Biobased Chemistry and Technology

MSc Thesis Biobased Chemistry and Technology

The potential role of urban waste biomass in the biobased economy – a case study for Amsterdam

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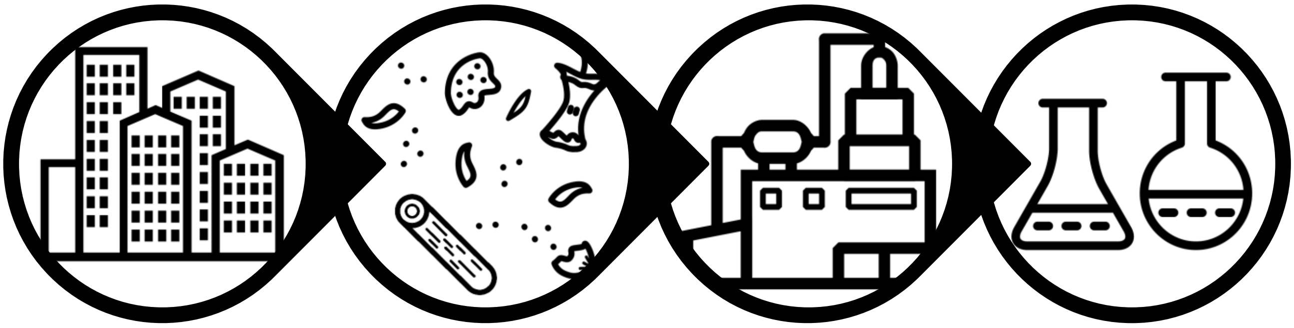

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The potential role of waste biomass in the biobased economy – a case study for Amsterdam

A research on the potential role of valorising urban waste biomass from the city of Amsterdam into value-added products.

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Abstract

Cities around the world are taking action to become more sustainable. One of the main problems within cities is waste management, with growing populations within the city waste becomes a pressing issue. A biobased economy can solve this problem, waste biomass from the cities can be used as a feedstock for the biorefineries. Biorefineries are capable of processing biomass into value-added products. The objective of this study is to explore the potential of urban waste biomass into valorisation to products. A model is developed that can process urban waste biomass through biorefineries and project future biorefineries configuration. This model's objective is to maximize the profit over the long run, this is to ensure that the valorisation is economically sustainable. It will give insight for policymakers on how to promote valorisation of waste biomass and support decision making. The model is applied using data from the city of Amsterdam, the Netherlands. From the results it was learnt that both grass and wood showed potential in a future biobased city. Organic municipal solid waste proved to be economically sustainable in a few decades when efficiency of valorisation is improved. It was discovered that the processing of leaves shows little potential for a biobased city. The underlying issue is that the quantity of waste leaves is too low. From the results it is clear that different climate policies have little effect on whether urban biowaste is valorised, it only influences the quantity of the economic gains.

Preface

I would like to thank Yu Jiang for the excellent supervision and pleasantly conversation during our meeting. I was delighted that Yu was always willing to help solve my problems, even if he was abroad our skype calls were valuable. In addition I would like to thank Karel Keesman for the motivation, assistance, and support during the writing of my thesis. Furthermore I would like to thank Klaas Hielke Dijkgraaf and Jeroen Zwietering for the coffee breaks in which we inspected the construction of the parking garage and talked about our dinner. Lastly I would like to thank the department of Biobased Chemistry and Technology for the support for writing my thesis.

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List of abbreviations

Abbreviation	Description
OMSW	Organic municipal solid waste
MSW	Municipal solid waste
NPV	Net present value
CEPCI	Chemical engineering plant cost index
DM	Dry matter

List of symbols

Set	Description	Unit
i	The set of different products	
j	The set of different biorefineries	
q	The different capacities	kg
t	The year	years
v	The vintage of technology	years

Parameter	Description	Value	Unit
A, B and C	Distinct sets of values used for the fit of the model		-
$C_{0,(j)}(t)$	Base cost of a biorefinery type j in year t with size Q_0 in €		€
$CEPCI(t)$	CEPCI in year t		-
$D_{(n)}(t)$	Total available biowaste of type n in year t		kg
$LR_{(j)}$	Learning effect of biorefinery type j	0.02	-
$p_{oil}(t)$	Price of oil in year t		US$ bbl.$^{-1}$
P_t	Prime loan rate in year t		%
Q_0	Size of the base biorefinery type j		kg
T	Run time of the simulation	2050	years
t_0	The starting year of the model	2020	years
δ	Fraction of the investment cost is variable cost	0.10	-
$\epsilon_{(j)}$	Increase of efficiency per year of biorefinery type j	0.00375	-
$\zeta_{(i)}$	Price growth of product i each year	0.0188	-
θ	Cost capacity factor	0.63	-
ι	Fraction of the total cost is fixed cost	0.15	-
κ	Technology capacity diminishing rate	0.05	-
ρ	The discount rate	0.035	-
$\omega_{(j,v)}$	Availability factor of biorefinery type j of vintage v	[0,1]	-

Variables	Description	Unit
$C(t)$	Cost in year t	€
$C_{fix,O\&M}(t)$	Fixed operation and management cost in year t	€
$C_{inv}(t)$	Investment cost in year t	€
$C_{var,O\&M}(t)$	Variable operation and management cost in year t	€
$D_{(n)}(t)$	Total available biowaste of type n in year t	kg
$K_{(j,v)}(t)$	Total installed capacity of biorefinery type j of vintage v in year t	kg
NPV	Net Present Value	€
$p_{(i)}(t)$	Price of product i in year t	€ kg^{-1}
$Q_{(j,v)}$	Expanded biorefinery capacity of technology j of vintage v	kg
$X_{(i)}(t)$	Amount of product i produced in year t	kg
$\alpha_{(j,v)}(t)$	Unit investment cost of biorefinery type j of vintage v	€ kg^{-1}
$\beta_{(j,v)}$	Unit fixed O&M cost of biorefinery type j of vintage v in year t	€ kg^{-1}
$\gamma_{(j,v)}$	Unit variable O&M cost of biorefinery type j of vintage v	€ kg^{-1}
$\eta_{(i,j,n,v)}$	Conversion efficiency of biomass n into product i with biorefinery j of vintage v	kg kg^{-1}
$\lambda_{(j,n,v)}(t)$	Allocation of waste biomass stream n to biorefinery j of vintage v in year t	kg year^{-1}
$\pi(t)$	Revenue in year t	€
$\psi_{(j,v)}$	Life time of biorefinery type j	years

1. Introduction

1.1. Background

It is expected that in 2050 6.4 billion people will be living in urban areas (Angel et al., 2011). The UN mentions that one of the most important development challenges of the 21st century will be managing cities (UN, 2014). The success of developing sustainable cities will be a huge asset in the success of a liveable cities post-2015 (UN, 2014). Globally cities are taking action to ensure cities to become more sustainable, for example, the C40 which is a network of the world's megacities taking action to mitigate and adapt to the climate change.

The transition towards a biobased economy is essential in reducing climate change (Kim and Dale, 2003; Langeveld et al., 2012; Miller et al., 2007; Scarlat et al., 2015). In a biobased economy, biomass is used for both non-feed and feed purposes (Vandermeulen et al., 2012). These non-feed purposes include biofuel, electricity, heat, biochemicals, and biomaterials (H Clark et al., 2009; Langeveld et al., 2012; Nowicki et al., 2008). A biobased economy will help to phase out the use of fossil fuels, the intergovernmental panel on climate change longs to have all fossil fuels banned in 2100 (IPCC, 2014).

One of the solutions for cleaner cities is to use waste biomass as a biomass feedstock for the biobased economy. Waste management is becoming an increasingly important issue, both in developing countries and in developed countries (Guerrero et al., 2013; Lin et al., 2013; Sharholy et al., 2008). It is expected that municipal waste will become an important source of waste biomass (Tuck et al., 2012). In this research biomass feedstock from waste will be addressed as "waste biomass" as described in Jiang et al. (2017). Current practices for treating waste biomass are anaerobic digesting and composting (D'Hondt and Voorspoels, 2012). The disadvantage of these process is that the end product (i.e. biogas and compost) has low value. One of the solutions for cleaner cities is to use waste biomass as a biomass feedstock for the biobased economy. The advantage of using waste biomass as feedstock is its non-competitiveness with food. Furthermore, waste biomass is continuously available throughout the year for a relatively low (or negative) cost (Ekşioğlu et al., 2009). The collection of waste biomass is already established in developed countries (Ekşioğlu et al., 2009).

The city of Amsterdam, the Netherlands is currently searching for new opportunities to make its metropolitan more circular (Bastein et al., 2016). An example is the Power-to-protein concept which aims at producing protein from sewage sludge (Brandes, 2016). The city of Amsterdam intends to connect stakeholders to participate in bringing forward ideas and removing potential obstacles for making the city circular. The city is also part of the C40 network.

Waste biomass can already be used to produce electricity (Iakovou et al., 2010; Thrän, 2015). The advantage of biomass as an electricity source is it being carbon-neutral and flexible (Fargione et al., 2008; Kothari et al., 2010; Kranert et al., 2010). Recent studies have shown that waste biomass also shows potential for other purposes such as biochemicals and biofuels (Arancon et al., 2013; Tsiropoulos et al., 2017; Van Dael et al., 2014). Biochemicals have the potential to contribute to a more circular economy in the city of Amsterdam. Royal Haskoning (2014) mentioned that urban waste biomass shows potential as a feedstock in the biobased economy.

1.2. Biorefinery

Biomass is composed of organic matter which is carbohydrates (cellulose and hemicellulose), lignin, protein and ash (Maity, 2015; Poincet and Parris, 2004). With the use of a biorefinery it is possible to extract these components from the biomass and transform them into a vast array of products. Cherubini et al. (2007) defines biorefineries as the sustainable processing of biomass into a spectrum of marketable products and energy. Expectations are that the share of biochemicals could reach 20% of the total biobased products (Meyer and Werbitzky, 2010). Currently, valorisation of waste biomass has been excluded from policy frameworks thus their diffusion in the market is limited (Carus et al., 2014; Dornburg et al., 2008). The study of Tsiropoulos et al. (2017) estimates that the production of biochemicals in 2020 in the Netherlands may reach 1.1 Mt.

1.2.1. Wood refinery

Wood mainly consists of cellulose, hemicellulose, and lignin as seen in Table 1 (Pande and Bhaskarwar, 2012). Materials rich in these components are often referred to as lignocellulose biomass, therefore wood refineries are often referred to as lignocellulose biorefinery (Carrier et al., 2011; Michels and Wagemann, 2010). The complex chemical composition of lignocellulose biomass causes the conversion to marketable products to be a challenge for high yield and quality (Zhou et al., 2011). The cellulose and hemicellulose are connected with each other, the structural rigidity of the tree is provided through the ester and ether linkages from the lignin (Nizami et al., 2017). These strong complex connections are also to protect the plant against chemical and physical stress. These rigid chemical connection are difficult to breakdown, causing the cost of conversion to be expensive (Mtui, 2009). The most difficult part of the conversion of lignocellulose biomass is the decomposition of cellulose (Pandey and Kim, 2011; Sun et al., 2011). However, it is possible to separate cellulose, hemicellulose from lignin due to their different reactivity (Collinson and Thielemans, 2010; Willauer et al., 2000). Examples of cost-effective conversion of lignocellulose biomass uses optimistic scenarios for cost and efficiency (Dornburg et al., 2006; Gray et al., 2006; Schneider and McCarl, 2003).

1.2.2. Grass refinery

The use of grass for refining has recently been investigated (Klop et al., 2012; O'Keeffe et al., 2011; Thumm et al., 2014; Van Dael et al., 2014). Most research is focused on extracting protein from the grass. Reason for this is that conventionally grass is an excellent protein source for cows (Sanders et al., 2016). Of the dry matter of grass, which is only 15-20%, protein and the fibres are the most common researched extractions (Honkoop, 2015). Grass can have a varying composition, this is the result of the growth stage of grass at harvest, the ratio of grass compared with other materials in the harvested material, soil type, species, and many others (Poincet and Parris, 2004). An overview of the composition of grass can be found in Table 1. O'Keeffe et al. (2011) stated that a grass refinery could be economically viable if located wisely. The first pilot grass refinery is already in development in the Netherlands (Klop et al., 2012).

1.2.3. Leaves refinery

Extracting valuable components for leaves has been mainly focused on protein, similar to grass. Leaves as a protein source have been investigated since the 1960's (Akeson and Stahmann, 1965; Gerloff et al., 1965). Reason for the interest in protein from plant leaves is based on their nutritional profile and their abundance in waste streams for the agricultural sector (Tenorio, 2017).

Many different leaves from crops have already been researched such as sugar beet leaves, Moringa olifera leaves and soybean leaves (Betschart and Kinsella, 1973; Teixeira et al., 2014; Tenorio, 2017). Four major components, independent on the plant species and growing period, can be found in all species: protein, lignin, hemicellulose and cellulose (Zhang, 2016). The composition of waste leaves is dependent on several factors, the most important factors are the species of tree, collection methods and weather prior to collection, storage of the leaves and the contamination by impurities (Heckman and Kluchinski, 1996; Pňakovič and Dzurenda, 2015). An overview of the composition of leaves can be found in Table 1.

The main issue with protein extraction is the low cost-efficient production process (Bals and Dale, 2011). The proteins that are extracted can be further valorised into amino acids for bulk chemicals (Sanders et al., 2007). Romero-García et al. (2016) comments that a biorefinery for olive tree pruning can be economically interesting. However a biorefinery for the application of valorising waste leaves has not been researched yet, thus in this research, it is assumed that biorefineries for other types of leaves can be utilized for waste leaves with the same yields.

1.2.4. Organic municipal solid waste refinery

Organic municipal solid waste (OMSW) consist of a mixture of compounds however, the largest fraction is water (Lay et al., 1999; Mata-Alvarez, 2002). Since the feedstock has a chemical complex structure with many different components suitable valorisation remains difficult. Treatment in literature discusses if OMSW should be incinerated or that different biorefinery technologies are more suitable. Münster and Meibom (2011) concluded that anaerobic digestion is more suitable than incineration however, Gómez et al. (2010) stated the opposite. Nevertheless, both studies looked at municipal solid waste (MSW) and not only the organic fraction. Since this study focuses on producing products from waste biomass, thus the organic fraction of MSW, anaerobic digestion is one of the promising techniques (Mata-Alvarez, 2002). Therefore in this research only digesters are investigated. Digesters can be classified as a biorefinery since they processes biomass into a marketable product (Cherubini et al., 2007).

Table 1 Average composition of wood, leaves, grass and organic municipal solid waste (OMSW). The given percentages of the components are weight percentages from the dry matter (DM) weight of the biomass.

	Wood	**Leaves**	**Grass**	**OMSW**
Dry Matter (%)	62-69	53-64	15-20	18-28
Cellulose (% DM)	38-49	13-26	20-30	~40
Hemi-cellulose (% DM)	25-30	9	15-25	~20
Lignin (% DM)	18–35	20-40	3-10	
Protein (% DM)		7-30	6-25	
Ash (% DM)	04-10	3-14	5-20	
Reference	Eriksson and Gustavsson (2010); Pérez et al. (2002); Pettersen (1984); Rowell et al. (2005)	Bals and Dale (2011); Garcia-Maraver et al. (2013); Lammens et al. (2012); Pňakovič and Dzurenda (2015); Romero-García et al. (2016); Telek and Graham (1983)	CVB (2011); Grass (2004); (Ros, 2017)	Levin et al. (2007); Schievano et al. (2010)

Amsterdam's current treatment for urban waste biomass is at a waste treatment facility (Afvalregistratie, 2016). The waste biomass is shredded and split into two groups: fine and coarse waste biomass. The fine waste biomass is put into an anaerobic digester, where biogas is formed (Didde, 2017). The residue of the digester is mixed with the coarse waste biomass and stored for fourteen days. During these fourteen days the waste biomass is dried with an hot dry air flow, causing microorganisms to break apart the waste biomass. During these fourteen days the waste biomass is transformed into compost and used for agricultural practices and gardens (Afvalregistratie, 2016; Didde, 2017).

1.3. Previous studies

Research by Bridgwater (2003), Buijzer et al. (2015), Cok et al. (2014), Daioglou et al. (2015), Demirbaş (2001), Gielen et al. (2001) and Tsiropoulos et al. (2017) do investigate multiple uses for waste biomass but mostly focus on fuel as biochemical. However, more value from biomass can be created by focussing on chemicals and materials (Bos-Brouwers et al., 2012). Furthermore, not all of these papers use waste biomass from cities as feedstock for their research. Buijzer et al. (2015) discusses the potential of valorizing waste streams from the city of Amsterdam but does not include technological and economic feasibility. Van Dael et al. (2014) investigates a single municipality and includes waste from farms. In Arancon et al. (2013) and Tuck et al. (2012) the advances on waste biomass valorisation are discussed however, these papers are limited to only discussing the bioconversion. Dugmore (2014), Sun et al. (2014) and Morone et al. (2017) discuss the valorisation of food waste, thus not including all potential waste biomass streams. The majority of researches are on pilot-scale or laboratory scale.

This paper will investigate the potential of valorising waste biomass from the city of Amsterdam. The research will give further insights into the optimal use of waste biomass on both the technical and economic aspect. It will look at current and future situations. Different scenarios will be used to reflect the uncertainty in future cost and development and climate policy goals. The novelty of this study is to contribute to the current research about uses of urban waste biomass.

1.4. Objectives

The objective of this research is to develop a framework to assess the potential use of waste biomass for different end-uses based on a modelling approach. The framework will support policy-makers in making strategies for uses of waste biomass. With these strategies waste management in the future can be improved to increase the liveability of cities and contribute to the biobased economy. The inputs of the model will consist of different types of waste biomass. The outputs of the model will be different chemicals and products, depending on the valorisation technique. The model will work on the principle of cascading, this principle allocates biomass to its most highly valued application.

The research questions for this study are:

1) What are potential valorisation technologies for waste biomass up to and including 2050?
2) What is the most economically advantageous use of waste biomass up to and including 2050?
3) What are the bottlenecks for the economic profitability of the valorisation of waste biomass?

Research question 1 will be answered by conducting a literature research. Literature that describes the technologies of valorising waste biomass will be searched. Data will be collected about these different technologies so it can be used for the model at a later stage. Research question 2 will be answered by creating a model that will be able to find the most economically advantageous use of waste biomass. Further data needs to be collected for the model, the amount of biomass and price of products will be found through a literature research. Research question 3 will be answered by applying different scenarios to the model and analyse its behaviour. Furthermore, a sensitivity analysis will be performed. From these results, a better indication of the bottlenecks for the valorisation of waste biomass will be given.

1.5. Scope

The focus will be on biobased economy activities that are capable to valorise urban biomass waste streams into high value products. As study case Amsterdam is chosen as it tries to become more sustainable in the near-future. Furthermore, the Netherlands needs a significant transformation to reach its GHG emission goals for the future. Since Amsterdam is the largest city in the country, it could significantly help in the reduction of GHG. The Netherlands has a goal to reduce GHG emission by 40% in 2030 compared to 1990 and a reduction of 80-95% in 2050 (EC, 2015). Therefore the study investigates the potential pathways for valorisation until 2050, since most long-term policy goals are set for the year 2050 (EC, 2015). In addition most studies show estimation for the supply of biomass until 2050 (Saygin et al., 2014). In this research it is assumed that the biorefineries are all sustainable. This assumption is based on the fundament that a biorefinery is better their counterpart which might include the usage of fossil fuel. The focus of this study is on how to realize a biobased economy from an economic perspective.

Waste biomass is all waste from within the cities excluding waste from industries. Industrial waste is not included due to its vastness and complexity and is already investigated in other studies (Angenent et al., 2004; Balu et al., 2012; Koutinas et al., 2014). Waste biomass includes municipal organic waste and waste from gardens and parks. In this study the waste biomass consists of the following four waste streams: wood, grass, leaves, and organic municipal solid waste.

To the knowledge of the author, no research has been done about the use of waste biomass from the city of Amsterdam or other urban areas for the potential use of valorisation into higher-value products from a techno-economic perspective.

1.6. Outline

This chapter has introduced the topic of the thesis. The objective and scope of the thesis have been described, the research questions have been addressed. Chapter 2 will discuss the framework of the model, together with its constraints and decision variables. Chapter 3 will discuss the collected data of different technologies and economic parameters. The different scenarios will be addressed in Chapter 4. In Chapter 5 the results from the model will be presented. In Chapter 6 the influence of parameters will be investigated with a sensitivity analysis. Chapter 7 will discuss the findings. Chapter 8 concludes the results and will answer the research questions.

2. Materials and methods

In this chapter the materials and methods are discussed. The framework and model with its constraints will be described in this chapter, the economic data, data on waste biomass, and biorefinery technologies will be introduced in chapter 3. The scenarios are described in chapter 4. The model description is divided into two subchapters: the bioconversion through biorefineries and economic aspect of the model. Lastly, some modifications are explained to reduce computation complexity of the model.

2.1. Methodological framework

Figure 1 depicts the main structure of the methodological framework. The framework consists of different constraints, mass balances, data inputs, and an objective function. The framework projects the future conversion of waste biomass to value-added products. The framework consists of four different inputs: biorefinery technologies, economic data, waste biomass data and scenarios. All these inputs will be given to the conversion system model, which as output has the net present value (NPV). As output the NPV is chosen since it as an established indicator in the identification of best valorisation technologies in the bio-based economy (Cheali et al., 2015; Gargalo et al., 2016a; Mellichamp, 2013).

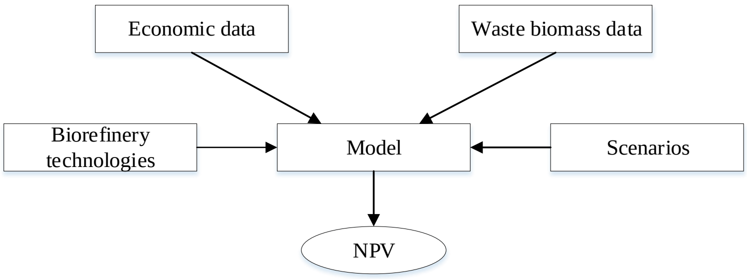

Figure 1 Main structure of the framework.

The framework has limitations because it does not include transportation and storage of waste biomass. Currently waste biomass is already collected by the city of Amsterdam, this will always be necessary therefore is a sunk cost. In addition, it is assumed that the waste biomass is immediately converted, in real-life practice this is probably also necessary due to the degradation of quality during storage.

First, the objective function is developed along with the different constraints and equations for the framework. The model will take into account the cost of the different biorefineries, with respect to their technology and capacity, and their revenue. As case study the city of Amsterdam is taken since it has a well-established infrastructure for collection and separation of waste (Raven, 2007). The model will take into account the change of cost and efficiency parameters of future biorefineries by adding a vintage term.

Secondly, the input data will be discussed. Since the model will go until 2050 data needs to be forecasted. The potential supply from the waste biomass streams, commodity prices and economic data about the different biorefineries will be included. Year 2020 is chosen as the starting year since the European Commission wants to establish a sustainable biobased economy starting from that year (Schmidt et al., 2012). A detailed description of the input data is given in chapter 3.

Thirdly different scenarios will be developed to take into account the uncertainties of future valorisation. These scenarios are based on the governmental policies and the research and development of new conversion methods. A detailed description of the different scenarios is given in chapter 4.

2.2. Model description

The research is focused on the effective location of waste biomass towards different biorefineries by cascading. Cascading is targeting the most highly valued products, therefore utilising the biomass to the fullest extent from an economic perspective. To ensure the model makes a trade-off between cost and revenue from biorefineries the objective function is the NPV. With the NPV both the cost and revenue of the biorefinery is taken into account, thus making a cost-benefit analysis. It is assumed there is perfect foresight, thus investment and allocation are flawless.

