FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

# Biomass Supply Chain Design and Planning Under Uncertainty

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# Resumo


A biomassa é uma fonte renovável que pode trazer uma alternativa às fontes atualmente utilizadas para aquecimento, eletricidade ou combustíveis para transportes, e é utilizada na produção de produtos químicos. Isto torna a procura de biomassa como fonte de energia uma vantagem quanto ao impacto ambiental, mas também contribui para a criação de empregos. Em particular, biomassa baseada em florestas pode ter um papel importante numa gestão mais eficiente das florestas ao contribuir para um ecossistema florestal saudável.

No entanto, um dos principais factores que impedem uma maior adoção da biomassa é o desafio de conseguir operações de cadeia de abastecimento mais sustentáveis e resilientes. Os custos logísticos associados ao armazenamento e ao transporte, juntamente com a sua disponibilidade sazonal e a sua degradação ao longo do tempo, impedem uma adoção e uma utilização mais amplas da biomassa florestal para várias aplicações. Como tal, uma gestão eficiente da cadeia de abastecimento que se centre na redução dos custos operacionais, evitando simultaneamente a degradação da biomassa, é vital para aumentar a eficiência e a resiliência da cadeia de abastecimento. Neste contexto, o trabalho a desenvolver visa desenvolver uma abordagem baseada na otimização multi-objetivo para apoiar a tomada de decisões relativas à conceção da cadeia de abastecimento e decisões de planeamento sob incerteza. O principal objetivo é conseguir alcançar as melhores soluções de compromisso entre a eficiência de custos e a resiliência.

# Abstract

Biomass is a renewable source of energy that could bring an alternative to currently used sources for heat, electricity, transportation fuels, or in the production of chemicals. This makes pursuing biomass as a source of energy a clear advantage regarding the environmental impact, but also in contributing to the creation of new jobs. In particular, forest-based biomass, can also play a key role in achieving a more efficient forest management by contributing to a healthier forest ecosystem. However, one of the biggest factors that prevents a major adoption of biomass is the challenge in achieving a more sustainable and resilient supply chain operations. The associated logistic costs related to storage and transportation, together with its seasonal availability and degradation over time, hinders a wider adoption and utilization of forest-based biomass for various applications. As such, an efficient management of the supply chain that focuses on lowering operational costs, while preventing the biomass degradation is vital to enhance SC efficiency and resiliency. In this context, the work to be developed aims to develop a multi-objective optimization-based approach to support decision-making regarding supply chain design and planning decisions under uncertainty. The main goals is to be able to achieve the best compromise solutions between cost-efficiency and resiliency.

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# Abbreviations

| | |
|---|---|
| SC | Supply Chain |
| BSC | Biomass Supply Chain |
| SCM | Supply Chain Management |
| GIS | Geographical Information System |
| MILP | Mixed Integer Linear Program |
| MIP | Mixed Integer Linear Program |
| BELCA | Biomass Element Life Cycle Analysis |
| GHG | Greenhouse Gas |
| VaR | Value-at-risk |
| CVaR | Conditional value-at-risk |

# Chapter 1

# Introduction

This section aims to present an introduction to the dissertation topic "Biomass Supply Chain design and planning under uncertainty". The following subsections will present the context in which the developed work is integrated (subsection 1.1), the motivation behind the used approach (subsection 1.2), the main goals of the work to be developed in this dissertation (subsection 1.3), the methodology adopted (subsection 1.4), and the dissertation structure (subsection 1.5).

## 1.1 Contextualization

The design and planning of forest-to-bioenergy supply chains (SC) is getting more and more critical as sustainability goals become more stringent towards, not only the increased use of renewable energy sources, but also the recognition of the importance of more sustainable forest management policies. So, with energy produced by biomass being less pollutant and capable of improving sustainability, there is an interest for biomass to substitute the currently widely adopted fossil fuels.

Sources of biomass feedstock include starch and sugar based, agricultural residues and livestock products, urban and industrial woody wastes and landfills, forest biomass, herbaceous energy crops, short rotation woody crops, oily crops, energy crops and algae[6]. The work to be developed in this dissertation will focus on biomass sources from forest-related activities.

Being an alternative to fossil fuels, there is an interest to make the production of biomass as sustainable, resilient, and efficient as possible. The efficient management of biomass supply chains (BSC) should result in a greater availability of biomass, and a more robust supply chain that will contribute to a more sustainable management of forests [7].

Biomass is used for heating, energy and the production of bioproducts. Its efficiency as an energy source however is dependant on multiple factors, such as rain, humidity and wind. Main costs of the biomass supply chain come from transport and storage activities, as well as material deterioration. In this context, decisions regarding resource allocation such as where to setup equipment and storage units as well as transport routes are crucial. Also important for the deployment of more efficient and sustainable SC are material flows and inventory management, particularly under these highly stochastic and dynamic environments. As the entity in charge of supplying biomass, agreements must be made with owners of forests to collect the residues resulting from foresting activities and with bioenergy plants which dictate the demand for processed biomass.

Since transportation and storage represent the main costs in the supply chain, after collecting the biomass there is a need to process it using methods such as chipping which increases bulk density of biomass or unitising the biomass by processing straw into bales, this is known as baling [8]. These processes help reduce the necessary storage space and number of trips by truck.

In conclusion, the design and planning of forest-to-bioenergy supply chains have become increasingly important due to stricter sustainability goals and the demand for renewable energy sources. Efficient management of biomass supply chains is crucial for ensuring a sustainable flow of biomass, considering factors such as resource allocation, transport routes, and processing methods.

## 1.2 Motivation

Biomass is primarily constituted by plants, wood and waste and presents itself as a source for heating, energy and can be used in the production of bioproducts, such as chemicals. As such, biomass has been considered a sound alternative to fossil fuels.

Beyond the economic advantages of exploring biomass as an energy source, the utilization of forest-agri-residues for bioenergy and biofuels could contribute to the improvement of air quality by reducing greenhouse gas (GHG) emissions that would come from mass burning facilities. Other environmental and social advantages would be decreasing waste mass and saving landfill spaces, diminishing fire risks through the collection of post-thinning residues, creation of job opportunities and the reduction of fossil fuel dependency [9].

While the use of biomass contributes to a more desirable situation for the climate, there are still challenges relating to the availability of biomass and its economic viability. As for availability, forest biomass is commonly scattered over a wide region, usually being generated from forest management activities and forest products manufacturing. So, there is an uncertainty not only related to when and where biomass is available for collecting but also the quality of the residues collected. On the other hand, the relatively low density of energy also results in high costs of transport and storage. The moisture and energy content, particle size, ash and contaminant contents present in biomass also constitutes a challenge, since it influences the selection of pre-processing operations such as sorting, chipping and drying as well as the conversion technologies, the conversion yields, and the transportation costs. In this context, more effective design and planning approaches are needed, addressing not only the biomass supply chain cost efficiency, but also balancing it with sustainability and resiliency strategies.

At this moment, biomass supply chain management (SCM) has not been explored so much in the context of sustainability and resiliency. According to [9], the number of publications that have addressed data analysis methods in this context is lacking.

## 1.3 Main goals of the dissertation

The main goal of this project is to develop a decision-support system for SC design and planning, based on optimization techniques capable of integrating different data sources to capture the main features of real stochastic environments. In this context, the developed model should withstand disruptive events such as forest fires. The resulting plan should give information encompassing both, strategic and tactical decisions, including: where to collect and store biomass material (at the roadside or at an intermediate storage facility); where the intermediate storage facilities should be located; when, where and how to process the collected biomass, and the amounts transported along the supply chain to fulfill the overall power plants demand.

Due to the highly uncertain context associated to the availability of biomass, the developed approach should provide robust plans able to cope with unexpected events and promote more resilient practices in this sector.

The system will be tested and assessed in a case study based on a representative real-world situation.

The successful development of a model capable of optimizing a biomass supply chain is expected to bring benefits at the social, economic and ecological level. A sustainable and profitable way to explore biomass resources would result in a more economically viable practice, less pollutant emissions to the environment, and also in job creation in forest-dependant communities, as well in contributing to achieving energy independence.

## 1.4 Adopted methodology

This section will introduce the methodology adopted in this dissertation. The methodology's features and capabilities are also summarised.

The adopted optimisation-based methodology will help evaluate the impact of disruptive events in the biomass supply chain and will serve as a decision-support system for strategic decisions within the supply chain. The proposed approach uses previously computed scenarios that modify the availability of unprocessed biomass depending on the impact of disruptive events which in this case are wildfires.

A two-stage stochastic model therefore seems adequate to incorporate the uncertainty of the supply chain. The model returns the strategic decisions made at the beginning of the planning horizon which are made by the biomass supplier without knowing if and what particular disruptive events will occur.

The first step is to determine what network nodes are present in the biomass supply chain and their requirements. Then, the integration of different scenarios and their effects on the supply chain is necessary for the model development.

Furthermore, a two-stage stochastic multi-objective model based on a MILP (mixed integer linear programming) mathematical formulation is developed. The model was developed in python using Google OR-Tools with the SCIP (Solving Constraint Integer Programs) solver. The model's input is from a previous work, where the coordinates of the network points and their characteristics are present. The distances between network nodes using GIS (Geographic Information System) are also provided. The model's multi-objective approach is used combining normalisation of each objective with a weighted-sum method.

By analysing the results from the model's solutions applied to various deterministic and a stochastic approach, the model is validated against a previously developed simulation model. The methodology will serve as a decision-support system capable of evaluation the effects of uncertainty in the biomass supply chain.

## 1.5 Dissertation structure

The structure of this dissertation results from the work realized in this project. The final structure is comprised of six chapters. The purpose of this section is to provide context into each chapter and the overall structure of the document.

In Chapter 2 an in-depth contextualization and literature review is made about the biomass supply chain. The supply chain structure, details, and attempts to improve it are included and presented. There is also a review on the studies which include stochasticity in the design of optimisation models for the supply chain.

Chapter 3 refers to the problem of this dissertation's focus, as well as its the defining characteristics and objectives.

Chapter 4 exposes the modelling approach used in this work, explaining the model's components and defining characteristics.

In Chapter 5 the model is validated and the results from applying the model are exposed. The results originating from different scenarios are analysed and discussed in relation to each other.

In the end, Chapter 6 contains final remarks and conclusions resulting from this dissertation. Possible extensions of the work and other variations are discussed.

# Chapter 2

# Background and Literature Review

In this section the fundamental knowledge and theoretical aspects essential to the development of the dissertation topic will be exposed.

The following subsections will explain the biomass supply chain and what it consists of and also the importance of optimization based techniques in the development of effective decision support systems.

## 2.1 The biomass supply chain

In order to develop a reliable optimization model and understand its output, it is necessary to know what actors and processes are involved in the biomass supply chain. According to [8], the logistics of bioenergy and biofuel generation make up the majority of costs. Therefore improvements in logistics and overall supply chain operations may play a significant role in a more widespread utilization of biomass.

The processes involved in a typical biomass supply chain may include ground preparation and planting, cultivation, harvesting, handling, storage, in-field/forest transportation, road transportation and utilization of the fuel at the power station [8]. Biomass fuel sources typically include farms or forests and the transportation infrastructure usually involves trucks travelling by road routes. Transportation by ship and train is less advantageous because of the usually short distances that the fuel needs to be transported. Transport of biomass fuel by truck also provides more flexibility than the alternatives.

From the harvesting of biomass to its delivery to a power station, a biomass supplier must manage these six different activities [8]:

1. Harvesting or collection of the biomass in the field or forest. This can be done manually or with the assistance of machinery. Typically this process is denominated "logging".

2. Storage of the biomass. Because of the seasonal availability of biomass and the year-round demand of it by the power stations, storage is of necessity. Biomass can be stored by the roadside or at intermediate stations.

3. Loading and unloading of the vehicles transporting the biomass.

4. Transport of the biomass along the supply chain.

5. Processing of the biomass to increase ease of transport and density. This can be done at any stage of the supply chain, as long as harvesting has occurred.

6. Distribution of biomass to the bioenergy plants.

An example of different paths from forest feedstock to energy conversion is shown below (figure 2.1).

