ECONOMIC ANALYSIS AND SUPPLY CHAIN OPTIMIZATION OF BIOMASS GASIFICATION AT A KRAFT PULP MILL

by

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B.Sc., University of Tehran, 2018

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF

THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES

(Forestry)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

February 2022

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Economic analysis and supply chain optimization of biomass gasification at a kraft pulp mill

submitted by Maziyar Khadivi in partial fulfillment of the requirements for

the degree of Master of Applied Science

in Forestry

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Abstract

Gasification is one of the processing technologies to convert biomass into syngas and renewable natural gas (RNG). The economic feasibility and amount of emission reduction are important factors affecting the investment decisions related to biomass gasification. Uncertainty and variability in parameters impact the economics and emissions of biomass gasification; however, they were not considered in evaluating gasification options in previous studies. The first objective of this research is to evaluate three biomass gasification alternatives with different capacities for syngas/RNG production at a Canadian Kraft pulp mill. The alternatives are evaluated based on the mean value and the risk associated with the net present value and emission reduction. After identifying the best gasification alternative for investment, it is important to minimize the costs and emissions of the biomass supply chain since the supply chain costs can be as high as 50% of the total gasification cost and emissions resulted from the supply chain activities can offset the emissions avoided by replacing fossil fuels with biofuels. Therefore, the second objective of this thesis is to develop a bi-objective optimization model for tactical planning of the forest-based biomass supply chains in order to analyze the trade-offs between the costs and emissions.

To evaluate the best investment alternative under uncertainty, Monte-Carlo simulation is first performed to derive the mean value and Value-at-Risk associated with the NPV and emission reduction of each capacity alternative. Next, using the outputs of the Monte-Carlo simulation as the evaluation criteria, the alternatives are ranked based on the multi-criteria decision-making method. According to the weights identified by the pulp mill for the criteria, the small-scale biomass gasification with 38 MW syngas production capacity is the most appropriate alternative for investment. The developed optimization model determines the optimal monthly biomass quantities to be transported, stored, and preprocessed. The case of a 38 MW biomass gasification for the same Kraft pulp mill was considered to apply the supply chain optimization model. The results indicate a maximum of 24% (217 t of CO_2 eq.) emissions reduction is possible if the supply chain cost is allowed to increase by 1.3% ($32,734).

Lay Summary

Syngas and renewable natural gas produced using biomass gasification are renewable energies that can replace natural gas. Previous studies analyzed the economics and emissions of biomass gasification; however, they overlooked the impact of uncertainty in evaluating the best alternative for investment. This research aims to identify the best capacity alternative for investment in biomass gasification under uncertain conditions. The results for the case of a Canadian pulp mill indicate when the net present value and emission reduction are important for decision makers, large-scale gasification suits them well. Small-scale gasification is recommended when decision makers are highly concerned with lowering the economic risks of the investment. Due to considerable impact of the biomass supply chain on the economics and emissions of the gasification, its costs and emissions are minimized through developing an optimization model. The results show there is a trade-off between the minimization of the supply chain costs and emissions.

Preface

All the work presented in this thesis was carried out by the author, Maziyar Khadivi, during his Master of Applied Science program. The work was conducted under the supervision of Dr. Taraneh Sowlati at the Industrial Engineering Research Group of the University of British Columbia, Vancouver, Canada.

Parts of this dissertation is presented in the following publications.

- A version of Chapter 2 has been submitted to a peer-reviewed journal for publication and is under revision.
    - Khadivi, M., and Sowlati, T. (2021) Biomass gasification investment: a multi-criteria decision considering uncertain conditions

  I was the main author of this article. I contributed in defining the problem, and collected data from the industrial collaborator and the literature, developed the economic and emission analysis models, and prepared the manuscript. Sowlati, T. was the corresponding author who identified the problem and the industrial partner, also advised in gathering data, developing and solving the economic and emission analysis models, and preparing the manuscript.

- A modified version of the mathematical formulation, input data and the solution approach used in the article below are presented in Chapter 3.

  Ahmadvand, S., Khadivi, M., Arora, R., & Sowlati, T. (2021). Bi-objective optimization of forest-based biomass supply chains for minimization of costs and deviations from safety stock. *Energy Conversion and Management: X*, *11*, 100101.

I contributed to defining the problem, developing the mathematical model and solution method, coding the problem in the software, collecting data, synthesizing the results of the optimization model, and writing the manuscript. The main author, Ahmadvand, S., contributed to defining the problem, developing the mathematical model, coding the problem in the software, collecting data, synthesizing the results of the optimization model and writing the manuscript. Arora, R. contributed to defining the problem, developing the mathematical model, coding the problem in the software, collecting data, synthesizing the results of the optimization model, and writing the manuscript. Sowlati, T. was the corresponding author who identified the problem and the industrial partner, also advised in gathering the data, developing the optimization model, analyzing the results and preparing the manuscript.

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List of Abbreviations

AW	Annual worth
AUGMECON	Augmented ε-constraint
BC	British Columbia
CEPCI	Chemical engineering plant cost index
CFB	Circulating fluidized bed
DFB	Dual fluidized bed
ERR	External rate of return
GHG	Greenhouse gas
HBS	Harvest billing system
IRR	Internal rate of return
LHV	Lower heating value
MCDM	Multi-criteria decision making
NG	Natural gas
NPV	Net present value
NPEs	Non-process elements
O&M	Operating and maintenance
ODT	Oven-dry tonne
ROR	Rate of return
RNG	Renewable natural gas
WSM	Weighted-sum method

Acknowledgements

I would like to deeply thank my supervisor, Prof. Taraneh Sowlati, for her whole-hearted support, invaluable advice, and constructive remarks throughout my Master's program. Her commitment to research, patience for hearing my ideas, and passion for guiding me constantly motivated me to progress in my research. I feel fortunate to have this opportunity to complete my Master's under her supervision.

I would like to extend my thanks to the other members of my supervisory committee, Mr. Tobias Ziegenbein, Dr. Tony Bi, and Dr. Scott Renneckar, for their excellent recommendations during the development of this work that helped me to enhance the quality of the research work presented in this thesis. I want to specially express my appreciation to the project manager of the pulp mill, Mr. Tobias Ziegenbein, for sharing the data and details on the case study of this thesis.

Online discussions with IERG members, Sahar Ahmadvand, Salar Ghotb, and Rohit Arora through Zoom meetings are truly a valuable memory for me. Our meetings helped me to always find the feeling of working in-person, while we had to work remotely due to Covid-19.

I am forever grateful to my second cousin, Dr. Rostam Namdari and Mrs. Antonia Dizon, for supporting me emotionally and hosting me during two years of my study. Rostam's advice for my life and education, his critical questions about my research, and his encouragements to apply for my PhD are very helpful for me to manage my many stressful situations, to polish my research ideas, and to find a great goal to pursue in my life. I will miss these valuable experiences soon as I am going to live apart from them.

And finally, I owe my particular thanks to my dear parents, my lovely sister, Gita, and my kind grandmother, Mahin, for their love and support throughout my life. Without their moral and financial support, I could not succeed in achieving of my goals.

Dedication

To my family and teachers

Chapter 1: Introduction

1.1 Background

The most expensive decision to avert the worst environmental and economic impacts of climate change is to take no action and wait for the inevitable consequences of global warming (World Meteorological Organization, 2020). Utilization of biomass to produce bioenergy and biofuels is one of the important actions to halt the pace of climate change. Biomass has the potential to fulfil 18% of the world total energy demand by 2050 (International Renewable Energy Agency, 2021). Gasification is one of the dominant and cost-effective thermochemical processes to convert biomass to bioenergy and biofuels (Sikarwar et al., 2017). It indirectly applies heat with limited amount of gasifying agents such as air, steam and oxygen to break the chemical structure of biomass feedstock (i.e., C, H, O, and other trace elements) to combustible gas mixture (i.e., syngas, which is also called product gas) (Hanchate et al., 2021; McKendry, 2002). Syngas has versatile applications, it can be either burnt to generate heat and power, or standardized and converted to biofuels such as renewable natural gas (RNG), Methanol, Fischer-Tropsch fuels, and Hydrogen (Hanchate et al., 2021; Isaksson et al., 2016b; Sikarwar et al., 2017).

In case of Kraft pulp mills, hot syngas coming out of gasifiers can be directly burnt in lime kiln burners to substitute fossil fuels including natural gas (NG) and fuel oil (Hart, 2020). Many Kraft pulp mills have been modernized during the recent decades to decrease their fossil fuel-based greenhouse gas (GHG) emissions through utilizing their waste wood and pulping liquor to generate green heat and power (Bajpai, 2018). However, the majority of modern Kraft pulp mills still burn large amount of fossil fuels in their causticizing unit to provide heat for the lime kilns. Lime kilns utilize heat to recover lime from lime mud. The recovered lime is then used in the recycling process of the pulping liquor (Taillon et al., 2018). Due to the fossil fuel combustion in lime kilns, they are the single largest contributors to GHG emissions in the modern Kraft pulp mills (Hart, 2020). Therefore, GHG emissions of lime kilns can be avoided by using a gasification technology to meet the energy demand of the lime kilns. Moreover, accessibility to a variety of forest-based biomass including hog fuel generated onsite, and wood residues generated off-site at the nearby sawmills and forest cut blocks is an opportunity for pulp mills to meet the feedstock demand of the gasifier (Hallbar Consulting, 2017).

When adequate amount of biomass is available for gasification, pulp mills can decide to scale up the gasifier capacity to generate additional syngas to produce biofuels, including RNG (Sikarwar et al., 2017). A major advantage of producing RNG from the surplus syngas is that it can be injected into the gas grid because pulp mills are commonly located at the vicinity of NG pipelines (Hallbar Consulting, 2017). The NG substitution with RNG in pipelines leads to further reduction in GHG emissions released by combustion of NG. Since RNG production capacity can be varied and is only constrained by the maximum available biomass, pulp mills can select among several alternatives for gasification of the available biomass. They can decide to produce syngas to only fulfill the lime kiln heat demand (Zero RNG production) or to generate additional syngas for RNG production at different capacities.

To make decision on selecting the best alternative for investment, it is essential to justify and compare the economic feasibility of the alternatives through economic assessment (Akhtari et al., 2021). Moreover, the amount of GHG emission reduction achieved from the establishment of each alternative needs to be assessed because one of the goals behind investment in such projects is to reduce the GHG emissions released by combustion of fossil fuels (Cambero et al., 2016). In particular, Canada has committed to cut its GHG emissions by 40-45% below 2005 levels by 2030 and to zero by 2050 (Government of Canada, 2021c). In BC, the provincial government enacted the Clean Energy Act that aims to reduce GHG emissions as well as waste by encouraging utilization of biomass (FortisBC Energy Inc., 2020). Finally, FortisBC, a gas supplier in BC that purchases gasified biomass from the BC industry made commitment to reduce its GHG emissions by 30% by 2030 (Province of British Columbia, 2020). To meet the mentioned federal and provincial targets, one main pathway has been defined as investment in renewable energy projects because they can lead to halting GHG emissions (Province of British Columbia, 2020). In the literature, many studies assessed the economic feasibility and carbon footprint of syngas and RNG production using gasification (e.g., Ahlström et al., 2017; Isaksson et al., 2016a; Kuparinen & Vakkilainen, 2017; Thunman et al., 2019). The focus of these studies, along with their common findings and limitations, are reviewed in Section 1.2.1.

After making a decision on the best alternative for investment, it is important to reduce the cost and GHG emissions associated with the biomass supply chain activities including biomass collection, transportation, preprocessing, and storage to the lowest possible value. Reduction in the supply chain cost and GHG emissions is important because the supply chain cost could be as high as 50% of the total production cost (e.g., Calderón et al., 2017; Kumar et al., 2003) and the GHG emissions of the supply chain could offset the emission reduction obtained by replacing fossil fuels with biofuels (Malladi & Sowlati, 2018).

In addition to the high costs and GHG emissions, there are several challenges in the biomass supply chain making its management a complex task. Low energy content, bulkiness, and scattered availability of forest-based biomass require significant volume of wood residues to be collected from multiple sources and transported to the mill, which lead to significant cost and GHG emissions (Akhtari, 2019; Cambero & Sowlati, 2014). In addition, forest-based biomass procured from different supply sources has different characteristics. Therefore, it may need to undergo multiple preprocessing steps to provide a uniform and acceptable quality of feedstock for the gasifier. As a result, it is important to determine the flow of biomass from each supply source to the plant considering the costs and GHG emissions associated with their preprocessing (Ahmadvand et al., 2021). Another challenge is the fluctuation in the availability of forest-based biomass throughout the year. Forest-based biomass is a by-product of harvesting activities and wood processing mills. As such, its availability varies depending on the seasonal accessibility to the forest roads and also operation of the wood processing mills (Akhtari et al., 2014a). To prevent shortage in the supply of forest-based biomass to the gasification plant, biomass storage in seasons of abundance may be essential.

Since the supply chain activities including collection, transportation, preprocessing, and storage are interdependent and each contribute to the total costs and GHG emissions, it is important to optimize the whole supply chain activities together. In the literature, many researchers have used mathematical programming models to minimize the costs and emissions of the supply chain activities. Section 1.2.2 reviews the literature on multi-objective optimization models that were developed to optimize the biomass supply chain for bioenergy/biofuel production based on the minimization of costs and GHG emissions.

1.2 Literature review

1.2.1 Economic analysis of biomass gasification for syngas and RNG production

In the literature, the only work related to economic analysis of syngas production using gasification for combustion in lime kilns was carried out by Kuparinen and Vakkilainen (2017). The authors evaluated the techno-economic feasibility of several forest-based biomass energy options including syngas, pulverized wood, torrefied wood, hydrogen, and lignin for replacing fuel oil in lime kilns. This evaluation was applied to the case of a South American pulp mill with 72 MW lime kiln capacity. It was shown that for their case study, the production of all the above-mentioned fuel options, except hydrogen, was economically profitable to substitute fuel oil combustion in the lime kiln.

The articles that focused on the economic and environmental analysis of forest-based biomass gasification for RNG production can be categorized into two groups. The first group focused on the RNG production at different capacities using different technologies (Ahlström et al., 2017; Gassner & Maréchal, 2009; Salman et al., 2017; Thunman et al., 2019). The second group compared RNG production with production of other biofuels (Isaksson et al., 2016b; Johansson, 2013; Kraussler et al., 2018; W. Zhang et al., 2015).

In the first group, Gassner and Maréchal (2009) and Salman et al. (2017) evaluated the efficiency and cost of RNG production using different gasification technologies in a stand-alone RNG plant and in a combined heat and power plant, respectively. Their analysis indicated that oxygen-blown circulating fluidized bed (CFB) gasifier and steam-blown dual fluidized bed (DFB) gasifier were the most suitable technologies for RNG production due to having a lower cost and a higher efficiency than other technologies. Ahlström et al. (2017) and Thunman et al. (2019) investigated the effect of gasification capacity on the economic feasibility of RNG production at a sawmill and a stand-alone RNG plant, respectively. The authors in both studies concluded that taking advantage of economies of scale would lower the fuel production costs.

In the second group of studies, the economics of RNG production via gasification were compared with (1) combined heat and power generation using gasification in a pulp mill (W. Zhang et al., 2015), (2) methanol, Fischer-Tropsch fuel, and power production using biomass gasification in a pulp mill (Isaksson et al., 2016b), and (3) biogas production via anaerobic digestion in a stand-alone RNG plant (Kraussler et al., 2018). Large scale RNG production in their case studies achieved higher net present value (NPV) and internal rate of return (IRR) compared to other biofuels except for the combined heat and power generation. The better economic performance of heat and power generation than RNG production was because the heat and power generation option did not require investment in costly equipment for syngas cleaning and upgrading.

In addition to economic analysis of RNG production, a number of previous studies evaluated the GHG emission reduction obtained by RNG production using biomass gasification at dififrent capacties (Ahlström et al., 2017) or compared the GHG emission reduction of RNG production with other biofuels (Isaksson et al., 2016b; Kraussler et al., 2018). These studies concluded that (1) GHG emssions from procurement, preprocessing, and conversion of biomass to RNG (and other biofuels) were low compared to the reduction achieved by replacing fossil fuels with biofuels including RNG, and (2) expanding the gasification capcity increased the amount of emssion reduction.