2.2.1. Objective function

The objective function of the model is to maximize the NPV. The NPV is often used to indicate the economic profitability of a project. A negative NPV indicates that a project is not profitable, thus not worth the investment. A positive NPV indicates that a project is profitable, a larger NPV indicates that the project earnings are higher. The net present function is given by:

$$\max_{\lambda_{(j,q,n,v)}(t),\, \mathrm{Q}_{(j,q,v)}} \mathrm{NPV} = \sum_{t=\mathrm{t}_0}^{T} (1+\rho)^{-(t-t_0)}\big(\pi(t) - C(t)\big) \qquad \text{(Eq. 1)}$$

Where t is the year, ρ the discount rate in a fraction, t_0 is the starting year of the model which is 2020, $\pi(t)$ is the revenue in year t in €, and $C(t)$ the cost in year t in €. The NPV is given in €, T stands for the run time of the simulation and for this study is until 2050. All variables are positive except for the NPV, which might become negative. To ensure that NPV earned in different years have the same value it is corrected with a discount rate, which is equal to 0.035. This discount rate reflects inflation and opportunity cost, correction for inflation is needed since the monetary value changes over the years. Opportunity cost reflect the possibility to invest the money into other opportunities which might have a higher return on investment. The cost and revenue variable in the objective function are determined by the decision variables.

The term vintage, v, indicates in which year the biorefinery is built. j is the set of different biorefineries, these are further discussed in chapter 3. The set q indicates the different capacities available. The constraints of the model include the available waste biomass and the capacity constraint. The indexes j, q and v are the three properties that are needed to distinguish between biorefineries.

The decision variables of the model are $\lambda_{(j,q,n,v)}(t)$, the allocation of waste biomass stream n to biorefinery j of capacity q of vintage v in year t in kg year^{-1}, and $Q_{(j,q,v)}$ the expanded biorefinery capacity of technology j with capacity q of vintage v in kg. For the expanded biorefinery capacity the year in which it is commissioned is equal to the vintage. The vintage thus indicates in which year a biorefinery is built. The capacity indicates how much biomass can be valorised in one year. $Q_{(j,q,v)}$ and q are interlinked, q is a given set with different possible capacities for the biorefineries from which $Q_{(j,q,v)}$ can select. $Q_{(j,q,v)}$ is a positive integer variable making the model a mixed integer problem, if $Q_{(j,q,v)} = 10.000$ kg it indicates that a biorefinery of type j with a capacity of 10.000 kg of vintage v is commissioned. The capacity of 10.000 kg is only possible if it is within the set of q.

The set of capacity size is different between technologies since the quantity of available biomass are different. The set q is made by specifying a minimum capacity and incremental increasing the capacity with a step size. This is continued until the maximum capacity is reached, the minimum and maximum capacities and the step size of each biomass are given in Table 2. The capacity is chosen to be within a range to reduce computational time, which is further described in the paragraph 2.2.3. The range of the capacity is not chosen arbitrary, first a small set was specified and then it was gradually increased until it did not influence the results of the model.

Table 2 Capacity size of different technologies

Feedstock for the technology	**Minimum capacity (tonnes)**	**Maximum capacity (tonnes)**	**Step size between capacities (tonnes)**
Wood	1.000	20.000	1.000
Grass	1.000	16.000	1.000
Leaves	100	300	10
OMSW	10.000	200.000	10.000

2.2.2. The model

The model will allocate different waste biomass streams towards different biorefineries. The bioconversion of the feedstock into products is based upon mass balances. The model consists of a large portfolio of different biorefineries, each with its own characteristics. The characteristics consist of the type of feedstock, efficiency, output and operating conditions. The model will decide each year if a new type of biorefinery needs to be built. This decision is based on available biomass, the price of product and their future predictions. It will create a most-profitable pathway for the total system. To illustrate this better, an example of a possible solution for an arbitrary year (e.g. 2045) is given in Figure 2.

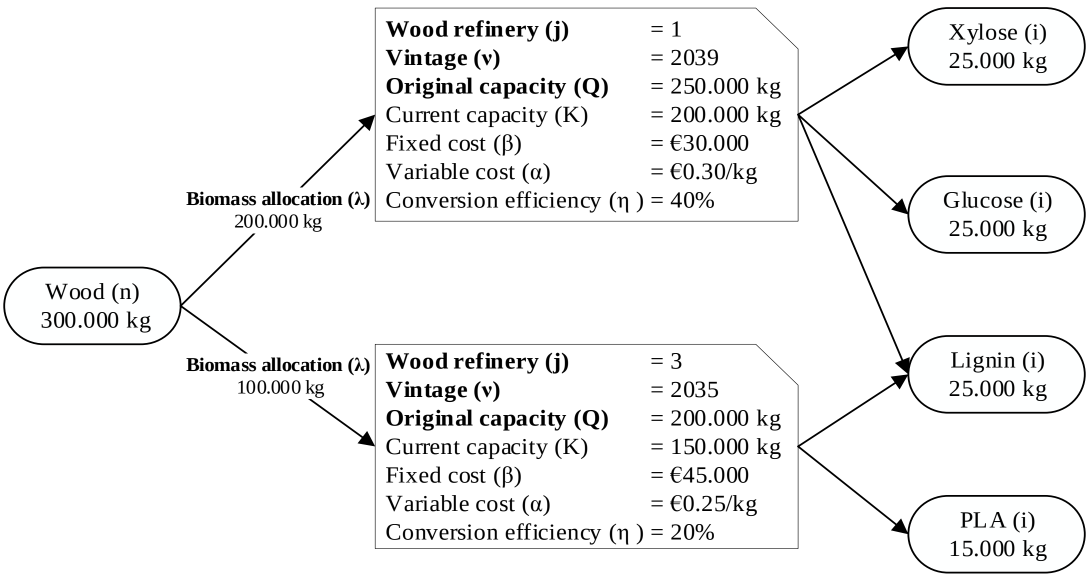

Figure 2 General scheme for the allocation of waste biomass towards biorefineries in the year 2045. Highlighted are the decision variables for the model.

It shows that the wood biomass is cascaded by two different refineries, both with their own specifications. These two refineries are built in different years since their vintages are different as well as their capacity. The highlighted text indicates the decisions which the model can make. Note that the original capacity and current capacity are different, due to diminishing capacity rate the original capacity degrades over time due to technical degradation. Since they are both different technologies, they produce different products at varying efficiency and cost. The price of the products is not included in the scheme however, it plays an important role in the allocation of the waste biomass towards a biorefinery. In addition, the lifetime of the biorefineries is not given in the figure.

Since technology improves it might be beneficial to build a new biorefinery with better efficiencies instead of continuing to operate with an old installation. Also, biorefineries close down after their lifetime has exceeded thus a replacement might be needed. In the model there is no restriction on how many or what type of biorefinery can be built. However, some technologies might not be available at the beginning owed to their technical readiness level being too low. Thus the model might not be able to build some types of biorefineries in the first few years.

The time horizon for the model is from 2020 to 2050. To avoid the end of time horizon effect, the model will run until 2070. The end of time horizon is applied so that the model will not stop at 2050, but will continue afterwards. This is to ensure the model will not only satisfy the constraints until 2050 but also afterwards since waste biomass and the biorefineries will still be available after 2050. This will mimic real-life scenarios where biorefineries are built for their lifetime span, not a specific given year. Only the results until 2050 are inspected since this is the time frame the research is interested in. After 2050 it is assumed all data stays constant since future predictions become more unpredictable. 2070 is not chosen arbitrary, the time horizon was extended gradually until the end of time had no effect on the results in 2050. The model and investment time step is one year. Investment is done at the beginning of each period, the available capacity is immediately available for biomass waste streams.

The model was written in General Algebraic Modelling System (GAMS, version 24.6.1) and solved with the CPLEX solver. The CPLEX solver is chosen since it is capable of solving large, difficult problems quickly. The CPLEX solver automatically sets the options at the best configuration for the problem, thus solving the problem quickly with minimal user intervention. Furthermore, CPLEX can handle mixed integer programming problems, which is needed for this model.

2.2.2.1. Bioconversion

All biorefineries are black box models in this study, this is to reduce the complexity of the model. The model assumes that from the incoming biomass stream a part is converted with a given efficiency into different products. The general formula for the biorefineries is:

$$X_{(i)}(t) = \sum_{v=t_0}^{t} \sum_{n=o}^{n_{end}} \sum_{q=o}^{q_{end}} \sum_{j=o}^{j_{end}} \lambda_{(j,q,n,v)}(t) \cdot \eta_{(i,j,n,v)} \qquad \text{(Eq. 2)}$$

In which i is the set of different products, $X_{(i)}(t)$ the amount of product i produced in year t in kg and $\eta_{(i,j,n,v)}$ is the efficiency of converting waste biomass stream n into product i with biorefinery j of vintage v in kg kg^{-1}. The end subscript used for the sets is to indicate that the summation is performed until the end of the set.

The sum of the different streams towards the biorefineries is equal to the total available waste biomass:

$$S_{(n)}(t) \geq \sum_{j=0}^{j_{end}} \sum_{q=0}^{q_{end}} \sum_{v=t_0}^{t} \lambda_{(j,q,n,v)}(t) \qquad \text{(Eq. 3)}$$

$S_{(n)}(t)$ is the total available waste biomass of type n in year t given in kg. As seen in the equation, the total available waste biomass exceeds the sum of streams towards the refineries. There is a relaxation in the model, making it not supply driven since the allocation of waste biomass is not equal to the available waste biomass. This relaxation is added to not force the model to valorise all of the waste if this is not profitable. Biomass that is not sent to a biorefinery is discarded and is further excluded from the model.

Since the quantity of biomass and quantity of products are directly related to each other through a conversion factor, it is also decided to not let the model be driven by the demand for products. When the model becomes demand driven it will be indirectly be supply driven, thus forcing the model to perhaps make unprofitable decisions.

The total installed capacity should always exceed the total allocated waste biomass. Thus the capacity constraint equation is expressed by the following formula:

$$\sum_{n=0}^{n_{end}} \lambda_{(j,q,n,v)}(t) \leq K_{(j,q,v)}(t) \cdot \omega_{(j,v)} \qquad \text{(Eq. 4)}$$

In which $K_{(j,q,v)}(t)$ is the total installed capacity of biorefinery type j with capacity q of vintage v in year t in kg. The total installed capacity is about how much feedstock each year can be processed, it can exceed the total available biomass. $\omega_{(j,v)}$ is the availability factor ($\omega_{(j,v)} \in [0,1]$) of biorefinery type j of vintage v. The availability factor indicates in which year a new technology becomes available for commercial application. Some of the technologies that are introduced in the model are currently in development state and cannot be applied on large scale yet. However these technologies will become commercial available in the near future, the availability factor indicates which year. More information about the availability factor is given in chapter 3.

Over time the capacity of a biorefinery degrades due to lifetime of the technology. The capacity degradation develops as follow:

$$\begin{aligned}
&\text{for } v = t \text{ and } \omega_{(j,v)} \neq 0, && K_{(j,q,v)}(t) = \mathrm{Q}_{(j,q,v)} \\
&\text{for } t - \psi_{(j,v)} \leq v < t, && K_{(j,q,v)}(t+1) = (1-\kappa) \cdot K_{(j,q,v)}(t) \qquad \text{(Eq. 5)} \\
&\text{for } v \leq t - \psi_{(j,v)}, && K_{(j,v)}(t) = 0
\end{aligned}$$

Where $\psi_{(j,v)}$ is the life time of biorefinery type j of vintage v and κ the technology capacity diminishing rate in fraction, which is equal to 0.05. When the vintage v technology is commissioned in period t, namely $v = t$, $K_{(j,q,v)}(t)$ is equal to the capacity that is invested, which is $\mathrm{Q}_{(j,q,v)}$. However, this is only possible if the technology is available therefore it should also satisfy $\omega_{(j,v)} \neq 0$. During its physical life time, the technology capacity diminish with a rate of κ. When a technology exceeds its lifetime, $v \leq t - \psi_{(j,v)}$, the capacity is set to zero to simulate the decommission of the biorefinery. Notice that $K_{(j,q,v)}(t)$ has the index q, this index tells what the original capacity was of the biorefinery when it was commissioned while $K_{(j,q,v)}(t)$ depicts the total installed capacity at year t.

In this study biorefineries are modelled as black box models. In a black box model, the physical and chemical phenomena are not modelled, a simple representation of the biorefinery is used. Equation 2 describes the process of the biorefinery where there is an input and an output with a certain efficiency. However due to research and development it can be expected that newer biorefineries will have a better efficiency (van Meijl et al., 2016). This improvement is only when the technology is commercialised, since then it is applied on industrial scale and new bottle-necks can be solved. Furthermore a restriction is placed on the total efficiency of the process. It is assumed that the sum of the conversion of the biomass to the products cannot exceed 95%. If this maximum is reached the efficiency of converting biomass to each commodity remains constant. The following conditional expression shows the improvement of efficiency:

$$\begin{cases} \text{if } \sum_{i=0}^{i_{end}} \eta_{(i,j,n,v)} \leq 0.95 \text{ and } \omega_{(j,v)} \neq 0 & \eta_{(i,j,n,v+1)} = \eta_{(i,j,n,v)} \cdot \left(1 + \epsilon_{(j)}\right) \\ \text{else,} & \eta_{(i,j,n,v+1)} = \eta_{(i,j,n,v)} \end{cases} \quad \text{(Eq. 6)}$$

$\epsilon_{(j)}$ is the increase of efficiency per year of biorefinery type j in fraction. If stated otherwise in this thesis, $\epsilon_{(j)}$ is assumed to be 0.00375 (Tsiropoulos et al.). The increase in efficiency happens whether a biorefinery is build or not built within the model, the improvement is applied on the moment the technology becomes commercialised. It is assumed that even though the technology is not built by the model, it is applied outside the model on commercial scale, so improvement is still happening.

All of these improvements are only applied on newly built refineries, an already built biorefinery will not improve. Thus an biorefinery that is built has the properties of that vintage year and shows no improvement over its lifetime. If one wants the newly improved efficiency or the extended lifetime a new biorefinery needs to be built. The same applies to the economic aspect of the technologies that is explained in the next section.

2.2.2.2. Economic part of the model

The economic part of the model consists of the cost of the biorefineries and the revenue from the commodities. All economic data are in euros if data is in dollars a rate of €0.84 is used. The investment costs of refineries from different years are adjusted to 2020 using the chemical engineering plant cost index (CEPCI), which is discussed further in chapter 3. Other cost or price data from previous years are adjusted according to inflation of the Netherlands, which is equal to 1.88% (CBS Statline, 2016)**.**

2.2.2.2.1. Costs

The cost of the biorefineries can be split into three different type of cost: investment cost, fixed cost, and variable cost as seen in Figure 3.

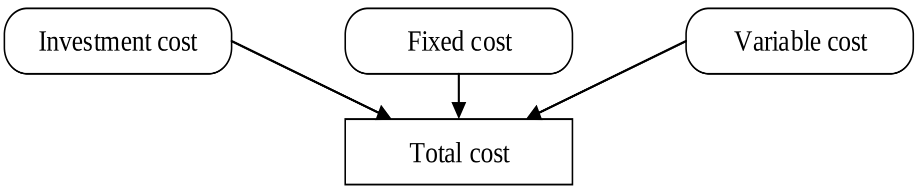

Figure 3 The different types of cost.

The investment cost only occurs in the year a biorefinery is commissioned, the fixed and variable cost occur every year when the operational. The summation of the three different type of cost results in the total cost as given by the following formula:

$$C(t) = C_{inv}(t) + C_{fix}(t) + C_{var}(t) \quad \text{(Eq. 7)}$$

In which $C(t)$ is the total cost in year t in €, $C_{inv}(t)$ the investment cost in year t in €, $C_{fix}(t)$ the fixed cost in year t in €, and $C_{var}(t)$ the variable cost in year t in €.

The investment cost depicts the cost of building a new biorefinery, therefore is dependent on whether a biorefinery is built in a certain year. The investment cost function is given by:

$$C_{inv}(t) = \sum_{j=0}^{j_{end}} \sum_{q=0}^{q_{end}} \alpha_{(j,q,v)} \cdot Q_{(j,q,v)} \ \ \forall t = v \qquad \text{(Eq. 8)}$$

In which $\alpha_{(j,q,v)}(t)$ is the unit investment cost of biorefinery type j with capacity q of vintage v in € kg^{-1}, the $\forall t = v$ term is to indicate that the investment cost is only calculated when the biorefinery is build. This unit investment cost is dependent on the size of the biorefinery that is built, thus not constant for all $Q_{(j,q,v)}$. Economy of scale reduces the unit investment cost when a larger facility is build. To calculate the unit investment cost for different capacities, data about a base biorefinery is needed. The cost and capacity of the base biorefinery can be used to scale towards different capacities. The unit investment cost for different capacities is calculated by the following formula:

$$\alpha_{(j,q,v)} = \frac{C_{0,(\mathrm{j})}(t) \cdot \left(Q_{(j,q,v)}/Q_{0,(\mathrm{j})}\right)^{\theta}}{Q_{(j,q,v)}} \qquad \text{(Eq. 9)}$$

In which $C_{0,(j)}(t)$ is the base cost of a biorefinery type j in the year t in €, $Q_{0,(j)}$ is the size of the base biorefinery in kg and θ is the cost capacity factor in fraction. For biorefinery the cost capacity factor is estimated to be 0.63 (McAloon et al., 2000; Schaidle et al., 2011; Wright and Brown, 2007). The term $\left(Q_{(j,q,v)}/Q_{0,(j)}\right)^{\theta}$ can be seen as the scaling factor of the investment cost, multiplying it with the base cost will give the investment cost of a biorefinery of size $Q_{(j,q,v)}$. By dividing the numerator with the size of the biorefinery the unit investment cost is calculated. The unit investment cost is used, from it the fixed and variable cost can be derived.

The fixed costs are yearly cost that are independent of the production of commodities. These costs include depreciation, maintenance, direct labour, and general overhead. The fixed cost is given by:

$$C_{fix}(t) = \sum_{v=\mathrm{t}_0}^{t} \sum_{j=0}^{j_{end}} \sum_{q=0}^{q_{end}} \beta_{(j,q,v)} \cdot K_{(j,q,v)}(t) \qquad \text{(Eq. 10)}$$

In which $\beta_{(j,v)}$ is the unit fixed cost of biorefinery type j with capacity q of vintage v in year t in € kg^{-1}. The capacity of the biorefinery degrades over time, thus the fixed costs also decrease over time. The slowly degradation of the fixed cost represent the depreciation of the installed biorefinery.

The variable costs are yearly cost that are dependent on the production of products. In the model the variable costs are dependent on the amount of feedstock that is fed towards the biorefinery since this is directly related to the production of the commodities. These variable costs include energy and input materials. The variable cost is given by:

$$C_{var}(t) = \sum_{n=0}^{n_{end}} \sum_{v=\mathrm{t}_0}^{t} \sum_{j=0}^{j_{end}} \sum_{q=0}^{q_{end}} \gamma_{(j,q,v)} \cdot \lambda_{(j,q,n,v)}(t) \qquad \text{(Eq. 11)}$$

In which $\gamma_{(j,v)}$ is the variable cost of biorefinery type j with capacity q of vintage v in € kg^{-1}.

Some papers give the fixed and variable cost of a biorefinery however, these are unreliable since they are for a given capacity. These costs do not reflect the costs of smaller or bigger capacities thus another approach for the calculation of fixed and variable cost is used. A common rule related to the fixed and variable cost is used, the fixed cost is generally 15% of the total cost, and the variable cost usually is around 10% of the investment cost (Peters et al., 2012) The unit variable cost is calculated through the unit investment cost with the following formula:

$$\gamma_{(j,q,v)} = \alpha_{(j,q,v)} \cdot \delta \qquad \text{(Eq. 12)}$$

In which the term δ is the fraction that determines the percentage of which the investment cost is related to the variable cost.

From the unit variable cost the unit fixed cost can be calculated since it is 15% of the total cost:

$$\beta_{(j,q,v)} = \gamma_{(j,q,v)} \cdot \frac{\iota}{1-\iota} \qquad \text{(Eq. 13)}$$

In which ι is the fraction which determines the percentage of total cost is fixed cost.

After experience is gained in the production of a commodity it can be expected that production cost will decrease. This cost decline is often referred to as the "learning effect", "learning rates", "learning curve" or "experience curves" (Ahmed, 2013; Daugaard et al., 2015; Farag and Chaouki, 2015; Vimmerstedt et al., 2015). The learning effect encompasses multiple learning mechanisms such as learning-by-searching, learning-by-using, learning-by-interacting, changes in production design, and standardization (Chen et al., 2012). Each of these stages have different learning mechanisms that result in cost reduction (e.g. Neij et al. (2003) and Junginger (2005)). This learning effect causes cost of biorefineries to decrease exponentially with the number of plants built (Farag and Chaouki, 2015). Henrich et al. (2009) states that cost reductions can reach up to two-thirds of the first plant cost. The learning effect is dependent on the stage of the industry growth and the economy, one can even experience a negative learning rate (Daugaard et al., 2015). Often learning rates can be derived from historical data (Antes et al., 2005; NETL, 2013). These rates are associated with the total installed capacities all over the world (Junginger et al., 2006). Endogenous learning could not be applied in this framework since the production of products could not be modelled due to a lack of data of the total installed capacities worldwide in the future, therefore it is chosen to apply exogenous learning by using a fixed rate. The consequence of the learning effect on the unit investment cost is expressed as follow:

$$\alpha_{(j,q,v)} = \alpha_{(j,q,v)} \cdot \left(1 - LR_{(j)}\right)^{t-t_0} \ \ \forall t = v \qquad \text{(Eq. 14)}$$

LR_j is the learning effect of biorefinery type j in fraction. Since little literature is available for the learning effect for each different biorefinery it is assumed to be 0.02.

2.2.2.2.2. Revenue

The revenue of the biorefineries is dependent on the sell price of the product. Since the framework models for multiple years, the price of commodities can change over time. The amount of commodities produced is dependent on the allocation of the waste biomass towards different biorefineries. The revenue function is given by:

$$\pi(t) = \sum_{i=0}^{i_{end}} X_{(i)}(t) \cdot p_{(i)}(t) \qquad \text{(Eq. 15)}$$

In which $p_{(i)}(t)$ is the price of product i in year t in € kg^{-1}.

Due to changes in demand, prices of commodities are expected to increase over time. Since it is difficult to predict prices in the future a constant growth in price is assumed each year. The following formula describes the price growth:

$$p_{(i)}(t+1) = p_{(i)}(t) \cdot \left(1 + \zeta_{(i)}\right) \quad \text{(Eq. 16)}$$

In which $\zeta_{(i)}$ is the price growth of product i each year in fraction. Since the price of products is difficult to predict the average inflation is used, which is equal to 1.88% (CBS Statline).

In the model the cost of the feedstock, the waste biomass, is assumed to be zero. This assumption is based on the principle that currently waste biomass is already collected and municipalities pay institutes to handle their waste biomass. Therefore the cost can even be assumed to be negative. Furthermore, since all waste biomass will be handled every year, the cost of feedstock has no influence on the behaviour of the model. Both the transport and storage of waste biomass are compulsory, regardless of their application, these are sunk cost which will not be included in the model.

2.2.3. Computation problem

In the model $Q_{(j,q,v)}$ can choose from a fixed set, q, to select the capacity of the biorefinery. It is not chosen to make $Q_{(j,q,v)}$ a free variable since this will make the model non-linear. If $Q_{(j,q,v)}$ is a free decision variable, $\alpha_{(j,v)}$ and consequently $\gamma_{(j,v)}$ are dependent on $Q_{(j,q,v)}$ (equation 8 and 11). In equation 10 $\gamma_{(j,q,v)}$ is multiplied with $\lambda_{(j,q,n,v)}(\mathrm{t})$, thus creating a nonlinear problem since $\lambda_{(j,q,n,v)}(\mathrm{t})$ is also a decision variable. By adding a restriction on the possible capacities of the biorefineries $\alpha_{(j,q,v)}$, $\beta_{(j,q,v)}$ and $\gamma_{(j,q,v)}$ can be calculated in advance. There results will be considered as parameter inputs for the model, thus removing the non-linearity in equation 10.

