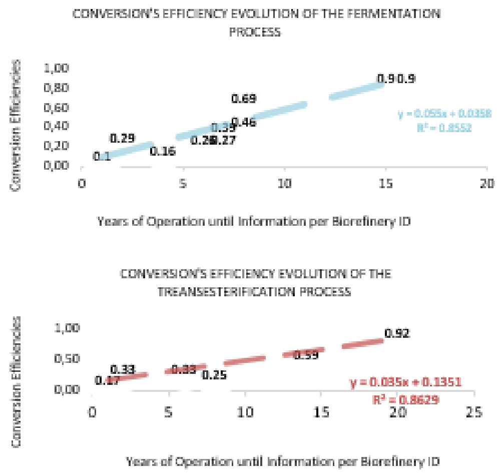

Figure 1 - Tendency lines of the conversion efficiency for fermentation and transesterification technology

conversion technologies, the only values found were in the study by de Wit et al. 2010. The learning rate considered with the increase of cumulative production for the transesterification process is 10% and for the fermentation process 20%. Both were estimated for bioethanol and biodiesel, respectively, using data form different biomasses without distinction.

Finally, information regarding **production costs** of the biorefineries was difficult to find. The study by de Wit et al., 2010 was the one found with more information available and 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, the differences between biomasses are discarded 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. This costs included operation costs, such as labor 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. Model Formulation

5.1 Learning Curve's Mathematical Formulation

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. This study considers that the conversion efficiency evolution happens after the biorefineries reach a commercial level. In these, once it is installed and operational, technology evolution and optimization are most likely to happen only 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.

Regarding learning system boundaries, these only include the technological process and all of its stages from the moment the birefinery enters a biorefinery 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 labor 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.

The costs development observed with a one-factor learning curve for each technology producing each type of biofuel, can be described by equation (1):

$$CC_{bmpt} = CC_{bmp}^{ref}\left(\frac{ACpq_{bmpt}}{X_{bmp}^{ref}}\right)^{-\varepsilon_{bmp}} \qquad (1)$$

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. This is the measure of experience defined in this study, as it represents the evolution of the conversion process and. CC_{bmpt} is the unitary cost of production of biofuel p from biomass b by conversion technology m at time period t, in €/ton. These are the costs that vary with the increase of experience. CC_{bmp}^{ref} and X_{bmp}^{ref} are the 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. $\left(\frac{ACpq_{bmpt}}{X_{bmp}^{ref}}\right)^{-\varepsilon_{bmp}}$ is 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. Finally, ε_{bmp} is a positive learning coefficient of conversion technology m when producing p from biomass b. This is the learning coefficient and measures the impact of the learning in the costs.

Regarding the relationship of the conversion efficiency and the chose measure of experience, this can be obtained with equation (1) by replacing the accumulated production with the sum, over time, of conversion efficiency multiplied by the biomass feedstock. This goes in line with the conversion efficiency definition of this study - the percentage of input that is turned into a useful output by an energy conversion process – and can be show in equation (2):

$$C_{bmpt} = CC_{bmp}^{ref}\left(\frac{\sum_t \mu_{bmpt} \cdot bf_{bmt}}{\mu_{bmpt_0} \cdot bf_{bmt_0}}\right)^{-\varepsilon_{bmp}} \qquad (2)$$

From equation (2) 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 costs CC_{bmpt}. 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 Figure 1 that shows 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.