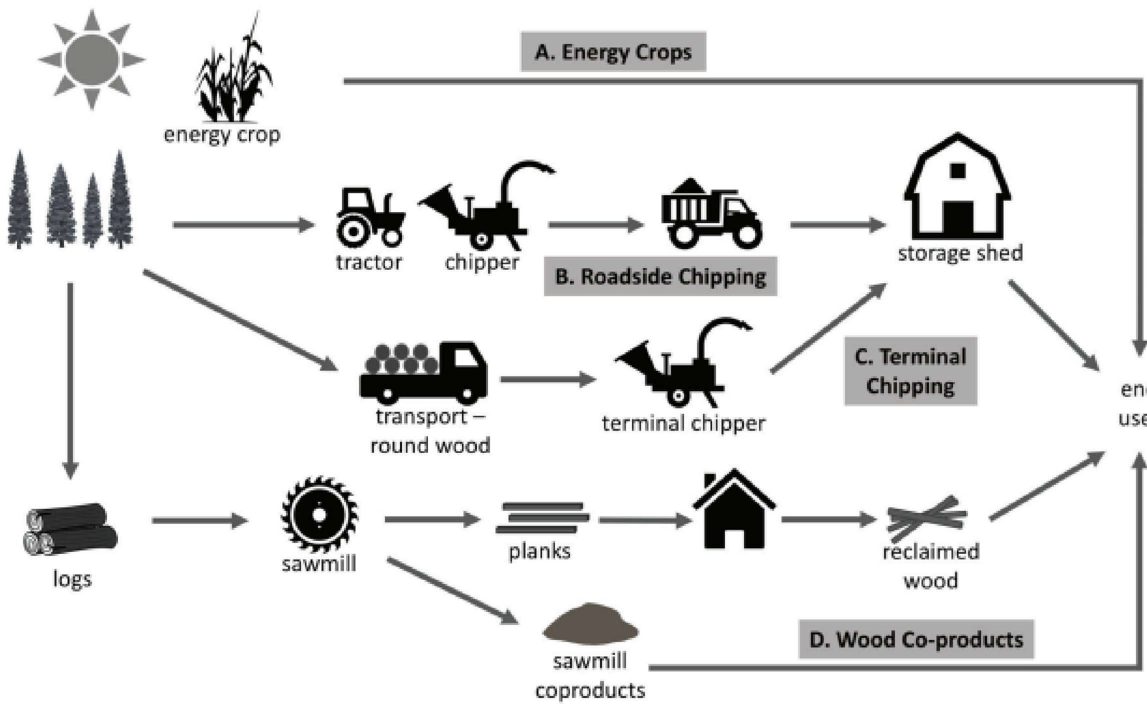


Figure 2.1: Example of forest biomass supply chain, as illustrated in [1]

### 2.1.1 Biomass harvesting and collection

The biomass feedstock can be divided into three generations. First-generation biofuel consists primarily of edible food crops. The exploration of this type of feedstock may compromise the food supply [6] and as a result non-food related feedstock has become more attractive. The second-generation of biofuels are the result from processing dry matter from plants, woody crops, agricultural residues and waste from municipal landscaping or citizen gardening activities [10]. Finally, third-generation biofuel is produced from algae.

The harvesting and collection of biomass is an activity related to uncertainty within the supply chain because of its seasonal availability. There is a limited time period when biomass is available to be collected, determined by the crop harvesting period, weather conditions and the need to re-plant the fields [8]. Harvesting efficiency depends on the size of harvesting areas and whether they are clustered or scattered across a wide region.

There are situations in which biomass is not readily available and harvesting operations must be completed, this is the case for agricultural residues and energy crops such as corn stover where the feedstock is the remainder of the plant and is only available after harvesting corn [11].

In [12], biomass collection can be categorized in two types of supply chain. The supply chain is characterized as a push system (supply-driven) if the biomass at each supply area is fully harvested/collected and as a pull system (demand-driven) if harvesting/collecting activities stop once the demand for biomass has been reached. A supply-driven approach to the collection of biomass is used when the collection must happen within a certain time frame as to not disturb agricultural or foresting activities and the storage space at the supply areas is limited. A demand-driven collection is done at supply areas with enough storage capacity for the leftover biomass at the site. This can be done in forests where biomass is left at the harvest site to lose moisture [13]. Leaving biomass to dry also has the benefit of reducing the overall weight of foresting residues and thus increasing the energetic density, this reduces the cost of transporting large volumes of water embedded in biomass but results in an increase of trips to the forest [13].

Upon collection, different types of biomass are gathered in different forms. Using a forage harvester, agricultural residues can be collected in the form of round bales, square bales or loose chop [14]. In the case of forest residues they are collected loose or they can be bundled at the site to ease the transportation [15]. However these residues can also be processed at the forest sites when using chip trucks to create wood chips [12].

It is important to note that the scattered availability of biomass presents challenges during collection activities. Long distances between supply areas, storage facilities and conversion sites result in higher transportation costs but even within the same supply site there may be various spread out piles of available biomass which pose an issue for the collecting process [12]. This issue requires a routing decision regarding the collection of biomass within a single supply area [16].

Collection is dependant on the seasonal availability of biomass. Agricultural biomass supply relies on the crops' harvesting season [8] and in some cases collection activity in forest areas is halted during winter months [17, 18]. This seasonal availability can result in an abundance of supply areas relative to resources at hand during some periods and a shortage of supply areas at times. During periods of abundance a decision of where to allocate resources must be made, making the scheduling of collecting biomass feedstock a complex issue [12].

Biomass quality varies from supply point due to external events, being another contributor to uncertainty. This does not impact supply-driven collection, however it does influence demand-driven collection since energy content depends on the quality of biomass [8].

The focus of this work will be in forest-related biomass feedstock available from various supply areas. This feedstock can be collected using machinery as seen in figure 2.2.

Figure 2.2: Forestry-related biomass collecting [2]

### 2.1.2 Storage options

When evaluating storage decisions, the quantity of biomass to store, the type of storage system and the location of the storage units are all taken into consideration.

Considering the uncertainty of biomass availability, storage of biomass is necessary to meet bio-energy plant demand throughout the year [19, 8, 12]. Facilities with drying capabilities also help avoid quality degradation of the biomass due to infections, fermentation and material loss, while also increase the energy content of the biofuel by reducing its moisture [8].

#### 2.1.2.1 Location

The location of the storage units can be at the power station, at an intermediate site or in the farm/forest [8, 19]. The latter case can also be referred as roadside storage.

Storage of agricultural biomass feedstock at the farms has a time constraint associated with the need to prepare the farms for planting season [11]. However, forest sites can be the storage space for forest residues for several months after harvest, with the added advantage of reducing the moisture content of the residues through open-air drying [12].

The use of intermediate storage allows for large volumes of stored biomass as well as for a longer duration. It is important to note that using intermediate storage implies an added number of trips transporting biomass, first from the forest/farm to the intermediate storage and then from the storage to the power station [8]. Because of the additional transportation requirements, this choice of location may increase the total logistics cost. The results in [13] show that the integration of an intermediate terminal resulted in an overall cost reduction compared to transporting biomass directly from the suppliers to the energy plants. The cost reduction came from the reduction in moisture content in biomass while in storage, which made transportation more inefficient. A higher level of moisture content also results in lower energy values, demanding a higher volume of biomass to be delivered.

When situated at the end user's location, stored biomass can be dried using the heat from the plant [20].

#### 2.1.2.2 Types of storage

Biomass can be stored by roadside or in storage facilities. These facilities can be open-air or enclosed, as shown in figure 2.3. For enclosed facilities there are options such as drying by hot air injection or roofed with metal or plastic [8]. Open-air storage provides lower cost however there is an associated significant loss of biomass material and the moisture content cannot be controlled [20]. For this reason it is best to consider this option only in arid locations. Drying capabilities in enclosed warehouses help avoid quality degradation of the biomass due to infections, fermentation and material loss, while also increase the energy content of the biofuel by reducing its moisture [8].

Grinding or densification can be done at intermediate storages to reduce storage costs and transportation costs from the terminal to the bioenergy plant [20].

Storage facilities are categorized in terms of ownership, being self-owned warehouses, public warehouses or subcontracted warehouses. Owning the warehouse brings advantages such as control and exposure of the brand to the market, but also brings substantial fixed costs. Public warehouses allow for flexibility to change location, size and quantity of products to store. Moreover, subcontracted warehouses generate lower costs while also providing flexibility[20].

#### 2.1.2.3 Quality loss

Storing biomass for a long duration is associated with quality deterioration, material loss, fire danger or even formation of microbes dangerous to human health [8]. However, depending on the type of storage, it can also help in preventing adverse effects. In [8], the differences in material loss are compared between closed warehouse with external drying, covered storage without external drying and ambient storage covered with plastic film. In spite of showing that ambient storage results in a higher material loss, it is concluded that the cheaper option still provides cost savings.

In [21] a study was conducted reviewing dry matter losses in woody biomass storage. In the case of freshly cut un-dried woody biomass, microorganisms are the main cause for material decay in pile storage. Soft rot or staining fungi may be present in the wood before harvesting, and will continue to act upon arranging the biomass in a pile. The soil, which contains other microorganisms which harm biomass, and water, which may introduce bacteria that start infections in the wood, are also responsible for biomass deterioration.

Temperature is another factor that contributes to the growth rate of wood decaying fungi, most of these grow at an optimal rate between 20-32ºC [22].

All wood decay fungi and bacteria require a minimum level of moisture for deterioration to occur, and freshly chipped biomass has very high moisture content, this moisture content is even higher during late spring or summer.

Negative consequences may arise from microbiological wood decay in storage. Self-heating can lead to ignition, loss of dry matter and excess moisture [21]. With this in mind, it is important to understand all the decay mechanisms that act upon biomass to better manage quality loss during storage of woody biomass.

For birch wood chips the monthly dry matter losses are expected to be between 0.7 and 2.3%. To avoid material loss it is recommended to not mix various biomass feedstocks within the same piles, organize the wood chips in a windrow shape, minimize compaction during construction of windrows, and limit storage time to 3-4 months [21].

Figure 2.3: Covered storage of biomass [3]

### 2.1.3 Transport of biomass

Transport by truck is the preferred mode of transport in the bio-energy supply chain. Costs related to transportation may account for up to a third of costs related to delivered forest biomass [23]. Road transportation is advantageous due to the flexibility it offers and the short distances involved in the biomass industry [20]. For long distance transport, moving biomass by ship or train are available options to consider [24].

In cases where various modes of transportation are used, trucks can be used to deliver biomass from the supply areas to shipment points and from these points a higher volume can be carried and delivered. This type of distribution is called hub-and-spoke network [12]. It may bring benefits related to cost reduction but turns the logistics into a more complex system adding planning and scheduling of the shipment points with the trucks.

While biomass is being transported, the travel time translates to costs in depreciation of quality, insurance, maintenance (tires, brakes, lubrication) and labour. Fuel consumption is another cost related to travel distance [25, 8]. In [8], traveling time included the return trip and the loading/unloading process. It is also mentioned that the vehicle's load is limited by the volume of the cargo and not by the weight since biomass has low density. However in [26] it is concluded that while densification of biomass results in a decrease of transport movement, there comes a point of redundancy where further densification does not bring any benefit and the transport is instead limited by weight. The baling or bundling of biomass could reduce costs in transportation and in storage, improving the efficiency of the supply chain [8, 15]. In figure 2.4, it is presented an example of a large volume of processed biomass being unloaded after transportation with higher density in comparison with feedstock found in supply areas. In [25] the cost of paying the truck drivers was considered, even in days where trucks were idle.

Figure 2.4: Example of a truck unloading biomass [4]

### 2.1.4 Pre-processing

Pre-processing of the biomass is done with the intent of increasing the energy density and decreasing the volume of biomass. The definition of pre-treatment techniques according to [19] is any processing that is not exclusively mechanical manipulation. However, in this section all types of manipulation will be listed and addressed. Pre-processing techniques include ensiling, drying, pelletization, torrefaction, pyrolisis, sorting and grinding/chipping [19, 12]. Chipping is a process that transforms wood into small bits or "chips", as presented in figure 2.5. This process will be considered in the work to be developed in this dissertation.

The type of pre-processing technique is based on the type of biomass and also harvesting method. Biomass derived from agricultural activities usually goes through a grinding operation before being collected as bales, these make transportation and storage more efficient. If a forage harvester is utilized in the collection activity then grinding is not necessary [12]. For forest-based biomass the type of feedstock may demand comminution or not. Sawdust and mill shavings can be used in the conversion process without any treatment while non-merchantable logs, tops and branches larger in dimension need comminution [12].

Chipping of forest residues can be done at the harvest site using chipping trucks, intermediate terminals or at the conversion facilities. Moving chipped resources is more efficient for transportation due to the densification of biomass [12]. However, chippers located at forest sites like truck-mounted chippers offer a lower productivity output than large mobile chippers at terminals [27]. Therefore the cost of moving unprocessed forest residues can be offset by the greater efficiency of chippers present at intermediate facilities. In [27] it is noted that residues should be moved for short distances and once transformed into chips they are transported over the longer distance.

Drying biomass results in more efficient combustion and gasification processes by reducing moisture levels. It also brings the benefit of providing biomass with a greater resistance to decomposition and fire hazards. Moreover, the weight reduction from drying aids transporting activities, decreasing their costs [26, 19]. While dependent on the weather and season [28], leaving biomass to dry in the open air can be considered as an option that does not rely on energy expenditure.

Treatment by pelletisation consists of drying and pressing of biomass under high pressure, producing cylindrical pieces of compressed and extruded biomass with increased bulk density and lower moisture content [29]. Pellets ease handling and transporting operations, having greater effects on longer transport distances [26]. Pellets can be stored for long periods without significant dry matter loss [30].

Pyrolisis is the direct thermal decomposition of biomass in an oxygen-free environment [29], it is process that involves high temperatures where the resulting products are present in gas and liquid form and also solid char. Torrefaction is also a process that is done in the absence of oxygen, making use of atmospheric pressure and high temperatures to achieve a product with low moisture content and high calorific value in comparison to fresh biomass [29].

## 2.2 Approaches to address uncertainty and increase Biomass Supply Chain resiliency

In this subsection, strategies to optimize the resiliency of the biomass supply chain under uncertainty will be addressed and the results listed. These strategies involve mathematical programming and heuristic algorithms. The biomass supply chain can be divided into different aspects and problems to solve such as: network design problems, scheduling problems, facility location problems, vehicle routing problems, and technology selection problems.