The CPLEX solver is still able to solve these type of models. The advantage of this method is also it reduces computation complexity, since $Q_{(j,q,v)}$ has limited options. Reducing the amount of equations in the model significantly reduces the computational problem.

3. Case study and data collection

Since data is not readily available it needs to be collected from different sources. There are three different categories of data that needs to be collected: biorefineries technologies, quantity of biomass, and economic data. It is assumed that for the model that the city of Amsterdam operates in an island mode, there is no interaction with surrounding cities or municipalities with respect to import and export of waste biomass or products. Since most data that is needed will be forecast, data might not be available for each year. When data is missing, interpolation is conducted between data points that are available.

3.1. Biorefineries

Different type of suitable biorefineries are found in literature. The type of feedstock, conversion efficiency, capacity, lifetime, cost and output are needed to apply the biorefinery into the model. First the different technologies and their conversion efficiencies are introduced in Table 3. In addition information about whether the processes are biological, mechanical or chemical is given. The efficiencies are based on the conversion of one kilogram dry matter biomass in kilogram product.

Table 3 The different types of biorefineries used for the model. Their conversion is given in kilogram of product produced from one kilogram of biomass.

Biomass	Technology	Conversion of biomass	Process	Reference
Wood	Wood refinery 1	Glucose 0.34 kg kg^{-1}; xylose 0.24 kg kg^{-1}; lignin 0.16 kg kg^{-1}	Chemical	Michels and Wagemann (2010)
	Wood refinery 2	Glucose 0.34 kg kg^{-1}; xylose 0.26 kg kg^{-1}; lignin 0.16 kg kg^{-1}	Chemical	Laure et al. (2014)
	Wood refinery 3	Lignin 0.24 kg kg^{-1}; PLA 0.68 kg kg^{-1};	Biological	Dornburg et al. (2006)
	Wood refinery 4	Ethyl levuinate 0.38 kg kg^{-1}; formic acid 0.11 kg kg^{-1}	Chemical	Win (2005)
	Wood refinery 5	Furfal 0.06 kg kg^{-1}; methyl alcohol 0.01 kg kg^{-1}; acetone 0.01 kg kg^{-1}; acetic acid 0.04 kg kg^{-1}; suplhuric acid 0.03 kg kg^{-1}	Chemical and mechanical	Hayes et al. (2006)
Grass	Grass refinery 1	Protein 0.14 kg kg^{-1}; fibres 0.33 kg kg^{-1}; whey 0.41 kg kg^{-1} phosphate 0.07 kg kg^{-1}	Mechanical	Ros (2017)
	Grass refinery 2	Protein 0.06 kg kg^{-1}; fibres 0.57 kg kg^{-1}	Mechanical	O'Keeffe et al. (2011)
	Grass refinery 3	Protein 0.06 kg kg^{-1}; fibres 0.55 kg kg^{-1}	Mechanical	O'Keeffe et al. (2011)
	Grass refinery 4	Protein 0.06 kg kg^{-1}; fibres 0.55 kg kg^{-1}; lactic acid 0.003 kg kg^{-1}	Mechanical	O'Keeffe et al. (2011)
Leaves	Leaves refinery 1	Protein 0.07 kg kg^{-1}	Mechanical	Bals and Dale (2011)
	Leaves refinery 2	Protein 0.09 kg kg^{-1}	Mechanical	Bals and Dale (2011)
	Leaves refinery 3	Protein 0.06 kg kg^{-1}	Mechanical	Bals and Dale (2011)
	Leaves refinery 4	Protein 0.06 kg kg^{-1}	Mechanical	Bals and Dale (2011)
	Leaves refinery 5	Glucose 0.01 kg kg^{-1}; xylose 0.01 kg kg^{-1}; mannitol 0.03 kg kg^{-1}; anti-oxidant 0.02 kg kg^{-1}	Biological	Romero-García et al. (2016)
OMSW	OMSW digester 1	Biogas 0.069 kg kg^{-1}	Biological	Rajendran et al. (2014)
	OMSW digester 2	Biogas 0.069 kg kg^{-1}	Biological	Rajendran et al. (2014)
	OMSW digester 3	Biogas 0.063 kg kg^{-1}	Biological	Rajendran et al. (2014)
	OMSW digester 4	Biogas 0.063 kg kg^{-1}	Biological	Rajendran et al. (2014)

In the model only OMSW is given as input for the digesters, the other types of waste biomass are not included. There reason is that an abundance of one type of waste biomass could potentially disrupt the microorganisms (Fitamo et al., 2017). In addition legislation limits the percentage of certain waste biomass in a digester due to odour nuisance. For example, when the amount of grass exceeds 30% of the total waste biomass in the digester the odour becomes an issue (Kenniscentrum, 2005). To prevent an abundance of one type of waste biomass in a digester it is chosen to only have OMSW as an input, which is a mixture of different type of waste biomass.

3.1.1. Research and development

The different biorefineries that are proposed in this study are at different technical readiness level. Some of the given biorefineries are already in commercial state, others are only on lab and pilot scale. To differentiate the different development phases of the biorefineries, distinction is made between the availability of the technologies. In the model it is assumed that biorefineries that are commercialised are available in the year 2020. For technologies that are in pilot plant phase it is assumed they become available in the year 2030, for technologies that are still in lab scale it is assumed they become available in 2040. An overview of the technical readiness level of the different technologies can be found in Table 4. The lifetime when the technology is commercialised is also given in the table.

Table 4 Data about the current state of development of different technologies.

Technology	Technical Readiness Levels	Lifetime (Year)	Reference
Wood refinery 1	Pilot plant	10	Michels and Wagemann (2010)
Wood refinery 2	Pilot plant	10	Laure et al. (2014)
Wood refinery 3	Lab	10	Dornburg et al. (2006)
Wood refinery 4	Commercialised	10	Win (2005)
Wood refinery 5	Pilot plant	10	Hayes et al. (2006)
Grass refinery 1	Commercialised	10	Ros (2017)
Grass refinery 2	Pilot plant	10	O'Keeffe et al. (2011)
Grass refinery 3	Pilot plant	10	O'Keeffe et al. (2011)
Grass refinery 4	Pilot plant	10	O'Keeffe et al. (2011)
Leaves refinery 1	Lab	10	Bals and Dale (2011)
Leaves refinery 2	Lab	10	Bals and Dale (2011)
Leaves refinery 3	Lab	10	Bals and Dale (2011)
Leaves refinery 4	Lab	10	Bals and Dale (2011)
Leaves refinery 5	Commercialised	15	Romero-García et al. (2016)
OMSW digester 1	Commercialised	20	Rajendran et al. (2014)
OMSW digester 2	Commercialised	20	Rajendran et al. (2014)
OMSW digester 3	Commercialised	20	Rajendran et al. (2014)
OMSW digester 4	Commercialised	20	Rajendran et al. (2014)

It can be expected that the lifetime of technologies increases once it is in commercial state due to development and research. It is assumed that the starting lifetime of a new technology is ten years unless stated otherwise in literature. Once the technology is commercialised it is assumed that the lifetime increases with five years for every ten years it is in commercialised state, this is given exogenously to the model.

3.2. Biomass

The model has as input the quantity of each type of waste biomass. It is assumed for this research that the different types of waste biomass are perfectly separated. Therefore the feedstock for the biorefinery consists of one type of waste biomass. In this research four different type of waste biomass are differentiated: wood, grass, leaves, and OMSW. The origin of the biomass can be differentiated into two different origins. One is the municipality that collects the biomass in the streets, parks and recreational areas. The other participants are the inhabitants of Amsterdam who collect their waste biomass which is collected by the municipality. The biomass from the citizens of Amsterdam is not clean biomass, it is a mixture of wood, grass, leaves and OMSW. For the model it is assumed that this waste biomass is mostly separated before being valorised. The expected quantity of waste biomass in the year 2020 is given in Table 5.

Table 5 The quantity of available waste biomass from the city of Amsterdam in the year 2020 given in tonnes.

	Wood	**Grass**	**Leaves**	**OMSW**
Quantity dry matter (tonnes)	6118	2675	61	67978

3.2.1. Wood

Wood consists of wood collected by the municipality and garden waste from the inhabitants of Amsterdam. For the wood collected by the municipalities, it is distinguished in different origins: solitary trees, deciduous groves, tree girth, hedgerows, tree rows, willow wood, and reed screens (Buijzer et al., 2015). Reason for this distinction between the origin of the wood biomass is due to future predictions and policies. Some of the origins of the biomass can be expected to grow over time, or with stimulating policies can grow in supply by planting more trees. However solitary trees are not expected to provide more biomass over time, usually, they are already full grown and during pruning the same amount of wood biomass is collected every year. Furthermore planting more solitary trees in the same area is unfeasible (Buijzer et al., 2015). The growth of biomass for wood in a good scenario is expected to increase with 10% from 2020 till 2050 (Boosten and Oldenburger, 2014).

Table 6 Growth of different sources of wood biomass in the city of Amsterdam (Buijzer et al., 2015).

Source of wood biomass	**Expected growth**
Willow wood	No growth
Deciduous groves	Growth
Reed screens	No growth
Hedgerows	No growth
Tree girth	Growth
Solitary trees	No growth
Tree rows	No growth
Garden waste	Growth

3.2.2. Grass

Similar to wood, grass also has two origins, from the municipality and from the residents. Grass from the municipality can be divided into two groups: recreational areas and roadside cuttings. It is not expected that this amount of grass will increase over the years, since there is no expectation that recreational areas or roadsides will expand in the future (Boosten and Oldenburger, 2014). The quantity of grass from the residents is expected to increase slightly, since Amsterdam is growing more housing is developed resulting in more gardens. A fraction of the garden waste is grass (Boldrin and Christensen, 2010).

3.2.3. Leaves

Data of the quantity of leaves collected by the municipality is not available. However, it is assumed that leaves are directly related to wood biomass since leaves grow on woody biomass, the leaves come available during pruning. It is presumed that 1% of the woody biomass is equal to the quantity of leaves available for valorisation. This assumption is only for woody biomass of the municipality, not for the leaves available from garden waste.

3.2.4. OMSW

Buijzer et al. (2015) describes the amount of OMSW produced by each citizen in Amsterdam, it states that the total amount of OMSW in Amsterdam in 2015 consists of 60.000 ton. However, this is only the waste from the household. OMSW also includes the waste from gardens (Buijzer et al., 2015). For the model it is assumed that the total citizens of Amsterdam are directly related to the amount of garden waste, thus an increase of inhabitants of Amsterdam is proportional to the amount of garden waste. It is not assumed this garden waste is separated from the OMSW.

3.2.5. Growth of biomass

In Boosten and Oldenburger (2014) the predicted growth of biomass is described. They describe the quantity of biomass in the year 2014 and potential biomass quantity for 2020 and 2050. For 2020 they explain two different scenarios, one where there is a stimulation in increasing the amount of biomass and one where no stimulation takes place.

For wood not all sources of biomass will increase the supply of woody biomass as described in Table 6. The prediction from Boosten and Oldenburger (2014) will only be applied to the woody biomass that is expected to grow, this growth is 10% from 2020 to 2050. The amount that is from garden waste is expected to increase proportionally to the population of Amsterdam. For grass, Boosten and Oldenburger (2014) does not expect that it will grow, which is obvious since recreational areas and roadsides are not increasing in size without human intervention. However grass form garden waste is expected to growth in this model. Since leaves are directly related to woody biomass it will follow the same trend as woody biomass. It is expected that there is no improvement in the efficiency of collecting leaves, since there is no indication this will happen. Furthermore the amount of leaves from garden waste is expected to growth. OMSW directly comes from the inhabitants of Amsterdam, therefore it is assumed that it will follow the same trend as the population growth of Amsterdam. The average OMSW production per inhabitant of Amsterdam is calculated and with the expected population growth of Amsterdam the total amount of OMSW for each year is forecasted.

The population growth of Amsterdam is prognosed by the municipality itself (Gemeente Amsterdam, 2017). The expected growth in Amsterdam is forecasted for the year 2030, 2040 and 2050 as seen in Table 7. The year 2015 is needed to interpolate the population of Amsterdam for the year 2020.

Table 7 Expected population growth of Amsterdam (Gemeente Amsterdam, 2017).

Year	Inhabitants Amsterdam
2015	822.272
2030	936.000
2040	980.000
2050	998.000

3.2.5.1. Interpolation

Since most prognoses of increase in biomass quantity and population growth do forecast each year, but certain years, interpolation between data points is needed. As trend line an order two polynomial equation is chosen since it is a good fit for the data points. The results from the interpolation and all data about the available biomass and growth can be found in Appendix A and B.

3.3. Economics

Since a techno-economic analysis is performed the economics are an import aspect of the model. The cost of biorefineries and the price of products are necessary and in addition, their cost in the future needs to be projected.

3.3.1. Cost of refineries

To estimate the order of the investment costs for building a biorefinery, data from different studies is used. Since most studies are done in different years, the costs are adjusted to 2020 using the Chemical Engineering Cost Price Index (CEPCI) as described in the next paragraph. The cost will change over time, by using the CEPCI and applying the learning effect, the future cost of biorefineries is predicted. The expected cost of the biorefineries and their capacity, derived from the literature, are given in Table 8.

Table 8 The capacity and investment cost in the year 2020 of the different biorefineries.

	Investment cost (million €)	**Capacity (million kg)**	**Reference**
Wood refinery 1	62	400	Michels and Wagemann (2010)
Wood refinery 2	69	400	Laure et al. (2014)
Wood refinery 3	218	323	Dornburg et al. (2006)
Wood refinery 4	3	10	Win (2005)
Wood refinery 5	188	365	Hayes et al. (2006)
Grass refinery 1	41	70	Ros (2017)
Grass refinery 2	6	7	O'Keeffe et al. (2011)
Grass refinery 3	6	7	O'Keeffe et al. (2011)
Grass refinery 4	8	7	O'Keeffe et al. (2011)
Leaves refinery 1	1669	175	Bals and Dale (2011)
Leaves refinery 2	2012	175	Bals and Dale (2011)
Leaves refinery 3	2053	175	Bals and Dale (2011)
Leaves refinery 4	884	175	Bals and Dale (2011)
Leaves refinery 5	614	330	Romero-García et al. (2016)
OMSW digester 1	34	55	Rajendran et al. (2014)
OMSW digester 2	29	55	Rajendran et al. (2014)
OMSW digester 3	37	110	Rajendran et al. (2014)
OMSW digester 4	39	110	Rajendran et al. (2014)

3.3.1.1. Chemical Engineering Cost Price Index

Since the model will run until 2050 it needs to predict future cost of biorefineries. Most cost data that is available is for immediate use and estimated on conditions in the past. Due to economic changes over time, a method is needed to update cost data to future references. With the use of cost indexes this can be achieved.

A cost index is a ratio between the cost at the present time with the cost at a certain base time. When the cost at the base time is known, the equivalent cost at the present time can be determined by multiplying the cost index of present time with the cost at the base time. This can be expressed by the following formula:

$$Present\ cost = Original\ cost \cdot \left(\frac{Index\ value\ at\ present\ time}{Index\ value\ at\ original\ cost}\right) \qquad \text{(Eq. 17)}$$

Different type of cost indexes can be used for estimating the different type of cost: equipment, labour, construction or materials. No cost index can take into account all factors that influence the cost, thus they generate a general estimate. These types of cost indexes are regularly updated and published in journals, some of these indexes date back until 1913 (Peters et al., 2012). In this research, the CEPCI is used since it is still updated and research has been done about future predictions of this index (Mignard, 2014). The index consists of four major components: equipment, labour, buildings, engineering and supervision. These components each are weighted and consist of further smaller components. Even though it is based on US cost data, it does not include local and specialised cost indexes, therefore it makes it applicable for other countries. Some studies apply a location factor to adjust for the US cost data, however, in this study it is assumed that due to globalisation cost estimation for western Europe is similar to US (Remer et al., 2008).

The CEPCI consists of a total of 53 different producer price indices (PPI). To forecast the CEPCI all 53 PPI need to be tracked, all of them have a certain prediction uncertainty. To simplify forecasting and thus reduce the dependence of the future predictions of all PPI, macroeconomic indicators can be used for the estimation of the cost of materials and labour. Macroeconomic indicators also have more widespread availability of data and forecasts. Mignard (2014) suggest using the oil price and prime loan rates. The following relation was found between the CEPCI and the oil price and prime loan rates:

$$CEPCI(t) = 340.7 \cdot \exp\left(A \cdot \sum_{t=t_0}^{t} P_t\right) + B \cdot p_{oil}(t) + C \qquad \text{(Eq. 18)}$$

In which $CEPCI(t)$ is the CEPCI in year t which is unitless, t the year of which the CEPCI is calculated, P_t the prime loan rate in year t in percentage, $p_{oil}(t)$ the price of oil in year t in US$/bbl., and A, B and C are a distinct sets of values used for the fit of the model. In this research, the CEPCI of the years 2013-2016 are used to find the values of A, B and C using model calibration with ordinary least squares (Lozowski et al., 2016). The CEPCI of these years can be found in Table 9.

Table 9 The chemical engineering cost price index (CEPCI) for the year 2013-2016 (Lozowski et al., 2016).

Year	**CEPCI**
2013	567.3
2014	579.7
2015	537
2016	541.7

With the values of A, B and C and future predictions of the oil price and prime loan rates, achieved from EIA (2017) and EIA (2015) respectively, future predictions of the CEPCI and thus cost price of biorefineries can be estimated. The values of A, B and C are given in Table 10. The oil price is of the West Texas Intermediate in $/bbl. and non-deflated.

Table 10 The distinct set of values for the fit of the model of the chemical engineering cost price index.

$\boldsymbol{A}$	$\boldsymbol{B}$	$\boldsymbol{C}$
0.71	1.02	122.87

The CEPCI is used to project future cost of investment of a biorefinery. As a baseline the year 2020 is used, this baseline is used to predict the cost of the biorefinery from 2020 till 2050. Equation 19 shows the mathematical formula to predict future cost using the CEPCI. The base cost of a biorefinery type j in year t with size Q_0 in € is used since the base cost will be used for scaling.

$$C_{0,(j)}(t) = C_{0,(j)}(2020) \cdot CEPCI(t) \qquad \text{(Eq. 19)}$$

The CEPCI gives a rough estimation of how cost increase over time, due to materials and labour getting more expensive and inflation (Advokaat et al., 2005; CBS Statline). However, over time technology advancement increases resulting in a learning effect, this result causes a cost reduction per vintage of technology as described in paragraph 2.2.2.2.1 (Daugaard et al., 2015).

3.3.2. Price of products

The price of products is found from literature and retailers. When different prices are found for the same product, the average is taken. The prices are corrected to 2020 using the average inflation of the Netherlands (CBS Statline). The prices of the commodities can be found in Table 11. For future price growth equation 16 is used.

Table 11 The prices of the different products in the year 2020.

Price of product	€ kg^{-1}	Reference
Acetic acid	0.20	ICIS (2018)
Acetone	0.24	ICIS (2018)
Anti-oxidants	80.80	Romero-García et al. (2016)
Biogas	1.01	Groen Gas Nederland (2015)
Ethyl levuinate	0.26	Hayes et al. (2006)
Fibres	1.16	O’Keeffe et al. (2011)
Formic acid	0.10	Hayes et al. (2006)
Furfal	1.11	Win (2005)
Glucose	0.59	Fornasiero and Graziani (2011)
Lactic Acid	0.30	ICIS (2018)
Lignin	0.45	Manesh et al. (2013)
Mannitol	8.28	Weymarn (2002)
Methylalcohol	0.58	ICIS (2018)
Phosphate	0.12	GB Minerals (2018)
PLA	0.42	Lin (2011)
Protein	0.15	Sanders (2014)
Sulphuric acid	0.29	ICIS (2018)
Whey	1.32	Ros (2017)
Xylose	6.19	Lundgren and Helmerius (2009)

4. Scenarios

With the model described in Chapter 2, the optimal allocation of waste biomass for different scenarios can be found. These scenarios capture the uncertainty in future cost and development and the effect of different climate policy goals. The following three different scenarios are used: *Benchmark, good conditions for biorefineries,* and *bad conditions for biorefineries*. A summary of the configurations of the scenarios can be found in Table 12.

Table 12 Summary of the characteristics of the four different scenarios.

	Benchmark	**Good conditions for biorefineries**	**Bad conditions for biorefineries**
Fossil fuel price	Normal	High	Low
Research and development	Normal	High	Low
Price of products	Normal	High	Low
Subsidies for biobased products	No	Yes	No

The *benchmark* scenario is to reflect the absence of climate policy goals in the Netherlands. In this scenario, the government does not apply any incentive to promote the biobased economy. In this manner the scenario reflects a free market where there is no government involvement. In this scenario garden waste is not separated, it is al used in the OMSW. An overview of the source of biomass can be found in Figure 4.

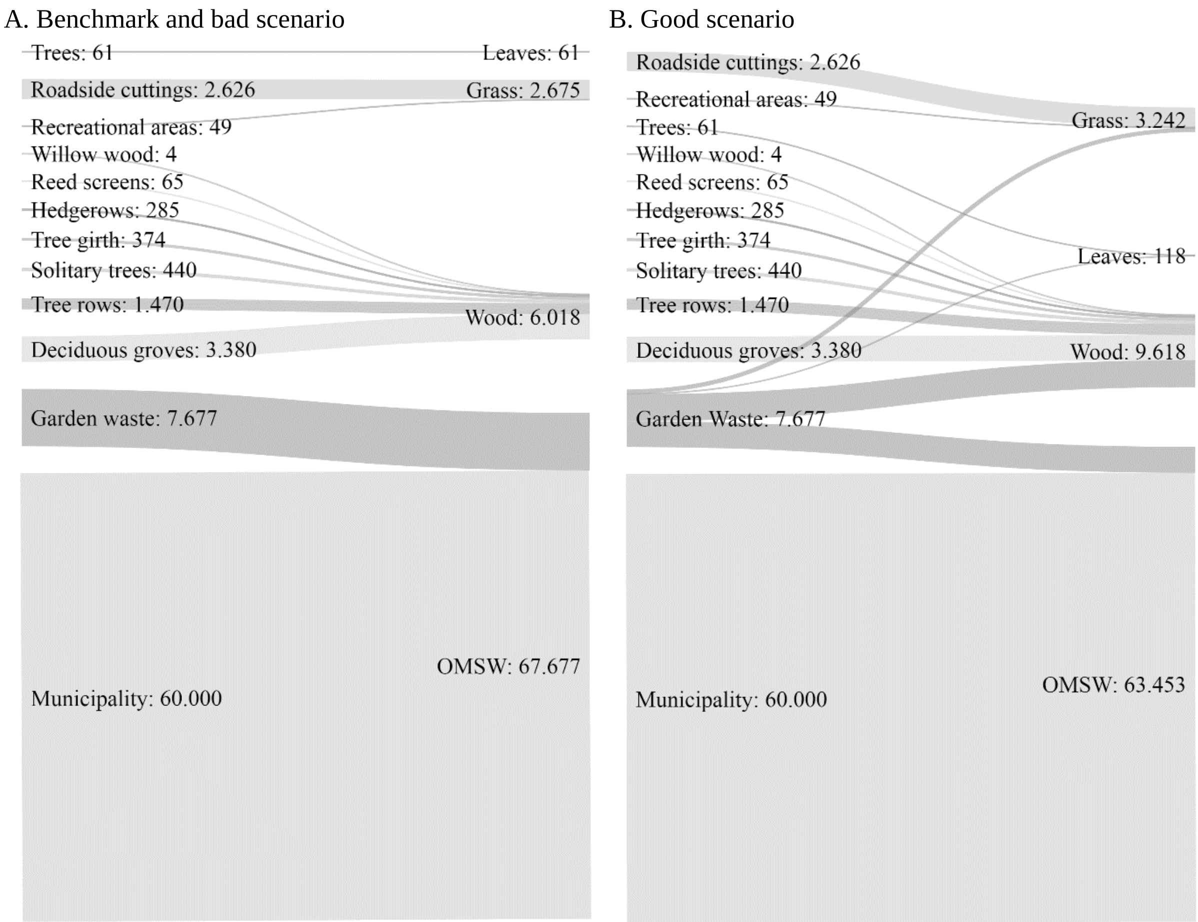

Figure 4 Biomass source of the benchmark and bad scenario (A) and the good scenario (B) in tonnes in the year 2020 (Boosten and Oldenburger, 2014; Buijzer et al., 2015). The benchmark and bad scenario are together since they are both similar in the year 2020.