Among the previous works, no study compared the production of syngas for heating applications such as burning in lime kilns with the co-production of syngas and RNG. Only Nwachukwu et al. (2020) compared the fuel production cost of syngas and RNG value chains for replacing natural gas in heating furnaces of the Swedish iron and steel industry. In RNG value chain, available sawdust at the nearby sawmill was gasified and converted to compressed methane for transportation to the steel plant, whereas in syngas value chain, sawdust was first delivered to the steel plant, then it was gasified to syngas for direct combustion at the steel plant site. Their study did not account for comparing syngas production with simultaneous production of syngas and RNG. This comparison in terms of economic and amount of GHG emission reduction is important to be conducted because the option of producing syngas for only heating applications such as burning in lime kilns requires simpler and less expensive gasifier technology than the gasifier types suitable for co-producing syngas and RNG (Hofbauer & Materazzi, 2019; Taillon et al., 2018). Additionally, the case of producing syngas only for combustion in lime kilns eliminates the need for substantial investment in syngas clean up and methanation processes, which can increase the economic attractiveness of this option (Nwachukwu et al., 2020) and reduce the investment risk. On the other hand, the capacity of co-producing syngas and RNG is not limited to the lime kiln energy demand and can be adjusted according to the desired level of RNG production and the maximum available biomass. Therefore, it not only takes advantage of economy of scale, but also can benefit from achieving greater revenue as well as more reduction in GHG emissions due to production of RNG in addition to syngas.

Absence of uncertainty analysis and decision making on the best alternative for investment are the other two major gaps in the pertinent literature. The results of previous works showed that the economic feasibility of biomass gasification for bioenergy and biofuels production mainly depends on the syngas and RNG production efficiency, fixed capital investment, government incentives, biofuel offtake prices, fossil fuel costs, and biomass procurement cost (e.g., Kuparinen & Vakkilainen, 2017; Taillon et al., 2018). These parameters may exhibit uncertainty at the same time, and thus vary the economics as well as GHG emission reduction level of the biomass gasification. The variation in the outputs may pose a risk to the project (Colantoni et al., 2021) and may change the decision making on selecting the best investment alternative (Gargalo et al., 2016). Previous studies that assessed the economic and environmental aspects of biomass gasification for syngas and RNG production only conducted local sensitivity analysis to find out the impact of variation in each parameter on the model outputs, considering one change at a time (Li et al., 2015). Such analysis helps to screen out the important parameters (Cardoso et al., 2019; Haeldermans et al., 2020), but it is not able to (1) determine the mean value of outputs under uncertainty, (2) measure the risk of having economically infeasible projects or obtaining less reductions in GHG emissions, and (3) identify the most impactful input parameters when they change simultaneously (Cardoso et al., 2019; Dellino & Meloni, 2015). In the literature, previous works employed Monte-Carlo simulation model to calculate the mean value and risk associated with the economic and environmental indicators of producing different bioenergy and biofuels including power, heat, bioethanol, and bio-char using different conversion methods such as gasification, fermentation, and pyrolysis (Amigun et al., 2011; Bartela et al., 2018; Cardoso et al., 2019; Colantoni et al., 2021; Copa et al., 2020; Gargalo et al., 2016; Haeldermans et al., 2020; Jonker et al., 2019; Li et al., 2015; Li & Hu, 2016; Mandegari et al., 2018). However, to the best of author's knowledge, none of these studies performed uncertainty analysis for syngas production to combust in lime kilns and RNG production via gasification. In contrast to local sensitivity analysis, global sensitivity analysis helps to identify the most influential uncertain parameters while they are changing simultaneously. Previous studies employed the so-called Sobol method, a variance-based sensitivity analysis approach, to perform global sensitivity analysis on the economic and environmental indicators of producing bio-oil and power from algae and crude palm oil (Brownbridge et al., 2014; Elias et al., 2021; Heo et al., 2019; Kächele et al., 2019; Tang et al., 2015; Xia & Tang, 2017), but no study carried out global sensitivity analysis on the gasification of biomass for syngas and/or RNG production. Regarding decision making, when several investment alternatives were involved for the production of bioenergy and biofuels, multi-criteria decision making (MCDM) was employed to rank the alternatives based on the given criteria such as economic and environmental factors. However, previous studies neither incorporated risks associated with investment in the alternatives as the criteria in MCDM nor considered syngas/RNG production via gasification as the given alternatives (Ahmadi et al., 2020; Fitó et al., 2021; Matzen et al., 2015; Mendecka et al., 2020; Sanaei & Stuart, 2018; Saraswat & Digalwar, 2021; Ukoba et al., 2020).

1.2.2 Biomass supply chain optimization

In the literature, the studies that optimized the economic and environmental aspects of the biomass supply chain for bioenergy and biofuel production, can be classified into strategic, tactical, and operational models. At the strategic level, previous works aimed to optimize the design of the supply chain over its lifetime by determining the optimal type, capacity, and location of conversion technologies and long-term flow of biomass and bioproducts (Sowlati, 2016). In strategic models, the economic aspect of the supply chain was optimized based on the minimization of the costs

(Akgul et al., 2012; Balaman, 2016; Juan, Aviso, Tan, Sy, et al., 2019; Singlitico et al., 2020) or maximization of the supply chain net present value (Cambero et al., 2016; Díaz-Trujillo & Nápoles-Rivera, 2019; Zhao & Li, 2016). For optimizing the environmental aspect, Cambero et al. (2016) and Díaz-Trujillo et al. (2020) maximized the net GHG emission reduction of bioenergy and biofuel production, while other studies minimized either the life cycle GHG emissions (Balaman, 2016; Juan, Aviso, Tan, & Sy, 2019; Singlitico et al., 2020) or only the fossil GHG emissions (Akgul et al., 2012; Zhao & Li, 2016). The models aimed to optimize the biomass supply chain for the production of one or multiple type of biofuels and bioenergy including RNG, heat, power and bio-oil. To solve the optimization models, authors applied either the augmented ε-constraint (AUGMECON) method to generate a set of Pareto-optimal solutions (e.g., Cambero et al., 2016) or the goal programming method to generate a single optimal solution (e.g., Juan, Aviso, Tan, & Sy, 2019). When a set of Pareto-optimal solutions was generated, the comparison among the solutions indicated that there is a trade-off between the economic and environmental performance of the supply chain. The ability of showing the trade-offs among the objectives and allowing the decision makers to select their most preferred solution from a set of solutions were reported as the main advantages of using the AUGMECON method (e.g., Cambero et al., 2016; Singlitico et al., 2020). Readers are referred to Section 3.5 to find a thorough comparison among the available solution methods for solving multi-objective problems and their individual advantages and disadvantages.

At the tactical level, optimization models were developed to prescribe medium-term (usually monthly) decisions for the collection, transportation, and storage of biomass as well as production and transportation of bioproducts to their markets. At the tactical level, authors developed single objective optimization models to minimize the costs or maximize the profit of the biomass supply chains. These models were developed to optimize the production of different biofuels and bioenergy including heat (Akhtari et al., 2014b), power (Liu et al., 2017; Saghaei et al., 2020; Shabani & Sowlati, 2013), and biofuels (Berry & Sessions, 2018; Wang et al., 2020; F. Zhang et al., 2016) from forest-based biomass. At the tactical level, to the best of the author's knowledge, none of the previous studies optimized the supply chain activities considering both economic and environmental aspects, expect Tan et al. (2017), who maximized the profitability and GHG emission savings of the biomass supply chain for power generation. The authors in the above-mentioned work solved the model as a single-objective model by considering particular weights for the cost and GHG emission objectives. As a result, they reported a single optimal solution for their case study. Providing the decision makers with a single optimal solution is helpful to manage and make a plan for the supply chain. However, it does not provide insights into the possible trade-off among the objectives. On the other hand, generating a set of Pareto optimal solutions in multi-objective problems would help the decision makers to find a thorough picture about the trade-off among the objectives (Konak et al., 2006). In particular, when the decision makers are provided with the trade-off between the costs and GHG emissions of the biomass supply chain, they could realize how much the cost of the supply chain will change if they decide to switch from one optimal solution with higher GHG emissions to another one with lower emissions. Therefore, they can understand how much it costs for them to gradually reduce their supply chain GHG emissions.

Finally, operational optimization models were developed to decompose the decisions made at the tactical level into short-term period plans. Operational planning models provide companies with decisions regarding inventory management, schedules for collection and transporting biomass to customers, and vehicle routing on a weekly, daily or hourly basis (Acuna et al., 2019; Ba et al., 2016). To manage the biomass supply chains at an operational level considering the economic and environmental aspects, only Malladi & Sowlati (2020a, 2020b) optimized the collection and transportation of biomass from suppliers to a district heating system considering minimization of the costs and GHG emissions. The Pareto curve in their case study demonstrated the trade-off between the costs and emissions of the supply chain.

1.3 Research gaps

1.3.1 Economic analysis of biomass gasification for syngas and RNG production

Reviewing the literature on the economic analysis of biomass gasification for syngas and RNG production revealed that the economic feasibility of the gasification projects is case dependent and varies depending on each case study. In addition to economic analysis, a number of previous works assessed the amount of GHG emissions reduced by commissioning of the gasification projects. In general, large-scale biomass gasification was found to improve the economics and amount of GHG emission reduction in all previous case studies.

Previous works reported the syngas and RNG production efficiency, fixed capital investment, government incentives, biofuel offtake prices, fossil fuel costs, and biomass procurement cost as the most influential parameters impacting the economics of their case studies (e.g., Kuparinen & Vakkilainen, 2017; Taillon et al., 2018). Despite the inherent uncertainty in these parameters and its effect on the economic model's output, previous works did not evaluate selecting the best investment option under uncertain conditions. A number of them only performed local sensitivity analysis to analyze one at a time impact of changes in each uncertain parameter on the economics of biomass gasification (e.g., Ahlström et al., 2017; Kuparinen & Vakkilainen, 2017; Nwachukwu et al., 2020; W. Zhang et al., 2015). Although local sensitivity analysis provides useful insights into individual impact of each input parameter on the output, it is not capable of (1) identifying the most influential parameters when they change all together, and (2) deriving the mean value and risk associated with the economics of the project. To address the limitations of local sensitivity analysis, previous studies in the literature (e.g., Brownbridge et al., 2014; Elias et al., 2021; Heo et al., 2019; Kächele et al., 2019; Tang et al., 2015; Xia & Tang, 2017) carried out global sensitivity analysis to evaluate the influence of each uncertain parameter on the output when the parameters change together. Other works in the literature (e.g., Colantoni et al., 2021; Copa et al., 2020; Haeldermans et al., 2020; Jonker et al., 2019; Mandegari et al., 2018) employed Monte-Carlo simulation to calculate the mean value and risk associated with the economics of the projects. However, none of these studies focused on the uncertainty analysis of biomass gasification to produce syngas and RNG.

Lastly, authors in previous studies employed multi-criteria decision making (MCDM) to identify the best alternative for investment in the production of bioenergy and biofuels when several conflicting criteria were considered in decision making (e.g., Ahmadi et al., 2020; Fitó et al., 2021; Mendecka et al., 2020; Saraswat & Digalwar, 2021; Ukoba et al., 2020). However, these works neither evaluated the best alternative considering uncertainty nor were carried out for production of syngas and RNG through gasification.

1.3.2 Biomass supply chain optimization

Due to considerable contribution of biomass supply chain activities to the total cost and GHG emissions of producing bioenergy and biofuels, many of the previous works developed bi-objective optimization models to optimize the economic and environmental aspects of the biomass supply chains at strategic and operational levels. At the strategic level, models were developed to determine the optimal type, capacity, and location of conversion technologies and long-term flow of biomass and bioproducts. At the operational level, the developed models aimed to optimize the weekly, daily or hourly schedule for the collection and distribution of biomass from suppliers to customers and determine the optimal vehicle routing. Some authors employed the goal programming method to solve the bi-objective models as a single-objective model or used the augmented ε-constraint (AUGMECON) method to generate a set of Pareto-optimal solutions. In the case of generating a Pareto-optimal set, the Pareto curve showed a trade-off between the optimal economic and environmental performance of the supply chains.

When it comes to tactical planning, previous works just minimized (maximized) the costs (profits) of the supply chains over the year. Only Tan et al. (2017) aimed to optimize both economic and environmental criteria of a biomass supply chain for power generation, but they limited their work to solving the model as a single-objective model. Since there might be a trade-off among the objectives in the optimization problems with multiple objectives, reporting a single optimal solution is not able to provide the decision makers with insights into the trade-off among objectives. On the other hand, a set of Pareto-optimal solutions in multi-objective optimization problems helps the decision makers to understand the trade-off between the objectives and then select their most preferred solution from the Pareto set. As a result, an unaddressed gap in the literature is bi-objective optimization of costs and emissions of the biomass supply chains at the tactical level and analyzing the trade-off between the two objectives. Lastly, there is no previous work that considered economic and environmental optimization of the supply chains for production of syngas and RNG via biomass gasification.

1.4 Research objectives

This research pursues two main objectives:

(1) Multi-criteria decision making on biomass gasification investment considering uncertain conditions. This objective is achieved by:

  a) developing deterministic models to assess and compare the economics and GHG emission reduction of biomass gasification for production of syngas and RNG at different capacities in a case study of a Canadian Kraft pulp mill;
  b) identifying the most influential uncertain parameters when they change one at a time and all together through local and global sensitivity analysis;
  c) deriving the probability distribution, mean value, and risk associated with the NPV and GHG emission reduction using Monte-Carlo simulation; and
  d) evaluating the investment alternatives for biomass gasification considering the mean and risk values of NPV and GHG emission reduction, and recommending the best alternative using multi-criteria decision making (MCDM)

(2) Minimization of the annual costs and GHG emissions of the supply chain for biomass gasification. This objective is achieved by:

a) developing a bi-objective mathematical programming model to optimize the monthly biomass transportation, handling, preprocessing, and storage for gasification at tactical level; and

b) deriving the trade-off between the total costs and GHG emissions of the supply chain by generating a set of Pareto-optimal solutions using the augmented ε-constraint method

1.5 Case study

The case study considered in this research is one of the largest Canadian Kraft pulp mills, located in the interior region of BC. The pulp mill has been generating electricity and thermal energy in a combined heat and power plant from combustion of black liquor and bark residues generated during the pulp production process. The generated heat is consumed internally to meet a portion of the thermal energy demand of the mill, while produced power is additional to the electricity demand of the mill. As a results, the mill obtains considerable income by selling its surplus green power to BC-Hydro (i.e., a provincial power utility in BC) under energy purchase agreements (EPA) (Lindstrom, 2017). However, BC-Hydro has announced that as of February 2019, the EPAs would not be offered or renewed in the future due to the expected increase in the hydropower generation by 2030 (GovTogetherBC, 2019). Consequently, the mill foresees a long-term decline in their annual revenue and to compensate this loss, the mill is considering investment in biomass gasification. The gasifier generates syngas, which has versatile applications. It can be either burnt directly in lime kilns, cleaned-up for combustion in power gas engines and gas turbines, or converted to biofuels such as RNG, Methanol, and Fischer-Tropsch fuel (Isaksson et al., 2016b).

The pulp mill in this study has the opportunity to utilize syngas for the lime kiln application and RNG production due to the financial incentives provided by FortisBC, a gas and power provider in BC, for replacing NG in lime kilns as well as producing RNG (Province of British Columbia, 2020). The pulp mill can procure the feedstock requirement of the gasifier from the available forest-based biomass, hereinafter referred to as biomass. The available biomass consists of (1) wood residues generated at the pulp mill site and their own nearby satellite yard, (2) wood residues available at three nearby sawmills, and (3) wood residues available from timber harvesting at 505 nearby cut blocks. Hereinafter, the mill residues available at the pulp mill, satellite yard, and sawmills are referred to as sawmill residues, while residues available at forest cut blocks is referred to as harvesting residues. The available sawmill and harvesting residues are equal to 81,625 and 148,898 oven-dry tonne (ODT) in total per year, respectively. In this case study, the syngas volume that can be produced by gasification using the total available biomass exceeds the energy demand of the lime kiln. For this reason, the pulp mill can have two options. The first option is to install a gasifier which has a syngas production capacity limited to the energy demand of the lime kiln, and the second option is to install a gasifier with syngas capacity more than the lime kiln's energy demand. The excess syngas in the second option can be cleaned up and upgraded to RNG.