5.2 Stochastic Optimization Model's Mathematical Formulation

To test if the learning curve formulation presented in section 4.1 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. The 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 and capacity - and the second-stage ones correspond to decisions being made after having full information on the uncertain parameters – process technology, 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 on the biorefineries and their processing technologies. Considering the sets $b, \bar{b} \in B$ as biomass type, $p \in P$ as the products, $i \in I$ as biomass collection sites, $k \in K$ as Integrated biorefinery site, $v \in V$ as market sites, $q \in Q$ as integrated biorefinery's conversion capacities, $m \in M$ as integrated biorefinery's conversion technology, $r \in R$ as biomasses transportation modes, $z \in Z$ as end product's transportation mode, $t, \bar{t} \in T$ as time periods, $s, \bar{s} \in S$ as scenario tree nodes and $n \in N$ as levels of accumulated production in the biorefineries, the next constraints were added to the ones developed in the working paper by Paulo et al. 2020. These enable the model to consider the impact of the experience and conversion efficiency evolution on costs using the learning curve theory. Equations (3-4) focus on the chosen definition of experience of the conversion technologies – the accumulated production. Equation (3) defines that or 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. Equation (4) defines for the remaining time periods that 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. Equations (5-6) focus on defining the level of total accumulated production $ACPQ_{bmpkst}$ each technology has reached. Equation (5) ensures the accumulated production of a conversion technology in each time period and scenario node belong to at most one level of accumulated production. Equation (6) defines the level of accumulated production a technological process m in each biorefinery has reached with a binary that is equal to 1, when the accumulated production is between two levels n of accumulated production. Finally, equations (7-8) focus on corresponding the level of accumulated production, and thus experience, a technology has reached in time period t and scenario s to the production PQ_{bmpkst} in the same scenario and time period that enabled the technology to reach it. 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.

$$ACPQ_{bmpkst} = PQ_{bmpkst} \; \forall k \in K \wedge \forall s \in S \wedge \forall m \in M \wedge \forall p \in P \wedge \forall b \in B \wedge (m,p) \in W_P \wedge (m,b) \in W_B \wedge \forall t = 1 \tag{3}$$

$$ACPQ_{bmpkst} = PQ_{bmpkst} + ACPQ_{bmpk\bar{s}(t-1)} \; \forall k \in K \wedge \forall s \in S \wedge \forall \bar{s} \in H \wedge \forall m \in M \wedge \forall p \in P \wedge \forall b \in B \wedge (m,p) \in W_P \wedge (m,b) \in W_B \wedge \forall t > 1 \tag{4}$$

$$\textstyle\sum_n Y^{N}_{kmnst} \leq 1 \; \forall k \in K \wedge \forall s \in S \wedge \forall m \in M \wedge \forall t \in T \tag{5}$$

$$\sum_n LAC_n \, Y^{N}_{kmnst} \leq ACPQ_{bmpkst} \leq \sum_n LAC_{n+1} \, Y^{N}_{kmnst}$$
$$\forall k \in K \wedge \forall s \in S \wedge \forall m \in M \wedge \forall p \in P \wedge \forall b \in B \wedge (m,p) \in W_P \wedge (m,b) \in W_B \wedge \forall t = T \tag{6}$$

$$PQ_{bmpkst} - (1 - yN_{kmnst}) * Max \leq PQ^{L}_{bmpknst} \leq PQ_{bmpkst} + (1 - yN_{kmnst}) * Max$$
$$\forall k \in K \wedge \forall n \in N \wedge \forall s \in S \wedge \forall m \in M \wedge \forall p \in P \wedge \forall b \in B \wedge (m,p) \in W_P \wedge (m,b) \in W_B \wedge \forall t = T \tag{7}$$

$$\textstyle\sum_n PQ^{L}_{bmpknst} \leq \sum_n yN_{kmnst} * Max$$
$$\forall k \in K \wedge \forall s \in S \wedge \forall m \in M \wedge \forall p \in P \wedge \forall b \in B \wedge (m,p) \in W_P \wedge (m,b) \in W_B \wedge \forall t = T \tag{8}$$

Having included this constrains, the objective function used in the working paper by Paulo et al. 2020 was modified to equation (9):

$$Min\ Cost^{SC} =$$
$$\textstyle\sum_s \Psi_s \begin{pmatrix} \sum_{b:(m,b)\in W_B} \sum_{i:(i,k)\in D_B} \sum_k \sum_m \sum_{r:(b,r,t)\in Z_B} \sum_t BF_{bikmrst} CB_{bit} \; + \\ \sum_{b(m,b)\in W_B} \sum_m \sum_{p:(m,p)\in W_P} \sum_k \sum_n \sum_t CC_{bmpnt} PQ^{L}_{bmpknst} \; + \\ \sum_{b:(m,b)\in W_B} \sum_{i:(i,k)\in D_B} \sum_k \sum_m \sum_{r:(b,r,t)\in Z_B} \sum_t BF_{bikmrst} DIK_{ik} \; CTB_{brt} \; + \\ \sum_{b:(m,b)\in W_B} \sum_{p:(m,p)\in W_P} \sum_m \sum_k \sum_v \sum_{z:(p,z,t)\in Z_P} \sum_t PF_{bmpkvzst} \; DKV_{kv} \; CTP_{pzt} \end{pmatrix} +$$
$$\textstyle\sum_k \sum_m \sum_q \sum_t O^{B}_{kmqt} \; CIB_{mqt} \; + \; \sum_k \sum_m \sum_q \sum_t Y^{B}_{kmqt} \; CFB_{mqt} \tag{9}$$