Notice that in the beginning, all the source of waste biomass are not different in size among the scenarios, the policies that are applied to the scenarios are introduced in the year 2020. Therefore it is expected that in the beginning all the scenarios are equal. The main difference in the sources of waste biomass is the garden waste, as seen in Figure 4. In both the benchmark and the bad scenario, the origin of the biowaste is equal. Consequently there is no different in biomass source in the year 2020 as seen in Figure 4.

In *the good conditions for biorefineries* scenario the government uses subsidies to promote biobased products. Due to the scarcity of fossil fuels, government policies might shift to further invest in the biobased economy. One of the options government can do is to subsidise the production of biobased commodities. A price subsidy is included in this scenario. Furthermore, investment in research and development will drastically increase the technological improvement of biorefineries. Therefore it is assumed technologies become available five years earlier available than in the benchmark scenario. However the higher fossil fuel price does influence the CEPCI negatively, increasing the index. The lower prime loan rate does lessen this negative influence on the CEPCI.

In addition, the government will promote more to separate waste biomass streams, thus creating more supply for the waste biomass refineries. Due to the increase of separation, less waste biomass streams end up in the OMSW. Normally the OMSW also includes garden waste, however in this scenario garden waste is separated from the OMSW. The garden waste consists of wood, grass, leaves and other small stuff as seen in Table 13. The separated waste biomass will be used to be valorised.

Table 13 Composition of garden waste (Boldrin and Christensen, 2010).

	Composition of garden waste (%)
Small stuff	75.6
Branches	19.5
Wood	4.5
Rest	0.4

The growth of gardens is directly related to the citizens of Amsterdam since an increase in citizens will also mean an increase in houses and gardens. In current practice, garden waste is not separated so no data is available of the amount of wood, leaves and grass from gardens. Boldrin and Christensen (2010) mentions garden waste consists of 19.5% branches and 4.5% wood, furthermore it classifies leaves and grass under small stuff which is 75.6%, it is assumed this is the same for Amsterdam.

Since the small waste consists of grass and leaves but also soil, it is assumed that the grass and leaves are only a small fraction of the small waste. It is assumed that grass is only 5% of the small waste since soil is much heavier than grass and the fractions are mass based. Since leaves are a smaller portion of garden waste than grass, it is assumed 1% of the small stuff is leaves. It is not expected that this fraction will change over time, however, the total quantity of garden waste will change.

The *bad conditions for biorefineries* scenario was to develop a worst case scenario for biorefineries, due to low fossil fuel prices there is less incentive to invest in alternative production technologies, since some of the products produced could potentially replace their fossil fuel counterpart. This low fossil fuel price would indicate that the CEPCI would drop, however the strong influence of the prime loan rate results in an increase of the CEPCI.

The low incentive to invest in alternative production technologies causes the availability of new technologies to be low, it is assumed this is five years later than in the benchmark scenario. In the availability of biomass this is reflected in a slower growth of quantity of available for wood. It is assumed that the municipality has no incentive to increase their quantity harvested wood, thus areas that show potential for growth of biomass as described in Table 6 are neglected. This directly influences the quantity of leaves available for cascading, since it was assumed this was directly related to the quantity of wood. For OMSW and grass it remains the same as the benchmark scenario since those are not influenced by governmental policies.

A full description of the values assigned to the parameters for the different scenarios is given in Table 14. Only the parameters that are relevant for the scenarios are altered, other parameter values are as described in Chapter 3. The values of the available biomass, availability of new technologies, CEPCI prime loan rate, and price of oil are given in B, C and D. A high growth for the prime loan rate indicates that the percentage is low, a low interest rate drives policymakers to invest.

Table 14 Full description of the parameter values for the four different scenarios.

	Benchmark	**Good conditions for biorefineries**	**Bad conditions for biorefineries**
$D(t)$	Normal	Increased	Low
$\omega_{(j,v)}$	Normal	Fast	Slow
P_t	Normal growth	High growth	Low growth
$p_{oil}(t)$	Normal oil price	High oil price	Low oil price
Price subsidy	None	10% of market value	None
$\zeta_{(i)}$	0.0188	0.025	0.01
$\epsilon_{(j)}$	0.00375	0.00500	0.00250
$LR(j)$	0.02	0.04	0.01

5. Results

In this section, firstly the results from the maximization of the NPV for the three different scenarios is presented together with the flow of biomass through the biorefineries. Subsequently, a more in-depth analysis of the benchmark scenario is presented in which the behaviour of the model is analysed. This will give policymakers more insight in how to influence the biobased transition in Amsterdam.

5.1. Scenario analysis

The effect of different policies on the valorisation of waste biomass in Amsterdam is yet unknown. By configuring three different scenarios and applying them to the model, the effect of different strategies gives more insight on the added value of such tactics. The NPV is investigated for each biomass individually, this to get more understanding of the influence of different scenarios.

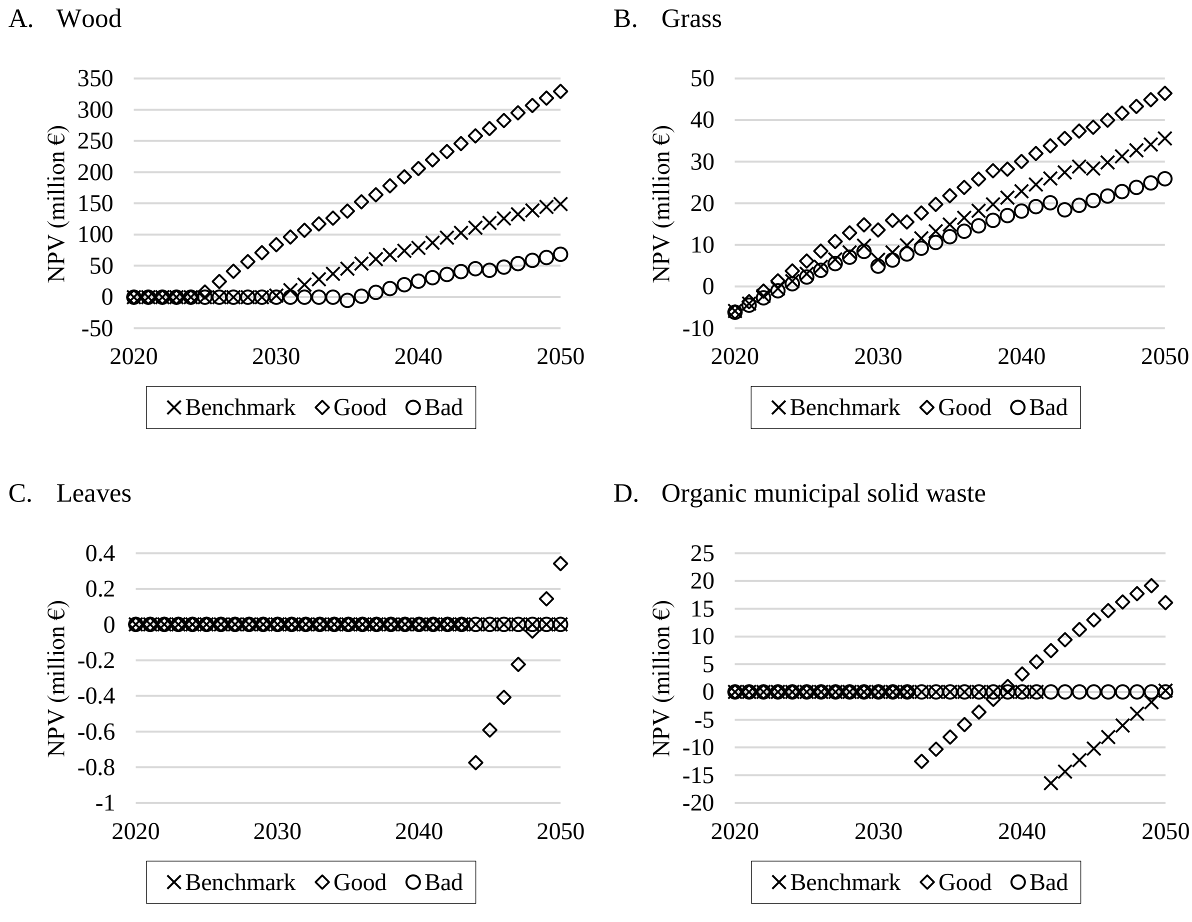

Figure 5 The net present value (NPV) of the valorisation of different biomass in the three different scenarios. The scale of the NPV is different among the four graphs.

Figure 5 shows the valorisation of the four different biomass in three different scenarios. It is clear that both wood and grass are both economically profitable since there NPV is positive in the year 2050. The different scenarios only influence the total NPV, not if it is profitable or not. For the cascading of leaves and OMSW it is clear that only at a later stage in the good scenario the NPV is positive, thus economically profitable. OMSW is slightly positive in the normal scenario. The total NPV can also be found in Table 15.

Table 15 The total net present value (NPV) of the three different scenarios.

	Benchmark	**Good**	**Bad**
NPV (million €)	185	393	94

Figure 5 does not depict smooth lines for the NPV, this is due to investment cost. When an investment is done in a specific year, the NPV drops with the value of the investment cost with a correction of the discount rate. These drops are best seen in the NPV of grass. This investment cost is also the reason that most NPV start negative and later on become positive, to make revenue from the valorisation of waste biomass there first needs to be invested in the technology. Over the long run the investment pays off, this is when the NPV becomes positive.

Figure 6 shows the Sankey diagrams of each scenario in the year 2050. The Sankey diagram depicts mass balance of the incoming waste biomass and the products that are produced from them. The Sankey diagram gives a good insight into the flow of the biomass and its purpose. It is chosen to depict the year 2050 since then the difference between the different scenarios is the largest. Therefore more insight into the flow of biomass under different policies is given.

From Figure 6 it is clear that in all scenarios a large part of the waste biomass not processed in value-added products. In the good scenario, most of the biomass is valorised resulting in the lowest amount of residue. In both the benchmark and bad scenario leaves are not valorised and remain unutilised. In the bad scenario also OMSW is not valorised, indicating that in the year 2050 it is not profitable to valorise OMSW. Even though in the good scenario there is less OMSW, there is more biogas production than in the benchmark scenario. This is the result of more efficient biorefineries for the processing of OMSW in the good scenario.

The quantity of grass for the benchmark and the bad scenario is equal, it is not possible to harvest more grass from the current areas. For the good scenario, the quantity of grass is higher since garden waste is separated which contains grass. In the benchmark and bad scenario also the quantity of the products from the valorisation of the grass is equal. This results from the technology being so matured that it reached the efficiency cap as described in equation 6. Even though the increase in conversion efficiency during the years is different among the bad and good scenario, they both reach this limit early. Consequently, the grass refineries conversion efficiency in the year 2050 is for both scenarios equal. For the good scenario, this cap is also reached however, the quantity of products from the grass refinery is larger since the input is higher. Beside roadside cuttings and recreational areas also grass from the garden waste is included as an input.

Wood is in all scenarios valorised into glucose, xylose and lignin. The quantity of these products differs between the scenarios since the quantity of wood and the conversion efficiency is unequal. However, for all scenarios it is economically profitable to process wood into value-added products.

Only in the good scenario leaves are processed, indicating that to increase the economic feasibility of cascading leaves cost reduction and increase in efficiency is needed. Even though in the good scenario leaves are processed, a fraction remains unutilized indicating that processing all leaves is too costly. Due to the diminishing capacity rate, the leaves refinery is not capable of processing all leaves in the year 2050.

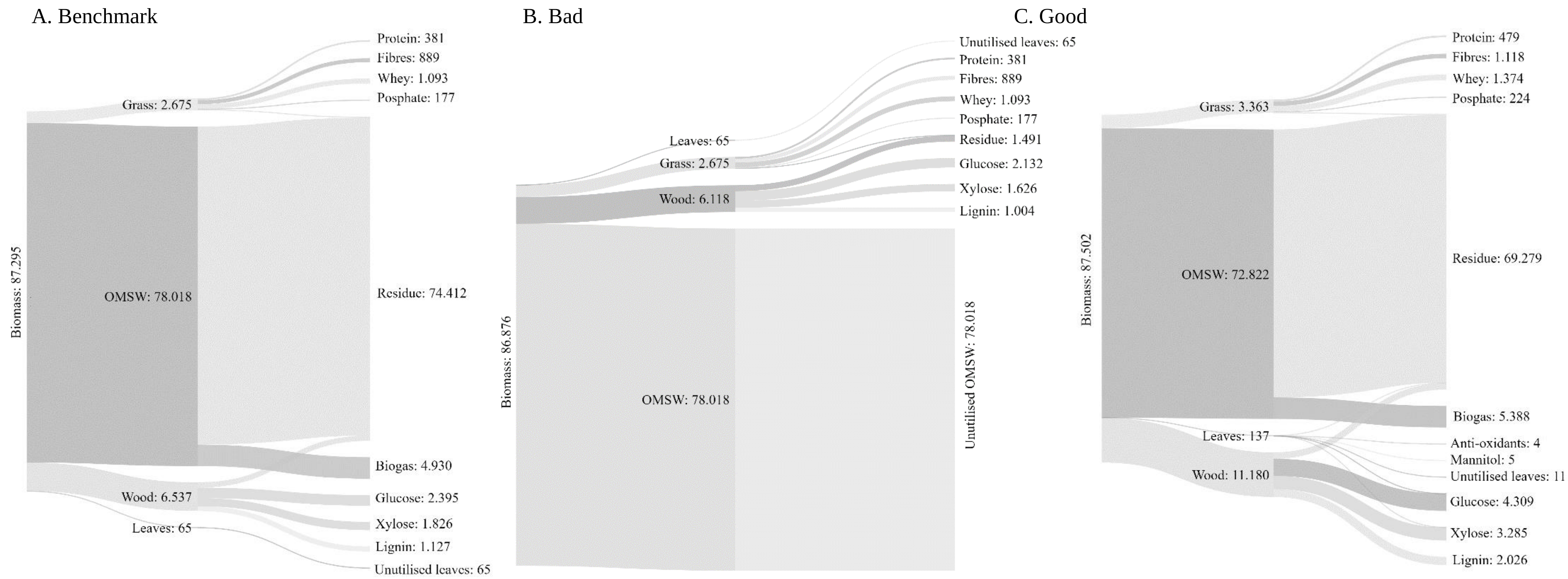

Figure 6 Sankey diagram of the mass balances in tonnes for each scenario in the year 2050. The difference between unutilised biomass and residue is that residue comes from the biorefinery, unutilised biomass indicates it has not been processed.

5.2. Benchmark scenario

To further understand how the model functions, the results of the benchmark configuration is further investigated. Figure 7 shows the capacity of the refineries that are built and the available biomass for each of the four different type of biomass. These results give insight how the model maximizes NPV with the given constraints and decision variables. As decision variable the expanded capacity of a biorefinery in a year is given, these are seen as columns in Figure 7. The dashed line indicates the quantity of biomass available each year.

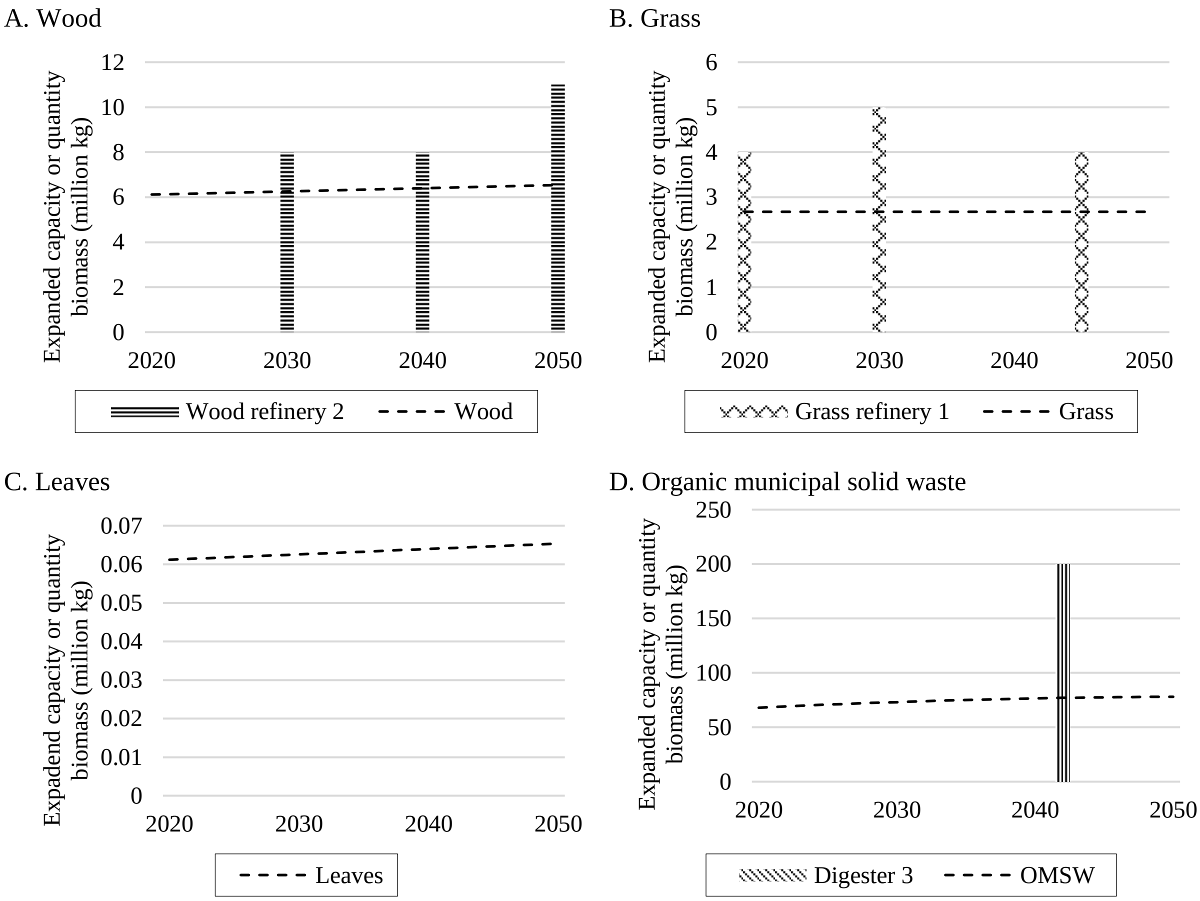

Figure 7 The capacity built of different refineries and the available biomass for each year. The capacity build or quantity of biomass scale is different among the four graphs.

Figure 7 shows that the capacity of the refineries always exceeds the available quantity of biomass. The capacity of biorefineries diminishes over time, thus to be able to valorise enough waste biomass in the future a larger capacity is needed.

Figure 7 A. depicts that the valorisation of wood starts in the year 2030 when the first wood biorefinery is built. In 2040 the lifetime of this biorefinery has exceeded thus a successor is needed, a new identical type of biorefinery is built. In the year 2050, it is profitable to build a new wood biorefinery for the future valorisation of waste biomass.

Figure 7 B. shows that grass valorisation starts in the year 2020. In the year 2030, a new grass refinery is built since the old one is decommissioned. Since this new biorefinery has newer technology, its lifetime is longer than the grass refinery built in 2020. Therefore this newer biorefinery is decommissioned in 2045, the year a new grass refinery is built. Since the biorefinery in 2030 has a longer lifetime, its initial capacity when built needs to be higher to valorise the enough biomass in the end of its lifetime since its capacity degrades over time.

Figure 7 C. shows that no leaves refinery is built in the benchmark scenario, indicating that the valorisation of leaves is not economically profitable.

Figure 7 D. shows that the building of a OMSW refinery takes place in the late stage of the model, indicating that technology beforehand was not profitable yet. Since digesters have a long lifetime, the initial capacity built needs to be large to cope with the waste biomass in the future when its capacity diminishes over time.

The results of the other scenarios about the capacity built of different biorefineries can be found in appendix E and F.

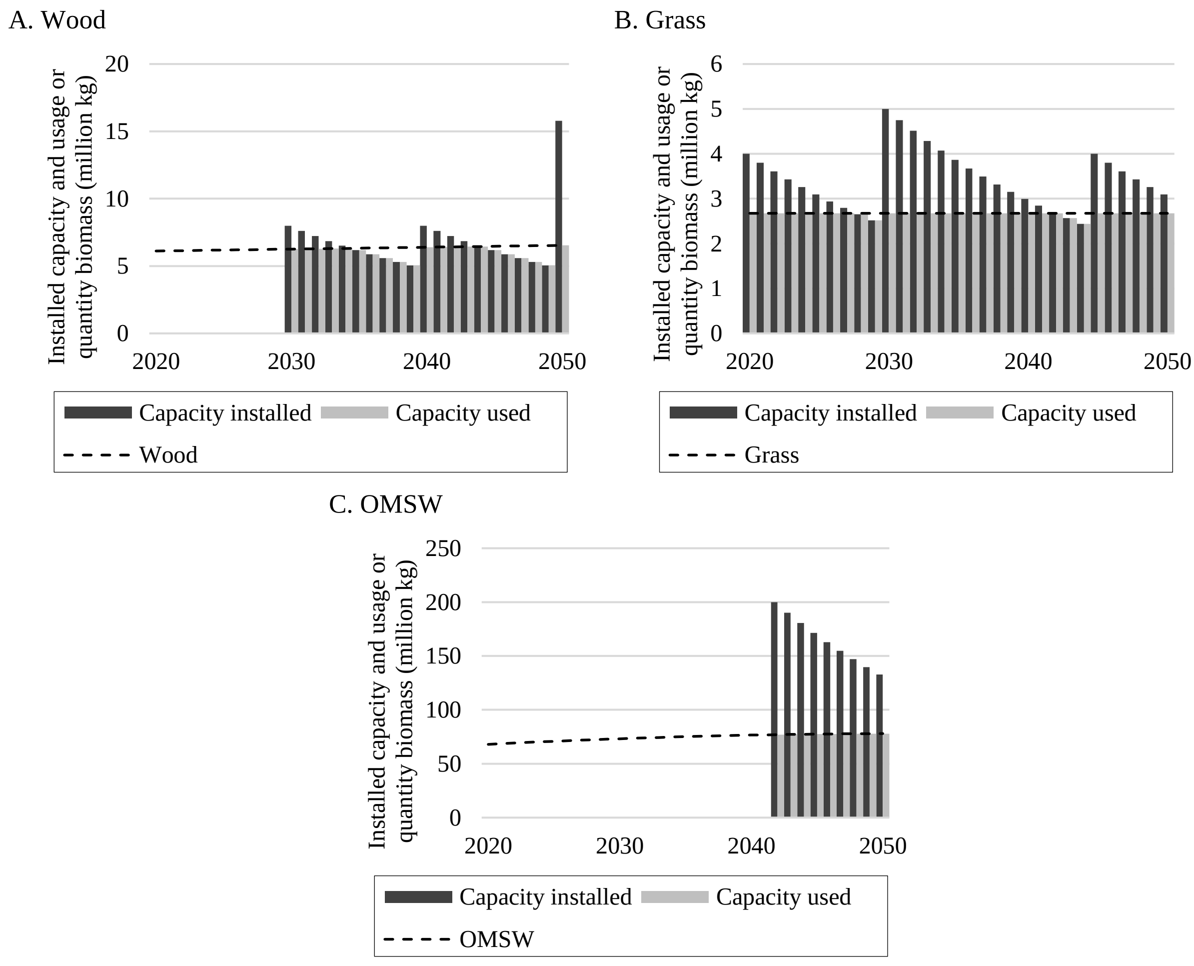

Figure 8 The total capacity installed and used of different refineries and the available biomass for each year. The total capacity installed and used or quantity of biomass scale is different among the three graphs.