1.6 Thesis structure

The thesis is organized as follows:

(1) Chapter 2: the best alternative for investment in biomass gasification is evaluated considering uncertainty.

(2) A bi-objective optimization model is developed in Chapter 3 to find the optimal monthly biomass transportation, storage, and preprocessing such that the total supply chain costs and emissions are minimized.

(3) Chapter 4: contains concluding remarks, limitations, and suggests directions for future work.

Chapter 2: Evaluating the best alternative for biomass gasification investment considering uncertain conditions

2.1 Synopsis

In this chapter, the best alternative for investment in biomass gasification to produce syngas and RNG in case of a Canadian Kraft pulp mill is evaluated. First, the alternatives and their associated value chain are defined. Then, the assumptions and results of the deterministic economic and GHG emission analysis models are presented. The NPV, annual worth (AW), rate of return (ROR), and payback period of all alternatives are calculated by the economic analysis model and the annual net GHG emission reduction achieved by investment in each alternative is calculated by the GHG emission analysis model. To identify the most impactful uncertain parameters on the NPV and GHG emission reduction of each alternative, sensitivity analysis is carried out on the key input parameters of the models. To incorporate uncertainty analysis, the mean value and value-at-risk of NPV and GHG emission reduction of each alternative are calculated by applying Monte-Carlo simulation to the deterministic models. Finally, multi-criteria decision making is employed to rank the alternatives according to Monte-Carlo simulation outputs.

2.2 Value chain considered for conducting economic and emission analyses

The assumed value chain in this study for syngas production (only for combustion in the lime kiln) and co-production of syngas and RNG are illustrated in Figure 2.1. As it can be seen, the logistics activities involved in the upstream biomass supply chain are common in both pathways. In other words, the sawmill and harvesting residues are preprocessed and dried before feeding to the gasifier to produce only syngas or co-produce syngas and RNG. The supply chain required for delivery, handling, and preprocessing of sawmill and harvesting residues prior to gasification are explained in Section 2.2.1. Next, the gasifier technologies and other downstream processing steps involved in the first and second options are discussed in Sections 2.2.2 and 2.2.3 , respectively. Based on these two options, three potential alternatives were defined in Section 2.3 for the pulp mill under study to utilize biomass for syngas and RNG production. The assumptions and details of economic and environmental analysis of these options are explained in Sections 2.4 and 2.5, respectively.

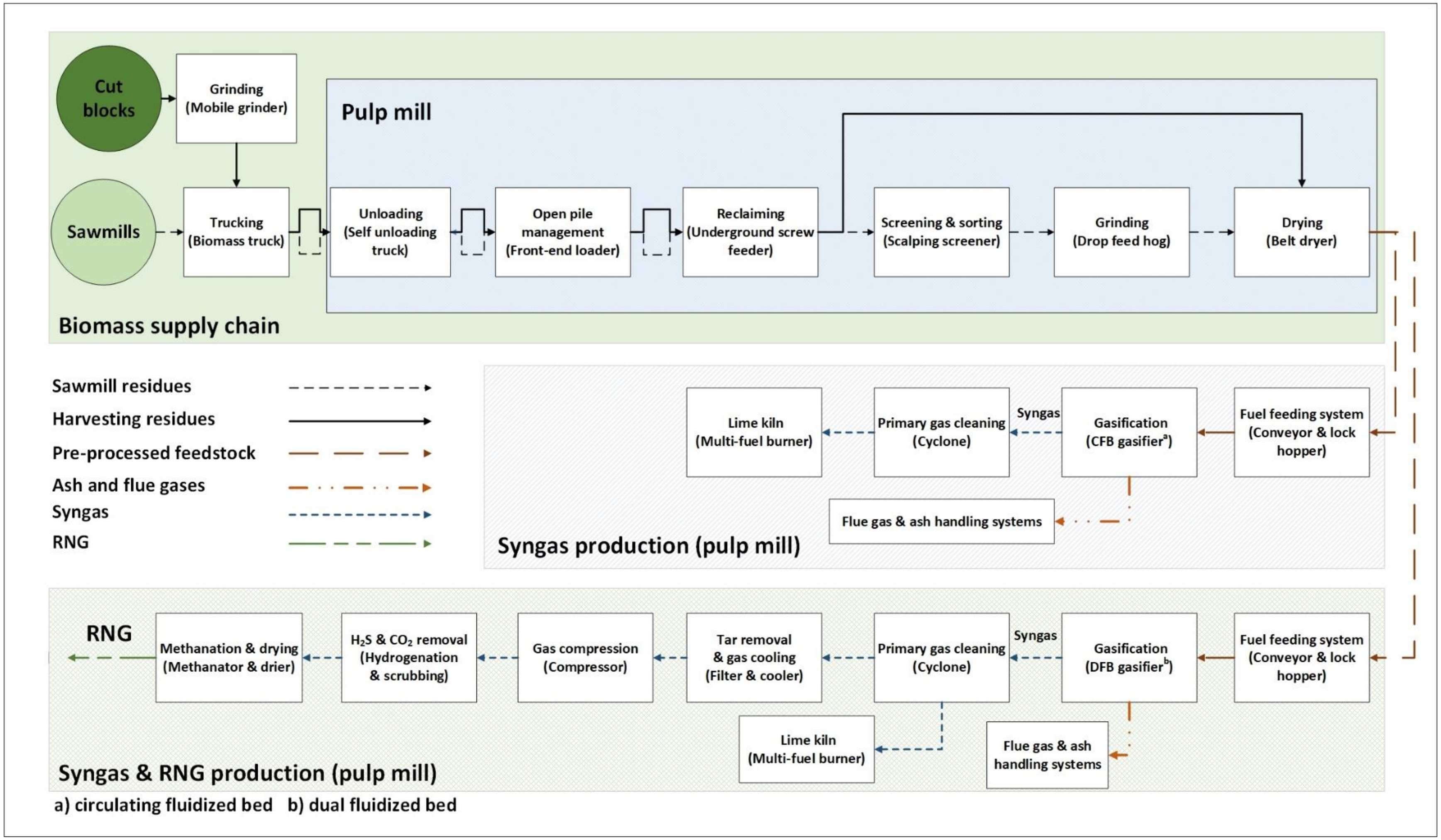


Figure 2.1 Schematic diagram of biomass supply chain (top), syngas production (middle), syngas and RNG coproduction (bottom)

2.2.1 Biomass supply chain

The logistics activities involved in the biomass supply chain to collect, transport, store and preprocess wood residues can account for up to 50% of the total production cost of produced biofuel/bioenergy (Calderón et al., 2017). The initial investment and annual operating and maintenance costs associated with these activities can impact the economic feasibility of the bioenergy/biofuel projects (Akhtari et al., 2014a). Likewise, GHG emissions released by these activities can offset the emission reduction obtained by replacing fossil fuels with bioenergy and biofuels (Malladi & Sowlati, 2018). Therefore, it is important to consider the cost and emissions of biomass logistics activities in calculating the economic indicators and GHG emissions of the biomass gasification.

The logistics activities involved in the upstream biomass supply chain are shown in Figure 2.1. These activities are common in syngas production for combustion in the lime kiln as well as co-production of syngas and RNG. The supply chain starts from supply sources and ends at the drying activity. Sawmill residues are hauled to the pulp mill, whereas harvesting residues are first ground by a mobile horizontal grinder at the forest roadsides and then transported to the pulp mill. Since harvesting residues include tops and branches of trees, they are ground at the forest roadsides in order to increase their density and transportation efficiency. To transport sawmill and harvesting residues, self-unloading trucks are utilized as they are the most economical mode of transportation and they do not require investment in a truck dumper or any other unloading equipment. Upon arrival of the trucks at the mill, wood residues are unloaded by the trucks. Then, they are transferred to the storage and piled in an open-air storage area using front-end loaders. As per the demand of the gasification unit for feedstock, harvesting residues can be directly reclaimed to the dryer because they are readily sized. Sawmill residues, however, need to be first screened and ground before feeding to the dryer. Sawmill residues are a mixture of bark, shavings, sawdust, and solid wood. The particle size of some of these contents may exceed the size requirement of the gasifier which is typically between 20-80 mm (McKendry, 2002). Therefore, they are first reclaimed to a screener to separate the coarse content from the sized ones. Thereafter, the unsized particles are ground using a stationary electrical drop feed hogger. At the drying stage, the moisture content of wood residues is reduced from a maximum of 60% (wet basis) to 10% using steam.

2.2.2 Syngas production to meet energy demand of the lime kiln

The heat demand of the lime kiln at the pulp mill is currently met by NG combustion. To replace the NG with syngas, the pulp mill is required to invest in a gasifier with 38MW thermal capacity. Syngas production in this capacity can replace 1,149,120 GJs of NG annually (Project Manager at the pulp mill, personal communication, July 15, 2020). This amount is equivalent to replacing NG consumption of about 15,466 houses in BC (Canada Energy Regulator, 2021). For this case study, an air-blown atmospheric CFB gasifier technology was selected to produce syngas for the lime kiln. CFB gasifiers are commercialized technologies with simple design that have been in operation for lime kiln applications since 1980s (Hart, 2020). CFB gasifiers can be scaled up from 10MW to 150MW thermal to meet the syngas demand of the lime kilns (ANDRITZ, 2021). ANDRITZ Carbona CFB gasifiers are among the widely installed gasification technology at pulp mills. For instance, ANDRITZ Carbona has installed CFB gasifiers at Metsä Fibre Joutseno in Finland (48MW), and Zhanjiang Chenming Pulp & Paper (68 MW) and Chenming Shouguang Meilun pulp mill (80MW), both in China (Taillon et al., 2018). Figure 2.1 depicts the schematic diagram of steps taken after the drying of biomass to convert the feedstock to syngas for burning in the lime kiln.

2.2.3 Syngas production for combusting in lime kiln and producing RNG

To produce syngas for both burning in lime kilns and producing RNG, air blown CFB gasifiers cannot be utilized since the nitrogen present in the air highly dilutes the syngas (Hossain & Charpentier, 2015). RNG synthesis requires nitrogen free syngas and consequently nitrogen needs to be removed. Nitrogen removal is not only difficult but also adds to the downstream processing cost and does not favor the project's economics (Karl & Pröll, 2018). To produce nitrogen free syngas, either directly heated oxygen/steam blown gasifiers or indirectly heated steam blown DFB gasifiers should be utilized (Gassner & Maréchal, 2009; Hanchate et al., 2021). Directly heated oxygen/steam blown gasifiers have less complexity in design compared to the indirectly heated steam blown DFB gasifiers because they operate with only one gasifier reactor. In the gasifier reactor, a part of the infeed biomass is combusted to provide the heat necessary for gasifying the rest of the biomass (Hofbauer & Materazzi, 2019). The disadvantage of directly heated oxygen/steam blown gasifiers is their requirement for an air separation unit to produce pure oxygen (Hofbauer & Materazzi, 2019). Investment in an air separation unit is associated with considerable cost that would be a burden on the plant economics. On the other hand, in indirectly heated steam blown DFB gasifiers, the combustion and gasification reactions take place in separate reactors (Hanchate et al., 2021). The heat necessary for gasification reactions is produced by burning a portion of infeed biomass in the combustion reactor. Then, the heat is transferred to the gasification reactor through heat exchangers or heat carriers (Hofbauer & Materazzi, 2019). Since air is only fed to the combustion reactor and steam is applied to the gasification reactor, mixing of flue gases from combustion, which contains nitrogen, with the syngas is avoided (Rauch et al., 2014). Syngas is mainly composed of CH_4 (9%) , H_2O (6%), CO_2 (20%), CO (24%), and H_2 (40%) (Alamia et al., 2017). While having high content of CH_4 is an advantage, H_2O and CO_2 contents will be removed through gas drying and cleaning. The CO and H_2 content of syngas are converted to CH_4 through the methanation step. For methanation reactions, it is desirable to have an H_2/CO ratio of 3 in the syngas. Directly heated oxygen/steam blown gasifiers produce a syngas with H_2/CO ratio of 1.0-1.5, while this ratio in indirectly heated steam blown gasifiers is higher, ranging between 1.8-2.0. This advantage of indirectly heated steam blown DFB gasifiers reduces the downstream upgrading processes that are required to adjust H_2/CO ratio to the desirable value of 3 (Hofbauer & Materazzi, 2019).

For the above-mentioned reasons, indirectly heated steam blown gasifier is selected as the gasifier technology for co-production of syngas and RNG in the present work. This gasifier technology uses two fluidized beds, one for gasification and the other for combustion. Therefore, they are also referred to as dual fluidized bed (DFB) gasifiers (Siedlecki et al., 2011). DFB gasification technology was also installed at one of the largest capacity RNG plants in the world, namely GoBiGas, to produce pipeline ready RNG at production scale of 20MW in Sweden (Alamia et al., 2017). In the present study, a DFB gasification technology similar to GoBiGas plant is selected for producing nitrogen free syngas. The syngas produced by DFB gasifiers can be directly burnt in the lime kilns because the raw syngas produced by the DFB gasifiers has a temperature of 770-870℃ and a high energy content of 10.9-12.8 MJ/Nm^3 (Hofbauer & Materazzi, 2019; Thunman et al., 2018), which are comparable with temperature (700-900℃) and energy content (5-7 MJ/Nm^3) of syngas produced by air-blown CFB gasifiers (Taillon et al., 2018). In this work, for the case of co-production of syngas and RNG, 38MW of hot syngas output of DFB gasifier after primary cleaning is utilized for direct combustion in the lime kiln to fulfill the lime kiln energy demand. The surplus raw syngas is entered to the downstream gas cleaning and upgrading processes for conversion into pipeline RNG. The sequence of syngas cleaning and upgrading technologies for RNG production in the present work is the same as those given in GoBiGas plant (Alamia et al., 2017). Figure 2.1 illustrates the simplified processing steps involved in the co-production of syngas and RNG.

2.3 Alternatives for syngas and RNG production

Based on the total available amount of residues, the lime kiln energy demand, gasifiers' efficiency for syngas production, and efficiency of RNG production process, three alternatives are defined to assess the economic and environmental attributes of syngas and RNG production in the pulp mill. Table 2.1 presents each alternative's gasification technology, efficiencies, feedstock consumption, and syngas and RNG production capacities.