In [31], the authors incorporate supply chain uncertainties such as biomass element characteristics, transport-related parameters, raw material pricing, biomass availability, market demand and selling price of final product to avoid an overestimation of financial performance in the supply chain. A hybrid framework is utilized integrating a stochastic Monte Carlo Simulation model with element targeting approach (BELCA-P-graph model) for scheduling and economic analysis in the

Figure 2.5: Wood chips [5]

biomass supply chain. Each input of biomass feedstock ratio was generated by the BELCA-P-graph model. The results showed that shortage of biomass contributed to the decrease of the mean Net Present Value by 1.39%-12.21% compared to not considering biomass shortage. The mean Net Present Value decreased by 11.59%-12.21% when taking into account storage capacity. It is concluded that uncertainty in synthetic gas demand and selling price significantly impacted the mean Net Present Value.

In [32], a Geographic Information System (GIS) is utilized in the logistic model to minimize uncertainty. Power generation plant location and capacity, logistic model design and interaction between logistic model and local conditions are evaluated. For overall profitability, it is concluded that for lower availability of agricultural residues the optimal pre-treatment technique is compression while torrefaction becomes the best option once availability increases due to significant cost reductions in storage. Using GIS, an estimated 0.02% reduction in transportation cost is achieved and a 0.01% reduction in $CO_2$ emission.

A mixed-integer linear programming model (MILP) for designing a multistage biofuel supply chain under uncertain conditions is developed in [33], utilizing conditional value at risk (CVaR) to evalute the financial risk on the optimal design and planning of the supply chain. The MILP model integrates multistage stochastic programming and takes into account biomass and biofuel demand as well as biomass feedstock seasonality. In this study the fast backward reduction method is used to decrease the number of scenarios. The results show that transportation cost is the aspect most affected by risk aversion. Higher risks is also responsible for a preference for lignocellulose-based biofuel at production facilities and an overall decrease in biofuel production.

In [8], the authors refer how a multi-biomass approach, defined by combining multiple biomass chains could be used to minimize the share of capital costs. This approach has the positive effect of mainly reducing the total system cost, particularly in the stage of storage, as the yearly inflow of biomass may smoother requiring a more reduced storage space. Moreover, smoother resource requirements could impact equipment and labor usage. An example is given of using two biomass sources instead of one, resulting in a 15% to 20% cost reduction. The main reason this approach has not been heavily researched involves the complexity of the supply chain when a variety of biomass streams are involved. Another issue of the multi-biomass approach is that when converting biomass into fuel the result will be a mixture of various biomass materials with varying fuel characteristics, or a fuel that does not maintain its characteristics throughout the year because of the seasonal availability of resources. While there are energy conversion technologies which are tolerant to various fuel characteristics, others are extremely sensitive even to small variations. It is important for the sources of biomass to be capable of similar treatment from the same equipment, requiring the fewest or no adjustments to maintain the advantage of cost reduction. In [8] it is concluded that a cheaper storage solution leads to significant cost reduction for the whole biomass logistics function, the cheapest biomass type available is recommended when choosing this approach. However multi-agricultural biomass approach seems attractive for systems where expensive storage solutions are used, to reduce the storage space required.

A model based on a Vehicle Routing Problem (VRP) is used in [10] to determine total transportation costs and emissions of carbon dioxide of second-generation biomass (SGB) processing in Overijssel. This paper determines the economic and environmental trade-offs between the mobile and fixed pyrolysis plants as well as between biofuel production and the convenience of refining and electricity production. The results show that the use of second-generation biomass processing is expensive compared to fossil fuels, oil and refined oil achieved from this method are at least 65% more expensive than their fossil counterparts.

A resilient approach to planning the supply chain needs to accommodate the occurrence of disruptive events. In [34] a simulation study is done utilizing discrete event simulation through Flexsim with GIS. The study focuses on providing a decision-making tool taking into account the influence of fires in increasing the supply of biomass and demand variability from the power plants. The tool developed provides a comparison of costs generated by the use of intermediate storage and additional chippers in varying scenarios of supply and demand uncertainty, thus increasing the supply chain's resiliency under disruptive events.

Moisture content variation in wood chips is addressed in [35]. Here, a mixed integer programming (MIP) model is used to determine the optimal delivery of wood chips from forest supply areas to power plants and terminals. Since the energy density present in wood chips decreases with a higher moisture content, a greater amount of chips may have to be provided to power plants to meet the agreed caloric value demanded. An optimal assignment of chippers and transportation synchronization to process forest residues at supply areas is also one of the main objectives of the model. The model takes into account the variation of moisture content while the chips are in storage and it reports a 5% increase in profits over considering a fixed storage time with expected moisture content at the end of that period.

From the various approaches analysed, the use of a MIP model is adequate to accurately represent the behaviour of the biomass supply chain. As such, the chosen approach to address uncertainty in this work utilised a two-stage stochastic model based on mixed integer programming.

## 2.3 Stochastic optimisation

This section aims to a brief literature review on optimization models targeting uncertainty aspects related to SC operations.

In [36] a two-stage stochastic formulation is presented, taking into account the variability of moisture and ash content in the total cost of producing biofuels and how they affect the design of the biomass supply chain. The model takes as input various facilities and their locations, as well as multiple biomass conversion technologies. The objective is to minimize the total costs, taking into account investment, transportation, facility selection, and the distribution of biomass. In the study's results it is noted that the depot capacity was the factor for the supply chain not being able to meet the demand for biochar from the power plants and bioethanol from the cities.

Another example of a two-stage stochastic programming model is presented in [37], here the model is developed to maximize the profit obtained and minimize emissions under different sources of uncertainties. The uncertainties considered for this problem were varying biomass availability and prices. Various scenarios were included with different values for these two parameters. According to the authors, the application of the developed model could contribute to a more flexible supply chain.

The uncertainty of user load and energy price is considered in an optimisation problem in [38]. A two-stage stochastic programming model was developed for the optimization of a biomass integrated energy system configuration, with the objective being to maximize the annual profit. The results showed that by changing the conditions of equipment configuration capacity and operating parameters, the solution was able to reduce the system operation risk due to random variation of uncertainty factors compared to a deterministic solution.

Despite these important contributions, it is worth noting the lack of works specifically addressing the high variability and seasonality associated to the availability of biomass material. This work will focus on this particular challenge of biomass supply chains management.

# Chapter 3

# Case study and Problem Definition

This chapter will focus on the case study considered for the design of the optimisation model. Each section is related to the approach used in this work. In 3.1 the case study is detailed.

## 3.1 Context

For the considered case study the role of a biomass supplier is assumed and its supply chain's problems studied. The biomass supplier is in charge of collecting unprocessed biomass from scattered supply areas in forests, processing the biomass via "chipping" and delivering the wood "chips" to a set of power plants. The expected amount of wood "chips" delivered by the supplier to each power plant is contractually agreed for each month.

The unprocessed biomass collected by the supplier consists of residues found in forests naturally or through forestry activities. These residues can be twigs, branches, leaves, and barks originated from trees and bushes. The supplier negotiates access to the forest residues with forest owners to be able to produce biomass. For convenience, these residues are moved from the forests into roadside piles to facilitate access for "chippers" and trucks. Since there are numerous supply areas, piles are scattered along the supplier's zone of interest.

In this study it is considered that the biomass supplier has at his disposal an unlimited number of trucks to transport both unprocessed and processed biomass. However, the number of "chippers" is limited to five. Each "chipper" has a production rate, which dictates how much biomass it can process in an hour, and defined usage costs for both standard and extra hours. To be able to use a specific "chipper", the biomass supplier must pay a fixed cost corresponding to the desired machine. "Chippers" with higher productivity have a higher fixed acquisition cost and hourly costs. Which "chippers" to use will be one of the core decisions to address.

The supplier makes use of intermediate warehouses to act as storage for biomass and processing centres. In this case study biomass processing into wood "chips" only occurs in intermediate warehouses. Similarly to the "chippers", to be able to use an intermediate terminal a fixed cost must be paid. Terminals with more capacity have an associated higher fixed cost. Besides the cost and capacity of a given terminal, its location is also an important factor that is taken into account when deciding which terminals to use. The location of the terminal may greatly influence the transport related costs therefore, the list of chosen intermediate terminals will be the other core decision addressed.

The focus of this study is on the supplier's tactical and strategic decisions. Strategic decisions are less frequent, are usually costly, and are often taken a small number of times. Tactical decisions are taken more often but usually have a smaller financial impact compared to strategic decisions. Therefore, this study will be focused on the following main decisions:

Strategic level:

- Investment in new intermediate warehouses (based on location, cost, and capacity);
- Investment in new "Chippers" (based on processing needs, productivity, and cost).

Tactical level:

- Inventory management;
- Material flows across the supply chain;
- Processing hours per "chipper".

In order to improve the overall supply chain efficiency and resiliency the decisions mentioned above need to be made with the intent to strike a necessary balance between profitability and unnecessary material loss. The profitability of the biomass supply chain is a difficult pursuit because of its characteristic seasonal dependence on biomass material and significant transport costs. At the same time, to keep the supply chain's sustainability in mind the avoidance of waste and as a consequence the resilience should be a priority.

## 3.2 Defining resilience in the context of the BSC

The topic of resilience in the biomass supply chain has been mentioned throughout the reviewed literature. However, it seems clear that an appropriate quantification and evaluation of supply chain resiliency is still an open challenge. In this regard a comprehensive analysis on how resiliency has been understood in biomass supply chain will be presented, as well as the metric that will be proposed in this work.

Resilience in the context of a supply chain is often approached from multiple perspectives, resulting in different definitions and metrics. It has been considered as the ability to react after a disruption in some cases while in others it is viewed as preparing for disruptions in a proactive manner [39]. In [40], resiliency as a property of supply chain networks is defined as "the ability of a system to return to its original state or move to a new, more desirable state after being disturbed", underlining that a resilient supply chain should also be flexible and adaptive.

A multidisciplinary perspective on the definition of supply chain resilience is proposed in [41] as "The adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function". This definition was reached after the authors analysed the concept of resiliency on different subjects such as ecological, social, psychological, economics, organizational, and emergency management.

In [39], a combination of reactive and proactive effort is included in the definition of supply chain resilience resulting in "the adaptive capability of a supply chain to reduce the probability of facing sudden disturbances, resist the spread of disturbances by maintaining control over structures and functions, and recover and respond by immediate and effective reactive plans to transcend the disturbance and restore the supply chain to a robust state of operations". This definition also associates concepts such as flexibility, adaptability and agility.

An example of resilience being measured in the biomass supply chain is present in [42], where a blue-sky or baseline scenario is considered in which the supply of biomass is not affected by any disruption and a black-sky scenario where disruptions in the supply chain occur. The biomass delivered is observed in each scenario, with the black-sky scenario having a reduction in biomass delivery of -11.3%. Resilience in this paper is measured as the percentage of loss of biomass delivered in black-sky scenario versus the blue-sky scenario, indicating that a smaller decline in biomass delivery relative to the blue-sky scenario would correspond to a more resilient supply chain, in this case the resilience to weather conditions.

A systematic literature review investigating the current status of resilience in forest biomass and bioenergy supply chain is done in [43]. The definition for biomass supply chain resilience given in the article is "the capability of forest biomass and bioenergy supply chain networks to return from sustained difficulties, for sustainable development during and after a foreseeable or unforeseeable event in a short period of time, by an efficient preventive-progressive procedure and with high performance quality, in keeping with environmental, economic, social, technical, and strategic standards". The study exposes barriers and enablers of biomass supply chain resilience in different dimensions and proposes that future works evaluate the interactions between these components and reach a conclusion about advantages, disadvantages and their importance in a resilience context.

In [44], value-at-risk (VaR) and conditional value-at-risk (CVaR) are used to measure and quantify disruption risks in a stochastic mixed integer programming model that determines supplier selection and customer order scheduling under risk of disruption. Although resilience is not mentioned in the referenced work, these same measures could be used to quantify resilience according to the aforementioned definitions.

Taking into account all the literature examples and definitions stated before, resiliency in this paper will be measured by the loss of useful biomass in the considered planning horizon. In practice, this measurement is achieved by taking into account the loss of unprocessed biomass at both piles in supply areas or terminals, and loss of wood "chips" at terminals. Additionally, any biomass left at piles at the end of the scenario is considered as lost. To avoid deterioration, an effort has to be made to process the available biomass into wood chips as early as possible. Wood chips suffer from deterioration, but at a much slower rate than raw forest biomass. Disruptive events, in this case wildfires, will force the system to exert more effort to maintain a low amount of deterioration throughout the planning period.

In this case, a disruption in the supply chain will not impact the ability to satisfy the demand of the power plants. Instead, the inability to collect and process biomass has as consequences the loss of useful fuel and impact to the forests' ecosystems and their management. Uncollected or abandoned biomass material in forests may lead to propagation of infectious bacteria capable of degrading the forest and increase the risk of fires.

The focus of this dissertation is to increase the biomass supply chain's resilience to uncertain disruptive events while keeping in mind its profitability. With this in mind, a Two-Stage Stochastic Multi-Objective model based on a MILP (Mixed Integer Linear Programming) mathematical formulation is presented. The model determines which warehouses to open , which "chippers" to acquire, when to collect each available pile of biomass, how many processing hours to dedicate each time period to convert unprocessed biomass into "chips", and when to deliver the processed "chips" to the power plants. The model follows a multi-objective approach to maximize the resilience of the supply chain and to minimize costs.

## 3.3 Problem definition

Considering the previous description, the problem being addressed can be defined as follows.