Once a biorefinery is built its capacity degrades over time, thus new refineries are needed to valorise all the waste streams. Also, new biorefineries are built due to the shutdown of old biorefineries when their lifetime has exceeded. The model needs to find an optimum capacity of the biorefinery, to understand how the model finds this optimum a look at the allocation of waste biomass and installed capacity is done. Figure 8 shows the total capacity of biorefineries that is installed for the valorisation of the waste biomass each year. Furthermore, it depicts the total capacity that is used of the biorefineries, which is equal to the allocation of the waste biomass towards the biorefinery. Only three graphs are presented, the graph of leaves is left out since no refineries are built for the valorisation of leaves. From the figure it is seen that two different constraints determine the utilization of the capacity, the available biomass and the installed capacity. From equation 3 it is seen that the available biomass always greater or equal to the capacity that is utilized. Therefore in Figure 8 it is observed that capacity used never exceeds available biomass. Equation 4 states that the capacity installed is always greater or equal to the capacity used, as seen in Figure 8.

As previously mentioned the model always builds a biorefinery with a capacity that exceeds the quantity of waste biomass. However, during the lifetime of the biorefinery the capacity diminishes, this can be observed in the figures since the capacity installed slowly decreases. In the early stages of the biorefinery, the quantity of biomass determines the capacity that is used. Once the capacity installed is below the quantity of biomass it will control the capacity that is used. This shift which variables determines the capacity used is different among the biorefineries. In Figure 8 A. it is observed that this happens after five years, while in Figure 8 B. it happens near the end of its lifetime. In Figure 8 C. there is no shift, only the quantity of biomass determines the capacity utilised. The shift between variables that controls the capacity used is determined by the cost. For grass it is seen that allowing the available biomass control the capacity used is more economically interesting since the quantity of biomass is the limitation of the capacity used during most of the biorefinery lifetime. Since the valorisation of grass is so economically interesting, the model tries to valorise as much grass as possible. The valorisation of wood and OMSW is also economically interesting, however, the cost of the biorefineries are also significant thus it is not always feasible to valorise all the waste biomass.

Figure 8 A. shows an increase in total capacity installed in the year 2050. In the year 2050 a new biorefinery is commissioned to valorise waste after 2050, this is done since the simulation of the model continues after 2050 due to end of time horizon effect. Furthermore, the biorefinery that was built in the year 2040 still has the left-over capacity, thus the total installed capacity is from both the biorefinery that was commissioned in the year 2040 and 2050. The results of the other scenarios about the capacity installed and usage of different biorefineries can be found in appendix E and F.

Figure 9 shows all the products that are produced each year, it is clear that in the beginning only grass is refined since only the commodity from the grass refinery are produced. There is a small drop in production in the year 2029, this is due to the capacity of the grass refinery being lower than the quantity of available grass as seen in Figure 8 B. In 2030 there is a peak in production of products, since both a new grass and wood refinery are commissioned as seen in Figure 8 A and B. Glucose, xylose and lignin are products from the wood refinery and their production drops after a few years due to a decrease in the capacity of the biorefinery. In 2040 a new wood refinery of the same type is built with a capacity large enough to valorise all the wood. Therefore there is a peak in the amount of glucose, xylose and lignin being produced in 2040. In 2042 a digester is built to valorise the OMSW into biogas, it is immediately clear a large quantity of biogas is produced. This quantity does not change significantly over time, the quantity of available OMSW does not increase significantly after 2042 and the capacity of the digester is of sufficient size to valorise all the OMSW. In the year 2043, the capacity of the grass refinery drops below the available biomass, thus less grass is processed. This causes the production of protein, fibres, whey and phosphate to slowly drop, however in the year 2045 a new grass refinery is built that is able to valorise all the available grass until 2050. In 2045 the production of glucose, xylose and lignin drops again since the capacity of the wood refinery is diminishing. In 2050 a new wood refinery is built so it is able to valorise all the wood.

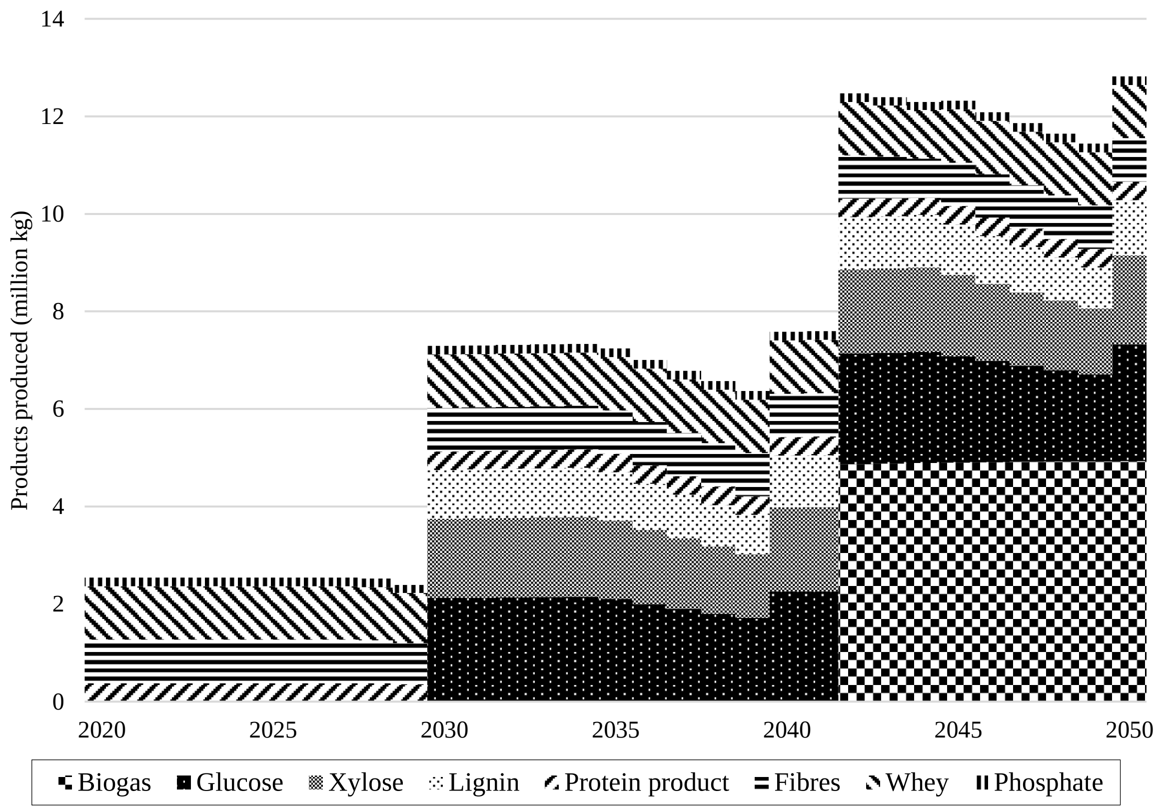

Figure 9 The total products produced from the waste biomass each year.

The production of each individual product increases slightly after a new biorefinery that produces those products is commissioned. This is due to an increase in efficiency of conversion in a newer vintage biorefinery. Furthermore in some cases the production increase due to an increase in waste biomass availability, thus more waste biomass is valorised into products. However, looking at Figure 9 these increases in production are small.

To conclude, the quantity of products in the early stage of a biorefinery is constant since it is able to process all the available waste biomass. This available waste biomass is not volatile, thus the production is stable. However, due to diminishing capacity, the biorefinery is not able to process all the available waste biomass in its later stage. Therefore the production of commodities slowly drops until a new biorefinery is built. The results of the other scenarios about the production of value-added products can be found in E and F.

6. Sensitivity analysis

Due to uncertainty related to the cost parameters of the different technologies, a sensitivity analysis is performed by varying these cost parameters. The sensitivity analysis is done with the benchmark scenario since the results of that scenario wood is not dominant in the NPV and the three largest waste biomass streams are valorised. The influence of the cost parameters on the NPV is investigated with the sensitivity analysis. The range of variation in the cost parameters is based on literature and can be found in Table 16.

Table 16 The cost parameter values used for the sensitivity analysis.

Parameter	**Benchmark value**	**Minimum value**	**Maximum value**	**Source**
Variable cost (δ)	0.10	0.03	0.20	(Junqueira et al., 2017; Peters et al., 2012)
Fixed cost (ι)	0.15	0.10	0.20	(Peters et al., 2012)
Cost capacity factor (θ)	0.63	0.6	0.7	(McAloon et al., 2000)
Capacity diminishing rate (κ)	0.05	0.05	0.10	(Brownbridge et al., 2014; de Melo et al., 2014)
Discount rate (ρ)	0.035	0.03	0.12	(Gonzalez et al., 2011; Short et al., 1995)

Eleven iterations are performed where the value of the cost parameters are changed with equal step size from the minimum to the maximum value as described in Table 16. Only the influence of one cost parameter at a time is investigated, the other parameters are held at their benchmark value.

6.1. Result sensitivity analysis

The result of the sensitivity analysis is presented in Figure 10. The range of the NPV from the sensitivity analysis is given for each cost parameter, the dark grey area indicates a negative influence on the NPV and the light grey area indicates a positive influence on the NPV. From the figure it is clear which cost parameters have the large influence on the NPV.

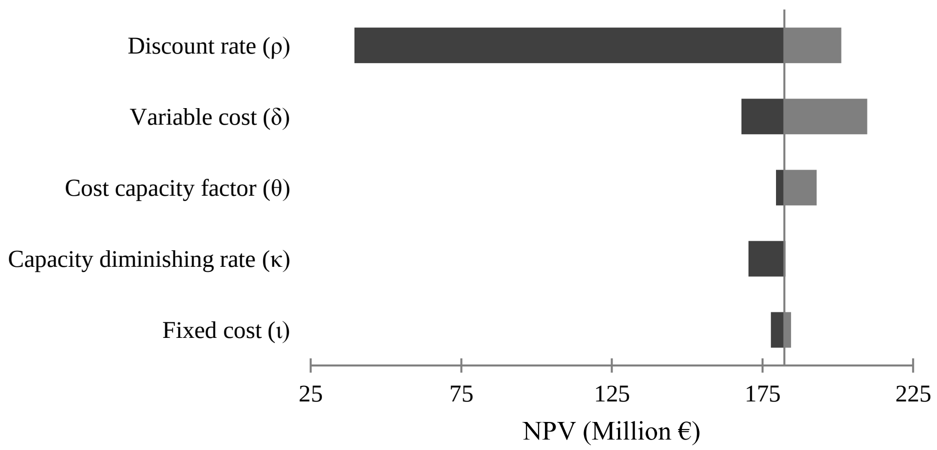

Figure 10 Results of the sensitivity analysis. Dark grey indicates a negative influence on the NPV, light grey a positive influence on the NPV. The cost parameters are ordered from largest influence to lowest.

The discount rate has the biggest negative influence on the NPV. That the discount rate has the biggest negative influence is expected, since in the benchmark scenario the value of the discount rate is relatively low. The discount rate influences both the profit and cost, in which a higher discount rate has a negative influence on the NPV. Since in the sensitivity analysis the discount rate mostly was increased, the influence is the highest.

The variable cost has the biggest positive influence on the NPV. It indicates that a low variable cost has the biggest influence on the NPV. This is expected since the variable cost is the largest cost after the investment cost, in some cases it can be even the largest dependent on the lifetime and capacity utilization of the biorefinery. Difference between the investment cost and the variable cost is the variable cost is every year while investment cost only when a biorefinery is commissioned.

The influence of the investment cost on the NPV is reflected by the cost capacity factor as seen in equation 8. However, the relation between the cost capacity factor and NPV seems contradicting when analysing the data. Figure 11 C. shows that an higher cost capacity factor decreases the NPV, while the opposite is expected. The cost capacity factor is used to calculate the cost of different sizes of biorefineries as described in equation 8. The cost capacity factor is used to introduce economy of scale, which suggests that building larger biorefineries reduce the relative investment cost. With relative investment cost, the investment cost per unit is meant, in this research the investment cost per kilogram capacity. The biorefineries that are commissioned in the model are of a smaller scale than from the literature they are derived. In the economy of scale a smaller biorefinery has a relatively larger cost, thus has a negative influence on the investment for small-scale biorefineries. A cost capacity factor closer to one indicates economy of scale has less effect on the relative investment cost, this has a positive effect on small-scale biorefineries. A cost capacity factor below one indicates economy of scale plays a role, thus has a negative effect on small-scale biorefineries. As previously mentioned, since the model uses small-scale biorefineries, increasing the cost capacity factor reduces the effect of economy of scale, thus reducing the relative investment cost.

The behaviour of the capacity diminishing rate on the NPV is as expected. A higher capacity diminishing rate advocates that biorefineries with higher capacities need to be constructed. This results in higher investment cost, thus a lower NPV. In the benchmark scenario the capacity diminishing rate used is the lowest value used for the sensitivity analysis. Consequently, in the sensitivity analysis the capacity diminishing rate is increased, resulting in lower NPV.

From Figure 10 it is clear that the NPV is the least sensitive towards the fixed cost. The fixed cost compared to the two other costs is the lowest, thus has the least impact on the NPV.

Figure 11 depicts the sensitivity analysis of each cost parameter, it is observed that all except the discount rate show non-linear behaviour. Figure 11 A. shows the sensitivity of the discount rate on the NPV. As expected the result shows that the discount rate has no influence on the decision variables of the model, only on the value of the NPV. This indicates that the model is robust as expected.

The reason that the other sensitivity results show non-linear results originates from the model. All the cost parameters have an influence on the decision variables. Since the model is a mixed integer problem, non-linear behaviour can be expected. The cost parameter have such an influence on the decision variable $Q_{(j,q,v)}$ that it shifts the year in which a type of biorefinery is built. This shift in which year a biorefinery is built influence the NPV significant, since it can influence if there is revenue in a year. This is seen in the figures, where the non-linearity of some sensitivity analysis indicates that the model shifts in which year a biorefinery is commissioned. When a biorefinery is commissioned a year later, it will have different properties due to the learning effect and change in cost, thus a different capacity of biorefinery might be built. From this sensitivity analysis, it is clear that the year in which a biorefinery is built also has an impact on the NPV.

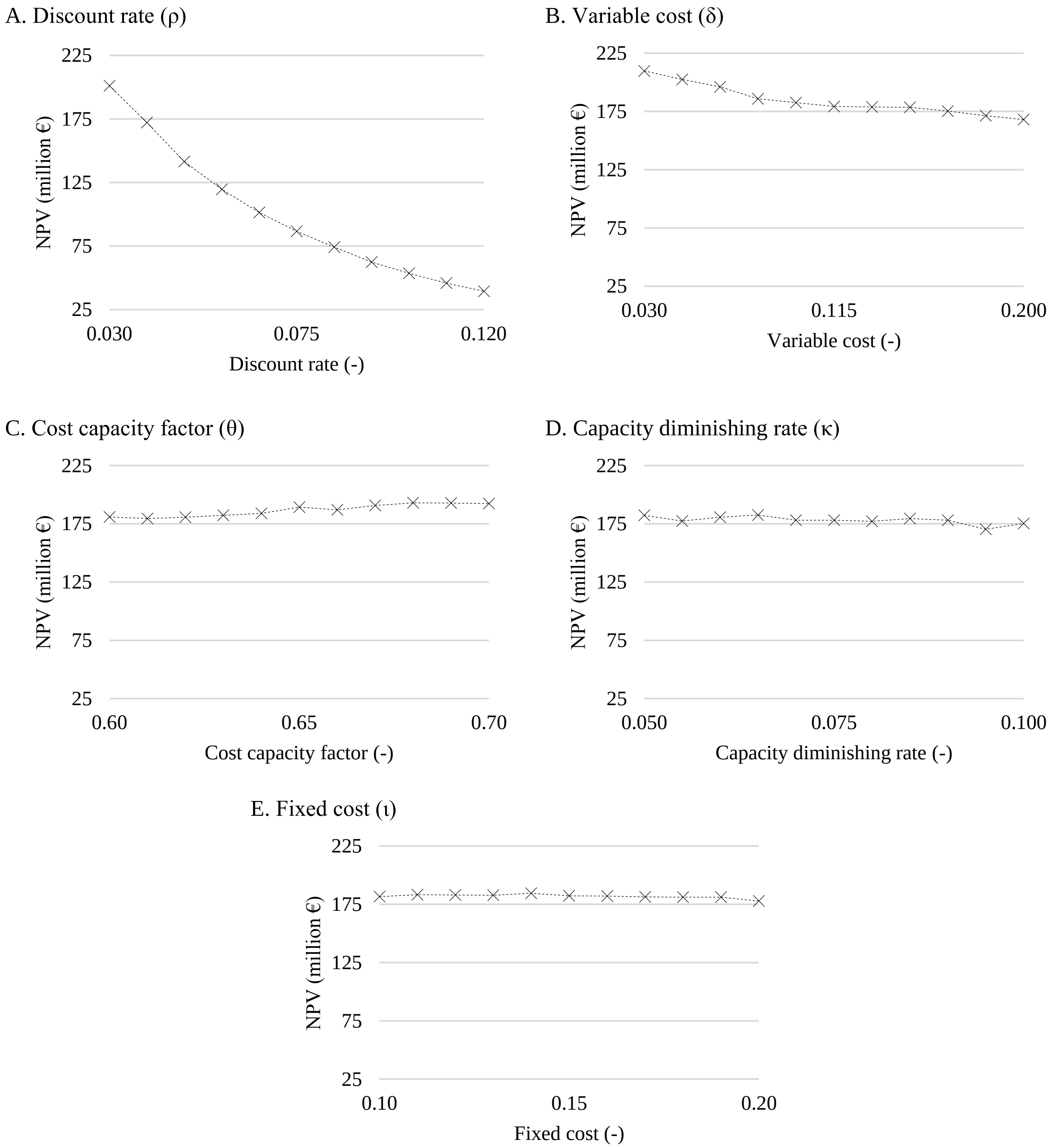

Figure 11 Results from the sensitivity analysis on the net present value (NPV) for each individual cost parameter in order of most dominant to least.

7. Discussion

In this research, the theoretical economic feasibility of valorising waste biomass of the city of Amsterdam is evaluated. However, during the research for both the technical and economic aspect assumptions were made. In this chapter a discussion about these assumptions is provided and some recommendations on how to proceed with further research about this topic.

The model discussed in this research assumes all biorefineries are black box models, this to simplify the process. Black box models can be a good representation of real-life scenarios however, they provide less insight into the process. Since the different papers which describes the biorefineries have varying level of details, it was not possible to model the biorefineries as they were, it was decided to standardize them into black box models. By using models with greater detail of the biorefineries, technological bottle-necks could be discovered.

Energy and CO_2 emission are not included in the model, since the papers that were investigated not all provide this information. By modelling each biorefinery individually the energy consumption could be calculated and their respective CO_2 emission. In addition, different scales of production were used in the model, it is unsure whether this influences the sustainability of a process. Perhaps small-scale can be economically interesting but not be environmentally sustainable. Modelling each biorefinery individually with different capacities could give information about these indicators.

When including CO_2 emission a constraint can be added in the model. The CO_2 emission can be used as a performance indicator, to indicate the environmental sustainability of the results. Currently the model uses economic sustainability as objective, however, the concept of valorisation of waste biomass is to achieve a biobased economy. The biobased economy is to reduce the environmental impact of the production of commodities.

The different valorisation techniques used in this framework consists of mechanical, chemical and microbial conversion technologies. The different technologies for the valorisation of wood consists of both chemical and mechanical. The technologies mentioned in Laure et al. (2014); Michels and Wagemann (2010); Zhou et al. (2011), and Win (2005) all use chemical conversion for the process of wood. These processes might need expensive solvents and chemicals, increasing the cost of the input materials. McAloon et al. (2000) uses microorganisms for the conversion of wood and Hayes et al. (2006) uses a combination of mechanical and chemical process steps for the valorisation. The valorisation of grass is all done mechanical for the proposed concepts, indicating there will be high energy cost but low cost of input materials. The processing of leaves is mostly done chemical, the cost of materials could be high if expensive chemicals are needed. Romero-García et al. (2016) uses enzymes for the valorisation of leaves, the price of the enzymes is unknown for the author. For the digesters microorganisms are needed to feed on the OMSW and produce biogas, only a small colony is needed since they can be self-sustainable if the conditions remain optimal.

The use of chemicals for the valorisation of waste biomass might not be most sustainable process. Some type of chemicals can be harmful for the environment or are produced using eco-unfriendly processes. In this research it is assumed all processes are not harmful for the environment, however if this assumption is true for the input materials also needs to be investigated.

The biorefineries in these models can only handle one type of feedstock, however, in this scenario it would be more interesting to have biorefineries that can handle multiple types of feedstock. These biorefineries that can handle different type of feedstock are called phase-III biorefineries (Michels and Wagemann, 2010). The single processes of valorising a single feedstock are used on an industrial scale, however, the of integration of these processes is difficult to achieve. Since no technical and economic data could be found on phase-III biorefineries it is not included in the model (Michels and Wagemann, 2010). Phase-III biorefineries could have a significant impact on the valorisation of waste biomass due to their flexibility of accepting feedstock. This flexibility could ensure that the biorefinery is always utilized to its maximum capacity.

In the current model, the capacity of some biorefineries is higher than their input in the first few years. This larger capacity is to ensure it can handle the growing amount of waste biomass in the future. However, this overcapacity is unwanted, since utilizing the biorefinery to the fullest is economically more interesting unless your variable cost per kilogram of waste biomass is higher than your profit per kilogram of waste biomass. However, in that scenario the biorefinery is economically infeasible. Thus it is more likely in a real-life scenario the left-over capacity will be eliminated by providing extra feedstock.

In the model the biomass available from the municipalities green spaces and inhabitants of Amsterdam is available. However waste biomass from industries in Amsterdam could also be used in biorefineries, since in some scenarios there is an overcapacity for the biorefineries. An overview of the available waste biomass from industries could give insight into whether these streams could be included. If waste from industries is used correctly, it could increase the economic feasibility of some biorefineries.

In addition, all waste that is treated in the model is assumed to be of good enough quality to process. If waste biomass is stored too long, the chemical properties of the biomass changes due to the growth of microbial organisms who feed on biomass (Sánchez, 2009). Thus waste biomass that is harvest needs to be processed as soon as possible to maintain the quality of the biomass. The effect of low-quality waste biomass for valorisation in a biorefinery is not been researched. Buijzer et al. (2015) mentions that some waste biomass is not suitable for valorisation due to its low-quality, this waste biomass is not included in the model. Buijzer et al. (2015) does not specify why it is not applicable for valorisation.

For the valorisation of waste leaves it is assumed that the composition of the leaves is similar to sugar beet and olive tree leaves. This assumption was made since no literature about the usage of a biorefinery to valorise waste leaves was found by the researcher. To include the valorisation of waste leaves, techniques that valorise other types of leaves was investigated. Sariyildiz and Anderson (2005) mentioned that there is a large variation between fresh leaves and waste leaves, where the composition of waste leaves show low values for cellulose, hemicellulose and lignin due to decomposition. In addition the composition of waste leaves is dependent the species of tree, collection methods and weather prior to collection, storage of the leaves and the contamination by impurities (Heckman and Kluchinski, 1996; Pňakovič and Dzurenda, 2015). Since the valorisation of waste leaves only showed economic feasibility in the good scenario, assuming the waste leaves have a high-quality composition, it is unlikely valorisation of waste leaves is worth further investigation.

The model operates in an island mode, which means there is no interaction between Amsterdam and other cities. The pprofitability of refineries might increase if the waste biomass of surrounding areas is also included.