Table 2.1 Gasifier technology, feedstock demand, efficiencies, and syngas and RNG production capacities in each alternative

Alternatives	I: 38MW Syngas	II: 38MW Syngas & 40MW RNG	III: 38MW Syngas & 62MW RNG
Gasifier technology	Air-blown CFB[a]	Steam-blown DFB[b]	Steam-blown DFB
Gasifier's feedstock consumption (ODT/year)[c]	69,868	172,566	229,313
Syngas efficiency[d]	86.70%[e]	87.30%[f]	87.30%[f]
Gasifier's syngas production capacity (MWth)	38.00	94.5	125.58

Lime kiln's syngas demand (MWth)	38.00	38.00	38.00
Remaining available syngas for RNG production	0.00	56.50	87.58
Syngas to RNG efficiency[d]	NA	70.79%[f]	70.79%[f]
RNG production capacity (MWth)	0.00	40.00	62.00

a) circulating fluidized bed; b) dual fluidized bed; c) feedstock consumptions were calculated using Equation (2.1); d) efficiencies were given using lower heating value (LHV) on dry ash-free biomass; e) (Mackėla, 2017); f) (Alamia et al., 2017)

In Alternative I, installing a gasifier with 38MW syngas production capacity to only fulfil 38MW energy demand of the lime kiln is assumed to be the case. Since in this alternative, syngas is only produced to fully replace the NG consumption of the lime kiln, air blown atmospheric CFB gasification technology is selected to gasify biomass (see Section 2.2.2). Equation (2.1) expresses how the oven-dry tonne (ODT) of biomass required to be fed to the gasifier, $W_{Biomass}$, is calculated based on the syngas production efficiency of the gasifier (η_{Syngas} [$\%LHV_{daf}$]), lower heating value of biomass in dry ash-free basis ($LHV_{Biomass\ (daf)}$), energy content of syngas (E_{Syngas}), and annual operating hours of the gasifier ($hours$). In this study, LHV_{daf} of biomass and operating hours of gasifier are assumed to be equal to 18.97 ($MJ.kg^{-1}$) (Stromberg, 2006) and 8400 hours (Project Manager at the pulp mill, personal communication, March 08, 2021), respectively.

$$W_{Biomass}(ODT) = \frac{E_{Syngas}\ (MW) \times hours\ \times\ 3.6\ (GJ.MWh^{-1})}{\eta_{Syngas}[\%LHV_{daf}] \times LHV_{Biomass\ (daf)}(MJ.kg^{-1})} \qquad (2.1)$$

In the second and third alternatives, RNG is produced at different capacities, in addition to the syngas produced for the lime kiln. For this reason, steam blown DFB gasifier is selected to produce syngas suitable not only for combustion in the lime kiln, but also for conversion to RNG (see Section 2.2.3). In the second alternative, 38MW syngas is produced for direct combustion in the lime kiln and additional syngas for 40MW production of RNG. Additional syngas required for RNG production is calculated using syngas to RNG conversion efficiency. With syngas to RNG efficiency 70.79% (Alamia et al., 2017), 94.5MW syngas is required in total to meet 38MW energy demand of the lime kiln and to produce 40MW RNG. The biomass amount required for producing 94.5MW syngas is calculated using Equation (2.1). In the third alternative, it is assumed that almost all available biomass amount including sawmill and harvesting residues are utilized for gasification. This assumption results in maximum possible production capacity of 125.58MW syngas, from which 38MW is directly burnt in the lime kiln, and the rest is converted to 62MW RNG.

2.4 Economic analysis

The main cost components of each alternative are: (1) fixed capital investment, and (2) operating and maintenance (O&M) cost. The fixed capital investment of each alternative comprises of purchase, delivery, and installation costs of equipment pieces required for handling, preprocessing, and gasification of biomass, and gas cleaning and upgrading of syngas to RNG for the case of RNG production. For the purchase cost of equipment pieces, cost data were collected from quotes provided by manufacturers and data available in the literature. When the cost data were for years other than 2020 (base year), they are updated from previous periods to 2020 using the corresponding Chemical Engineering Plant Cost Index (CEPCI) to account for the inflation (Chemical Engineering, 2021). The purchase cost of each equipment is adjusted in each alternative according to its capacity using the order of magnitude method (D. Green & Perry, 2008). Equation (2.2) shows the cost calculation of an equipment piece based on CEPCI and the order of magnitude method. $Cost_0$ and $Cost_{new}$ refer to the cost of the base equipment and the scaled new equipment;

$Size_0$ and $Size_{new}$ represent the size of the base equipment and the scaled new equipment. n is the specific scaling factor for a particular type of equipment ranging from 0.6 to 0.8. $CEPCI_{2020}$ and $CEPCI_0$ refer to Chemical Engineering Plant Cost Index in the base year 2020 and the year when cost data of the base equipment are given. It should be noted that the purchase cost of biomass handling and preprocessing equipment are scaled up according to the sawmill and harvesting residues throughput to the gasifier in each alternative. The purchase costs of biomass gasification, primary syngas cleaning, and flue gas and ash handling systems are adjusted based on the syngas production capacity in each alternative. Finally, purchase costs of syngas cleaning and upgrading equipment are scaled up according to the RNG production capacity in each alternative.

$$Cost_{new} = Cost_0 \times \left(\frac{Size_{new}}{Size_0}\right)^n \times \left(\frac{CEPCI_{2020}}{CEPCI_0}\right) \qquad 2.2)$$

To estimate the installation cost of equipment pieces in the pulp and paper sector, an escalation factor of 2.6 is applied to the purchase cost of equipment pieces (Project Manager at the pulp mill, personal communication, November 17, 2021). Likewise, this factor is employed in the present study to account for the installation cost. The installation cost comprises of civil, structural, mechanical, electrical, instrumentation, design and engineering costs of equipment pieces. The delivery cost is assumed to be 10% of the equipment purchase cost (Sales Manager at TerraSource, personal communication, December 1, 2020). The fixed capital investment cost in each alternative is presented in Table 2.2. The detailed cost data, base capacities, and scale factors are given in Table A.1 in the Appendix.

Table 2.2 Total fixed capital investment, O&M costs, and biomass delivery cost of each alternative

Item description ($1 Million CAD)	I: 38MW Syngas	II: 38MW Syngas & 40MW RNG	III: 38MW Syngas & 62MW RNG
Fixed capital investment cost	86.30	442.97	544.82
Annual O&M costs	8.88	18.89	23.37
Annual delivery cost of sawmill residues	2.10	2.45	2.45
Annual delivery cost of harvesting residues	-	11.80	19.16

The O&M costs include cost of personnel, maintenance, consumables, overheads, ash disposal, make-up lime, biomass handling, and biomass preprocessing, but it excludes biomass delivery cost. The cost data including personnel, maintenance, consumables, and overheads reported for GoBiGas plant are applied to this study as they were actual costs available in the literature which incurred to maintain and operate a 20MW RNG plant during a year (Thunman et al., 2019). Authors in (Thunman et al., 2019) mentioned that the number of personnel in 100MW RNG plant would be almost the same as that of a 20MW RNG plant. Likewise in this study, the personnel cost is assumed to be the same for the three alternatives and equal to that of GoBiGas plant. Regarding the cost of consumables, they are increased linearly according to the capacity of equipment pieces required for syngas and RNG production in each alternative (Thunman et al., 2019). The maintenance cost of each alternative is escalated using the order of magnitude method (See Equation (2.2)) (Thunman et al., 2019). The make-up lime cost accounts for the new lime added cyclically to the lime kiln in order to neutralize the effect of None Processed Elements (NPEs). Syngas contains rare amount of NPEs, mainly silica (Si), that are not filtered by cyclones in the primary gas cleaning step. Consequently, the NPEs are entered to the lime kiln when syngas is combusted (Taillon et al., 2018). The NPEs negatively affect the quality of burnt lime mud, and therefore, their concentration should be monitored (Kuparinen & Vakkilainen, 2017). To avoid accumulation of NPEs introduced by the syngas to the lime mud, pulp mills operate with lime cycle opening through which make-up lime is added to the lime mud (Taillon et al., 2018). Lastly, biomass handling and preprocessing costs comprise of maintenance and fuel consumption of the equipment. The total O&M costs in each alternative is given in Table 2.2. The detailed data on the components of O&M costs are tabulated in Table A.2 in the Appendix.

Biomass delivery cost consists of all the costs incurred up to the gate of the pulp mill. For the sawmill residues, it includes biomass purchase cost from the suppliers and transportation to the mill. The delivery cost of harvesting residues comprises of loading/unloading of residues, grinding at the forest roadside, transportation to the mill, and the road network cost. To estimate delivery cost per unit of biomass for each residue type, the average delivery cost of sawmill residues and harvesting residues is used. In addition, it is assumed that the available sawmill residues are first utilized for gasification. Then, if the demand of the gasifier is not fully met, harvesting residues will be procured. This assumption is made due to the fact that forest cut blocks are mainly located farther from the mill than the sawmills, and thus they have higher transportation cost on average. In addition, the per unit cost of roadside grinding is higher. For these reasons, procuring residues from the sawmills is less costly than procuring residues from the forest cut blocks. The total feedstock delivery cost of sawmill residues and harvesting are separately shown in Table 2.2.

It is assumed that investment in the project takes place in 2020 and the gasification plant operates for 20 years, starting from 2021. It is also assumed that 50% of the fixed capital investment cost is financed with a bank loan and will be paid back over the 20-year lifetime of the project. The funding available from the federal government of Canada (NRCan, 2020) and government of British Columbia (Community Energy Association, 2020; Province of BC, 2020a, 2020b) as incentives for bioenergy projects are considered as a positive cash flow in the base year in the economic analysis. As shown in Table 2.3, the available incentives totals CAD $28 million. The revenue from replacing NG with syngas and RNG sale to FortisBC, a gas and power provider in BC, are included as annual positive cash flows over the lifetime of the project. FortisBC purchases syngas and RNG with an offtake price of $30/GJ and $60/GJ, respectively (Project Manager at the pulp mill, personal communication, May 05, 2021). However, in case of syngas, pulp mills still should pay the NG cost and its associated carbon tax (Project Manager at the pulp mill, personal communication, May 05, 2021). Therefore, the fuel cost and carbon tax of NG are subtracted from the offtake price of $30/GJ. The carbon tax in the first operation year (i.e., 2021) is $45/t of CO_2 eq. in BC (Province of British Columbia, 2021),is increased by $5/t of CO_2 eq. in 2022 and $15/t of CO_2 eq. from 2023 to 2030 until it reaches $170/t CO_2 eq. in 2030 (Government of Canada, 2021d). There are no data available on the annual rate of carbon tax increase in BC and Canada from 2031 to 2040 when the lifetime of the project will end. Therefore, it was assumed that the most reasonable case for annual increase in carbon tax from 2031 to 2040 is that it will continue to increase by the same rate of $15/t of CO_2 eq. yearly as before. Since the pulp mill would earn income from biomass gasification, they are required to pay the corporate tax, which is 27% of taxable income in Canada (Government of Canada, 2021b). The annual taxable income is calculated by deducting the allowable expenses (i.e., operating and maintenance cost, feedstock delivery, and annual depreciation of assets) from the annual revenue. The half year rule and declining balance methods are applied to calculate the annual depreciation of equipment pieces as these methods are required by the Canadian tax law for determining the corporate tax (Government of Canada, 2021a). Finally, the salvage value is assumed to be equal to the undepreciated capital cost (i.e., the remaining book value of the asset) at the end of project's lifetime. The salvage value is added to the income after-tax in the last year. All assumptions that are made for conducting the economic analysis are summarized in Table 2.3. In (BC Bioenergy Network, 2020), the authors performed pre-feasibility study of hydrogen production in the BC pulp and paper sector in 2020, considering discount rate of 8%. Due to similarity between the context of this study and that of (BC Bioenergy Network, 2020), the same discount rate of 8% is applied to the economic model in the present work. To evaluate and compare the economics of the three gasification alternatives, their individual Net Present Value (NPV), Annual Worth (AW), Rate of Return (ROR), and Payback Period are calculated. Readers are referred to (D. Green & Perry, 2008; Whitman & Terry, 2012) for thorough explanation on the mathematical formulation as well as the concept behind the before-mentioned factors.

Table 2.3 Detailed data for economic analysis

Parameter	Value	Parameter	Value
Base year	2020	Governments' bioenergy investment incentives (million $, CAD)	28[d]
Lifetime (yr)	20[a]	Equipment depreciation rate	30%[e]
Operating days in a year	350	Corporate tax rate	27%[f]
Operating hours in a day	24	RNG offtake price ($/GJ)	60[g]
Discount rate	8%[b]	Syngas offtake price ($/GJ)	30[g]
Interest rate for loan	10%[c]	NG price	5.22[h]
Loan share (% of fixed capital investment cost)	50%	Carbon tax rate ($/tonne CO_2 eq.)	45[i] (yr 2021)
Loan payment period (yr)	20	Annual carbon tax rate increase ($)	5 (2022)[j]
		Annual carbon tax rate increase ($)	15 (2023-2040)[j]

a) (Thunman et al., 2019); b) the same discount rate as the one used in (BC Bioenergy Network, 2020) to evaluate pre-feasibility of hydrogen production in the BC pulp and paper sector in 2020 is applied to this study; c) (Chau et al., 2009); d) (Community Energy Association, 2020; NRCan, 2020; Province of BC, 2020a, 2020b); e) (Government of Canada, 2021a); f) (Government of Canada, 2021b); g) (Project Manager at the pulp mill, personal communication, May 05, 2021); h) (FortisBC, 2018); i) (Province of BC, 2021); j) (Government of Canada, 2021d)

2.5 GHG emission reduction

In BC, pulp mills could trade the net GHG emission reduction of biomass to FortisBC, a gas and power provider in BC, for receiving $30 and $60 for every produced GJ of syngas and RNG, respectively. In this way, pulp mills would help FortisBC to achieve its commitment for substitution of 15% gas content of pipeline by renewable content until 2030 (Province of British Columbia, 2020). The annual net GHG emission reduction can be estimated based on the emission reduction that are obtained by replacing NG with syngas and RNG minus GHG emissions emitted for (1) biomass procurement, (2) biomass conversion to syngas and RNG, and (3) ash disposal. In this work, the scope of GHG emission reduction analysis only accounts for non-biogenic (fossil fuel-based) GHG emissions and does not consider the biogenic GHG emissions.

In this case study, fossil fuel-based GHG emissions are released during biomass procurement for transportation, loading/unloading, and preprocessing of biomass. Biomass conversion to syngas and RNG requires electricity mainly in the gasification and gas compression steps. It is assumed that the pulp mill fulfills the power demand of the biomass conversion to syngas and RNG by the electricity purchased from the local power grid. The local power grid generates part of the electricity by consumption of fossil fuels (BC Hydro, 2020). Therefore, GHG emissions intensity associated with the combusted fossil fuels for electricity generation is used for calculating GHG emissions released for biomass conversion. Lastly, for disposal of ash, it is required to load the gasifier's bottom ash to trucks by a front-end loader and haul it to the landfill for disposal. According to (Hope et al., 2017) who performed cost analysis of bioenergy-generated ash disposal options in Canada, the landfills are typically located with 5 km of the ash producer's facility. In the present work, it was assumed that the landfill for ash disposal is 5 km away from the pulp mill. GHG emissions associated with loading and round-trip transportation of ash are included in the calculations. The fuel type and GHG emissions intensity of equipment pieces required for biomass procurement, biomass conversion to RNG and syngas, and ash disposal are provided in

Table A.3 in the Appendix.

2.6 Uncertainty analysis

In deterministic models, complete information is assumed to be available for the input parameters and thus a certain value is assigned to each parameter; however, such perfect information is only available in very few decision-making circumstances (Gargalo et al., 2016). Instead, the input parameters are given with a degree of uncertainty. The uncertainty stems from either the random nature of the parameter, incomplete understanding of a system due to its complexity, or errors in the measurement (Vose, 2013). Overlooking uncertainty in the input parameters can lead to having infeasible projects or obtaining outcomes in practice that differ from those computed by the deterministic model (Shabani et al., 2014). Moreover, in uncertain situations, the decision makers are not only concerned with the value of the output, but also would like to identify the extent of impact that uncertainty in each input parameter has on the output variation and the level of risk accompanying the output (Gargalo et al., 2016). In the present work, local and global sensitivity analyses are carried out to identify the influence of uncertainty in the parameters on the variation of NPV and GHG emission reduction of each alternative when the parameters vary individually and simultaneously, respectively. In addition, the mean value and risk associated with the outputs are computed using Monte-Carlo simulation.

2.6.1 Local sensitivity analysis

Local sensitivity analysis is performed to determine the impact of variation in one parameter at a time on the NPV and annual net GHG emission reduction of each alternative. In this work, the uncertainty is considered in the main input parameters including the availability, cost, energy content, transportation emissions of biomass, syngas and RNG production efficiencies, fixed capital investment cost, initial governments incentives, O&M costs, discount rate, NG price, annual carbon tax rate increment, and syngas/RNG offtake prices. For all the above-mentioned parameters, except syngas production efficiency, the uncertainty range was assumed to be ±20%, which is according to the expected accuracy range that was suggested in (Vancas, 2003) for the feasibility study of industrial projects. Although some of the parameters might experience lower level of uncertainty, assuming the same uncertainty range for them helps to compare their impact on the model's output in the similar condition. According to Table 2.1, assuming a 20% increase in the syngas production efficiency results in efficiency greater than 100%, which is not possible. Thus, the increase in the syngas production efficiency is considered to be +%15, which limits the increase in these parameters to 100%. Similar to other parameters, the decrease in the syngas production efficiency is assumed to be 20%.