The difference is in the **total variable operating costs** of the biorefineries. These account for utilities, direct labor, production, maintenance 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 5.1, 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.

6. Case-study

6.1. The Portuguese Case

As explained in chapter 1.1, 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. 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. Portugal has been registering a good progress in its renewable energy objectives as the "Resolução do Conselho de Ministros nº53/2020" states that in 2018, around 30.3% of the final energy consumption 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. Moreover, in 2017, the "Resolução do Conselho de Ministros nº163/2017" approves the National Plan for the Promotion of Biorefineries (PNPB) which enforces the valorisation of renewable sources of energy by supporting the use of biomass as an alternative source 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.

6.2- Case-study's Data Collection

The network structure used was similar to the used by Paulo et al. 2020, but without the pre-processing facilities. 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 were adapted according to the research done in the present study. For the biomass collection sites, 150 out of 278 Portuguese municipalities were considered. Also, the collection sites are assumed to exist in the headquarters of each. The biomass availability on each, was searched for the types of biomass found with research in chapter 3.3 and using as sources the National Statistics Institute of Portugal's website, the Direção-geral dos Território's website. For the integrated biorefinery's sites, there are 28 potential sites considered for 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. have installed. The two technological conversion processes considered in the biroefineries 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. 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 the biofuels considered in this study. To find their demands in Portugal, the website of the National Statistics Institute of Portugal was consulted. These were assumed to be constant over time.

The scenario tree approach in the model was used to study possible future situations of conversion efficiencies of each technology/technological conversion process when processing a type of biomass into a type of biofuel. Having the equations of the tendency lines for the different technologies in chapter 3.3, 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 – 4 years - and that are based on reality. 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 and the other, represents the case where there is no learning or no attempt to learn, thus the efficiency remains the same. 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. Also, consecutive increases in conversion efficiency are less likely to happen over time, given 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 would still have a higher efficiency than the node, from the same predecessor, that represents a static conversion efficiency. All this considerations result in a tree with 4 periods of time and 15 scenarios.

Regarding the other parameters of the model, the biomass cost used 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. The installation costs used for a biorefinery with the fermentation process and 75000 tonnes of production capacity are 36415463 € and the fixed costs are 2798404,35€ (McAloon et al., 2000). For a biorefinery using the transesterification process with 50000 tonnes of capacity, the installation costs considered are 12164061.2 € and the fixed costs are 1190851 € (Abo El-Enin et al., 2013). For all costs, an average inflation rate of 2.17% to update the cost for 2020 and then an exchange rate of 0.85 from dollars to euros were used. 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). The variable costs are calculated for each level of accumulated production using the learning curve of equation (1) for each technology. The learning rates LR_{bmp} used to obtain learning coefficients ε_{bmp} are the ones presented in subchapter 3.3. 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. The levels n associated to the calculate 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 (one level higher than the maximum accumulated production a biorefinery with the technology that has available the biggest production capacity can produce in the time horizon of this study). Regarding transportation costs, for both biomasses 0.111 €/tonne/km is used (Hellmann and Verburg, 2011), after being actualized using an average inflation rate of 1.50% for the pound an exchange rate of 1.11% from pounds to euros. For both 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.

7. Model Implementation and Case-Study Results

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. 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. 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.

7.1 – Model Construction's and Uncertainty Representation Validation

In order to validate the model before running it with the real data, a deterministic version of the model was used, smaller quantity of data to test the model was inputted and the data was changed to reach conclusions on the model's behavior. For the ultimate validation of the model and testing of the adequacy of the learning curve theory to conversion efficiency's evolution representation with the actual data from the case-study, a stochastic model with only three time periods, thus less scenario nodes, is firstly analyzed and used. This decision was made after in the first attempts to run the stochastic model with 4 periods of time and efforts were made to make it more efficient by using CPLEX options, the amount of time it needed to find an optimized solution was too high. The scenario tree used for three time periods remained the same, but only accounting the first three time periods. Thus, probabilities and conversion efficiencies remain the same for each node. Also, this tree still has represented the relevant characteristics of the conversion technology evolution of the two technologies.