Perhaps farmland near Amsterdam could use the grass refinery to process their grass into higher valued products. The import of biomass from further areas is not always economically interesting due to the transportation cost.

Transportation cost in the biobased economy can be of influence on the economic feasibility of certain technologies (Langeveld et al., 2012). In this model transportation has been left out since in the city of Amsterdam waste biomass is already collected, indicating collection for waste biomass shows no issues (Ekşioğlu et al., 2009). It is assumed that this collection is similar to what is needed for the valorisation of the waste biomass. However, the location of current waste treatment facilities might not be optimal for biorefineries since these processes need different conditions than waste treatment facilities. Furthermore, the chemicals of biorefineries might not be allowed to be transported in certain areas of the city (Adriaansen, 2006). By creating a logistic model that can cooperate with the current model, suitable locations for the biorefineries can be found.

The research on the biorefineries is from different countries, but the cost of a biorefinery is dependent on their location (Bünger, 2012). Only accurate measurements for a specific biorefinery can be performed if also the location is known. Many assumptions made for the investment cost of a biorefinery are different among countries. One of these assumptions is that the location factor is similar to the Netherlands as the USA, this factor is used for the calculation of the CEPCI (Wright and Brown, 2007).

For the prices changes of the biorefineries over the years different parameters are applied. The CEPCI is a price index used for the price prediction and comparison of chemical plants. In this study this index is applied for biorefineries, if this index can be used for this purpose has not been investigated. A biorefinery could be categorised as a chemical plant, Gargalo et al. (2016b) used it for the economic evaluation of different biorefineries. In addition, the accuracy of the prediction of CEPCI decreases over time making it less reliable (Mignard, 2014).

When looking at the CEPCI of the different scenarios, given in Appendix D, it is shown that the CEPCI for the benchmark scenario starts lower than the good scenario. Around the year 2040 the benchmark scenario overtakes the good scenario. This seems unlikely since an higher CEPCI indicates an higher cost of biorefineries. In the good scenario it is expected that the CEPCI is the lowest. This is the result of the price of oil, which in the good scenario is high since that is beneficial for a biobased economy. However it causes the CEPCI to increase, thus has negative influence on the cost of biorefineries.

Since cost parameters for biorefineries are mostly unknown due to the low technical readiness level of most technologies, cost parameters of other sectors are applied. Some of the references for cost parameters are from research about the bio-energy and oil-refinery sectors, since those are closely related to the biorefinery sector. Bio-energy consists also of technologies that use waste biomass for the production of electricity, while the technique of oil-refinery is closely related to the biorefinery sector (Cherubini, 2010; Jiang et al., 2017).

In the model salvage value of biorefineries for whom the lifetime has exceeded is not included. Determining the salvage value is difficult when the salvage value is minimal it can be included in the depreciation and assumed that it is zero when reaching its lifetime. However the salvage value of the biorefineries is unknown, thus assumed to be zero. This assumption is based on that the cost decommissioning a biorefinery is equal to its salvage value.

The learning rate is given exogenously to the model, where a fixed value is given for each year. In industry-learning it is known that these values can be volatile and uncertain, thus prediction is problematic (Daugaard et al., 2015). Furthermore, from theory the learning factor is linked with the cumulative production. The learning effect describes how cost reduces due to production experience, the sum of production describes this experience. In this model the learning rate is given exogenously instead of being a function of production. The reason is that production in our model only takes place in the city of Amsterdam, while outside our boundary also biorefineries might be constructed that influence the learning factor (Junginger et al., 2006). Since these are not included, the learning effect cannot be an accurate function of production within this model.

A maximum conversion efficiency is given to the model, based on the assumption perfect conversion is not feasible. The conversion of waste biomass is gradually increased to reflect the improvement in the technologies of biorefineries. However, the theoretical maximum efficiency for the different technologies is not used in this research since it is unknown. Since some of the products valorised from the waste biomass are dependent on the chemical components in the biomass a theoretical maximum efficiency can be derived. Since the literature from which the biorefinery technologies are derived do not discuss these maximum efficiencies it is decided to fix it at 95%.

In the research of Ros (2017) the conversion of grass into value added products an efficiency of 100% was used. Since the maximum conversion efficiency in this research was assumed to be 95%, the conversion described in Ros (2017) was adjusted by multiplying the conversion efficiency with 0.95.

Currently the city of Amsterdam does not separate all of its waste biomass. It is assumed that is changed in the year 2020, however extra investments might be needed to achieve separation. These costs have not been included in the model and might influence the economic feasibility of some biorefineries. Especially separating the garden waste can be problematic.

In the current model the garden waste consists of four different categories as seen in Table 13. It is assumed in the small fraction a portion is leaves and grass, the rest of the fraction is combined with the OMSW. However, this small fraction might also include stones and sand, heavy materials that are not applicable in the technologies for valorising the OMSW (Boldrin and Christensen, 2010). Since the quantity of garden waste that is not valid for valorising is unknown it is assumed all garden waste is appropriate for refining.

From the digester for the valorisation of OMSW only a small fraction is processed, a large fraction of the OSMW becomes residue. This residue could have other application, from digesters digestate is a by-product that can be used as a fertilizer. However, legislation prevents digestate from OMSW to be utilized in the agricultural sector. Dactech Milieu et al. (1992) mentions that this digestate holds no monetary value.

Van Dael et al. (2014) a research about the valorisation of waste biomass was also conducted. In that research it was concluded that also OMSW was not profitable, as solution an extra step to valorise the biogas was introduced. In this research only the first process step of converting the waste biomass into a product was conducted. The output of products can be valorized into higher valued products, this might make the valorization process economically feasible as in Van Dael et al. (2014). Extra operating units for the conversion of products have not been included into this model. It was assumed the price of the commodity would reflect the opportunity cost of valorizing it into a higher valued product.

Currently OMSW is processed in digester to produce biogas even though our results show this is not economically profitable. However, in our model only the OMSW from the city of Amsterdam is used in the digester, current practices for the processing of OMSW also include waste biomass from other municipalities. Since larger quantities of OMSW are processed economy of scale has a positive influence on the economic profitability. In addition, subsidies are available for the production of biogas from OMSW, increasing the economic viability of digesters (Beumer and Verbong, 2005; Peene et al., 2011). These subsidies are not included into this model.

OMSW shows much variation in its composition, due to seasonal variation but also origin. Hanc et al. (2011) shows that OMSW has a different composition when coming from apartment than houses. Since the city of Amsterdam has both types of housing, for this model it is assumed that the composition is as described in Rajendran et al. (2014), since they designed the valorisation of the OMSW from households. However, it is unknown if the composition of OMSW in the city of Amsterdam is identical as in Rajendran et al. (2014). Furthermore, seasonal variation has an influence on the composition of OMSW (Boldrin and Christensen, 2010). However since the model uses time steps of one year, seasons are not included.

The influence of a smaller time step in the model is not investigated. From the sensitivity analysis it can be concluded that the time step of one year causes non-linear results. A smaller time-step might solve this non-linearity in the sensitivity analysis. How this will affect the results cannot be concluded, the hypothesis is that the NPV would increase. More flexibility in the dates of commissioning a biorefinery could result in cost reduction. The biorefinery does not need to be commissioned at the beginning of the year, but when required in the year. Therefore the utilisation of the biorefinery is better since it might be low at the beginning of a year. Furthermore, the effect of seasonal variation in the waste biomass could be included in the model.

Syngas is not included as a viable option for the valorisation of waste biomass. It is decided to not include it due to the production method of syngas, where the complex molecular structures of waste biomass are broken down. Syngas is not a circular production method, therefore not included in the model. In addition, it is not expected that syngas will have an impact on the valorisation for biomass in the next 30 years (Haveren et al., 2008).

The calculation of the NPV is performed by adding the discounted cash flows of the year 2020 until 2050. However, the model is set to maximize the NPV until 2070, due to the end of time horizon effect. The cash flows after 2050 are disregarded, however they influence the objective function since they are included. It was tested if changing the objective function to maximize the NPV until 2050 and let the model run until 2070, however, due to the relaxation of constraint equation 3 the model decided to not valorise any waste biomass anymore after 2050. Therefore it is decided to maximize the NPV until 2070 and only to investigate the NPV until 2050. If the NPV is negative, it is assumed to be zero, since a negative NPV indicates economic infeasibility thus would not be financed.

From the sensitivity analysis the profitability of the valorisation of waste biomass is mostly dependent on the discount factor. This parameter represents the trade-off between risk and reward of investing into processing waste biomass. The parameter is subjective for investors, indicating no “true” value exists. This subjectivity can influence the incentive of policy makers to participate in a biobased economy.

Tsiropoulos et al. (2017) estimated that the total production of biochemicals could be 1.1 Mt in the year 2020 for the Netherlands. The total amount of products valorised from the waste biomass could reach up to 0.3%

however, this result is low since only grass is valorised in the year 2020 for all scenarios. When applying the year in which the most waste biomass is valorised the most efficient it could account for 1.6% of the total production of biochemicals. This figure might seem low, however the study of Tsiropoulos et al. (2017) investigates all biomass, the waste biomass from the city of Amsterdam is only a small fraction but can still have an impact. In addition globally the population of cities is increasing, other cities might have even bigger impact on the biobased economy (Angel et al., 2011).

8. Conclusion

In this study a technical and economic analysis of the potential of valorising urban biomass waste streams into high value products is performed. The objective of the research was to find the most economically advantageous use of the waste biomass for the forthcoming decennia. As case study the city of Amsterdam is chosen, it's one of the global leaders in making its city sustainable, from the city four different waste biomass are processed: wood, grass, leaves and OMSW. The four processing technologies in this case study are: wood refineries, grass refineries, leaves refineries and digesters.

In all scenarios the economic profitability of valorising wood and grass were positive, indicating that investment into these technologies is worthwhile. For the valorisation of leaves and OMSW more incentives are needed to make them economic profitable. The main issue for the valorisation of leaves is the low quantity in combination with high investment cost, causing for an unprofitable concept. The processing of OMSW is unprofitable due to its low conversion efficiency, resulting in a low revenue that cannot cover the costs. For all four cases the small-scale biorefineries have negative influence on the NPV, when processing large quantities of biomass benefits from economy of scale can be achieved.

It was shown that whether waste biomass was processed was not much influenced by the different scenarios, only the year in which the valorisation started shifted. However, there was a difference among the size of the NPV between the different scenarios, thus indicating that a good scenario could stimulate the investment in valorising urban waste biomass.

To conclude it is shown that valorising urban waste biomass shows potential for the city of Amsterdam. The methodological framework proposed in this theses can help policy-makers in the decision-making of the allocation of urban waste biomass streams in the future. The result showed that the usage of waste biomass for the biobased economy is promising.

9. References

Adriaansen, S. 2006. Vervoer gevaarlijke stoffen en stedelijke ontwikkeling: een spanningsveld. *Externe Veiligheid. Jaargang* 3.

Advokaat, W., J. van Cruchten, J. Gouweleeuw, E. Nordholt, and W. Weltens. 2005. Loon naar beroep en opleidingsniveau: het Loonstructuuronderzoek 2002. *Sociaal-economische Trends, Statistics Netherlands, The Hague*.

Afvalregistratie, W. 2016. Afvalverwerking in Nederland, Gegevens 2016. *AgentschapNL, Werkgroep Afvalregistratie*.

Ahmed, S. 2013. Looking at Possible Future Change: Biochar Deployment Scenario for UK in 2030.

Akeson, W. R., and M. A. Stahmann. 1965. Leaf Proteins as Foodstuffs, Nutritive Value of Leaf Protein Concentrate, an In Vitro Degestion Study. *Journal of Agricultural and Food Chemistry* 13(2):145-148.

Angel, S., J. Parent, D. L. Civco, A. Blei, and D. Potere. 2011. The dimensions of global urban expansion: Estimates and projections for all countries, 2000–2050. *Progress in Planning* 75(2):53-107.

Angenent, L. T., K. Karim, M. H. Al-Dahhan, B. A. Wrenn, and R. Domíguez-Espinosa. 2004. Production of bioenergy and biochemicals from industrial and agricultural wastewater. *TRENDS in Biotechnology* 22(9):477-485.

Antes, M., S. Yeh, and M. Berkenpas. 2005. Estimating future trends in the cost of CO2 capture technologies. *Final report to IEA GHG R&D Program*.

Arancon, R. A. D., C. S. K. Lin, K. M. Chan, T. H. Kwan, and R. Luque. 2013. Advances on waste valorization: new horizons for a more sustainable society. *Energy Science & Engineering* 1(2):53-71.

Bals, B., and B. E. Dale. 2011. Economic comparison of multiple techniques for recovering leaf protein in biomass processing. *Biotechnology and bioengineering* 108(3):530-537.

Balu, A. M., V. Budarin, P. S. Shuttleworth, L. A. Pfaltzgraff, K. Waldron, R. Luque, and J. H. Clark. 2012. Valorisation of orange peel residues: waste to biochemicals and nanoporous materials. *ChemSusChem* 5(9):1694-1697.

Bastein, A., J. Verstraeten-Jochemsen, E. Rietveld, M. Hauck, E. Frijters, O. Klijn, and B. Driessen. 2016. Circular Amsterdam. A vision and action agenda for the city and metropolitan area.

Betschart, A., and J. E. Kinsella. 1973. Extractability and solubility of leaf protein. *Journal of agricultural and food chemistry* 21(1):60-65.

Beumer, G., and G. Verbong. 2005. *Co-vergisting op boerderijschaal in Nederland: Een verkennende studie naar implementatie*. Technische Universiteit Eindhoven.

Boldrin, A., and T. H. Christensen. 2010. Seasonal generation and composition of garden waste in Aarhus (Denmark). *Waste management* 30(4):551-557.

Boosten, M., and J. Oldenburger. 2014. *Biomassapotentieel NBLH-sector in 2020 en 2050*. Stichting Probos.

Bos-Brouwers, H., H. Langelaan, J. Sanders, M. van Dijk, and A. van Vuuren. 2012. Chances for biomass: Integrated valorisation of biomass resources. Wageningen UR.

Brandes, E. 2016. Nieuw platform voor reststoffen en duurzame innovaties. Duurzaam bedrijfsleven.

Bridgwater, A. V. 2003. Renewable fuels and chemicals by thermal processing of biomass. *Chemical Engineering Journal* 91(2):87-102.

Brownbridge, G., P. Azadi, A. Smallbone, A. Bhave, B. Taylor, and M. Kraft. 2014. The future viability of algae-derived biodiesel under economic and technical uncertainties. *Bioresource Technology* 151:166-173.

Buijzer, E. d., T. v. d. Brand, E. Versteeg, J. Hofman, and K. Roest. 2015. Terugwinnen van energie en grondstoffen in de regio Amsterdam.

Bünger, M. 2012. Breaking the Model: Why Most Assessments of Biobased Materials and Chemicals Costs Are Wrong. *Industrial Biotechnology* 8(5):272-274.

Carrier, M., A. Loppinet-Serani, D. Denux, J.-M. Lasnier, F. Ham-Pichavant, F. Cansell, and C. Aymonier. 2011. Thermogravimetric analysis as a new method to determine the lignocellulosic composition of biomass. *Biomass and Bioenergy* 35(1):298-307.

Carus, M., L. Dammer, A. Hermann, and R. Essel. 2014. Proposals for a reform of the Renewable Energy Directive to a Renewable Energy and Materials Directive (REMD). *Going to the next level: Integration of bio-based chemicals and materials in the incentive scheme. Nova paper*(4):2014-2005.

CBS Statline. 2016. Consumentenprijzen; inflatie vanaf 1963. 2016.

Cheali, P., J. A. Posada, K. V. Gernaey, and G. Sin. 2015. Upgrading of lignocellulosic biorefinery to value-added chemicals: Sustainability and economics of bioethanol-derivatives. *Biomass and Bioenergy* 75:282-300.

Chen, X., M. Khanna, and S. Yeh. 2012. Stimulating learning-by-doing in advanced biofuels: effectiveness of alternative policies. *Environmental Research Letters* 7(4):045907.

Cherubini, F., G. Jungmeier, M. Mandl, C. Philips, M. Wellisch, H. Jrgensen, I. Skiadas, L. Boniface, M. Dohy, and J.-C. Pouet. 2007. IEA Bioenergy Task 42 on Biorefineries: Co-production of fuels, chemicals, power and materials from biomass. In *IEA Bioenergy Task*, 1-37.

Cherubini, F. 2010. The biorefinery concept: Using biomass instead of oil for producing energy and chemicals. *Energy Conversion and Management* 51(7):1412-1421.

Cok, B., I. Tsiropoulos, A. L. Roes, and M. K. Patel. 2014. Succinic acid production derived from carbohydrates: An energy and greenhouse gas assessment of a platform chemical toward a bio‐ based economy. *Biofuels, Bioproducts and Biorefining* 8(1):16-29.

Collinson, S., and W. Thielemans. 2010. The catalytic oxidation of biomass to new materials focusing on starch, cellulose and lignin. *Coordination chemistry reviews* 254(15):1854-1870.

CVB, F. T. 2011. Centraal Veevoederbureau. *Lelystad, The Netherlands*.

D'Hondt, E., and S. Voorspoels. 2012. Maximising value making the most of biowaste. *Waste Management World Jan. ÀFeb., 19À21*.

Dactech Milieu, Systems Organic Waste, and Vam. 1992. *De verwerking van Nederlands GFT-afval op een DRANCO-installatie : droge anaërobe conversieproef met gescheiden ingezameld, opgewerkt GFT-afval uit Nederland op de DRANCO demonstratie-installatie te Gent, Belgie*. Utrecht: Dactech Milieu.

Daioglou, V., B. Wicke, A. P. Faaij, and D. P. Vuuren. 2015. Competing uses of biomass for energy and chemicals: Implications for long‐ term global CO2 mitigation potential. *Gcb Bioenergy* 7(6):1321-1334.

Daugaard, T., L. A. Mutti, M. M. Wright, R. C. Brown, and P. Componation. 2015. Learning rates and their impacts on the optimal capacities and production costs of biorefineries. *Biofuels, Bioproducts and Biorefining* 9(1):82-94.

de Melo, M. M., H. M. Barbosa, C. P. Passos, and C. M. Silva. 2014. Supercritical fluid extraction of spent coffee grounds: measurement of extraction curves, oil characterization and economic analysis. *The Journal of Supercritical Fluids* 86:150-159.

Demirbaş, A. 2001. Biomass resource facilities and biomass conversion processing for fuels and chemicals. *Energy conversion and Management* 42(11):1357-1378.

Didde, R. 2017. Schillen scheiden in de stad: Amsterdam lukt het wél. In *Volkskrant*.

Dornburg, V., A. Faaij, M. Patel, and W. Turkenburg. 2006. Economics and GHG emission reduction of a PLA bio-refinery system—Combining bottom-up analysis with price elasticity effects. *Resources, conservation and recycling* 46(4):377-409.

Dornburg, V., B. G. Hermann, and M. K. Patel. 2008. Scenario projections for future market potentials of biobased bulk chemicals. ACS Publications.

Dugmore, T. 2014. Food waste: a new biorefinery feedstock. *Food Science & Technology* 28(3):22-24.

EC. 2015. Intended Nationally Determined Contribution of the EU and its Member States pp. 1–5. E. C. (EC), ed. Riga, Lithuania.

EIA, U. 2015. Annual energy outlook 2015. *Washington DC: Energy Information Administration, United States Department of Energy*.

EIA, U. 2017. Annual energy outlook 2017 with projections to 2050. *Washington DC: Energy Information Administration, United States Department of Energy*.

Ekşioğlu, S. D., A. Acharya, L. E. Leightley, and S. Arora. 2009. Analyzing the design and management of biomass-to-biorefinery supply chain. *Computers & Industrial Engineering* 57(4):1342-1352.

Eriksson, L., and L. Gustavsson. 2010. Comparative analysis of wood chips and bundles – Costs, carbon dioxide emissions, dry-matter losses and allergic reactions. *Biomass and Bioenergy* 34(1):82-90.

Farag, S., and J. Chaouki. 2015. Economics evaluation for on-site pyrolysis of kraft lignin to value-added chemicals. *Bioresource technology* 175:254-261.

Fargione, J., J. Hill, D. Tilman, S. Polasky, and P. Hawthorne. 2008. Land clearing and the biofuel carbon debt. *Science* 319(5867):1235-1238.

Fitamo, T., L. Treu, A. Boldrin, C. Sartori, I. Angelidaki, and C. Scheutz. 2017. Microbial population dynamics in urban organic waste anaerobic co-digestion with mixed sludge during a change in feedstock composition and different hydraulic retention times. *Water Research* 118:261-271.

Fornasiero, P., and M. Graziani. 2011. *Renewable resources and renewable energy: a global challenge*. CRC press.

Garcia-Maraver, A., D. Salvachúa, M. J. Martínez, L. F. Diaz, and M. Zamorano. 2013. Analysis of the relation between the cellulose, hemicellulose and lignin content and the thermal behavior of residual biomass from olive trees. *Waste Management* 33(11):2245-2249.

Gargalo, C. L., A. Carvalho, K. V. Gernaey, and G. Sin. 2016a. A framework for techno-economic & environmental sustainability analysis by risk assessment for conceptual process evaluation. *Biochemical engineering journal* 116:146-156.

Gargalo, C. L., P. Cheali, J. A. Posada, K. V. Gernaey, and G. r. Sin. 2016b. Economic risk assessment of early stage designs for glycerol valorization in biorefinery concepts. *Industrial & Engineering Chemistry Research* 55(24):6801-6814.

GB Minerals. 2018. http://www.gbminerals.com/phosphate/phosphate_prices/: GB Minerals LTD. Accessed 25-02-2018.

Gemeente Amsterdam. 2017. Bevolkingsprognose 2016: Meer groei door woningbouw. Gemeente Amsterdam.

Gerloff, E. D., I. H. Lima, and M. A. Stahmann. 1965. Leaf proteins as foodstuffs, amino acid composition of leaf protein concentrates. *Journal of Agricultural and Food Chemistry* 13(2):139-143.

Gielen, D., M. De Feber, A. Bos, and T. Gerlagh. 2001. Biomass for energy or materials?: A Western European systems engineering perspective. *Energy policy* 29(4):291-302.

Gómez, A., J. Zubizarreta, M. Rodrigues, C. Dopazo, and N. Fueyo. 2010. Potential and cost of electricity generation from human and animal waste in Spain. *Renewable Energy* 35(2):498-505.

Gonzalez, R., T. Treasure, R. Phillips, H. Jameel, D. Saloni, R. Abt, and J. Wright. 2011. Converting Eucalyptus biomass into ethanol: Financial and sensitivity analysis in a co-current dilute acid process. Part II. *Biomass and Bioenergy* 35(2):767-772.

Grass, S. 2004. Utilisation of grass for production of fibres, protein and energy. *Biomass and agriculture: sustainability, markets and policies. Biomass Project Services, Switzerland*:169-177.

Gray, K. A., L. Zhao, and M. Emptage. 2006. Bioethanol. *Current opinion in chemical biology* 10(2):141-146.

Groen Gas Nederland. 2015. Financieringsmogelijkheden voor biogasprojecten.

Guerrero, L. A., G. Maas, and W. Hogland. 2013. Solid waste management challenges for cities in developing countries. *Waste management* 33(1):220-232.

H Clark, J., F. EI Deswarte, and T. J Farmer. 2009. The integration of green chemistry into future biorefineries. *Biofuels, Bioproducts and Biorefining* 3(1):72-90.

Hanc, A., P. Novak, M. Dvorak, J. Habart, and P. Svehla. 2011. Composition and parameters of household bio-waste in four seasons. *Waste management* 31(7):1450-1460.

Haveren, J. v., E. L. Scott, and J. Sanders. 2008. Bulk chemicals from biomass. *Biofuels, Bioproducts and Biorefining* 2(1):41-57.

Hayes, D. J., S. Fitzpatrick, M. H. Hayes, and J. R. Ross. 2006. The biofine process–production of levulinic acid, furfural, and formic acid from lignocellulosic feedstocks. *Biorefineries–Industrial Processes and Product* 1:139-164.