Considering a set of known elements and data, namely:

- Geographical coordinates of supply areas, intermediate warehouses, and power plants;
- Intermediate warehouse storage capacity;
- Cost of purchasing intermediate warehouse;
- Expected quantity of available biomass;
- Time interval where biomass is available to be processed;
- Expected demand of processed biomass to be delivered;
- Chipper processing speed;
- Hourly cost of chipper usage;
- Cost of purchasing a chipper;
- Transporting truck capacity for processed and unprocessed biomass;
- Cost of truck transporting biomass.

The goal is to determine:

- To open an intermediate warehouse or not;

- Geographical coordinates of intermediate warehouses;
- Allocation of chipping trucks to supply areas;
- To purchase or rent an additional chipper or not.

**Decisions**

A set of strategic and tactical decisions will be determined.

Strategic decisions comprise the highest level of organizational business decisions and are usually less frequent and made by the organization's executives. Decisions made at this level involve significant expenditure. However, they are generally non-repetitive in nature and are taken only after careful analysis and evaluation of many alternatives.

Tactical decisions occur with greater frequency (weekly or monthly). The impact of these types of decisions is medium regarding risk to the organisation and impact on profitability

Strategic Level:

- Infrastructure (location, capacity, size and type);
- Biomass (sourcing and location);
- Biomass storage environment selection (near supply areas or at intermediate warehouses).

Tactical Level:

- Inventory (quantity, storage or order timing);
- Fleet management (transportation model, shipping size, route and scheduling).

### 3.3.1 Objectives

Define evaluation criteria capable of indicating that one decision is preferable to others (define objective function)

- Minimize total costs;
- Maximize supply chain resilience.

### 3.3.2 Constraints

Identify which constraints limit the decisions to be taken (Define sets of equations or inequalities)

- Amount of biomass transported in a trip cannot exceed a truck's capacity;
- Amount of biomass stored cannot exceed a warehouse's storage or available space near a supply area;
- Amount of energy content delivered to a power plant cannot exceed the demand;
- Due to biomass loss during transportation and storage, the actual amount of biomass required should be higher than the ideal demand [32].

# Chapter 4

# Solution approach

This section demonstrates the proposed modelling approach for the biomass supply chain problem intended to serve as a decision-support tool. A two-stage stochastic model is adopted and explained in detail in the following sections.

## 4.1 Main concepts and assumptions

The developed model in this work was a two-stage stochastic model. Being a stochastic optimisation program, some parameters are uncertain, in this case the biomass availability. First stage decisions need to be made before the realization of any uncertain data while second stage decisions are made dependent on the data that becomes available.

As part of the two-stage stochastic model, various scenarios were included with varying levels of stress applied to the supply chain and each with its own probability. In each scenario, the biomass supplier has as options the same chippers to buy and the intermediate terminals to open. A baseline scenario is included where a disruptive event does not occur. All remaining scenarios are characterized by the intensity of the wildfire disrupting the supply chain. A higher intensity wildfire affects piles among a larger area and results in more available biomass within the same time period. The biomass availability level represents a good parameter to introduce a necessary trade-off between profitability and resilience. Attempting to avoid big losses of biomass material through deterioration implies an increase in costs which decreases profitability. Therefore, the biomass supplier is faced with a decision. This study aims to provide a decision-making tool that the biomass supplier can utilize to balance both objectives and arrive at a reasonable solution.

There are no variations in demand for all scenarios considered, the total amount of wood chips to be delivered in each scenario is of 38075 tons.

### 4.1.1 Stochastic approach

A two-stage stochastic approach involves two distinct phases of decision making. The first stage decisions are made at the beginning of the planning horizon taking into consideration all the scenarios and their probabilities. The second stage decisions are made during the planning horizon and are scenario specific.

In this model binary decision variables are included to keep track of the first stage decisions. These are what intermediate terminals are chosen and what chippers are acquired. A decision variable $\lambda_o$ takes value 1 if terminal $o$ is open and available. When this is the case, the opened terminal is able to store both unprocessed and processed biomass. The decision variable $\lambda_k$ follows the same principle, taking the value 1 if chipper $k$ has been acquired which allows biomass processing to occur at a terminal.

In the case of the second stage decisions the following decision variables are used. Continuous decision variables track the number of hours worked per chipping crew. This information provides context for the preferred chippers used, since the machines have different hourly costs and productivity rates for processing biomass. The number of hours also indicates if a decision to work extra hours to avoid biomass deterioration in a certain time period is made. Moreover, tracking the number of standard and extra hours allows for a better understanding of the time periods where the supply chain is more stressed.

The continuous variables constituting the biomass flows from and into the intermediate terminals allow for a detailed view of the choices involving transportation.

### 4.1.2 Disruptive events

In order to assess how resilient the biomass supply chain is, the effects of disruptive events will be tested. In this study the considered disruptive events are wildfires that happen in the hottest months of the year. The occurrence of a wildfire results in a sudden increase in available biomass material in the same month. The rise in supply will stress the supply chain in the same time period, requiring more chipping hours and transport costs to avoid big material losses. Operations take place between March and November to avoid the most rainy periods of the year. The following picture highlights which months have a higher risk of wildfires.

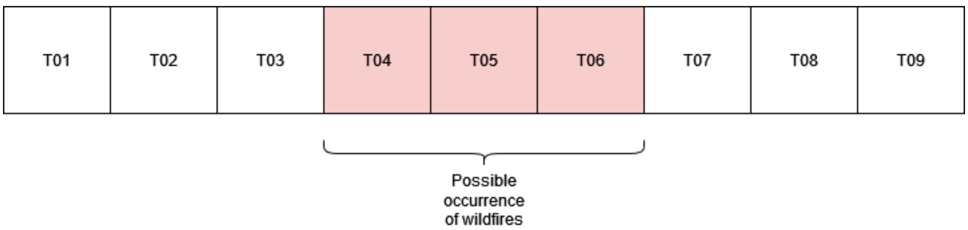


Figure 4.1: Possible occurrence of wildfires

In the face of a disruptive event a decision needs to be made regarding all the sudden available biomass. A higher workload on chipping crews and possible opening of new terminals will avoid huge material losses within a time period at the expense of increased transport and extra hours costs.

The probability of each scenario occurring was obtained from running an adapted optimisation model from the one proposed by [45] that simulates the dynamics of a wildfire. This model takes into account various parameters such as wind speed and direction, the ignition point, the type and density of vegetation, and the slope. The vegetation's type and density, as well as the slope are taken from real maps provided by ICNF, the Portuguese Institute for the Conservation of Nature and Forests. The remaining parameters such as wind and ignition points were assigned random values. A fire duration period was also defined bases on the average duration of wildfires in that region. The output is a matrix of burned points, the period in which the fire occurs, and the affected regions of the biomass piles. Depending on the number and size of trees present in these biomass piles regions, an estimated volume of wood is calculated. Each region has a conversion ratio of burned wood converted to biomass since it will no longer have quality for the wood market. This conversion ratio is based on the forest's typology of the region, with parameters such as tree age, variety, and density.

To achieve the scenarios and their probabilities, the model was run 500 times generating as output the piles affected and the estimated biomass generated as a result of the wildfire. The results were then split into wildfire severity levels with estimated biomass intervals of 10 000 tons. The number of generated scenarios in each level was used to obtain the probability of each scenario considered in this dissertation.

### 4.1.3 Multi-objective approach

The developed model aims to simultaneously maximize the expected profit and the expected resilience of the supply chain. As such, the model has two objectives to satisfy. Following the weighted sum method, the multi-objective problem is represented by a single objective. This objective can be modified according to the weight assigned to the profit and resilience.

The optimisation model will incorporate a multi-objective solution and each objective needs to be defined in order to evaluate the results. In the case of profit it was defined as achieving the highest possible profit at the end of a scenario, taking into account the revenue obtained from delivering biomass to the power plants and the costs associated with opening terminals, acquiring chippers, transport, and "chipper" usage. Resilience was defined as the symmetric of the total tons of biomass lost during the planning horizon.

The solution depends on the priority assigned to each objective. A weighted-sum approach was used to solve the multi-objective problem and determine sound trade-offs between costs and resiliency under a stochastic environment. A normalization approach was taken for each objective, adapted from [46], represented in the following equation:

$$F_i^{trans} = \frac{F_i(x) - F_i^o}{F_i^{max} - F_i^{min}} \tag{4.1}$$

, where $F_i^{trans}$ represents the normalized values of objective function (i), resulting in all objective functions scaled from zero to one, $F_i(x)$ represents the solution of the given objective, and $F_i^{max}$ and $F_i^{min}$ represent the upper and lower bounds of each objective function (i).

**Biomass content loss**

The loss of biomass content throughout the supply chain was incorporated using a fixed decay rate. The decay rate of unprocessed biomass was much bigger than the decay rate of processed biomass. This biomass degradation occurs both at supply piles and intermediate terminals.

Biomass availability in a certain pile $p$ is affected by the unprocessed biomass decay rate, resulting in a loss of material at the pile. This useful content loss is represented by the variable $\pi_{spt}$. The biomass loss occurs between time periods, affecting the material present at a pile in the previous time period.

Biomass material present at a terminal $o$ suffers from degradation according to the same principle, with the added detail that after processing via chipper, the amount lost due to decay is much smaller. The variables tracking unprocessed biomass and wood chips content loss are $\chi_{sot}$ and $\nu_{sot}$, respectively.

Variables $\delta^{w}_{sot}$ and $\delta^{u}_{sot}$ keep track of the stock present in a terminal $o$. It is assumed that any material lost is immediately disposed of and the storage space is recovered. The resulting storage space results in a higher availability for the intermediate terminal to receive input flow of surrounding piles.

**Expected profit**

The expected profit takes into account the revenue and all the costs considered in the model.

Revenue is calculated by multiplying the decision variable that represents the amount of wood chips delivered to power plants in tons ($\beta_{somt}$) with the parameter that represents the price of sale per ton delivered ($p_m$).

The initial investment costs are represented by the cost of acquiring a chipper ($c_k$) multiplied by a binary variable that contains the value 1 if that chipper was used ($\lambda_k$). The cost of opening terminals follows the same logic, the cost of an intermediate terminal ($c_o$) is multiplied by the binary variable that has the value 1 if the intermediate terminal was used ($\lambda_o$). These costs are associated with the first stage decisions.

The costs resulting from chipping activity are calculated from multiplying the number of standard hours worked by a chipper in a time period ($\varepsilon_{skot}$) with the standard hourly chipping cost of using that chipper ($w_k$), these are summed with the costs from overtime chipping activity which follow the same logic ($\varepsilon^{*}_{skot}$ and $w^{*}_{k}$).

Transport costs from the piles to the intermediate terminals are calculated using the decision variable that tracks the amount of unprocessed biomass transported from a pile to a terminal in a time period ($\mu_{spot}$), multiplying it by the distance from the pile to the terminal ($d_{po}$) and the unit transportation cost of unprocessed biomass ($o_u$), the result from the multiplication is then divided by the transportation capacity of each truck ($c_e$). The same method is applied for the transport costs of wood chips between intermediate terminals and power plants. The decision variable that tracks the amount of wood chips transported from a terminal to a power plant in a time period ($\beta_{somt}$) is multiplied by the distance between the intermediate terminal and the power plant ($d_{om}$)

and the unit transportation costs of wood chips ($o_w$), the result from the multiplication is then divided by the transportation capacity of each truck ($c_e$).

**Expected resilience**

The expected resilience is calculated using the symmetric of the total tons of biomass lost during the planning horizon.

It is calculated by summing the amount of unprocessed biomass lost due to degradation in all terminal($\chi_{sot}$), the amount of wood chips lost due to degradation in all terminal($\nu_{sot}$), and the amount of unprocessed biomass lost due to degradation in all piles ($\pi_{spt}$) over the planning horizon and adding the amount of unprocessed present in all piles at the end of the planning horizon ($\rho_{spt}$).

## 4.2 Two-stage Stochastic Multi-objective model

In the following section the model is formulated, with its sets, parameters, decision variables, objectives and constraints stated.