2.6.2 Monte-Carlo simulation

Local sensitivity analysis helps to evaluate the changes in the model outputs when each individual parameter varies one at a time; however, it cannot measure the changes in the outputs when all parameters are varying at the same time (Cardoso et al., 2019). To address this issue, Monte-Carlo simulation can be used. In Monte-Carlo simulation, the deterministic model is run repeatedly by considering possible values that each uncertain parameter can take using its probability distribution function. The output of Monte-Carlo simulation allows to: (1) derive the probability distribution of the model outputs, (2) evaluate model behavior and stability under uncertainties in the system, and (3) evaluate possible risks posed by the uncertainty of the input parameters (Vose, 2013). In the present work, Monte-Carlo simulation is employed to calculate the probability distribution and mean values for NPV and net GHG emission reduction of each alternative and to measure the risks associated with having low NPV and low annual net GHG emission reduction in each alternative.

The same uncertain parameters considered for local sensitivity analysis are involved in Monte-Carlo simulation. The uncertainty ranges reported in the literature for each parameter are used in the Monte-Carlo simulation. As such, the minimum and maximum values for the syngas to RNG conversion efficiency, syngas production efficiency, feedstock LHV are obtained from the literature and since no distribution is given, uniform distribution is used. The ranges are given in Table 2.4. For the other uncertain parameters that no data are available (i.e., annual carbon tax rate increment, discount rate, delivery cost, availability, and transportation emissions of sawmill residues/harvesting residues, fixed capital investment, government incentives, O&M cost, NG price, RNG offtake price and syngas offtake price), the range of uniform distributions are calculated assuming ±20% variability (Vancas, 2003).

Table 2.4 The ranges assumed for uncertain parameters to run Monte-Carlo simulation

Parameter	**Minimum**	**Maximum**	**Data source**
Syngas to RNG efficiency	68%	74%	(Alamia et al., 2017)
Syngas production efficiency	83%	90%	(Alamia et al., 2017)
Feedstock LHV	18.15 MJ/Kg	19.27 MJ/Kg	(Stromberg, 2006)

Microsoft Excel spreadsheets are used to generate samples from the specified ranges and distributions. Then, NPV and annual net GHG emission reduction associated with each sample are calculated. The number of iterations required for Monte-Carlo simulation depends on the standard deviation and mean value of output, acceptable accuracy, and the desired confidence level. Using Equation (2.3), the number of required iterations can be calculated (You et al., 2009):

$$N = \left(\frac{Z \times \sigma}{\varepsilon \times \mu}\right)^2 \tag{2.3}$$

Where N is the number of iterations, σ and μ are the standard deviation and mean value of model's output, ε is the maximum allowable marginal error and Z is the minimum required confidence interval of a two-tailed normal distribution. Based on the standard deviation and mean value of model's output estimated for 1000 runs, the confidence level of 95% (Z = 1.96), and marginal error of 15%, the required number of iterations for N is calculated. Monte-Carlo simulation is run for 20,000 iterations to satisfy the given confidence level and marginal error for NPV and annual net GHG emission reduction of all alternatives.

In the literature, previous studies employed variance to quantify the risk associated with the model outputs, herein NPV. However, variance suffers from symmetry property (i.e., treating the NPVs higher and lower than the mean NPV in the same way) and inability to consider the risk of low probability events. NPV-at-Risk is free from these pitfalls (Baker & Filbeck, 2015; Ye & Tiong, 2000). For this reason, to measure the risk associated with the investment in each alternative, NPV-at-Risk of alternatives are calculated using Equation (2.4) (Baker & Filbeck, 2015; Ye & Tiong, 2000):

$$NPV\text{-}at\text{-}Risk_{\alpha}(X) = \inf\{x \in \mathbb{R} : F_X(x) > \alpha\} \tag{2.4}$$

Where $F_X(x)$ is the cumulative probability distribution function of NPV (which can be derived using the output of the Monte-Carlo simulation), and $100(1-\alpha)\%$ is the confidence level.

$NPV\text{-}at\text{-}Risk_{\alpha}$ represents the minimum NPV that the project can suffer from in $100(1-\alpha)\%$ of the best cases (Baker & Filbeck, 2015). The confidence level for calculating NPV-at-Risk is commonly chosen to be either 95% or 99% (Baker & Filbeck, 2015). In this study, 99% is used for calculations to hold a conservative viewpoint toward investment in biomass gasification. The same concept as NPV-at-Risk is used to calculate the net GHG emission reduction-at-Risk for three alternatives at confidence level of 99%.

2.6.3 Global sensitivity analysis

Contrary to the local sensitivity analysis, global sensitivity analysis ranks and identifies the most influential uncertain parameters while they change at the same time (Dellino & Meloni, 2015). In this way, the possible contribution of the interactions among parameters to the model outputs' variation is also captured (Dellino & Meloni, 2015). In this study, global sensitivity analysis is employed to address the above-mentioned limitation of local sensitivity analysis. The SobolGSA software developed by Kucherenko & Zaccheus (2021) is used to conduct the global sensitivity analysis on the NPV and annual net GHG emission reduction of the alternatives. In order to provide a realistic view towards ranking and calculating the impact of each uncertain parameter on the models' outputs, the same uncertainty ranges for the uncertain parameters as those in the Monte-Carlo simulation were considered to carry out the global sensitivity analysis. As such, the sample data consisting of inputs (uncertain parameters) and outputs (NPV and emission reduction of each alternative) generated by the Monte-Carlo simulation are uploaded to this software using Microsoft Excel spreadsheets.

In SobolGSA, Sobol method is selected to perform global sensitivity analysis. The Sobol method is a variance-based sensitivity analysis (Dellino & Meloni, 2015). It decomposes the model output's variance to elementary fractions, which can be attributed to a given input or combination of inputs (Saltelli et al., 2008). Based on the calculated elementary fractions of output's variance, the so-called Sobol indices are defined. The total effects are the main indices calculated by the Sobol method. The total effect of each input parameter considers: (1) the contribution of changes in that parameter to the variance of the output, and (2) its combined contribution with other parameters to the variance of the output due to its interaction with other uncertain parameters (Dellino & Meloni, 2015). Moreover, the total effect of an input parameter can also be interpreted as the percentage of reduction in the output variance when this parameter is fixed to a certain value (Saltelli et al., 2008). Such information helps the decision maker to allocate time on collecting data to reduce the uncertainty in the input parameters which have the highest impact on the variation of the output (Saltelli et al., 2008). In this work to conduct global sensitivity analysis, the sample data that was previously generated by the Monte-Carlo simulation model is provided for the software to calculate the total effects.

2.7 Multi-criteria decision making

Multi-criteria decision-making (MCDM) helps the decision makers to select the best alternative among multiple alternatives when several conflicting criteria are involved in decision making (Fitó et al., 2021; Triantaphyllou, 2000). In this study, the weighted-sum method (WSM) is applied to conduct MCDM. The WSM is the simplest and well-known MCDM method in decision theory through which all the criteria are integrated into one goal function by calculating their weighted sum (Triantaphyllou, 2000). WSM requires the criteria to have the same dimensions. When criteria differ in dimensions, the data should be normalized before using WSM. Commonly, the linear model, formulated in Equation (2.5), is applied to normalize the data (Goulart Coelho et al., 2017). Equation (2.5) expresses how the value of alternative j under criterion i (M_{ij}) is normalized to N_{ij}. The terms $\min_j M_{ij}$ and $\max_j M_{ij}$ refer to the minimum and maximum value of M_{ij} under criterion i, respectively.

$$N_{ij} = \frac{M_{ij} - \min_j M_{ij}}{\max_j M_{ij} - \min_j M_{ij}} \tag{2.5}$$

After normalization, the weighted sum score for each alternative j, W_j, can be calculated as shown in Equation (2.6) (Triantaphyllou, 2000), where W_i is the weight assigned to each criterion. The weights should be non-negative and $\sum_i W_i = 1$.

$$W_j = \sum_i W_i \times N_{ij} \quad \forall\, j \in J \tag{2.6}$$

2.8 Results and discussion

2.8.1 Economic analysis

The initial investment of each alternative is given in Table 2.5. The initial investment represents the capital cost of each alternative after subtracting the loan and governments incentives. In other words, it represents the project’s cash flow in the base year (i.e., 2020). Initial investment is equal to the total fixed capital investment cost minus the loan provided by a bank and the incentives provided by the government. According to Table 2.5, the initial investment rises when biomass gasification capacity increases. Alternative III has the highest initial investment ($246 million), closely followed by Alternative II ($195 million). Alternative I requires only financing $16 million, which is the least investment among all alternatives. The initial investment cost of Alternatives II and III are approximately 12 and 15 times greater than that of Alternative I, respectively. This is because in Alternative I, the pulp mill would only invest in a CFB gasifier and its auxiliary equipment, whereas in the other two alternatives, in addition to investment in a steam-blown DFB gasifier, they are required to invest in technologies for syngas cleaning and upgrading to RNG.

Table 2.5 Results of economic analysis

Alternatives	I: 38MW Syngas	II: 38MW Syngas + 40MW RNG	III: 38MW Syngas + 62MW RNG
Initial investment	-$16 M	-$195 M	-$246 M
NPV	$7 M	$57 M	$168 M
AW	$658,774	$5,815,481	$17,078,326
Rate of Return of the project	9.20%	9.39%	10.84%
Incremental Rate of Return of the project	9.20% (I)	9.35% (II-I)	14.42% (III-II)
Payback Period	3 years	7 years	6 years

Table 2.5 also presents the net present value (NPV), annual worth (AW), rate of return (RoR), incremental RoR, and payback period of each alternative. All alternatives have positive NPV and AW; therefore, they are feasible for investment under the economic assumptions given in Section 2.4. Alternatives II and III obtain greater NPVs and AWs despite having higher initial investment due to generating more revenue over the project service life. The NPV of Alternative III is equal to $168 million over 20-year lifetime of the project at a discount rate of 8% and 3 times greater than the NPV of Alternative II. This is because Alternative III generates 20MW more RNG than

Alternative II, which increases the annual revenue. Additionally, Alternative III takes advantage of economy of scale because its RNG production capacity is 50% more than Alternative II, while its initial investment cost is increased by 26%. Lastly, Alternative I achieves the least NPV ($7 million) due to producing only syngas.

To compare the alternative's rate of return (RoR), the external rate of return (ERR) is employed instead of internal rate of return (IRR). The reason for using ERR is that as shown in Figure 2.3, the annual cash flows of Alternative I become negative in year 12 and beyond. Since Alternative I experiences negative cash flows after positive cash flows, it could have multiple IRR, causing difficulty to evaluate its performance. To solve this issue, ERR can be used (Whitman & Terry, 2012). The RoR of all alternatives is greater than the assumed discount rate of 8%, indicating that they are all acceptable for investment under the given economic assumptions. However, since only one alternative from the three alternatives can be selected for investment, i.e. these alternatives are mutually exclusive, the incremental rate of return has to be calculated (Whitman & Terry, 2012). According to the incremental rate of return (or incremental ERR) analysis, Alternative III has the best performance, followed by Alternative II and I.

Looking at the payback period of alternatives in Table 2.5, Alternative I's cumulative cash flow becomes positive within 3 years, while that of Alternative III after 6 years. Alternative II has the longest payback period and turns to profitability period after 7 years. The shorter payback period of Alternative I is because it substantially has lower initial investment compared to the other alternatives. Therefore, from the NPV, AW, and incremental RoR point of view, Alternative III is the most economical option, followed by Alternatives II and I, whereas from the payback period perspective, Alternative I is the best option, followed by Alternatives III and II.

Figure 2.2 depicts the generated net annual cash flows in alternatives during the project service life. Alternatives II and III take advantage of having significant higher annual positive cash flows throughout their lifetime as compared to Alternative I. In Alternative I, only 38MW syngas is produced to fully meet the lime kiln energy demand. As a result, the pulp mill would earn annual revenue just from syngas production. Contrarily, in Alternatives II and III, 40MW and 62MW RNG would be produced in addition to 38 MW syngas. Thus, the pulp mill is able to earn revenue not only from the syngas production, but also from selling RNG. According to Figure 2.2, the annual net cash flow of all alternatives gradually decreases. The gradual decline of cash flows in all cases is attributed to continuous increase in the carbon tax rate. As it was elaborated earlier in Section 2.4, the pulp mill would receive \$30 for every GJ of NG replaced by syngas and \$60 for every GJ of RNG sold to the local gas provider. However, it still has to pay the fuel cost of NG and its carbon tax, even though it does not factually consume NG in the lime kiln. The carbon tax in the first year of project's operation (i.e., 2021) is \$45/t of CO_2 in BC (Province of British Columbia, 2021) and it increases annually by \$5 per t of CO_2 in 2022, and \$15 per t of CO_2 in 2023 and beyond (Government of Canada, 2021d). Due to the constant increase in the carbon tax, the revenue from syngas production decreases annually, and thus the net cash flow of all alternatives declines. In Alternatives II and III, the annual net cash flow declines to \$16 and \$32 million in the last year of the project, respectively, while the annual net cash flow in Alternative I goes below zero in year 12 and beyond. Since the annual carbon tax rate increase, syngas/RNG offtake prices, and other key input parameters may exhibit uncertainty and consequently vary the annual cashflows and economic feasibility of the alternatives, it is essential to identify the most sensitive parameters and make decision on the best alternative for investment considering uncertainty.

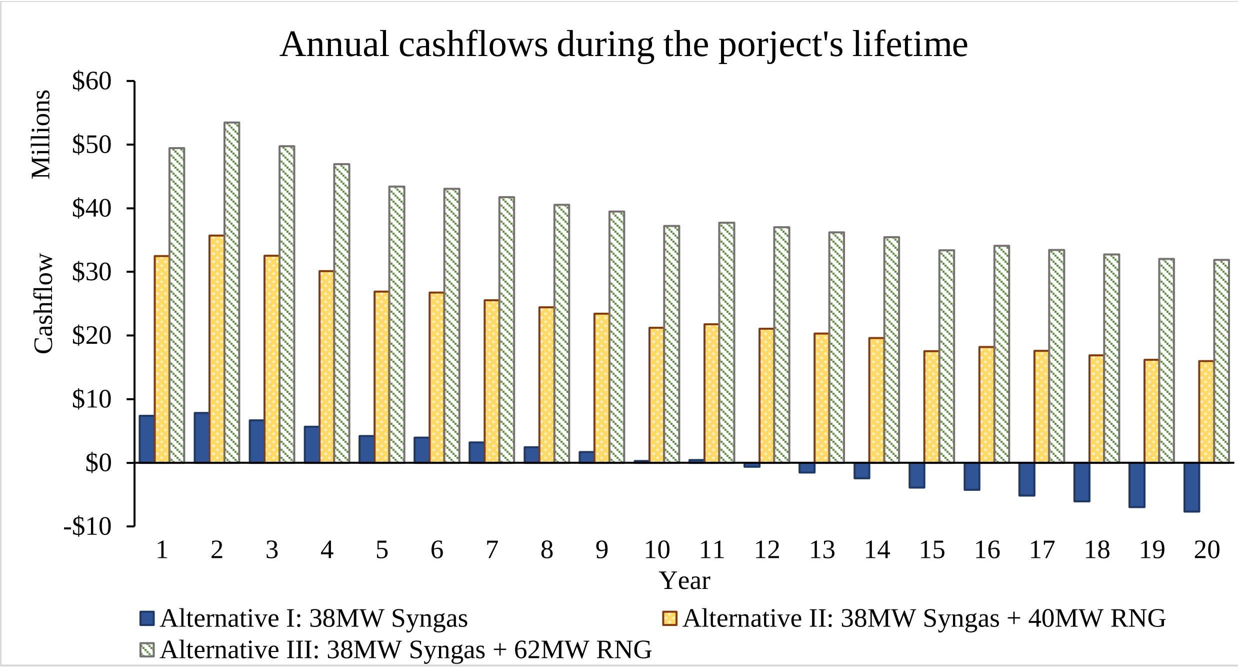


Figure 2.2 Annual net cash flows of alternatives during the project service life

2.8.2 GHG emission reduction

Table 2.6 shows the contribution of supply chain activities (i.e., transportation, preprocessing, and handling), syngas and RNG production, and ash disposal to the total generated GHG emissions in each alternative. In Alternative I, transportation of sawmill residues from the suppliers to the pulp mill is the largest contributor of GHG emissions (86.6%), followed by biomass handling (10.4%). Since sawmill residues transportation and biomass handling are carried out by diesel trucks and diesel front-end loaders, respectively, they are the main GHG contributors. On the other hand, biomass preprocessing activities (i.e., screening, grinding, and reclaiming) and biomass conversion to syngas only require electricity. GHG intensity of electricity is low in BC, and thus, the total contribution of these activities to the total emitted GHGs in Alternative I is equal to only 2.5%. The GHG emissions from transportation and roadside grinding of harvesting residues is zero. This is because the availability of sawmill residues is sufficient to fulfill the feedstock demand of the gasifier in Alternative I, and there is no requirement for procuring harvesting residues.