Heckman, J., and D. Kluchinski. 1996. Chemical composition of municipal leaf waste and hand-collected urban leaf litter. *Journal of environmental quality* 25(2):355-362.

Henrich, E., N. Dahmen, and E. Dinjus. 2009. Cost estimate for biosynfuel production via biosyncrude gasification. *Biofuels, Bioproducts and Biorefining* 3(1):28-41.

Honkoop, W. A., Bas. 2015. Verkenning mogelijkheden betere nutriënten benutting, en lagere kosten met GRASSA! In *PPP Agro Advies*.

Iakovou, E., A. Karagiannidis, D. Vlachos, A. Toka, and A. Malamakis. 2010. Waste biomass-to-energy supply chain management: a critical synthesis. *Waste management* 30(10):1860-1870.

ICIS. 2018. https://www.icis.com/chemicals/channel-info-chemicals-a-z/. Accessed 24-02-2018.

IPCC. 2014. Climate change 2014 synthesis report.

Jiang, Y., E. van der Werf, E. C. van Ierland, and K. J. Keesman. 2017.

Junginger, H. M. 2005. *Learning in renewable energy technology development*. Utrecht University.

Junginger, M., E. de Visser, K. Hjort-Gregersen, J. Koornneef, R. Raven, A. Faaij, and W. Turkenburg. 2006. Technological learning in bioenergy systems. *Energy Policy* 34(18):4024-4041.

Junqueira, T. L., M. F. Chagas, V. L. Gouveia, M. C. Rezende, M. D. Watanabe, C. D. Jesus, O. Cavalett, A. Y. Milanez, and A. Bonomi. 2017. Techno-economic analysis and climate change impacts of sugarcane biorefineries considering different time horizons. *Biotechnology for biofuels* 10(1):50.

Kenniscentrum, B. 2005. *BBT voor composteer-en vergistingsinstallaties*. Academia Press.

Kim, S., and B. E. Dale. 2003. Cumulative energy and global warming impact from the production of biomass for biobased products. *Journal of Industrial Ecology* 7(3- 4):147-162.

Klop, A., J. Zonderland, and G. de Haan. 2012. Grasraffinage: gras door de mangel halen. *V-focus* 9(2):34-35.

Kothari, R., V. Tyagi, and A. Pathak. 2010. Waste-to-energy: A way from renewable energy sources to sustainable development. *Renewable and Sustainable Energy Reviews* 14(9):3164-3170.

Koutinas, A. A., A. Vlysidis, D. Pleissner, N. Kopsahelis, I. L. Garcia, I. K. Kookos, S. Papanikolaou, T. H. Kwan, and C. S. K. Lin. 2014. Valorization of industrial waste and by-product streams via fermentation for the production of chemicals and biopolymers. *Chemical Society Reviews* 43(8):2587-2627.

Kranert, M., R. Gottschall, C. Bruns, and G. Hafner. 2010. Energy or compost from green waste?–A CO 2–based assessment. *Waste Management* 30(4):697-701.

Lammens, T., M. Franssen, E. Scott, and J. Sanders. 2012. Availability of protein-derived amino acids as feedstock for the production of bio-based chemicals. *biomass and bioenergy* 44:168-181.

Langeveld, H., J. Sanders, and M. Meeusen. 2012. *The biobased economy: Biofuels, materials and chemicals in the post-oil era*. Earthscan.

Laure, S., M. Leschinsky, M. Fröhling, F. Schultmann, and G. Unkelbach. 2014. Assessment of an organosolv lignocellulose biorefinery concept based on a material flow analysis of a pilot plant. *Cellul Chem Technol* 48(9-10):793-798.

Lay, J.-J., Y.-J. Lee, and T. Noike. 1999. Feasibility of biological hydrogen production from organic fraction of municipal solid waste. *Water Research* 33(11):2579-2586.

Levin, D. B., H. Zhu, M. Beland, N. Cicek, and B. E. Holbein. 2007. Potential for hydrogen and methane production from biomass residues in Canada. *Bioresource Technology* 98(3):654-660.

Lin, C. B. 2011. High polymer prices make PLA an attractive alternative. In *ICIS News*. Independent Chemical Information Service.

Lin, C. S. K., L. A. Pfaltzgraff, L. Herrero-Davila, E. B. Mubofu, S. Abderrahim, J. H. Clark, A. A. Koutinas, N. Kopsahelis, K. Stamatelatou, and F. Dickson. 2013. Food waste as a valuable resource for the production of chemicals, materials and fuels. Current situation and global perspective. *Energy & Environmental Science* 6(2):426-464.

Lozowski, D., G. Ondrey, S. Jenkins, and M. Bailey. 2016. Chemical engineering plant cost index (CEPCI). *Chem Eng* 119:84.

Lundgren, J., and J. Helmerius. 2009. Integration of a hemicellulose extraction process into a biomass based heat and power plant. In *International Conference on Efficiency, Cost, Optimisation, Simulation and Environmental Impact of Energy Systems: 31/08/2009-03/09/2009*. ABCM, Brazilian Society of Mechanical Sciences and Engineering.

Maity, S. K. 2015. Opportunities, recent trends and challenges of integrated biorefinery: Part I. *Renewable and Sustainable Energy Reviews* 43:1427-1445.

Manesh, A., K. Tabrizi, and T. Yang. 2013. Lignin and Economics of Lignocellulosic Biomass Fractionation. American Science Technology. BioRen Chemical.

Mata-Alvarez, J. 2002. *Biomethanization of the organic fraction of municipal solid wastes*. IWA publishing.

McAloon, A., F. Taylor, W. Yee, K. Ibsen, and R. Wooley. 2000. Determining the cost of producing ethanol from corn starch and lignocellulosic feedstocks. National Renewable Energy Lab., Golden, CO (US).

Mellichamp, D. A. 2013. New discounted cash flow method: Estimating plant profitability at the conceptual design level while compensating for business risk/uncertainty. *Computers & Chemical Engineering* 48:251-263.

Meyer, H. P., and O. Werbitzky. 2010. *How green can the industry become with biotechnology*. John Wiley & Sons Inc.: Hoboken, NJ.

Michels, J., and K. Wagemann. 2010. The German lignocellulose feedstock biorefinery project. *Biofuels, Bioproducts and Biorefining* 4(3):263-267.

Mignard, D. 2014. Correlating the chemical engineering plant cost index with macro-economic indicators. *Chemical Engineering Research and Design* 92(2):285-294.

Miller, S. A., A. E. Landis, and T. L. Theis. 2007. Feature: Environmental trade-offs of biobased production. ACS Publications.

Morone, P., F. Papendiek, and V. E. Tartiu. 2017. Food Waste Reduction and Valorisation.

Mtui, G. Y. 2009. Recent advances in pretreatment of lignocellulosic wastes and production of value added products. *African Journal of Biotechnology* 8(8).

Münster, M., and P. Meibom. 2011. Optimization of use of waste in the future energy system. *Energy* 36(3):1612-1622.

Neij, L., P. D. Andersen, M. Durstewitz, P. Helby, M. Hoppe-Kilpper, and P. E. Morthorst. 2003. *Experience curves: a tool for energy policy assessment*. Environmental and Energy Systems Studies, Univ.

NETL. 2013. Technology Learning Curve FOAK to NOAK. U. S. d. o. e. National Energy Technology Laboratory, ed.

Nizami, A., M. Rehan, M. Waqas, M. Naqvi, O. Ouda, K. Shahzad, R. Miandad, M. Khan, M. Syamsiro, and I. Ismail. 2017. Waste biorefineries: enabling circular economies in developing countries. *Bioresource technology* 241:1101-1117.

Nowicki, P., M. Banse, C. Bolck, H. Bos, and E. Scott. 2008. Biobased economy: State-of-the-art assessment. LEI.

O'Keeffe, S., R. Schulte, J. Sanders, and P. Struik. 2011. I. Technical assessment for first generation green biorefinery (GBR) using mass and energy balances: Scenarios for an Irish GBR blueprint. *Biomass and bioenergy* 35(11):4712-4723.

Pande, M., and A. N. Bhaskarwar. 2012. Biomass conversion to energy. In *Biomass Conversion*, 1-90. Springer.

Pandey, M. P., and C. S. Kim. 2011. Lignin depolymerization and conversion: a review of thermochemical methods. *Chemical Engineering & Technology* 34(1):29-41.

Peene, A., F. Velghe, and I. Wierinck. 2011. Evaluatie van de vergisters in Nederland. *OWS en AgentschapNL*.

Pérez, J., J. Muñoz-Dorado, T. de la Rubia, and J. Martínez. 2002. Biodegradation and biological treatments of cellulose, hemicellulose and lignin: an overview. *International Microbiology* 5(2):53-63.

Peters, M. S., K. D. Timmerhaus, R. E. West, K. Timmerhaus, and R. West. 2012. *Plant design and economics for chemical engineers*. McGraw-Hill New York.

Pettersen, R. C. 1984. The chemical composition of wood. ACS Publications.

Pňakovič, Ľ., and L. Dzurenda. 2015. Combustion characteristics of fallen fall leaves from ornamental trees in city and forest parks. *BioResources* 10(3):5563-5572.

Poincet, T., and K. Parris. 2004. Biomass and Agriculture. Sustainability, Markets and Policies. OECD-report.

Rajendran, K., H. R. Kankanala, R. Martinsson, and M. J. Taherzadeh. 2014. Uncertainty over techno-economic potentials of biogas from municipal solid waste (MSW): a case study on an industrial process. *Applied Energy* 125:84-92.

Raven, R. 2007. Co-evolution of waste and electricity regimes: multi-regime dynamics in the Netherlands (1969–2003). *Energy Policy* 35(4):2197-2208.

Remer, D. S., S. Lin, N. Yu, and K. Hsin. 2008. An update on cost and scale-up factors, international inflation indexes and location factors. *International Journal of Production Economics* 114(1):333-346.

Romero-García, J., A. Sanchez, G. Rendón-Acosta, J. Martínez-Patiño, E. Ruiz, G. Magaña, and E. Castro. 2016. An olive tree pruning biorefinery for co-producing high value-added bioproducts and biofuels: economic and energy efficiency analysis. *BioEnergy Research* 9(4):1070-1086.

Ros, N. N. 2017. The potential of a circular grass refinery supply chain in the Netherlands.

Rowell, R. M., R. Pettersen, J. S. Han, J. S. Rowell, and M. A. Tshabalala. 2005. Cell wall chemistry. *Handbook of wood chemistry and wood composites. Boca Raton, Fla.: CRC Press, 2005: pages 35-74.*

Royal Haskoning. 2014. Marktverkenning Biobased Economy in De GFT-Sector. HaskoningDHV Nederland B.V.

Sánchez, C. 2009. Lignocellulosic residues: biodegradation and bioconversion by fungi. *Biotechnology advances* 27(2):185-194.

Sanders, J., E. Scott, R. Weusthuis, and H. Mooibroek. 2007. Bio‐ refinery as the bio‐ inspired process to bulk chemicals. *Macromolecular bioscience* 7(2):105-117.

Sanders, J., J. Liere, and J. de Wilt. 2016. *Geraffineerd voeren*. Innovatie Agro & Natuur-Netwerkorganisatie voor grensverleggende vernieuwingen.

Sanders, J. P. M. 2014. Dicht bij huis meer rendement halen uit gras, maïs en andere eiwitbronnen Wageningen University and Research.

Sariyildiz, T., and J. M. Anderson. 2005. Variation in the chemical composition of green leaves and leaf litters from three deciduous tree species growing on different soil types. *Forest Ecology and Management* 210(1):303-319.

Saygin, D., D. J. Gielen, M. Draeck, E. Worrell, and M. K. Patel. 2014. Assessment of the technical and economic potentials of biomass use for the production of steam, chemicals and polymers. *Renewable and Sustainable Energy Reviews* 40:1153-1167.

Scarlat, N., J.-F. Dallemand, F. Monforti-Ferrario, and V. Nita. 2015. The role of biomass and bioenergy in a future bioeconomy: policies and facts. *Environmental Development* 15:3-34.

Schaidle, J. A., C. J. Moline, and P. E. Savage. 2011. Biorefinery sustainability assessment. *Environmental Progress & Sustainable Energy* 30(4):743-753.

Schievano, A., G. D'Imporzano, L. Malagutti, E. Fragali, G. Ruboni, and F. Adani. 2010. Evaluating inhibition conditions in high-solids anaerobic digestion of organic fraction of municipal solid waste. *Bioresource Technology* 101(14):5728-5732.

Schmidt, O., S. Padel, and L. Levidow. 2012. The bio-economy concept and knowledge base in a public goods and farmer perspective. *Bio-based and Applied Economics* 1(1):47-63.

Schneider, U. A., and B. A. McCarl. 2003. Economic potential of biomass based fuels for greenhouse gas emission mitigation. *Environmental and resource economics* 24(4):291-312.

Sharholy, M., K. Ahmad, G. Mahmood, and R. Trivedi. 2008. Municipal solid waste management in Indian cities–A review. *Waste management* 28(2):459-467.

Short, W., D. J. Packey, and T. Holt. 1995. A manual for the economic evaluation of energy efficiency and renewable energy technologies. National Renewable Energy Lab., Golden, CO (United States).

Sun, Y., X. Lu, S. Zhang, R. Zhang, and X. Wang. 2011. Kinetic study for Fe (NO 3) 3 catalyzed hemicellulose hydrolysis of different corn stover silages. *Bioresource technology* 102(3):2936-2942.

Sun, Z., M. Li, Q. Qi, C. Gao, and C. S. K. Lin. 2014. Mixed food waste as renewable feedstock in succinic acid fermentation. *Applied biochemistry and biotechnology* 174(5):1822-1833.

Teixeira, E. M. B., M. R. B. Carvalho, V. A. Neves, M. A. Silva, and L. Arantes-Pereira. 2014. Chemical characteristics and fractionation of proteins from Moringa oleifera Lam. leaves. *Food chemistry* 147:51-54.

Telek, L., and H. D. Graham. 1983. Leaf protein concentrates.

Tenorio, A. T. 2017. Sugar beet leaves for functional ingredients. Wageningen University.

Thrän, D. 2015. *Smart bioenergy: technologies and concepts for a more flexible bioenergy provision in future energy systems*. Springer.

Thumm, U., B. Raufer, and I. Lewandowski. 2014. Novel products from grassland (bioenergy & biorefinery). *The Future of European Grasslands*:429.

Tsiropoulos, I., R. Hoefnagels, S. de Jong, M. van den Broek, M. K. Patel, and A. P. Faaij. Utrecht University.

Tsiropoulos, I., R. Hoefnagels, M. Broek, M. K. Patel, and A. P. Faaij. 2017. The role of bioenergy and biochemicals in CO2 mitigation through the energy system–a scenario analysis for the Netherlands. *GCB Bioenergy*.

Tuck, C. O., E. Pérez, I. T. Horváth, R. A. Sheldon, and M. Poliakoff. 2012. Valorization of biomass: deriving more value from waste. *Science* 337(6095):695-699.

UN. 2014. World Urbanization Prospects: The 2014 Revision, Highlights. Department of Economic and Social Affairs. In *Population Division, United Nations*. U. Nations, ed.

Van Dael, M., N. Márquez, P. Reumerman, L. Pelkmans, T. Kuppens, and S. Van Passel. 2014. Development and techno-economic evaluation of a biorefinery based on biomass (waste) streams–case study in the Netherlands. *Biofuels, Bioproducts and Biorefining* 8(5):635-644.

van Meijl, J., I. Tsiropoulos, H. Bartelings, M. van den Broek, R. Hoefnagels, M. van Leeuwen, E. Smeets, A. Tabeau, and A. Faaij. 2016. *Macroeconomic outlook of sustainable energy and biorenewables innovations (MEV II)*. LEI Wageningen UR.

Vandermeulen, V., M. Van der Steen, C. V. Stevens, and G. Van Huylenbroeck. 2012. Industry expectations regarding the transition toward a biobased economy. *Biofuels, Bioproducts and Biorefining* 6(4):453-464.

Vimmerstedt, L., B. W. Bush, and S. O. Peterson. 2015. Dynamic Modeling of Learning in Emerging Energy Industries: The Example of Advanced Biofuels in the United States. In *The 33rd International Conference of the System Dynamics Society, Cambridge, Massachusetts, USA*.

Weymarn, N. 2002. *Process development for mannitol production by lactic acid bacteria*. Helsinki University of Technology.

Willauer, H. D., J. G. Huddleston, M. Li, and R. D. Rogers. 2000. Investigation of aqueous biphasic systems for the separation of lignins from cellulose in the paper pulping process. *Journal of Chromatography B: Biomedical Sciences and Applications* 743(1):127-135.

Win, D. T. 2005. Furfural-Gold from garbage. *Au J Technol* 8:185-190.

Wright, M. M., and R. C. Brown. 2007. Comparative economics of biorefineries based on the biochemical and thermochemical platforms. *Biofuels, Bioproducts and Biorefining* 1(1):49-56.

Zhang, C. 2016. Biorefinery of leafy biomass using green tea residue as a model material. Wageningen University.

Zhou, C.-H., X. Xia, C.-X. Lin, D.-S. Tong, and J. Beltramini. 2011. Catalytic conversion of lignocellulosic biomass to fine chemicals and fuels. *Chemical Society Reviews* 40(11):5588-5617.

Appendices

Appendix A. Population growth of Amsterdam

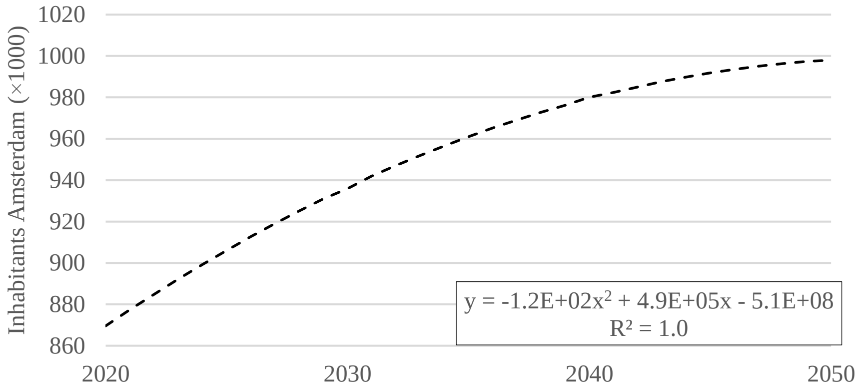

Figure 12 The growth prognosis of the inhabitants of the city of Amsterdam (Gemeente Amsterdam, 2017). The fit of the trendline is given, a second order polynomial is used.

Appendix B. Available waste biomass growth

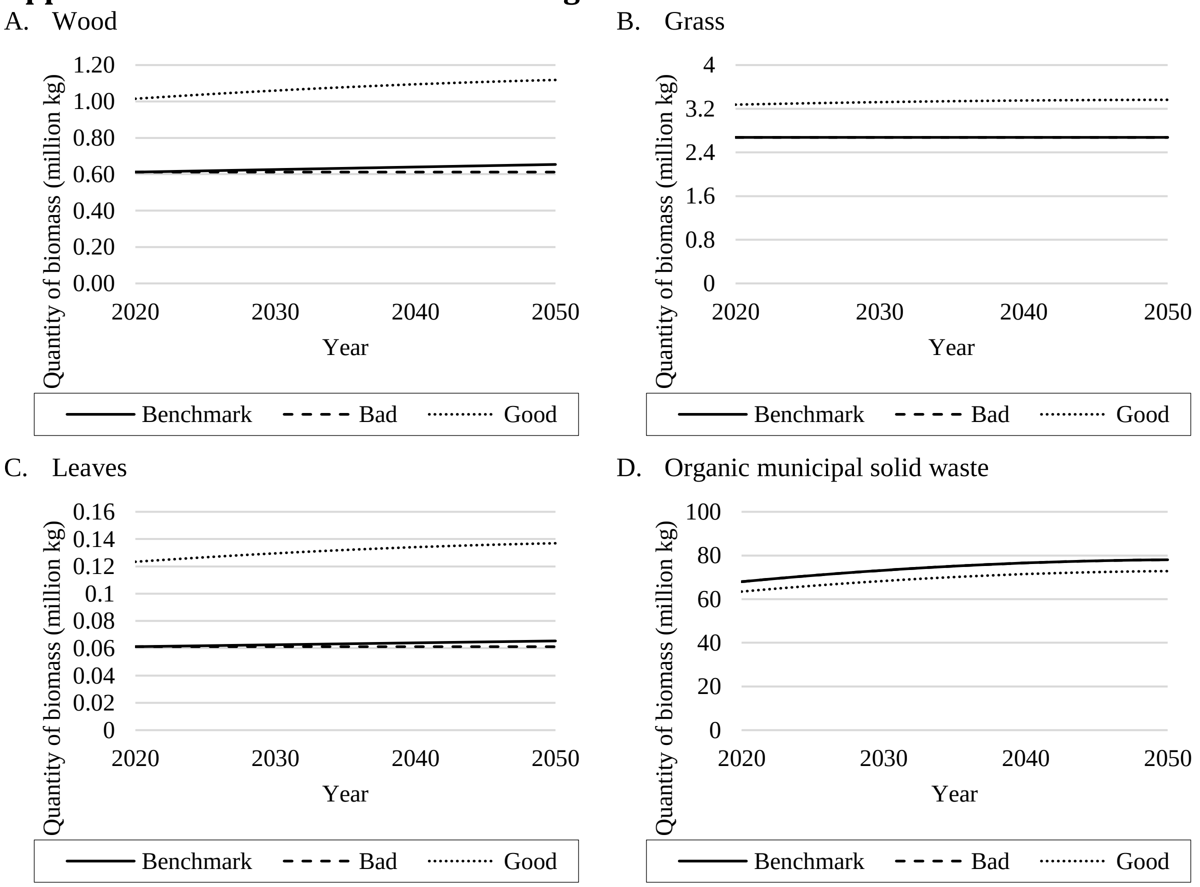

Figure 13 The quantity of waste biomass each year for different scenarios, for grass and organic municipal solid waste the good and bad scenario are overlapping. The scale of the quantity is different between the biomass.

Appendix C. Availability of new technologies

	Benchmark scenario			Good scenario			Bad scenario		
	2020	2030	2040	2020	2025	2035	2020	2035	2045
Wood refinery 1	0	1	1	0	1	1	0	1	1
Wood refinery 2	0	1	1	0	1	1	0	1	1
Wood refinery 3	0	0	1	0	0	1	0	0	1
Wood refinery 4	1	1	1	1	1	1	1	1	1
Wood refinery 5	0	1	1	0	1	1	0	1	1
Grass refinery 1	1	1	1	1	1	1	1	1	1
Grass refinery 2	0	1	1	0	1	1	0	1	1
Grass refinery 3	0	1	1	0	1	1	0	1	1
Grass refinery 4	0	1	1	0	1	1	0	1	1
Leaves refinery 1	0	0	1	0	0	1	0	0	1
Leaves refinery 2	0	0	1	0	0	1	0	0	1
Leaves refinery 3	0	0	1	0	0	1	0	0	1
Leaves refinery 4	0	0	1	0	0	1	0	0	1
Leaves refinery 5	1	1	1	1	1	1	1	1	1
OMSW digester 1	1	1	1	1	1	1	1	1	1
OMSW digester 2	1	1	1	1	1	1	1	1	1
OMSW digester 3	1	1	1	1	1	1	1	1	1
OMSW digester 4	1	1	1	1	1	1	1	1	1

Figure 14 The availability of new technologies (ω) where a zero indicates the technology is not available and an one indicates that technology becomes available in that year. When a technology becomes available, it remains available in the next coming years.