### Sets

| | |
|---|---|
| **S** | Set of scenarios |
| **T** | Set of macro planning periods, $T = \{0, ..., \|T\| - 1\}$ |
| **P** | Set of piles of raw material at the roadside |
| **M** | Set of power plants |
| **O** | Set of intermediate warehouses |
| **K** | Set of chipping machines/crews |
| **E** | Set of transport trucks |

**Parameters**

| | |
|---|---|
| $p_s$ | Probability of scenario $s \in S$ occurring (%) |
| $a_{spt}$ | Availability of unprocessed biomass in pile $p \in P$ $(ton)$ in macro period $t \in T$ in scenario $s \in S$ (ton) |
| $d_{mt}$ | Demand of wood chips at plant $m \in M$ in period $t \in T$ $(ton)$ |
| $c_o^O$ | Storage capacity in terminal $o \in O$ $(ton)$ |
| $c_o$ | Terminal opening cost (€) |
| $c_e$ | Transportation capacity of each truck $(ton)$ |
| $c_k$ | Cost of acquiring a chipper (€) |
| n | Number of available trucks |
| $r_k$ | Productivity of chipper $k \in K$ (ton/h) |
| $y_k; y_k^*$ | Maximum standard and extra-hours working time of chipper/crew $k \in K$ (h/day) |
| $y_t$ | Number of days in a period $t \in T$ |
| $w_k; w_k^*$ | Standard and overtime hourly chipping cost of using chipper $k \in K$ (€/h) |
| $o_w$ | Unit transportation cost of wood chips (€/$ton$/km) |
| $o_u$ | Unit transportation cost of unprocessed biomass (€/$ton$/km) |
| $d_{ij}$ | Distance between point of origin i (pile or terminal) and point of destination j (terminal or power plant) (km) |
| $p_m$ | Price paid for wood chips unit delivered to plant $m \in M$ (€/$ton$) |
| $x_u$ | Degradation rate of unprocessed biomass $(ton/month)$ |
| $x_w$ | Degradation rate of wood chips $(ton/month)$ |

### Decision variables

| | |
|---|---|
| $\lambda_o$ | 1, if terminal $o \in O$ is open; 0, otherwise |
| $\lambda_k$ | 1, if chipper $k \in K$ is in use; 0, otherwise |
| $\beta_{somt}$ | Amount of wood chips transported from terminal $o \in O$ to plant $m \in M$ in period $t \in T$ in scenario $s \in S$ (ton) |
| $\mu_{spot}$ | Amount of unprocessed biomass transported from pile $p \in P$ to terminal $o \in O$ in period $t \in T$ in scenario $s \in S$ (ton) |
| $\delta^w_{sot}$ | Amount of wood chips stored at terminal $o \in O$ at period $t \in T$ in scenario $s \in S$ (ton) |
| $\delta^u_{sot}$ | Amount of unprocessed biomass stored at terminal $o \in O$ in period $t \in t$ (ton) in scenario $s \in S$ (ton) |
| $\varepsilon_{skot}$ | Number of standard hours used by machine/crew $k \in K$ in terminal $o \in O$ in period $t \in T$ in scenario $s \in S$ (h/month) |
| $\varepsilon^*_{skot}$ | Number of overtime hours used by machine/crew $k \in K$ in terminal $o \in O$ in period $t \in T$ in scenario $s \in S$ (h/month) |
| $\chi_{sot}$ | Amount of unprocessed biomass lost due to degradation in terminal $o \in O$ in period $t \in T$ in scenario $s \in S$ (ton) |
| $\nu_{sot}$ | Amount of wood chips lost due to degradation in terminal $o \in O$ in period $t \in T$ in scenario $s \in S$ (ton) |
| $\pi_{spt}$ | Amount of unprocessed biomass lost due to degradation in pile $p \in P$ in period $t \in T$ in scenario $s \in S$ (ton) |
| $\rho_{spt}$ | Amount of unprocessed biomass present in pile $p \in P$ in period $t \in T$ in scenario $s \in S$ (ton) |

### Model [M1]

Expected profit:

$$
\begin{aligned}
max\, P = \sum_{s \in S} p_s( \sum_{m \in M} \sum_{o \in O} \sum_{t \in T} \beta_{somt} * p_m \\
- \sum_{k,o,t} \varepsilon_{skot} * w_k + \varepsilon^*_{skot} * w^*_k \\
- \sum_{p \in P} \sum_{t \in T} \sum_{o \in O} \frac{d_{po} * \mu_{spot} * o_u}{c_e} \\
- \sum_{o \in O} \sum_{m \in M} \sum_{t \in T} \frac{d_{om} * \beta_{somt} * o_w}{c_e}) \\
- \sum_{o \in O} c_o * \lambda_o \\
- \sum_{k \in K} c_k * \lambda_k
\end{aligned}
\tag{4.2}
$$

Expected resilience:

$$min\, R = \sum_{s\in S} p_s(\sum_{t\in T}(\sum_{o\in O}\chi_{sot} + \nu_{sot} + \sum_{p\in P}\pi_{spt}) + \sum_{p\in P}\rho_{spt^{end}}) \quad ,\forall s \in S \tag{4.3}$$

Subject to:

$$\sum_{o\in O}\beta_{somt} \leq d_{mt} \quad \forall m\in M, \forall t\in T, \forall s\in S \tag{4.4}$$

$$\sum_{o\in O}\varepsilon_{skot} \leq y_k y_t \lambda_k \quad \forall t\in T, \forall k\in K, \forall s\in S \tag{4.5}$$

$$\sum_{o\in O}\varepsilon^*_{skot} \leq y^*_k y_t \lambda_k \quad \forall t\in T, \forall k\in K, \forall s\in S \tag{4.6}$$

$$\delta^u_{sot} + \delta^w_{sot} <= c^O_o \quad \forall t\in T, \forall o\in O, \forall s\in S \tag{4.7}$$

$$\delta^u_{sot} = \delta_{uso(t-1)} - \chi_{sot} + \sum_{p\in P}\mu_{spot} - \sum_{k\in K}(\varepsilon_{skot} + \varepsilon^*_{skot})r_k \quad \forall o\in O, \forall t\in T, \forall s\in S \tag{4.8}$$

$$\delta_{usot_1} = \sum_{p\in P}\mu_{spot_1} - \sum_{k\in K}(\varepsilon_{skot_1} + \varepsilon^*_{skot_1})r_k \quad \forall o\in O, \forall s\in S \tag{4.9}$$

$$\delta^w_{sot} = \delta_{wso(t-1)} - \nu_{sot} + \sum_{k\in K}(\varepsilon_{skot} + \varepsilon^*_{skot})r_k - \sum_{m\in M}\beta_{somt} \quad \forall o\in O, \forall t\in T, \forall s\in S \tag{4.10}$$

$$\delta_{wsot_1} = \sum_{k\in K}(\varepsilon_{skot_1} + \varepsilon^*_{skot_1})r_k - \sum_{m\in M}\beta_{somt_1} \quad \forall o\in O, \forall s\in S \tag{4.11}$$

$$\rho_{spt} = \rho_{sp(t-1)}(1-x_u) + a_{spt} - \sum_{o\in O}\mu_{spot} \quad \forall o\in O, \forall t\in T, \forall s\in S \tag{4.12}$$

$$\rho_{spt_1} = a_{spt_1} - \sum_{o\in O}\mu_{spot_1} \quad \forall o\in O, \forall s\in S \tag{4.13}$$

$$\chi_{sot} = \delta_{suot} * x_u \quad \forall o\in O, \forall t\in T, \forall s\in S \tag{4.14}$$

$$v_{sot} = \delta_{swot} * x_w \quad \forall o \in O, \forall t \in T, \forall s \in S \tag{4.15}$$

$$\pi_{spt} = \rho_{spt} * x_u \quad \forall p \in P, \forall t \in T, \forall s \in S \tag{4.16}$$

$$\mu_{pot} \leq c_o^O * \lambda_o \quad \forall p \in P, \forall o \in O, \forall t \in T \tag{4.17}$$

$$\beta_{omt} \leq c_o^O * \lambda_o \quad \forall o \in O, \forall m \in M, \forall t \in T \tag{4.18}$$

$$\sum_{k \in K} (\varepsilon_{kot} + \varepsilon^*_{kot}) r_k \geq \sum_{m \in M} \beta_{omt} \quad \forall o \in O, \forall t \in T, \forall s \in S \tag{4.19}$$

$$0 \leq \varepsilon_{kot} \leq y_k \quad \forall k \in K, \forall p \in P, \forall t \in T \tag{4.20}$$
$$0 \leq \varepsilon^*_{kot} \leq y^*_k \quad \forall k \in K, \forall p \in P, \forall t \in T \tag{4.21}$$

Figure 4.2 represents the relationship of the biomass logistics supply chain with the considered decision variables associated with the operations.

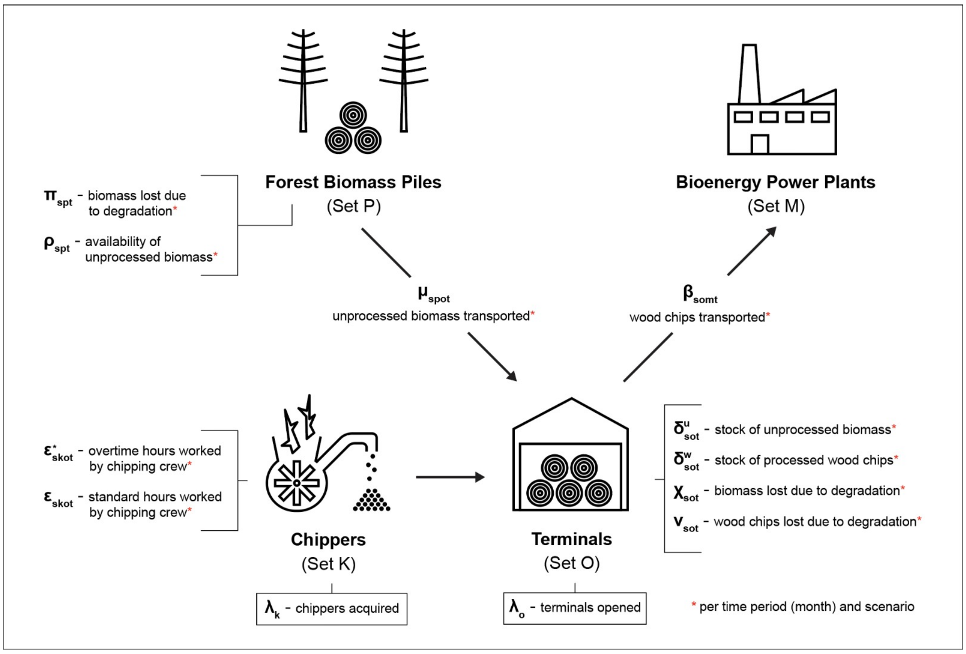


Figure 4.2: Logistics supply chain.

The objective function 4.2 maximizes the total profit by taking into account the revenue generated from the sales of wood chips to the power plants and measuring the costs. These are the hourly costs of chipping operations taking into account overtime work, expenses resulted from transporting unprocessed biomass and wood chips, costs related to the opening of intermediate terminals, and costs associated with acquiring chippers.

The objective function 4.3 minimizes the amount of wasted biomass material during the scenarios considered. Wasted biomass here consists of useful biomass lost due to degradation in piles ($\pi_{spt}$), in terminals ($\chi_{sot}$), wood chips material lost due to degradation in terminals ($\nu_{sot}$), and also the remaining biomass left at piles at the end of a scenario ($\rho_{spt}$).

The multi-objective function 4.22 uses the normalization method in 4.1 and a weighted-sum approach to achieve a result that maximizes profit and resilience and prioritizes one or the other depending on the priority given.

Constraint 4.4 defines the amount of processed biomass delivered to a power plant must not be greater than the demand of that plant m at period t. Constraint 4.5 defines that the number of standard processing hours is upper bounded by the maximum standard hours in a period t. Constraint 4.6 ensures that the number of extra processing hours is upper bounded by the maximum extra hours in a period t. Constraint 4.7 defines that the amount of stored biomass in a terminal is upper bounded by the terminal's capacity Constraints 4.8 and 4.9 ensure that the amount of unprocessed biomass at a terminal is determined by the amount in the previous period plus the amount received from piles and subtracting the amount processed in the current time period plus the amount lost due to degradation. Constraints 4.10 and 4.11 ensure that the amount of processed biomass at terminal is determined by the amount in the previous period plus the amount processed in the current period minus the amount sent to plants plus the amount lost due to degradation. Constraints 4.12 and 4.13 ensure that the amount of available at a pile is calculated by taking into account the amount available in the previous period with degradation applied, adding the new incoming supply in that period and subtracting the amount of biomass that was transported away from the pile. Constraints 4.14, 4.15, and 4.16 are calculations of lost biomass material. Constraints 4.17 and 4.18 indicate that material can only be transported into or out of an intermediate terminal if it has been purchased. Constraint 4.19 defines that the number of hours worked by a chipper at a terminal times the productivity of that chipper must be greater than or equal to the amount of wood chips delivered from that terminal. Constraints 4.19 and 4.21 make sure that the possible standard and overtime working hours are within bounds.

The multi-objective function is calculated using the weighted sum method and the normalized values of the expected profit and resilience. multi-objective function:

$$max\,F = \alpha P^{trans} + (1-\alpha)R^{trans} \tag{4.22}$$

, where $P^{trans}_s$ and $R^{trans}_s$ are the result of the normalization formula demonstrated in 4.1.

# Chapter 5

# Results analysis and discussion

This chapter presents the obtained results after applying the developed two-stage stochastic programming model to the considered scenarios.

The results achieved are meant to serve as a tool to aid in decision making and to evaluate the different trade-offs that occur when choosing to prioritize a certain objective. An analysis of the tests conducted should contribute to a more informed and detailed view into the effect of uncertainties and disruptive events in the biomass supply chain.

The application of the optimisation model will allow for a collection of information about the impact of cost-saving in the overall resilience of the biomass supply chain. An interpretation of the differences in planning and resource allocation given different scenario considerations could provide aid for decision-making.

For all the presented tests, the model was run on a machine with an Intel Core i5-7400 3.00GHz CPU and 16GB 2133MHz DDR4 RAM. The model was developed and tested using Python 3.9.13 with Google OR-TOOLS using the SCIP solver.

## 5.1 Optimisation model validation

In order to verify the model's integrity, the results after running the optimisation model with only the baseline scenario were compared to a previously validated simulation model present in [34] using the same input parameters except the biomass decay detail.

The baseline scenario does not include the occurrence of any disruptive events (wildfires) and has the same intermediate terminals and chippers available as the compared simulation model. Moreover, the demand from the power plants and the biomass availability match the base simulation model ran in [34].