7.2 – Case study results for stochastic model with three periods of time

Figure 2 shows, five integrated biorefineries are installed so as demand can be satisfied. Two are installed with the Fermentation technology with 75000 tonnes of capacity in Lisboa and Vila Real. Other two with the same technology but with 250000 tonnes of capacity), 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 near the areas where there are higher quantities of biomass available (Centre and Alentejo region), approximately in the center of the areas of greater density of biomass availability of each type and the capacities and their locations are also installed considering high focuses of demand and the proximity to them.

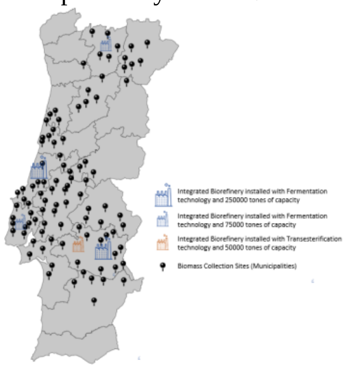

Figure 2- SC network for Stochastic model with three time periods

In terms of conversion efficiency, analyzing its evolution for the biorefinery installed in Évora, it 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. As the time periods increase, the accumulated production also increase, thus experience is gained and, consequently, costs decrease. This is verified in the third time period, in which the costs of the same biorefinery's technology now vary between 138.56 and 148.21€/tonnes. Regarding total costs of the supply chain, this solution had a total cost of 1726658280.96€. The biomass acquisition and production costs are the higher costs, as they are the highest unitary costs considered in the case study (corn/cereals and the seeds/animal fats 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. After an analysis on the cost evolution over time and scenarios, the total production costs for each time period decrease and in cases of increase of conversion efficiency the total biomass acquisition costs decrease. Given the demand is constant over time, high efficiencies traduce into lower feedstock quantities needed.

7.3 – Stochastic vs Deterministic Model with three periods of time

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. Thus, the optimization model of chapter 4 is compared to the deterministic version of it to reach conclusions on the effects of considering the conversion efficiency evolution over time. In terms of the production costs, the total production costs of the stochastic model are lower than the deterministic 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, givens the unitary production costs are high for these types of products.

7.4- Uncertainty Analysis

A $\pm$ 5% and $\pm$ 5% variation of the tendency line's slope of the fermentation and transesterification technology, respectively, is introduced, as it is a line obtained from researched data from which assumptions were made. From the analysis on the fermentation process, it is concluded 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%. This is what is expected given higher conversion efficiencies over time, thus, faster learning, result in greater reductions of the unitary production costs. For the transesterification process, 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. This happens given, since the demand on biodiesel in Portugal is low, the slopes variations don't influence costs reductions. 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 the time horizon of this study. Thus they don't reduce costs significantly to have influence in the total SC costs. These cost variations are then associated to a possible solution given by the model as result of the 9% relative gap.

7.5 – Case study results for Stochastic model with four periods of time

After validating the stochastic model's construction and the effects of considering the conversion efficiencies evolution of the technologies over time, 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 0.14 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 reliable solution.

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, as well as near the demand focuses. The SC costs result was 2 135 217 851.58 €, with more than a half being biomass acquisition costs.

7. Conclusions and Future Work

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. A major limitation in this process is the enormous lack of data on biorefineries and their specifications, thus assumptions many assumptions are made.

The implementation results of the proposed model proved the mathematical representation of the conversion efficiency to be a success, as costs are lower than the models that do not consider these aspects, thus don't accurately represent reality. This is also positive, as it helps the biomass and biofuels on becoming more attractive.

For recommendations and future work opportunities, it can be interesting to dedicate in the further optimization of the proposed model or applying decomposition methods so its performance can be more efficient. A high number of scenarios always requires some computational effort. Moreover, this model does not consider the demand as deterministic, importations and exportations and the production of co-products in the 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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