As it can be seen from in Table 2.6, in Alternatives II and III, harvesting residues transportation to the pulp mill is the dominant emission contributor, followed by sawmill residues transportation and grinding at roadside. The transportation of harvesting residues releases more GHG emissions than the transportation of sawmill residues in Alternatives II and III because: (1) more harvesting residues than sawmill residues are procured in both cases, and (2) the GHG emission intensity of transporting harvesting residues is significantly greater than that of sawmill residues as forest cut blocks are located at farther distances from the pulp mill than the sawmills on average.

Table 2.6 Results of GHG emission reduction

Emissions source	Alternatives		
	(I) 38MW Syngas	(II) 38MW Syngas + 40MW RNG	(III) 38MW Syngas + 62MW RNG
Sawmill residues transportation	86.6%	15.8%	10.5%
Harvesting residues transportation	0.0%	63.8%	69.0%
Grinding at roadside	0.0%	12.4%	13.4%
Biomass handling	10.4%	5.8%	5.2%
Biomass preprocessing	0.8%	0.2%	0.1%
Biomass conversion to Syngas/RNG	1.7%	1.6%	1.6%
Ash disposal	0.6%	0.3%	0.3%
Total GHG emissions (t of CO_2 eq.)	1,890	12,076	18,157

Annual gross emission reduction due to replacement of NG (t of CO_2 eq.)	57,307	117,629	150,807
Annual net emission reduction (t of CO_2 eq.)	55,417	105,553	132,650

According to Table 2.6, the total GHG emissions of Alternatives II and III is about 6 and 9 times greater than that of Alternative I due mainly to GHG emissions released by transportation and grinding of harvesting residues. However, the annual gross emission reduction achieved by replacing NG with syngas and RNG in Alternatives II and III offset the generated emissions. As a result, the annual net GHG emission reduction of Alternatives II and III are remarkably greater than that of Alternative I.

2.8.3 Uncertainty analysis

2.8.3.1 Local sensitivity analysis

Figure 2.3 illustrates the sensitivity of NPV of Alternative I with respect to the changes in each individual parameter. The results of local sensitivity analysis on NPV of Alternatives II and III are presented in Figure 2.4 and Figure 2.5, respectively. In general, the sensitivity of each alternative's NPV to the changes in parameters is different. The influential uncertain parameters that their ±20% change either turn NPV of the alternatives to a negative value (i.e., greater than -100% change) or double the NPVs (i.e., greater than 100% change) are listed below.

- **Alternative I (38MW Syngas):** syngas offtake price, fixed capital investment, O&M cost, carbon tax rate increment, LHV of feedstock, syngas production efficiency, NG price;
- **Alternative II (38MW Syngas & 40MW RNG):** RNG offtake price, fixed capital investment;

- **Alternative III (38MW Syngas & 62MW RNG):** LHV of feedstock, syngas production efficiency, syngas to RNG conversion efficiency, RNG offtake price.

The NPV of alternatives is primarily most sensitive to the offtake prices of syngas and RNG because they directly impact the annual revenue obtained in each alternative. Authors in (Cardoso et al., 2019; Copa et al., 2020) also identified biofuel/bioenergy selling price as the most impactful parameter. For instance, sensitivity analysis on NPV of electricity generation via biomass gasification in (Cardoso et al., 2019) indicated that ±10% variation in the electricity selling price led to about ±360% change in the project's NPV. From the result of local sensitivity analysis on the NPV of the three alternatives, it can be realized that the impact of fixed capital investment, O&M cost, government incentives, NG price, annual carbon tax rate increment, syngas offtake price, and sawmill residue delivery cost become less when moving from Alternative I (the lowest capacity) to Alternative III (the highest capacity). Conversely, the influence of harvesting residue availability, and syngas to RNG efficiency increases when moving from Alternative I to Alternative III. The syngas production efficiency, sawmill residue availability, and feedstock LHV become less impactful in Alternative II, but more influential in Alternatives I and III. Finally, discount rate, RNG offtake price and harvesting residues delivery cost become more impactful in Alternative II, but less influential in Alternatives I and III.

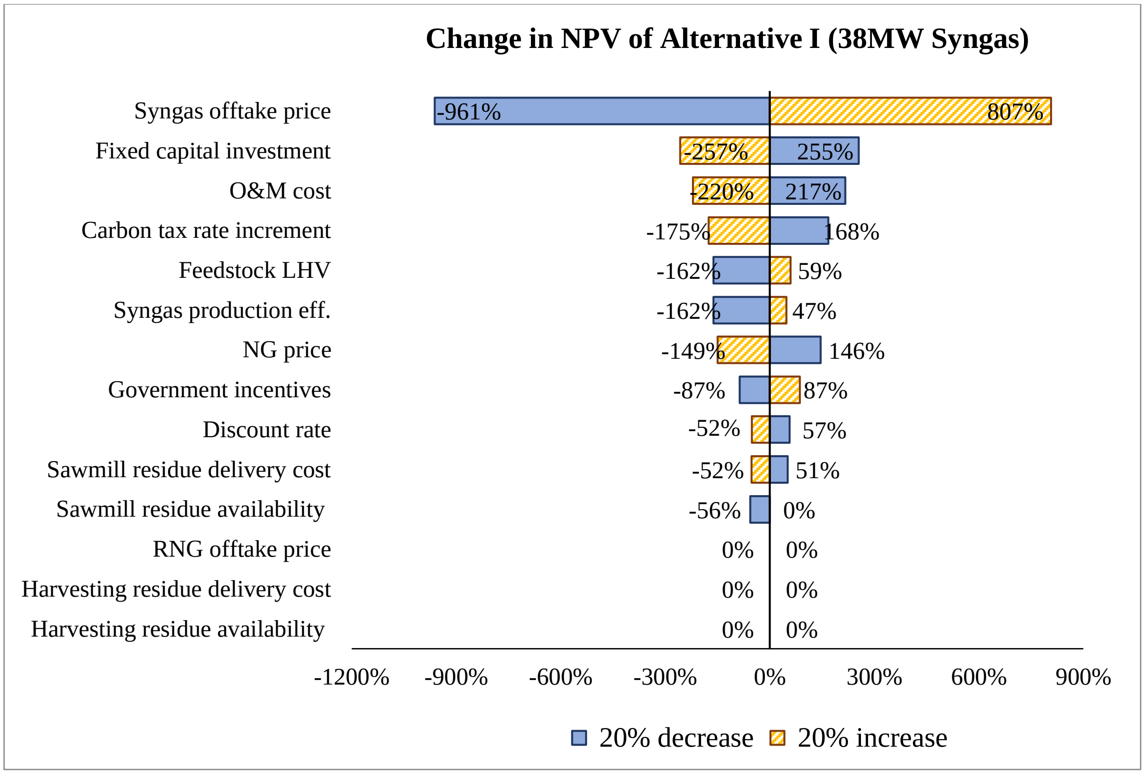


Figure 2.3 Local sensitivity analysis on NPV of Alternative I (38MW syngas)

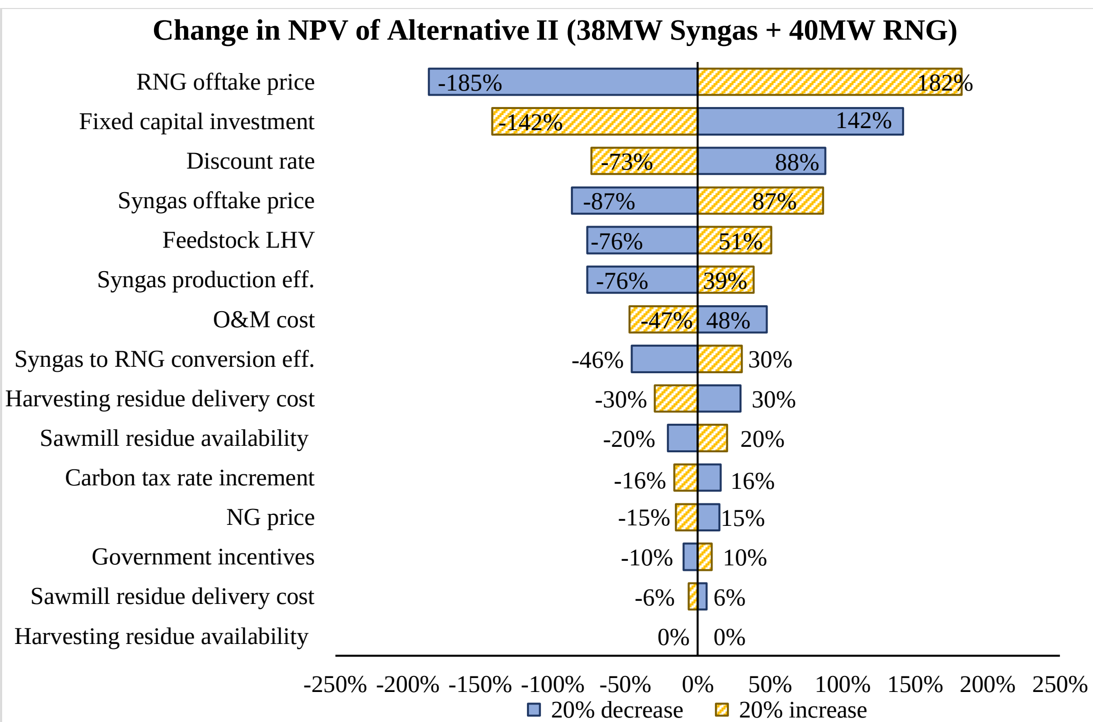


Figure 2.4 Local sensitivity analysis on NPV of Alternative II (38MW syngas and 40MW RNG)

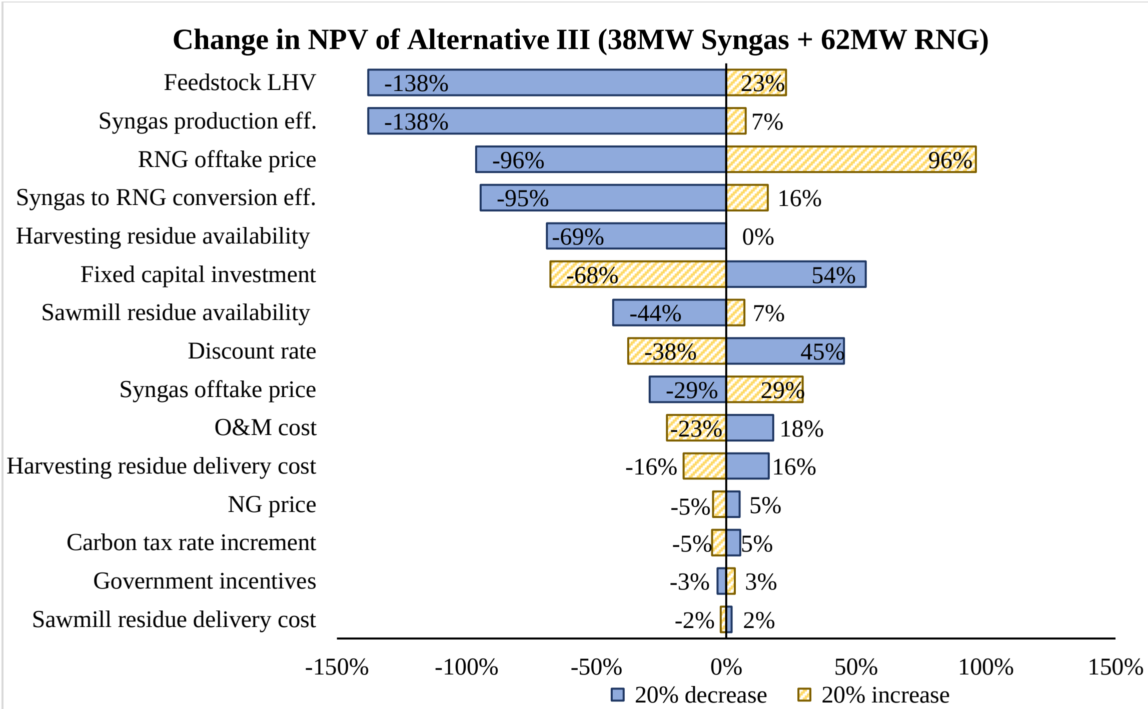


Figure 2.5 Local sensitivity analysis on NPV of Alternative III (38MW syngas and 62MW RNG)

In particular case of Alternative I, +20% and -20% changes in the syngas offtake price result in 807% and -961% change in its NPV, respectively, which is considerably higher than the impact of ±20% changes in the syngas offtake price on the NPV of Alternatives II and III. The reason behind the significant sensitivity of Alternative I's NPV to the syngas offtake price can be traced back to the initial value and the absolute changes of alternatives' NPV (See Table 2.7). According to Table 2.7, the absolute change in the NPV of alternatives does not differ significantly when the syngas offtake price changes because the syngas production capacity of all alternatives is the same and is equal to 38MW. However, since the initial value of Alternative I's NPV is substantially lower than the initial value of NPV of Alternatives II and III, the percentage of changes in Alternative I's NPV becomes greater compared to Alternatives II and III.

Table 2.7 Initial value and absolute changes of alternatives' NPV when syngas offtake price vary by ±20%

		Syngas offtake price		
	Percentage of change	-20%	Initial value	20%
	Absolute change	-12	30	12
NPV of Alternative I	Percentage of change	-961%	-	807%
	Absolute change	-$62 M	$7 M	$52 M
NPV of Alternative II	Percentage of change	-87%	-	87%
	Absolute change	-$50 M	$57 M	$49 M
NPV of Alternative III	Percentage of change	-29%	-	29%
	Absolute change	-$49 M	$118 M	$49 M

The sensitivity of annual net GHG emission reduction of Alternatives I,II, and III with respect to the changes in each individual parameter is depicted in Figure 2.6 - Figure 2.8. Overall, the annual net GHG emission reduction of alternatives has less sensitivity to ±20% change in the uncertain parameters compared to the NPVs. This is because the amount of annual GHG emissions released by each alternative is negligible as compared to their annual gross GHG emission reduction (See Table 2.6). For instance, according to Table 2.6, annual GHG emissions of Alternative I is 1,890 ton of CO_2 eq., that is very much lower than the annual gross GHG emission reduction of this alternative (57,307 ton of CO_2 eq.).

Due to the above-mentioned reason, the impact of changes in the input parameters on the annual net GHG emission reduction of alternatives is insignificant (i.e., up to 20%). Nonetheless, the syngas production efficiency, syngas to RNG conversion efficiency, and feedstock LHV relatively have a greater influence on the annual net GHG emission reduction of Alternative III than the other parameters. In particular, 20% decrease in the values of above-mentioned parameters decline the annual net GHG emission reduction in Alternative III between 14% and 20%. This change is because a drop in efficiencies or feedstock LHV directly trigger an increase in the feedstock consumption. Since Alternative III utilizes almost all the available biomass, there is no more available biomass to fulfill the increase in the feedstock demand, and therefore, the level of RNG production declines in Alternative III. Reduction in RNG production leads to decrease in the amount of GHG emission reduction. Due to this reason, a drop in the value of efficiencies and feedstock LHV impacts the net GHG emission reduction in Alternative III more than the other two alternatives.