As the simulation model was focused on minimizing total costs, the results taken from the reference are compared to the ones from the optimisation model after giving full priority to maximizing profit over resilience. The baseline scenario considered has 3 power plants and 52 piles of biomass, 5 intermediate terminals, and 4 chippers. The resulting costs and their comparison with the simulation model can be observed in table 5.1. The resource allocation results of the optimisation model's solution were to buy chippers 1 and 2. The solution also included the opening of 4 intermediate warehouses. These decisions match the ones obtained in the simulation reference model. The chipper usage cost differences arise from the simulation model's inclusion of deployment costs, which occur every time a chipper is re-located from one intermediate warehouse to another. In this case, the deployment costs of the simulation model (500 €) match the difference observed in costs related to chipping activities. The difference in transport costs can be explained by the loss of biomass material at supply piles in the optimisation model's case, which results in less biomass material to be transported to intermediate warehouses. Another factor that contributes to the reduction in transport cost in comparison to the reference model is the simulation model's constraint that forces all available biomass to be collected and transported to an intermediate warehouse within the considered time periods.

Table 5.1: Cost comparison between reference simulation base model and baseline scenario of optimisation model

| **Cost** | **Simulation ([34])** | **Optimisation model (present work)** |
|---|---|---|
| Fixed | Intermediate warehouses: 12 000€<br>Chippers: 7 500€ | Intermediate warehouses: 12 000€<br>Chippers: 7 500€ |
| Chippers (C) | Chippers used: C1, C2<br>Chipper usage cost: 358 987€ | Chippers used: C1, C2<br>Chipper usage cost: 333 230€ |
| Transport | Transport cost: 244 810€ | Transport cost: 217 713€ |
| **Total cost** | **623 297€** | **570 443€** |

In spite of the previously mentioned differences between the costs obtained in each model, the optimisation model can be considered validated since it appears to follow the same behaviour in resource allocation as the considered reference.

## 5.2 Deterministic analysis

In this section scenarios with varying levels of wildfire intensity will be analysed in terms of the model solution obtained. For each scenario, resilience and profit are plotted over 20 points according to the weight assigned to each objective.

As previously mentioned, the difference between each scenario is related to the intensity of the disruptive event, namely which and how many piles are affected by a wildfire. Therefore, the supply chain will respond to varying levels of biomass availability spikes that occur in a specific month.

### 5.2.1 Baseline scenario (no wildfire occurrence)

The baseline scenario does not include a disruptive event, the total biomass available is considered deterministic with the value of 45530 tons. In figure 5.1 the results from the model's solutions can be seen plotted according to weight distribution between profit and resilience. The deterministic model contains 5 076 decision variables and 4 765 constraints. The model run time for the baseline deterministic scenario was of 8 minutes and 30 seconds to achieve twenty solutions that are represented in figure 5.1. All solutions were optimal.

A common characteristic of all the plotted scenarios results is that the first point plotted which has any weight attributed to profit (resilience weight = 0.95 and profit weight = 0.05) performs significantly better than the solution focusing only on resilience. Here, the model appears to arrive at a solution where the profit is considerably higher while maintaining roughly the same value for the resilience metric. In this case the values for resilience weight = 1 and profit weight = 0 were 439 tons of biomass lost and a profit of 146 643€ while the values for resilience weight = 0.95 and profit weight = 0.05 resulted in 467 tons of biomass lost and a profit of 423 846€.

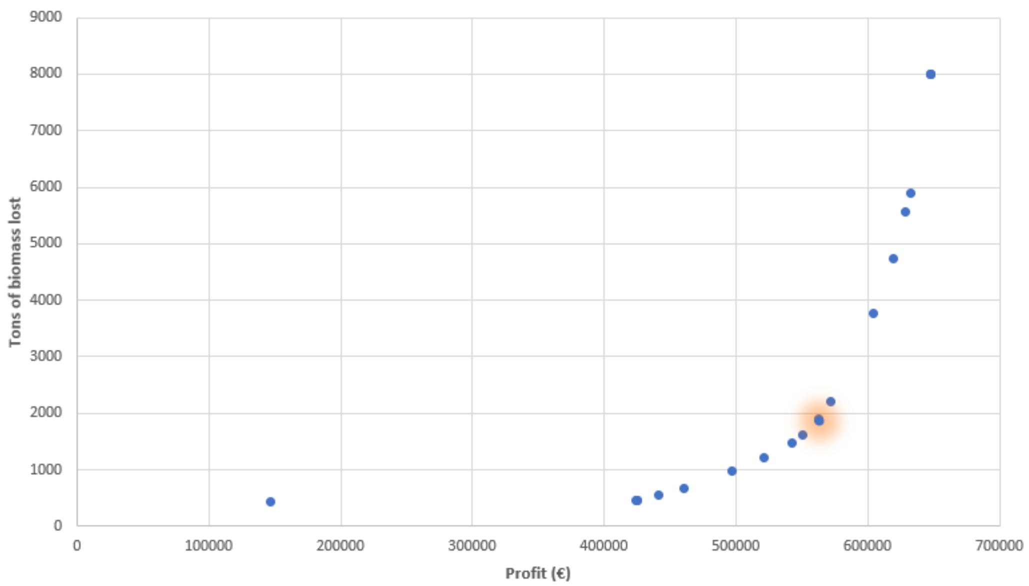


Figure 5.1: Pareto front approximation for baseline scenario.

To compare the trade-offs between prioritizing an objective over the other, the results of the weight distribution with a 0.95 to 0.05 split as well as the results for an equal distribution split were compared in table 5.2.

Table 5.2: Baseline scenario weight distribution result comparison

| **Weight distribution** | **Profit** | **Tons of biomass lost** | **Total biomass delivered** |
|---|---|---|---|
| Rw = 0.95, Pw = 0.05 | 423 846€ | 467 tons | 36 470 tons (95%) |
| Rw = 0.5, Pw = 0.5 | 562 518€ | 1 868 tons | 38 075 tons (100%) |
| Rw = 0.05, Pw = 0.95 | 647 956€ | 8 009 tons | 38 075 tons (100%) |

In the solution with the weight distribution Rw = 0.95 and Pw = 0.05, a bigger investment was made to prevent biomass loss. This included the acquisition of the two most productive chippers (C1 and C3) which imply a bigger hourly cost. In this solution an effort was made to process as much biomass as soon as possible. Therefore, 380 tons out of the 467 tons of biomass lost were from already processed wood chips at terminals, with the rest being biomass lost at supply piles. As the focus was not entirely on profit, the biomass delivered did not correspond completely to the demand.

The solution for the weight distribution Rw = 0.05 and Pw = 0.95, out of the 8009 tons of biomass lost, none came from the intermediate terminals and instead consisted of biomass left and lost at piles. In this solution only the minimum required biomass from piles was transported and processed so the demand was met and the profit was prioritized.

The chippers acquired and intermediate terminals opened in the selected weight distributions are shown in table 5.3.

Table 5.3: Resource selection for baseline scenario solution

| Weight distribution | Chippers acquired (C) | Terminals opened (T) |
|---|---|---|
| Rw = 0.95, Pw = 0.05 | C1, C3 | T1, T2, T4, T5 |
| Rw = 0.5, Pw = 0.5 | C1, C2 | T1, T2, T4, T5 |
| Rw = 0.05, Pw = 0.95 | C1, C2 | T1, T2, T4, T5 |

For the equal split solution, all the terminals were opened except the most expensive one (intermediate terminal 3) and the chippers acquired were chipper 1 with high productivity rate and hourly cost and chipper 2 with lower productivity rate and hourly cost. As for the chipper usage, chipper 1 was most utilized with 1583 hours worked compared to chipper 2 with 752 hours worked.

The option with more focus on resilience (Rw = 0.95 and Pw = 0.05) differs from the others by choosing to acquire chipper 3 instead of chipper 2. Chipper 3 has a higher productivity rate but is also more expensive to use.

The values of investment costs, which consist of expenses from opening terminals and acquiring chippers, and operational costs, which consist of transport and chipping usage costs are shown in figures 5.2 and 5.3. The values in the x axis represent the respective weight distributions. A label of "0.95/0.05" in the x axis represents a weight distribution of resilience weight = 0.95 and a profit weight of 0.05.

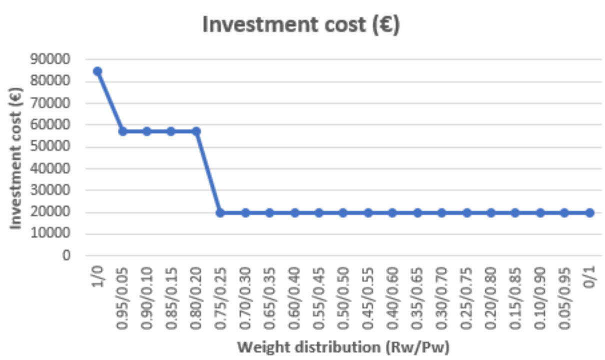


Figure 5.2: Investment costs for baseline scenario.

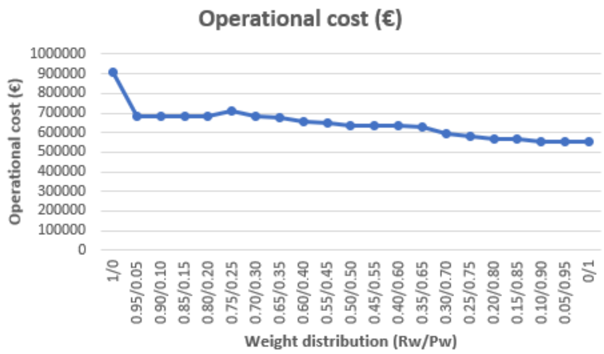


Figure 5.3: Operational costs for baseline scenario.

By analysing figures 5.2 and 5.3 it is possible to see a decrease in both investment costs and operational costs as the focus shifts from resilience to profit. When the focus is solely on profits the highest investment and operational costs are achieved. There is a drop off in investment costs going from the weight distribution 0.8/0.2 to 0.75/0.25, this explains why the 0.75/0.25 weight distribution is able to achieve higher operational costs and still result in an overall lower total cost than the previous weight distribution.

### 5.2.2 Low intensity wildfire scenario

In this section a scenario was considered with a wildfire occurring on the fourth month affecting a total of 5 piles. The total available biomass in this scenario is of 56 675 tons. The results from the model's solutions can be seen in figure 5.4. The highlighted point represents the solution for a weight distribution of resilience weight = 0.5 and profit weight = 0.5. The deterministic model contains 5 076 decision variables and 4 765 constraints. The model run time for the low intensity wildfire deterministic scenario was of 6 minutes and 45 seconds to achieve twenty solutions that are represented in figure 5.4. All solutions were optimal.

As done with the baseline scenario, a table was created exposing the trade-offs between prioritizing one objective over another. The values are shown in table 5.4.

For this scenario, the same logic and behaviour was observed in the solution as in the results from the baseline scenario. In the results prioritizing resilience, extra hours and an additional chipper are utilized to avoid big losses in biomass material resulting in all the losses coming from wood chips stored at terminals. The solution prioritizing profit once again only transports and processes the necessary biomass material to meet the demand from the power plants.

Table 5.4: Low intensity wildfire scenario weight distribution result comparison

| **Weight distribution** | **Profit** | **Tons of biomass lost** | **Total biomass delivered** |
|---|---|---|---|
| Rw = 0.95, Pw = 0.05 | 300 879€ | 974 tons | 37 580 tons (99%) |
| Rw = 0.5, Pw = 0.5 | 406 294€ | 2 200 tons | 38 075 tons (100%) |
| Rw = 0.05, Pw = 0.95 | 688 388€ | 19 823 tons | 38 075 tons (100%) |

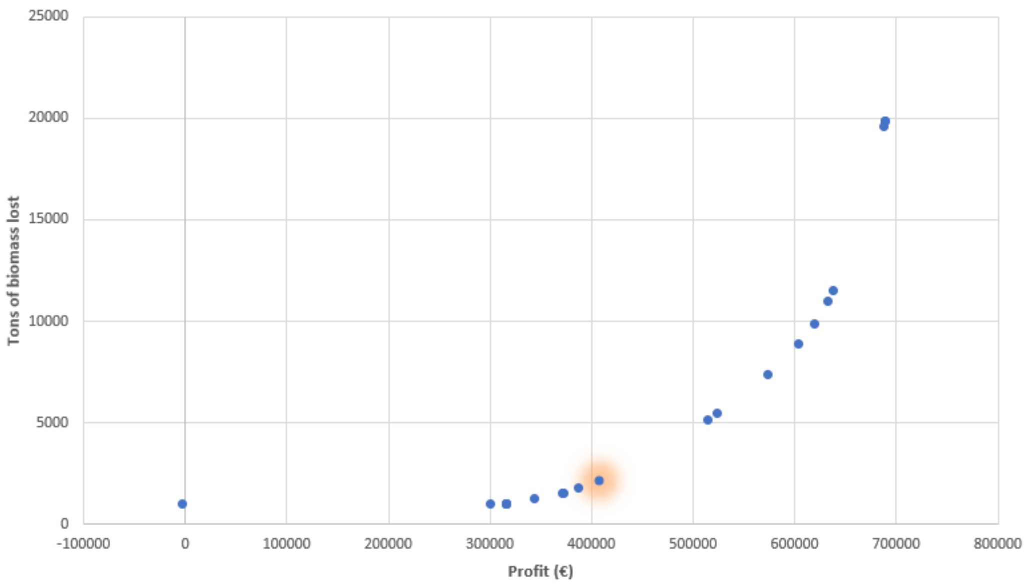


Figure 5.4: Pareto front approximation for scenario with low intensity wildfire.