Appendix D. CEPCI, prime loan rate and oil price

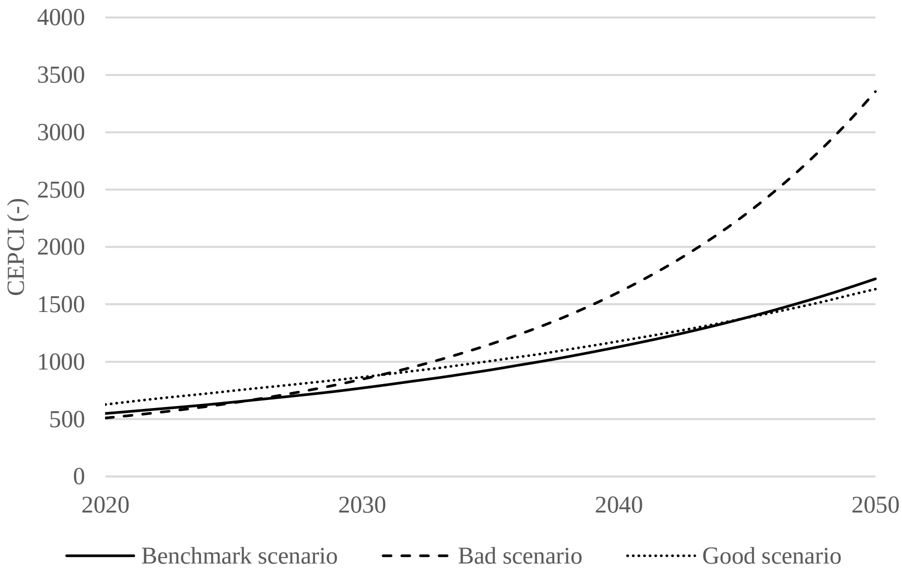

Figure 15 The chemical engineering plant cost index (CEPCI) for the three different scenarios.

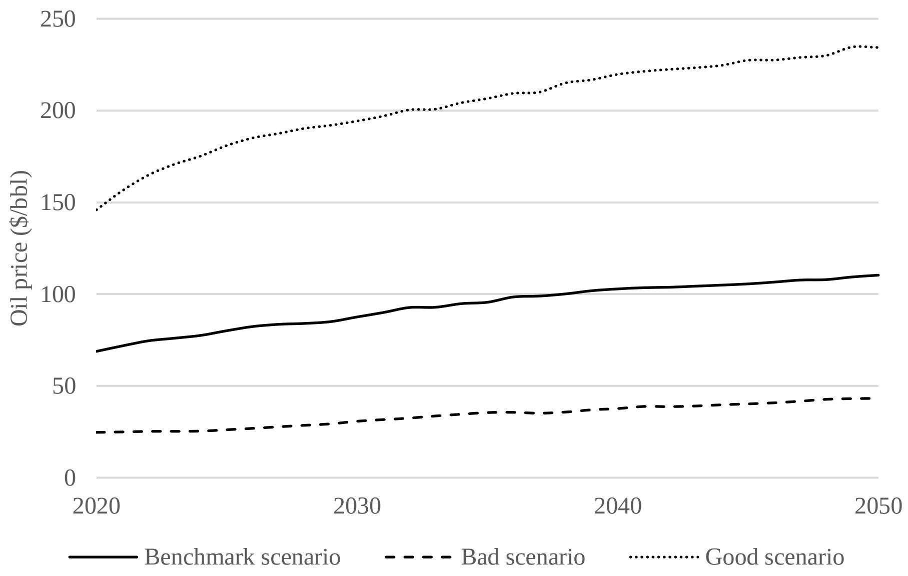

Figure 16 The oil price for the three different scenarios (EIA, 2017).

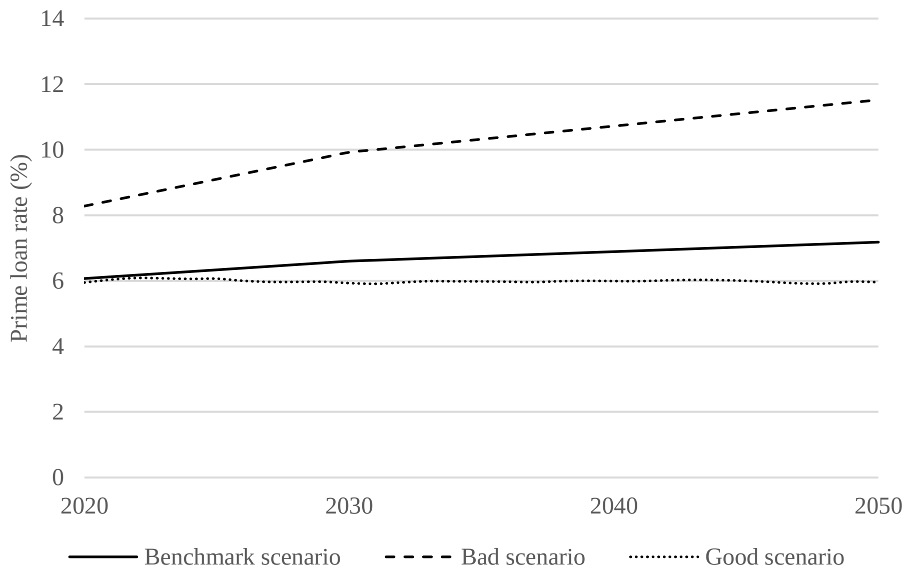

Figure 17 The prime loan rate for the three different scenarios (EIA, 2015).

Appendix E. Results for the bad scenario

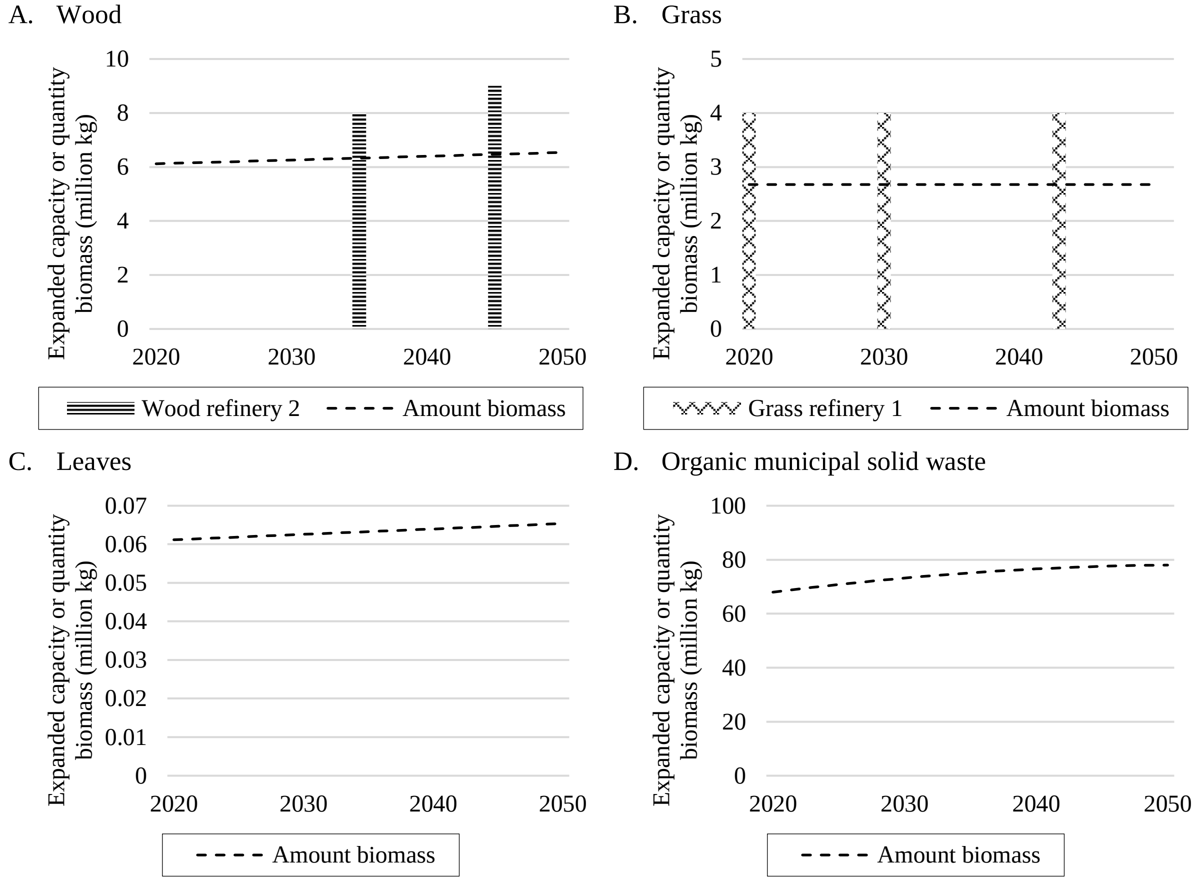

Figure 18 The capacity built of different refineries and the available biomass for each year in the bad scenario. The capacity build or quantity of biomass scale is different among the four graphs.

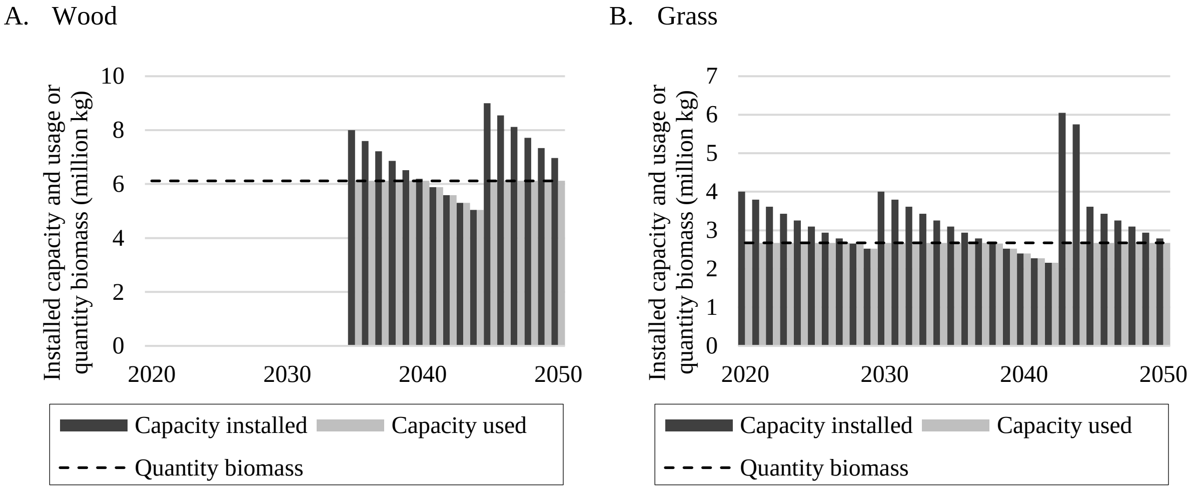

Figure 19 The total capacity installed and used of different refineries and the available biomass for each year for the bad scenario. Only wood and grass are presented, for those biomass a biorefinery was built. The total capacity installed and used or quantity of biomass scale is different among the two graphs.

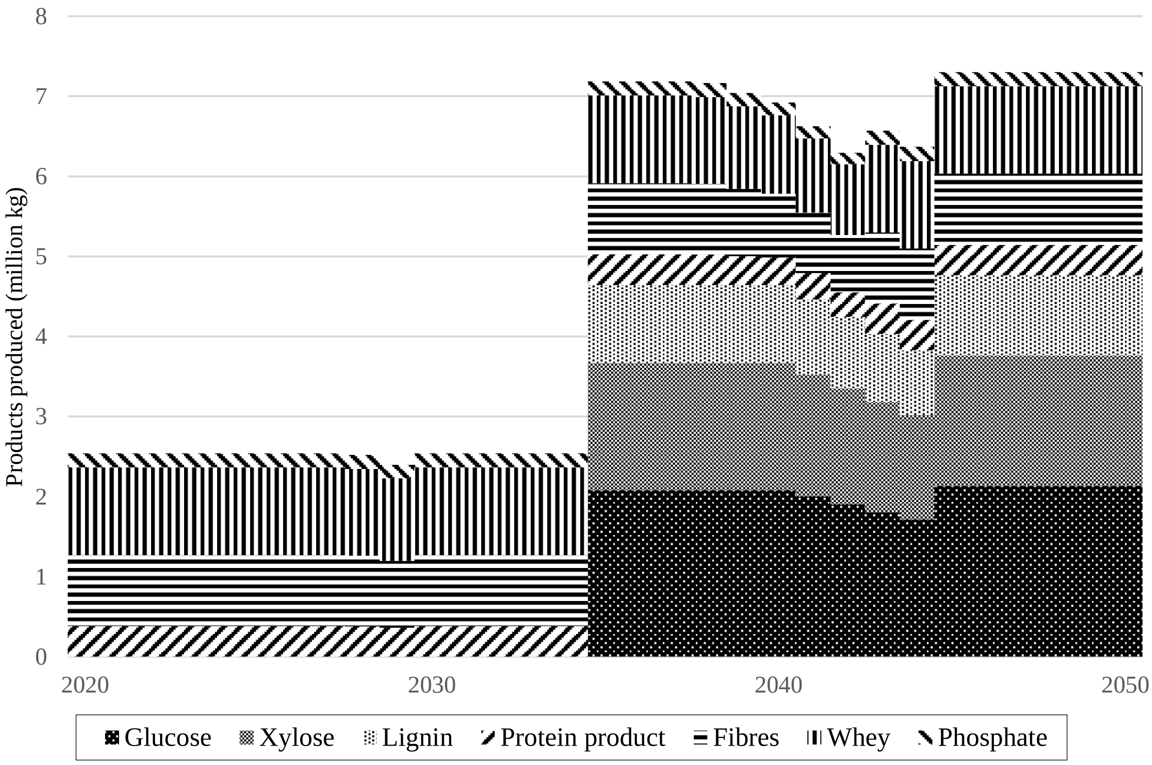

Figure 20 The total products produced from the waste biomass each year for the bad scenario.

Appendix F. Results for the good scenario

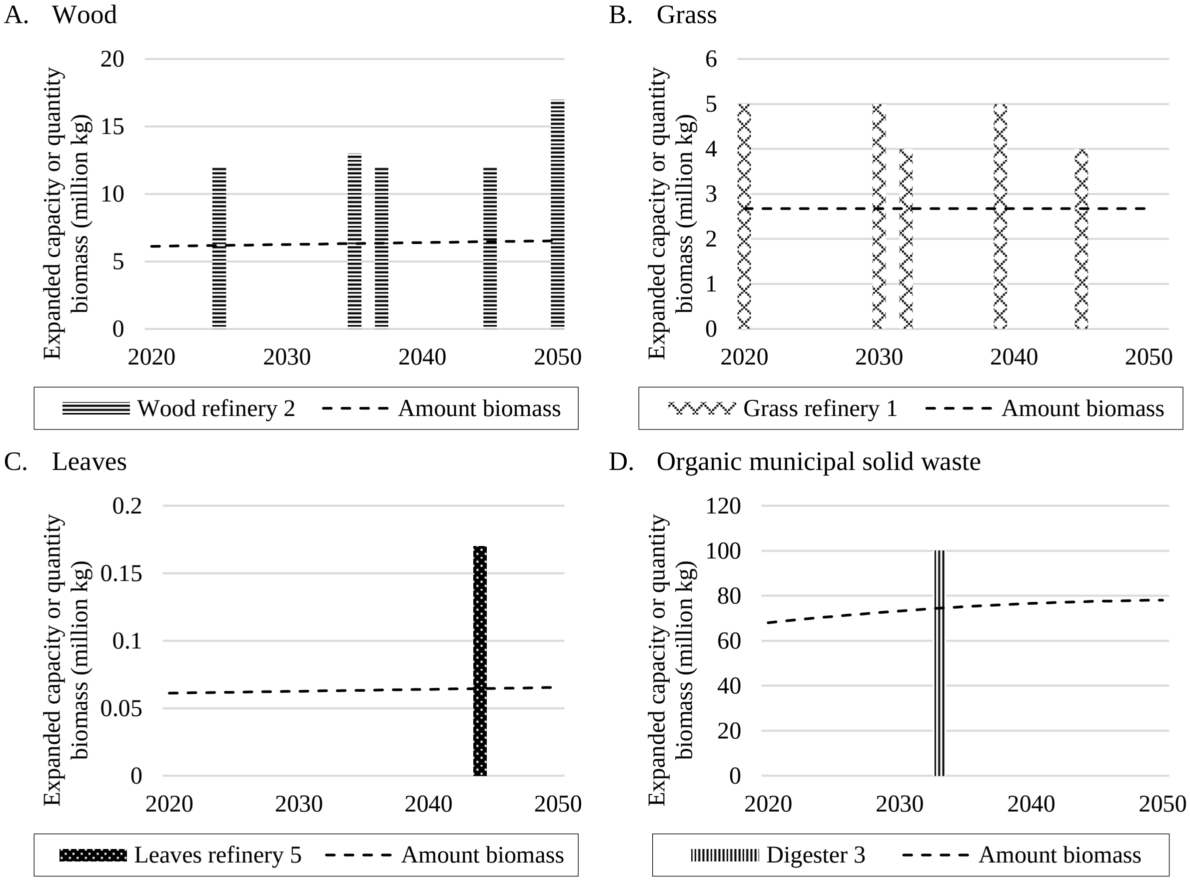

Figure 21 The capacity built of different refineries and the available biomass for each year in the good scenario. The capacity built or quantity of biomass scale is different among the four graphs.

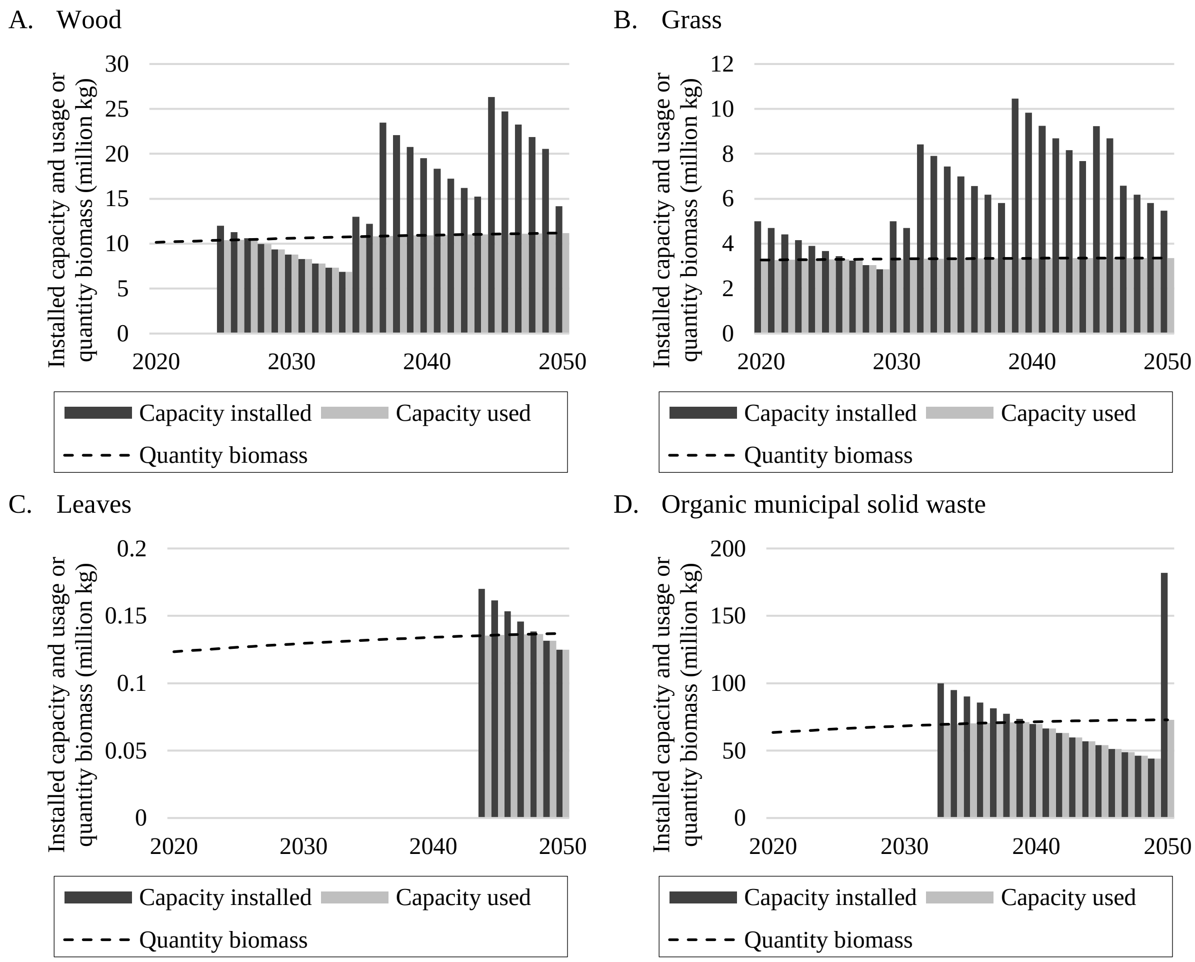

Figure 22 The total capacity installed and used of different refineries and the available biomass for each year for the good scenario. The total capacity installed and used or quantity of biomass scale is different among the two graphs.

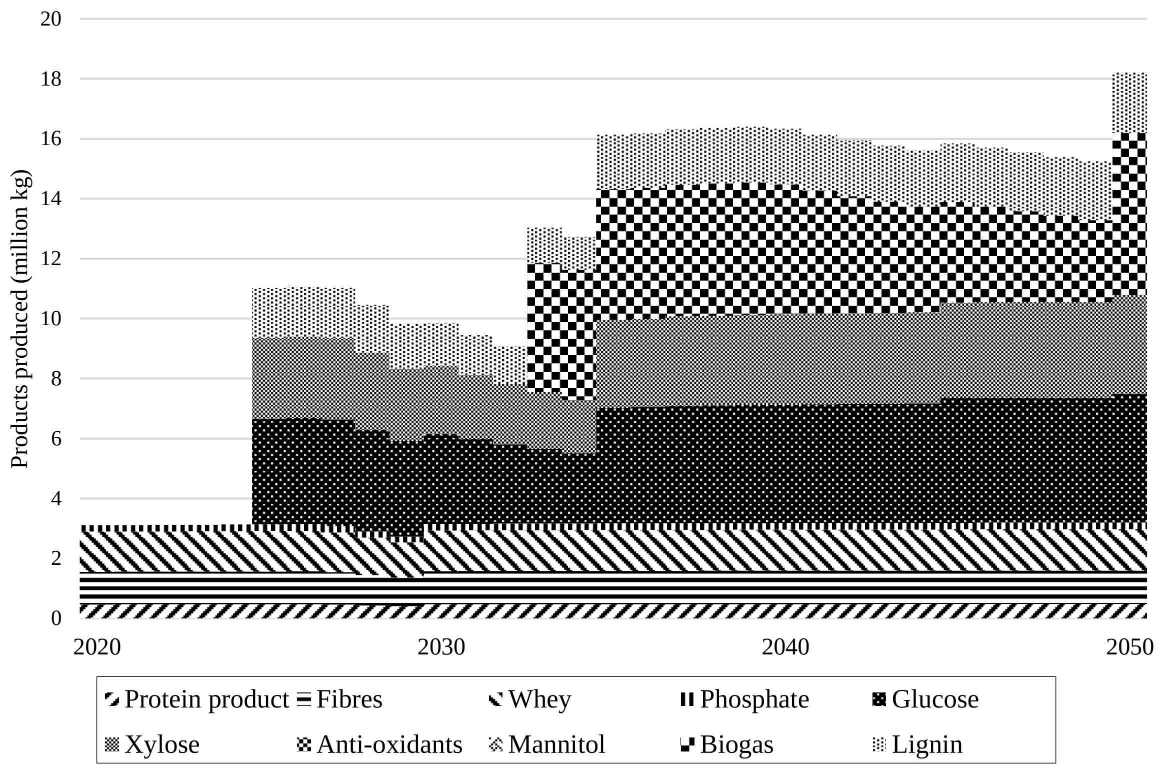

Figure 23 The total products produced from the waste biomass each year for the good scenario.