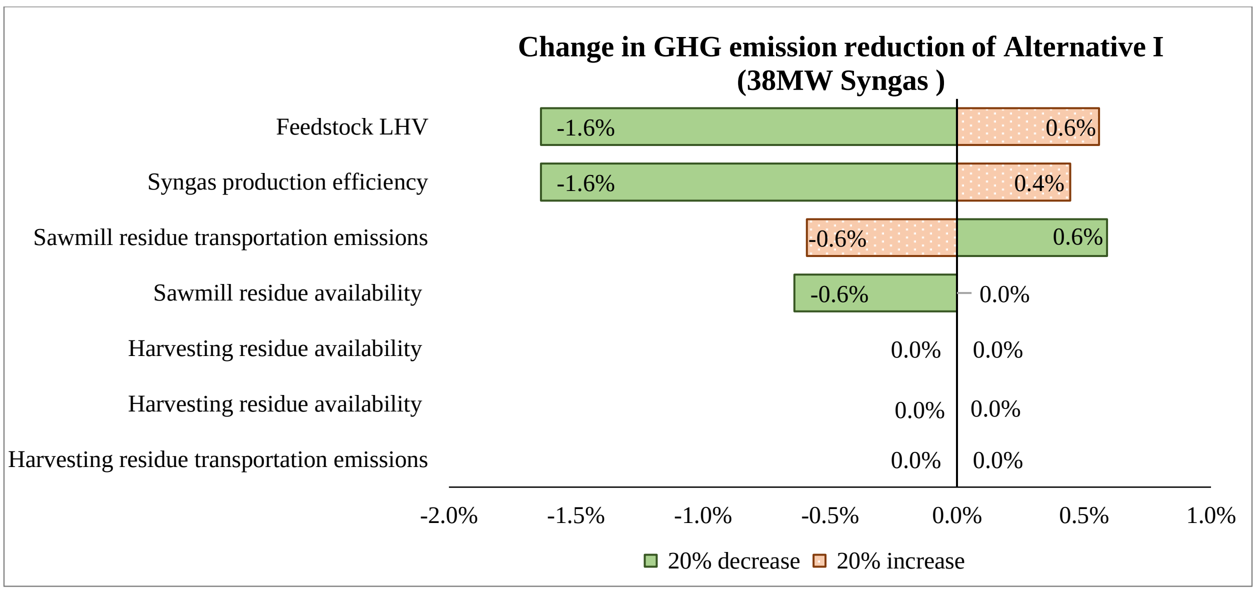


Figure 2.6 Local sensitivity analysis on GHG emission reduction of Alternative I (38MW syngas)

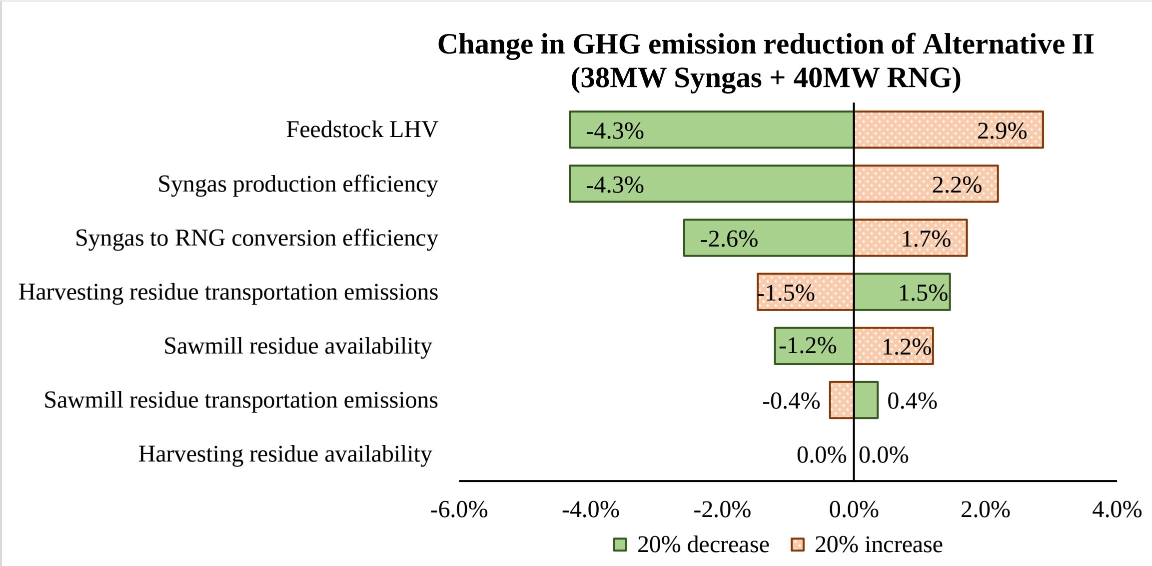


Figure 2.7 Local sensitivity analysis on GHG emission reduction of Alternative II (38MW syngas and 40MW RNG)

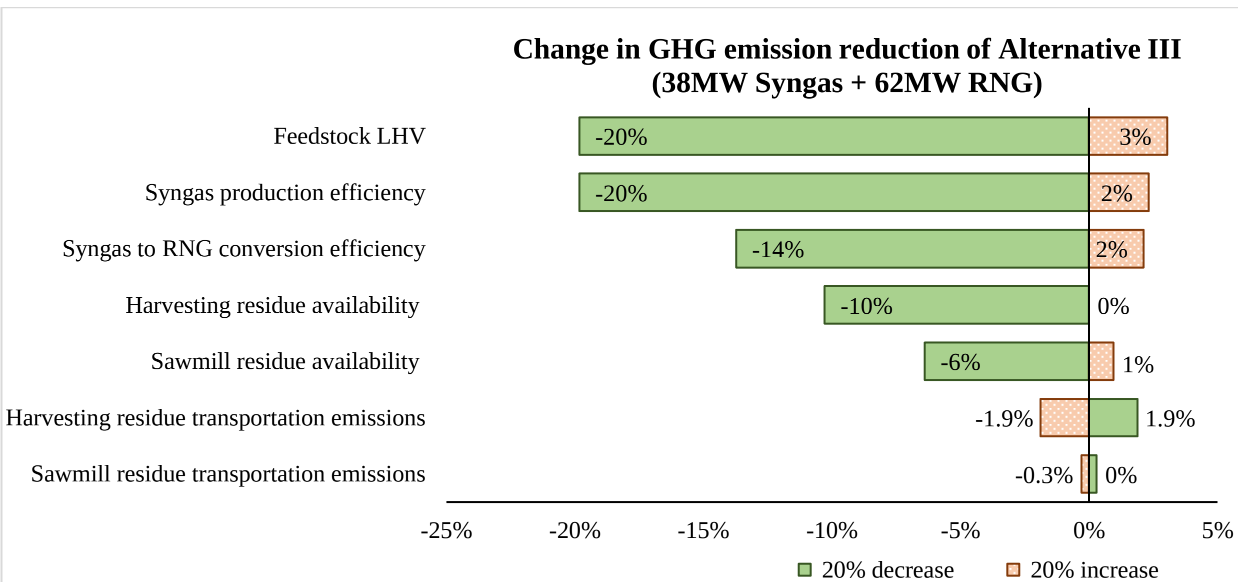


Figure 2.8 Local sensitivity analysis on GHG emission reduction of Alternative III (38MW syngas and 62MW RNG)

2.8.3.2 Monte-Carlo simulation

The minimum, mean, maximum, Value-at-Risk and deterministic values of NPV and net GHG emission reduction of each alternative are given in Table 2.8. Under uncertain conditions, the mean NPV of all alternatives are less than their deterministic value, calculated in Section 2.8.1, but Alternative III similar to the deterministic conditions still has the highest mean NPV ($128 million), followed by Alternative II ($56 million) and Alternative I ($4 million). Likewise, the maximum NPV of Alternative III is greater and equal to $583 million, whereas NPV of Alternatives II and I are lower and would be up to $373 million and $100 million, respectively. As it can be seen from the probability and cumulative distributions of alternatives' NPV in Figure 2.9, Figure 2.10 and Figure 2.11, there is a high probability of having negative NPV (i.e., infeasible project) in all alternatives. More exactly, the minimum NPV of alternatives in Table 2.8 demonstrate that Alternative III can lead to the highest loss of -$367 million, while Alternative I has the least loss of -$104 million. This highlights the fact that uncertainty in the input parameters poses the risk of having negative NPV and thus economically infeasible projects. To measure the investment risk, the NPV-at-Risk of each alternative is computed using the cumulative distribution functions of alternatives' NPV (Figure 2.9, Figure 2.10, and Figure 2.11). The NPV-at-Risk for each alternative is given in Table 2.8. Alternative I has the least NPV-at-Risk of -$75 million, indicating that the decision makers can rest assured with 99% confidence level that the NPV of this alternative does not go below -$75 million. Contrarily, the NPV-at-Risk of Alternatives II and III are greater than that of Alternative I, equal to -$139 million and -$158 million, respectively. This reveals that although Alternatives III and II have higher mean NPV under the given uncertainty, but they are exposed to risk of generating a greater negative NPV. Conversely, Alternative I is exposed to risk of having a lower negative NPV but at the expense of having lower mean NPV.

Table 2.8 Results of Monte-Carlo simulation

Alternatives:	**I: 38MW Syngas**	**II: 38MW Syngas + 40MW RNG**	**III: 38MW Syngas + 62MW RNG**
	NPV (Million $)		
Minimum	-$104	-$242	-$367
Mean	$4	$56	$128
Maximum	$100	$373	$583
NPV-at-Risk	-$75	-$139	-$158
Deterministic value from economic analysis	$7	$57	$168
	Annual net GHG emission reduction (thousand t of CO_2 eq.)		
Minimum	54.19	100.92	101.36
Mean	55.34	105.28	127.77
Maximum	55.82	109.02	137.40
Net GHG emission reduction-at-Risk	54.67	102.14	109.33
Deterministic value from environmental analysis	55.42	105.55	132.65

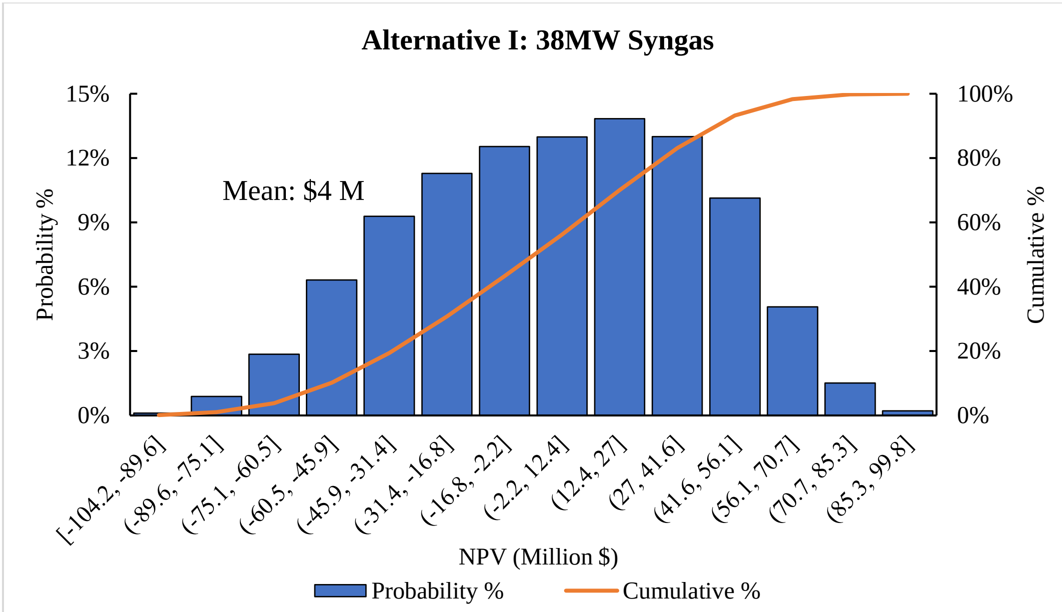


Figure 2.9 Probability and cumulative distribution functions of NPV for Alternative I

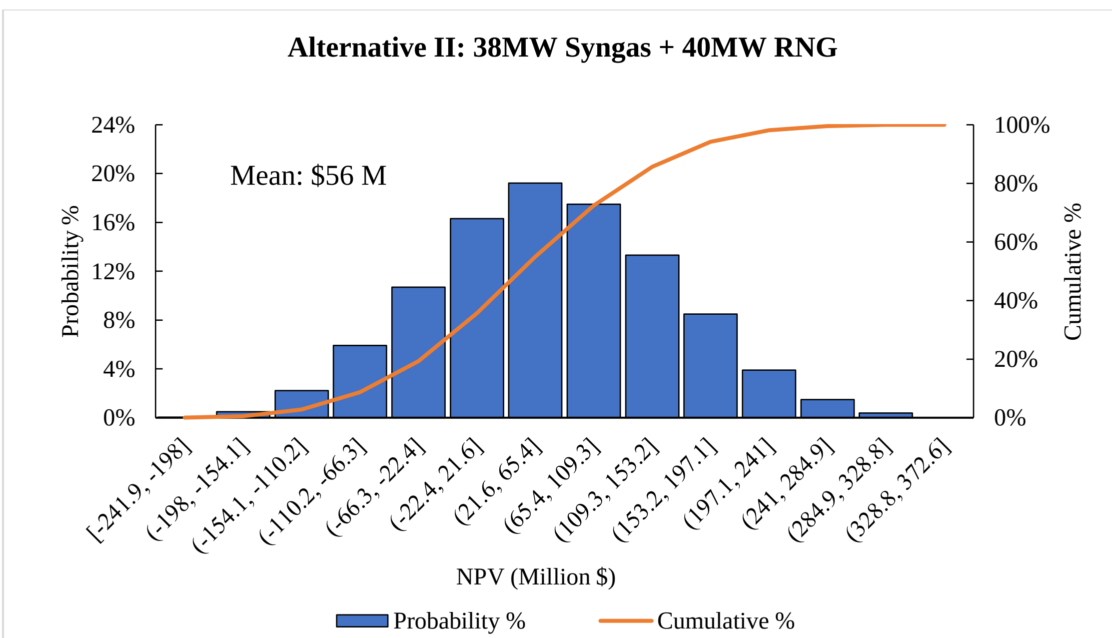


Figure 2.10 Probability and cumulative distribution functions of NPV for Alternative II

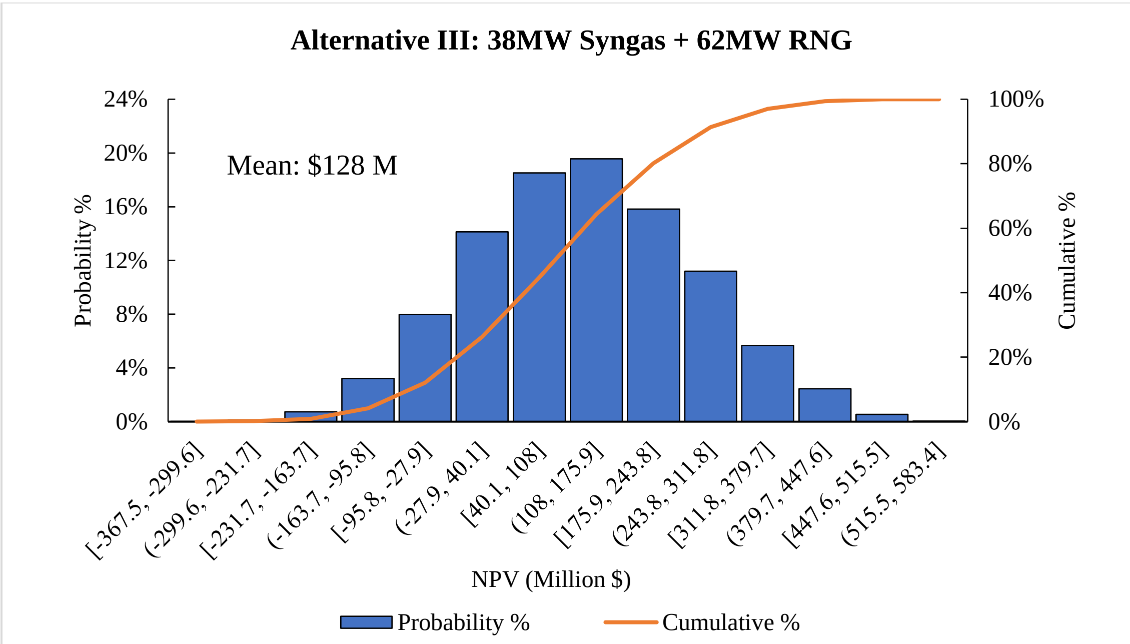


Figure 2.11 Probability and cumulative distribution functions of NPV for Alternative III

According to Table 2.8, when uncertainty is present, the mean annual net GHG emission reduction of all alternatives are less than their deterministic value, calculated in Section 2.8.1, but Alternative III still has the highest amount of the annual net GHG emission reduction of 128 thousand t of CO_2 eq., followed by alternative II and I. Similarly, the maximum value of the annual net GHG emission reduction of Alternative III is higher and equal to 137 thousand t of CO_2 eq., whereas that of Alternatives II and I are lower and would be up to 109 and 56 thousand t of CO_2 eq., respectively. Moreover, as the probability and cumulative distributions of the annual net GHG emission reduction illustrate in Figure 2.12, Figure 2.13, and Figure 2.14, there is a probability of having net GHG emission reduction lower than the mean value in all alternatives. Based on Table 2.8, Alternatives III and II guarantee greater minimum value for the annual net GHG emission reduction, equal to approximately 101 thousand t of CO_2 eq., than Alternative I (54 thousand t of CO_2 eq.). Due to the fact that the value of annual net GHG emission reduction can vary between the minimum and maximum values reported in Table 2.8, there is a risk of having annual net GHG emission reduction lower than the mean values. To account for this risk, the net GHG emission reduction-at-Risk of alternatives are calculated. The net GHG emission reduction-at-Risk of alternative III is equal to 109 thousand t of CO_2 eq., closely followed by Alternative II (102 thousand t of CO_2 eq.). These values are greater than the Value-at-Risk of Alternative I (55 thousand t of CO_2 eq.), demonstrating that at 99% confidence level, Alternatives II and III guarantee GHG emission reduction higher than Alternative I, and thus they are exposed to lower level of risk.