The chosen chippers and intermediate terminals for each considered weight distribution are shown in table 5.5.

Table 5.5: Resource selection for low intensity wildfire scenario

| Weight distribution | Chippers acquired (C) | Terminals opened (T) |
|---|---|---|
| Rw = 0.95, Pw = 0.05 | C1, C2, C3 | T1, T2, T4, T5 |
| Rw = 0.5, Pw = 0.5 | C1, C2, C3 | T1, T2, T4, T5 |
| Rw = 0.05, Pw = 0.95 | C1, C2 | T1, T2, T4, T5 |

In this scenario, for the equal split solution an additional chipper was acquired compared to the baseline solution and the same number of intermediate warehouses opened. The additional chipper acquired (chipper 3) has higher productivity rate and hourly cost. The most utilized chipper was chipper 1 with 1512 hours, followed by chipper 3 with 886 hours and then chipper 2 with 298 hours and no extra hours were utilized. Therefore, it seems the solution shows an advantage in acquiring an additional chipper to process all the excess biomass instead of utilizing extra chipping hours, which are costly.

The solution for the weight distribution focused on profit (Rw = 0.05 and Pw = 0.95) does not acquire chipper 3 unlike the solutions for the other weight distributions. Chipper 3 has an expensive hourly usage rate so it would make sense to avoid using it if the focus is on profit.

The evolution in investment and operational costs can be seen in figures 5.5 and 5.6.

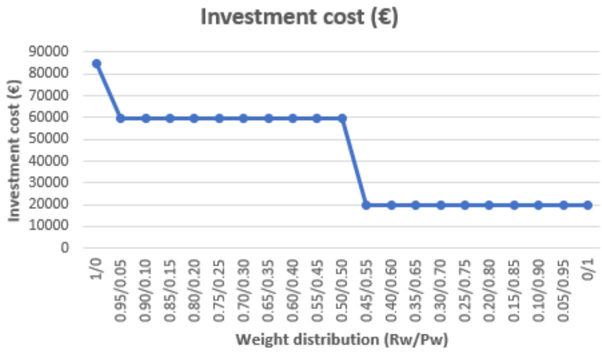


Figure 5.5: Investment costs for low intensity wildfire scenario.

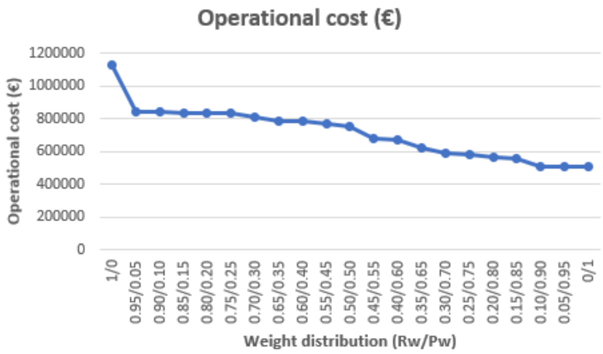


Figure 5.6: Operational costs for low intensity wildfire scenario scenario.

By analysing the evolution of investment and operational costs it is possible to see a decrease in both values as the priority shifts from resilience to profit. When the priority is solely on resilience the investment costs are highest and from the distribution Rw = 0.5 and Pw = 0.5 to Rw = 0.45 and Pw = 0.55 there is another shift in investment costs. This shift is caused by the decision not to acquire chipper 3.

### 5.2.3 High intensity wildfire scenario

The high intensity wildfire scenario considered for this section affected a total of 34 piles of biomass, the highest out of every created scenario. The wildfire takes place in the fourth month and the total available biomass is 107 125 tons. Figure 5.7 shows the solution results for the considered scenario with the point of equal weight distribution (Rw = 0.5 and Pw = 0.5) highlighted. The deterministic model contains 5 076 decision variables and 4 765 constraints. The model run time for the high intensity wildfire deterministic scenario was of 8 minutes to achieve twenty solutions that are represented in figure 5.7. All solutions were optimal.

Table 5.6 shows the results for the previously addressed weight distributions. For this scenario when resilience is prioritized all chippers were acquired and all intermediate terminals were opened due to the excessive amounts of available biomass added. In this scenario the biggest differences in profit and resilience values are also observed. The reason for the increase in profit for

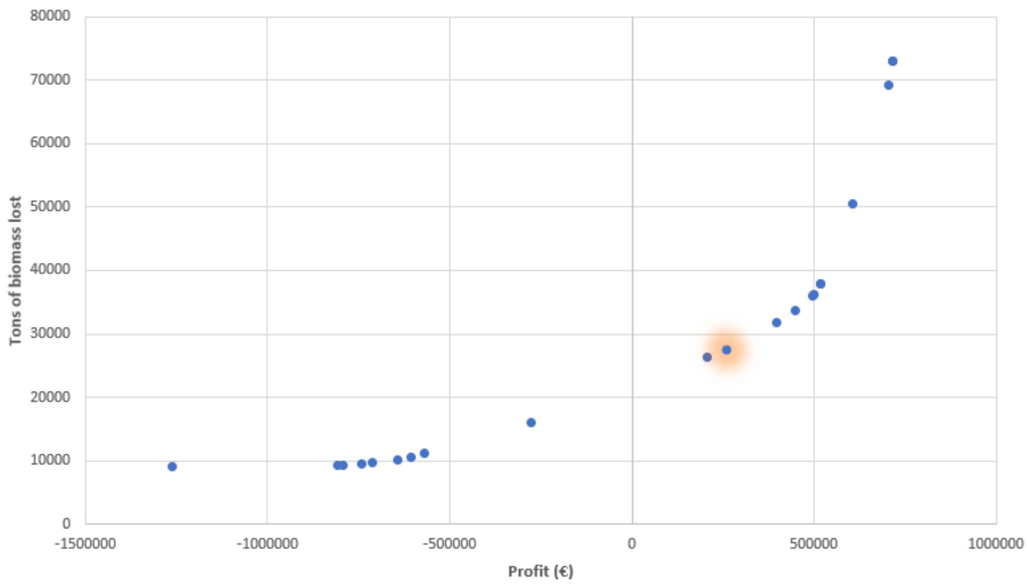


Figure 5.7: Pareto front approximation for scenario with high intensity wildfire.

the solution with resilience weight = 0.05 and profit weight = 0.95 is the geographical availability of the piles which suffer from a spike in available biomass. This results in big savings in transport costs from piles to intermediate terminals. Once again, when profit was given most priority the solution only transported and processed the biomass needed to meet the demand of the power plants, which is the same for every considered scenario.

Table 5.6: High intensity wildfire scenario weight distribution result comparison

| **Weight distribution** | **Profit** | **Tons of biomass lost** | **Total biomass delivered** |
|---|---|---|---|
| Rw = 0.95, Pw = 0.05 | -807 886€ | 9 215 tons | 35 867 tons (94%) |
| Rw = 0.5, Pw = 0.5 | 256 424€ | 27 623 tons | 38 075 tons (100%) |
| Rw = 0.05, Pw = 0.95 | 714 721€ | 72 943 tons | 38 075 tons (100%) |

The chosen chippers and intermediate terminals for the considered weight distributions are shown in table 5.7.

Table 5.7: Resource selection for equal weight split solution in low intensity wildfire scenario

| **Weight distribution** | **Chippers acquired (C)** | **Terminals opened (T)** |
|---|---|---|
| Rw = 0.95, Pw = 0.05 | C1, C2, C3, C4 | T1, T2, T3, T4, T5 |
| Rw = 0.5, Pw = 0.5 | C1, C2, C3 | T1, T2, T3, T4, T5 |
| Rw = 0.05, Pw = 0.95 | C1, C2 | T1, T2, T4, T5 |

In comparison to the baseline solution, an additional chipper was acquired (chipper 3) and an additional intermediate terminal was opened (terminal 3). Chipper 3 provides higher productivity rate to accommodate the spike in biomass availability . The additional terminal allows for more biomass to be processed and stored, reducing the rate at which it decays resulting in considerable savings of biomass material. The significant increase of biomass material available results in lower profits when compared to the other considered scenarios.

In this case the solution with the highest priority on resilience acquires additionally chipper 4 which has the highest investment cost. With all the chippers available all the available biomass can be processed as soon as it becomes available and therefore avoiding big material losses. The solution that focuses on profit (Rw = 0.05 and Pw = 0.95) includes the purchase of only chipper 1 and chipper 2 and does not open intermediate terminal 3 to save on costs. If in this solution only the necessary biomass is processed to meet the demand then there is no need to invest in additional storage space or chippers.

The evolution in investment and operational costs for the high intensity wildfire scenario can be seen in figures 5.8 and 5.9.

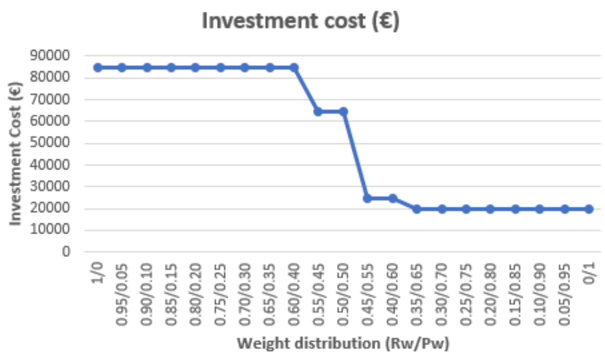


Figure 5.8: Investment costs for high intensity wildfire scenario.

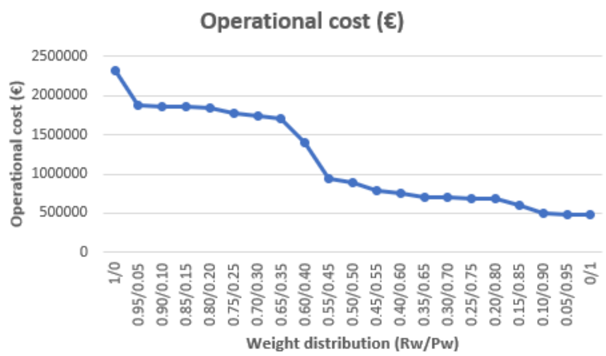


Figure 5.9: Operational costs for high intensity wildfire scenario.

When resilience is given the most priority the investment costs are the highest given the significant increase in biomass availability. As such from the weight distribution of Rw = 1 and Pw = 0 to Rw = 0.60 and Pw = 0.40 the solution includes the acquisition of every chipper and intermediate terminal available. From Rw = 0.55 and Pw = 0.45 to Rw = 0.50 and Pw = 0.50 chipper 4 is no longer included in the solution. Another cost decrease happens at the distribution Rw = 0.40 and Pw = 0.60 where chipper 3 is not acquired and the final decrease at Rw = 0.35 and Pw = 0.65 happens due to the exclusion of intermediate Terminal 3 in the solution. The operational costs follow the expected behaviour of decreasing as the profit priority increases, stagnating from the weight distribution of Rw = 0.10 and Pw = 0.90 onward.

## 5.3 Two-stage stochastic programming model solution

This section includes the results and analysis of the two-stage stochastic programming model based on mixed integer programming. The results represent a solution that takes into consideration a total of 25 scenarios, each with an corresponding expected probability of occurrence, with 24 of them containing a disruptive event (wildfire) in one of the three previously explained considered time periods. The obtained results do not represent an ideal solution for each scenario but instead a solution introducing a compromise that is sufficiently prepared for every scenario.

The solutions according with the weight distribution given to the profit and resilience objectives can be observed in figure 5.10, the highlighted point indicates the equal weight distribution. The deterministic model contains 126 684 decision variables and 119 125 constraints. The model run time for the baseline deterministic scenario was of 35 minutes to achieve twenty solutions that are represented in figure 5.10. All solutions were optimal.

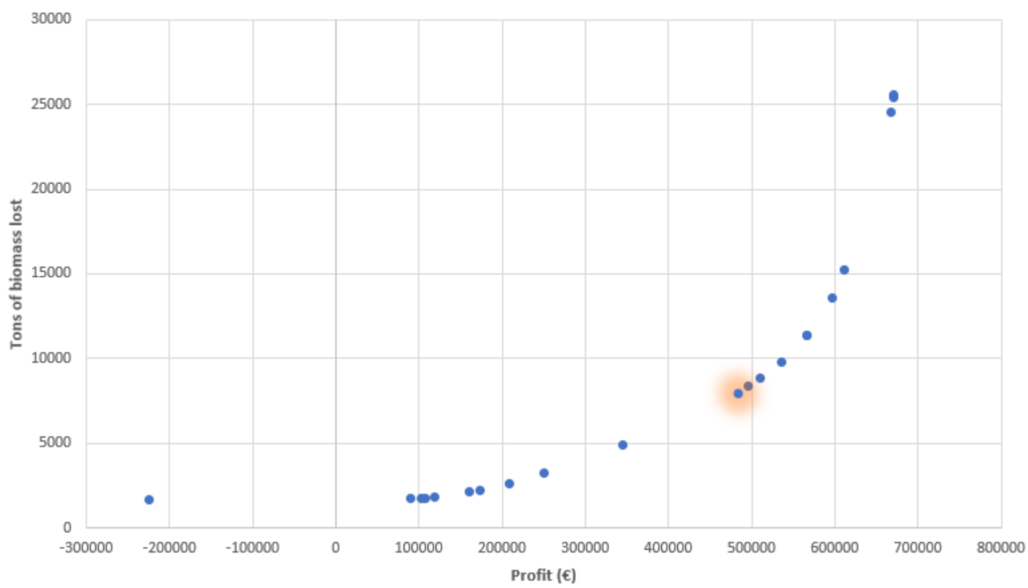


Figure 5.10: Pareto front approximation for the stochastic solution.

As was done with the individual scenario results, the solutions for the weight distributions of Rw = 0.95 and Pw = 0.05, Rw = 0.5 and Pw = 0.5, and Rw = 0.05 and Pw = 0.95 are highlighted and analysed. These results are depicted in expected values for profit and resilience in Table 5.8. The biomass delivered almost satisfies the demand for the weight distribution of Rw = 0.95 and Pw = 0.05 and fully satisfies the demand for the other selected distributions. When focusing on resilience, delivering processed biomass has the benefit of clearing storage space in intermediate terminals.

Table 5.8: Optimisation model weight distribution result comparison

| Weight distribution | Profit | Tons of biomass lost | Total biomass delivered |
|---|---|---|---|
| Rw = 0.95, Pw = 0.05 | 89 356€ | 1 722 tons | 37 039 tons (97%) |
| Rw = 0.5, Pw = 0.5 | 483 684€ | 8 004 tons | 38 075 tons (100%) |
| Rw = 0.05, Pw = 0.95 | 670 124€ | 25 429 tons | 38 075 tons (100%) |

The results in table 5.8 are expected given the results shown for individual scenarios above. The supply chain's necessity to be resilient to uncertain disruptive events results in compromises made in terms of resource management. Looking at the choices for chippers and intermediate terminals in table 5.9.

Table 5.9: Resource selection considering every scenario

| Weight distribution | Chippers acquired (C) | Terminals opened (T) |
|---|---|---|
| Rw = 0.95, Pw = 0.05 | C1, C2, C3, C4 | T1, T2, T3, T4, T5 |
| Rw = 0.5, Pw = 0.5 | C1, C2 | T1, T2, T4, T5 |
| Rw = 0.05, Pw = 0.95 | C1, C2 | T1, T2, T4, T5 |

The equal split solution includes the choice of chipper 1 with a productivity of 20 tons of biomass processed per hour and chipper 2 with half the productivity of chipper 1. These chippers have a very low acquisition cost compared to chipper 3 and 4. All terminals except terminal 3 were included in the solution, which is the most expensive but also the intermediate terminal with the most capacity. These choices are in line with the results from the individual results. As high intensity wildfire scenarios were not considered as very likely to occur, the optimisation model solution's choice of chippers seems appropriate. The considered solution that focuses on profit includes the same investment decisions. For the weight distribution of Rw = 0.95 and Pw = 0.05 all chippers are acquired and all intermediate terminals are opened.

The evolution in investment and operational costs for the stochastic solution is shown in figures 5.11 and 5.12.

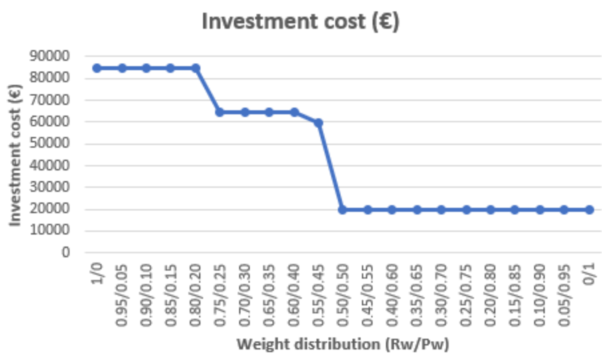


Figure 5.11: Investment costs for the stochastic solution.

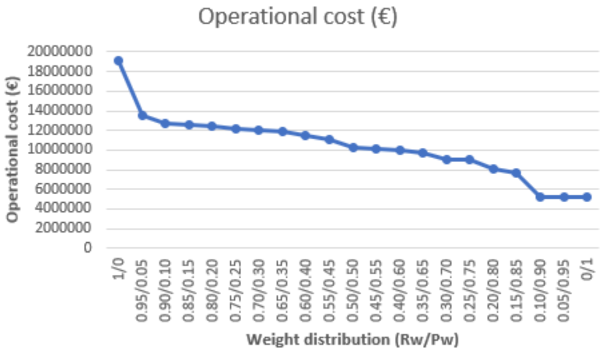


Figure 5.12: Operational costs for the stochastic solution.

Investment costs stay constant from the weight distribution of Rw = 0.5 and Pw = 0.5 until Rw = 0 and Pw = 1, this translates to the acquisition of chippers 1 and 2 which are the least expensive and opening intermediate terminals 1, 2, 4 and 5. On Rw = 0.55 and Pw = 0.45 chipper 3 is included in the solution on top of the other mentioned chippers and terminals, increasing the investment cost. From Rw = 0.75 and Pw = 0.25 to Rw = 0.60 and Pw = 0.40 all terminals are opened and chippers 1, 2, and 3 are acquired. From Rw = 0.85 and Pw = 0.15 to when the focus is solely on resilience, every terminal and chipper is included in the solution and the investment cost is highest. Operational costs decrease as the focus shifts from resilience to profit. A considerable difference in operational costs occurs from the solution where the focus is solely on resilience compared to the weight distribution Rw = 0.95 and Pw = 0.05.

By analysing the different solutions achieved, a biomass supplier could make an informed decision taking into account the supplier's biases toward resilience and profit. A biomass supplier could for instance prefer to store and preserve as much biomass as possible during the planning horizon in order to guarantee meeting the demand of power plants in the future, in the case of a lack of biomass availability in the following year.

## 5.4 Deterministic and stochastic comparison

In this section the results from the solutions obtained in the previously analysed individual deterministic scenarios and the stochastic approach will be compared.

The considered deterministic scenarios are the baseline scenario where no wildfire occurs, a scenario including a low intensity wildfire affecting 5 piles of biomass, and a scenario involving a high intensity wildfire affecting 34 piles of biomass. The stochastic solution includes 25 scenarios, including the previously mentioned scenarios used in the deterministic approaches. In the stochastic approach the probability of no wildfire occurrence or of a low intensity wildfire are higher than the probability of scenarios that include higher intensity wildfires.

For a better ease of comparison, the results of every considered deterministic and stochastic solution for a weight distribution of resilience weight = 0.5 and profit weight = 0.5 is presented in table 5.10.

Table 5.10: deterministic vs stochastic results comparison for equal weight distribution

| | **Baseline deterministic** | **Low intensity wildfire deterministic** | **High intensity wildfire deterministic** | **Stochastic approach** |
|---|---|---|---|---|
| **Profit** | 562 518€ | 406 294€ | 256 425 € | 483 684€ |
| **Tons of biomass lost** | 1 868 tons | 2 200 tons | 27 623 tons | 8 004 tons |
| **Biomass delivered** | 38 075 tons (100%) | 30 075 tons (100%) | 30 075 tons (100%) | 38 075 tons (100%) |
| **Chippers acquired (C)** | C1, C2 | C1, C2, C3 | C1, C2, C3 | C1, C2 |
| **Terminals opened (T)** | T1, T2, T4, T5 | T1, T2, T4, T5 | T1, T2, T3, T4, T5 | T1, T2, T4, T5 |

For the deterministic solutions, the equal focus on profit and resilience results in a lower profit when the biomass availability is high. The higher biomass availability present in higher intensity wildfire scenarios requires more effort to avoid biomass material loss, resulting in higher chipping and transporting costs. At the same time, a higher biomass availability results in more biomass being lost due to degradation since the solution has to keep profit as a goal. The expected profit in the stochastic approach has the second highest value present in table 5.10, this is reflective of the probabilities in the scenarios considered.

The stochastic solution includes the acquisition of chippers 1 and 2 as well as intermediate terminals 1, 2, 4 ,and 5. This consists of the same initial investment decisions as in the baseline solution. If the biomass supplier chooses to follow the solution obtained in the stochastic approach, the supply chain will achieve the desired results when no wildfire occurs. However, this decision compromises the supply chain's ability to respond to the occurrence of wildfires. If a low intensity wildfire occurs, the non inclusion of chipper 3 (as in the low intensity wildfire deterministic solution) will result in bigger biomass losses unless a significant amount of extra hours are utilized which will result in a lower profit. In the event of a high intensity wildfire, the biomass supplier will be missing chipper 3 as well as intermediate terminal 3 and as such will obtain worse results in either profit or biomass loss.

The stochastic solution is not expected to outperform the deterministic solutions. Instead it presents a solution that compromises the ability to perform optimally in certain scenarios while simultaneously being prepared to achieve acceptable results considering every scenario and its associated probability. In this way, the stochastic approach acts as a risk management tool. With the considered scenarios and probabilities, the stochastic solution obtained considers that the investment in chipper 3 and intermediate terminal 3 is not advisable since it would result in significant profit losses in cases where those resources are not necessary for an optimal solution.

# Chapter 6

# Conclusions and future work

In this chapter conclusions about the work done throughout the project are presented. The objectives of this dissertation are revisited and evaluated, with a focus on confirming that the initial goals were fulfilled. Suggestions for future work are also included, keeping in mind improvements to be made.

## 6.1 Conclusions

The goal of this dissertation was to develop a decision-support system for a biomass supply chain, based on an optimisation methodology taking uncertainty into account to enhance the supply chain's resilience to disruptive events. In this dissertation, a two-stage stochastic multi-objective model based on a MILP (Mixed Integer Linear Programming) mathematical formulation was developed. The optimisation model was developed considering the characteristics of a forest biomass supply chain. The disruptive events considered were wildfires that impact the supply chain in the form of a spike in the biomass availability. The developed optimisation model used a multi-objective approach using a weighted sum method to achieve varying solutions based on the priority given to each objective, profit and resilience. Resilience in this work was defined as the ability of a supply chain to be flexible under the occurrence of disruptive events and was measured by the the loss of useful biomass in the considered planning horizon. The developed optimisation model was validated against a simulation model, proving the behaviour of the model was as intended and the results trustworthy. Three different deterministic scenarios and a stochastic approach considering all the scenarios and their probabilities were tested and compared in terms of results achieved when varying the weight distribution between profit and resilience.

The developed optimisation model's solution provides the selected chippers to acquire and intermediate terminals to open considering scenario or scenarios given as input. Other decision variables of the optimisation model provide insight into operational decisions that occur during the planning horizon such as the amount of standard and extra hours spent processing biomass during each time period (month) in the planning horizon. Additional decision variables tracking the biomass lost at piles and intermediate terminals allowed a quantifiable measure of resilience to evaluate the performance of the supply chain.

Regarding the performance of the model when considering various deterministic scenarios, the changes in objective priority from resilience-focused to profit-focused showed a consistent behaviour of increase in profit but also useful biomass material lost. When focusing solely on profit, higher intensity wildfire scenarios achieved higher profit values due to the ability to transport only the closest biomass available and processing only the necessary amount of biomass to meet the demand of the power plants, thus reducing transporting and chipping costs. The results in the deterministic scenarios aiming for a split priority between profit and resilience show that as the biomass availability increases, investment costs into new chippers and intermediate terminals increase, profit decreases due to the effort required to avoid losing useful biomass, and the total amount of biomass lost also increases. For the equal split weight distributions, in every solution the biomass demand of the power plants was met. The achieved stochastic solution included compromises, being less prepared for the occurrence of wildfires than the deterministic approaches but being able to optimally respond to a scenario that did not involve a wildfire occurrence.

In terms of overall conclusions, the optimisation model developed in this work seems able to be used as a decision-support system, assisting in the selection of strategic decisions and taking into account uncertain events in a biomass supply chain. The model also provides a detailed view into the investment and operational costs, the number of standard and overtime hours worked by the chipping crews, the amount of biomass stored and processed, and the amount of biomass lost both at piles and intermediate terminals in the form of unprocessed material or processed wood chips. This dissertation's objectives are then considered fulfilled, as this work has demonstrated itself to be of advantageous as a decision-support system in supply chain management.

## 6.2 Future work

The proposed optimisation-based methodology was developed for the forest-to-bioenergy sector. Despite that, it would be possible to use the methodology to develop new optimisation models for not only energy sectors but also other sectors involving supply chain and logistics. Additionally, the considered uncertainties and disruptive events which can affect supply are also present in other industries, making it appropriate to be replicate the approaches developed in this work to other cases.

Future work could be developed to incorporate different types of uncertainty, such as limited transport units, transport delays, demand unpredictability, or even machine failure.

Additionally, other constraints could be integrated in the optimisation model such as penalties for unsatisfied deliveries, the inability to collect from certain piles that are being affected by a wildfire in a time period, and chipper unavailability while travelling between intermediate terminals. In this work only the possibility of buying a chipper or intermediate terminal was considered. However, additional constraints could be implemented to allow for the renting of chippers and intermediate terminals, allowing for strategic decisions in the middle of the planning horizon.

To further improve the developed model's credibility and accuracy, real-life practical data could be used to determine the input parameters of the model. Values such as chipper productivity, intermediate terminal storage, investment and upkeep costs, truck capacity, and selling price of wood chips could be modified to represent specific practical cases. Moreover, the number of considered scenarios could be increased to achieve a more trustworthy end solution.

Finally, an integration of this optimisation model into a simulation model with a dashboard would benefit decision-makers, allowing for a clearer view into the effects of the decisions taken.

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