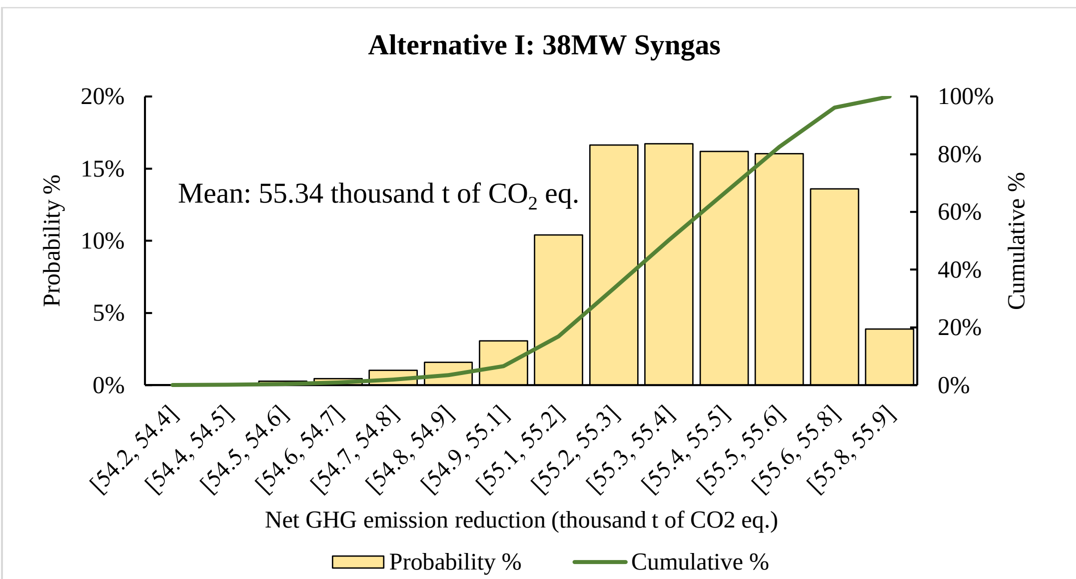


Figure 2.12 Probability and cumulative distribution functions of annual net GHG emission reduction of Alternative I

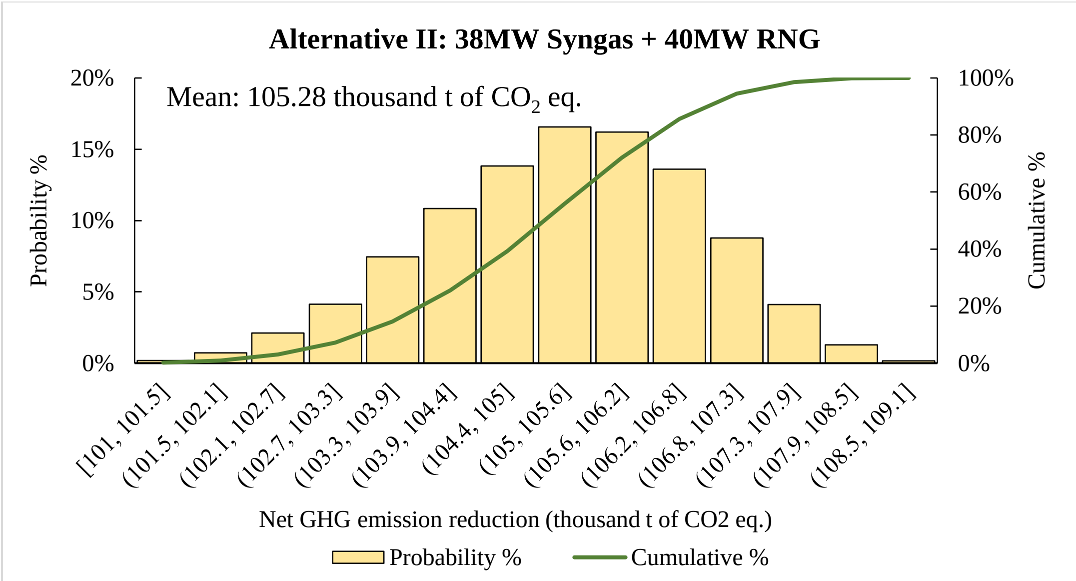


Figure 2.13 Probability and cumulative distribution functions of annual net GHG emission reduction of Alternative II

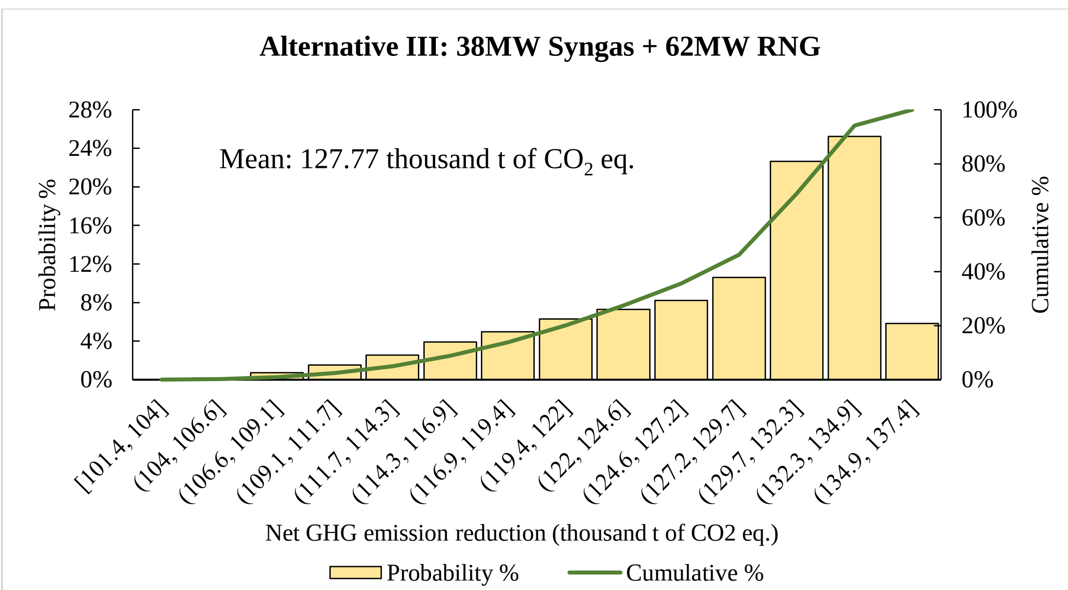


Figure 2.14 Probability and cumulative distribution functions of annual net GHG emission reduction of Alternative III

2.8.3.3 Global sensitivity analysis

The results of Monte-Carlo simulation revealed that the presence of uncertainty in the key input parameters of the models leads to variation in NPV and GHG emission reduction of alternatives and poses the risk of having lower NPVs and GHG emission reductions than the mean values. In order to determine the contribution of uncertainty in each input parameter to the variation of the output, it is required to perform a sensitivity analysis that considers simultaneous variation in all the input parameters. As elaborated earlier in Section 2.6.3, global sensitivity analysis aims to analyze the impact of each uncertain input parameters to the output while the parameters vary at the same time.

In Figure 2.15, the total effects of uncertain parameters on the NPV of each alternative are presented by the size of the bubbles. Due to the negligible total effect (i.e., less than 5%) of sawmill residues and harvesting residues delivery cost, annual carbon tax rate increment, NG price, government incentives, LHV of feedstock and efficiency parameters on NPVs, they are not shown in Figure 2.15. The contribution of other input parameters to the variance of NPV varies depending on the alternative. In Alternative I, variation in the syngas offtake price has the largest impact on NPV, accounting for 82% of the NPV variance because syngas sale is the only source of annual revenue in Alternative I. In Alternative II and III, variation in the RNG offtake price is the most influential parameter on the NPV variance because RNG sale is the primary source of annual revenue in Alternative II and III. Therefore, the syngas offtake price plays a key role in determining the amount of annual positive cash flows in Alternative I and the RNG offtake price has a similar role in Alternatives II and III. The second influential parameter in all alternatives is the fixed capital investment due to its great amount in all alternatives, which impacts not only the initial cashflow in the base year (year zero) but also the annual loan payments. The order of impact of other parameters on the NPVs changes depending on the alternative.

Based on the comparison between the results of local and global sensitivity analysis on NPV, they both identified the syngas offtake price, fixed capital investment, and O&M cost as the most sensitive parameters on the NPV of Alternative I. Similarly, both analyses identified the same ranking for influential parameters on the NPV of Alternative II. This consistency between the results of global and local sensitivity analyses in terms of the parameters' order of ranking indicate that in this case study, the interaction among the uncertain parameters has low contribution to the variance of the outputs. Therefore, although when the parameters vary simultaneously, their contribution to the NPV variance changes compared to when they vary one at a time, they still have the same order of ranking.

When it comes to Alternative III, the order of identified impactful parameters through local and global sensitivity analyses differs. According to the local sensitivity analysis, the feedstock LHV and efficiency parameters are among the top impactful parameters on the NPV of Alternative III, but based on global sensitivity analysis, the total effect of each of these parameters on the NPV of Alternative III is negligible and less than 5%. This is because different uncertainty ranges have been assumed for the feedstock LHV and efficiency parameters in local and global sensitivity analyses. In local sensitivity analysis, the uncertainty range for all parameters was assumed to be ±20%, except for the increase in the syngas production efficiency that was assumed to be +15%, whereas for global sensitivity analysis, the available uncertainty ranges reported in the literature for feedstock LHV and efficiency parameters were applied. Since the reported ranges in the literature lead to less than ±5% uncertainty in the above-mentioned parameters, their impact on the

NPV variation of Alternative III in global sensitivity analysis decreases in comparison with the local sensitivity analysis. Regarding other parameters, they almost exhibit the same order of impact on the NPV of Alternative III through both local and global sensitivity analysis.

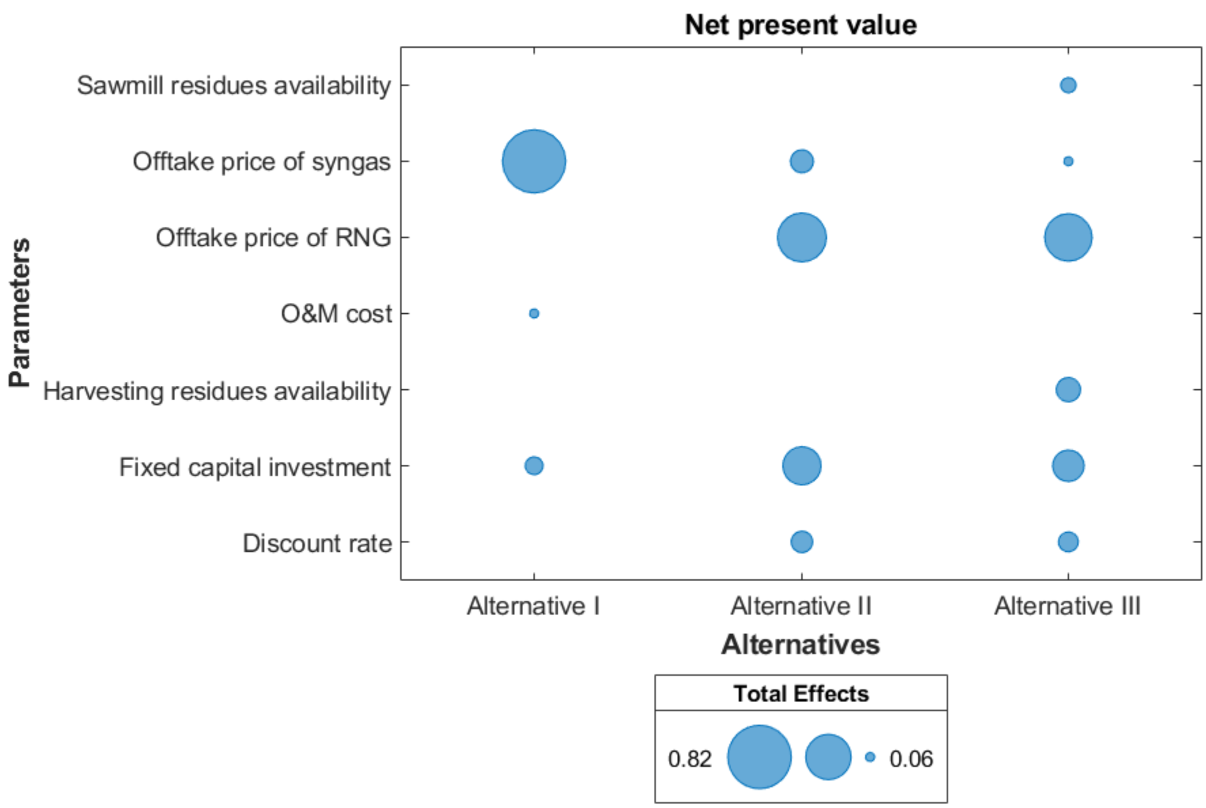


Figure 2.15 Global sensitivity analysis on alternatives' NPV

Figure 2.16 depicts the results of global sensitivity analysis on the annual net GHG emission reduction of each alternative. GHG emission reduction of Alternatives I and II is primarily sensitive to the variation in the transportation emissions of sawmill residues and harvesting residues, respectively. GHG emission reduction of Alternative III is mainly influenced by the harvesting residue availability since in this alternative, almost all harvesting residues are utilized. Thus, any reduction in their availability declines the RNG production level and emission reduction level. The next impactful parameter on the emission reduction of all alternatives is sawmill residue availability, followed by syngas production efficiency and feedstock LHV. Overall, the ranking of parameters' impact on the GHG emission reduction is the same according to local and global sensitivity analyses, except for feedstock LHV and efficiency parameters. According to the global sensitivity analysis, the feedstock LHV and efficiency parameters have the lowest impact on the variance of GHG emission reduction in all alternatives, while based on the local sensitivity analysis, they have the highest impact on the GHG emission reduction. As explained earlier for the results of global sensitivity analysis on NPV, the observed difference is due to assuming different uncertainty ranges for feedstock LHV and efficiency parameters in local and global sensitivity analysis.

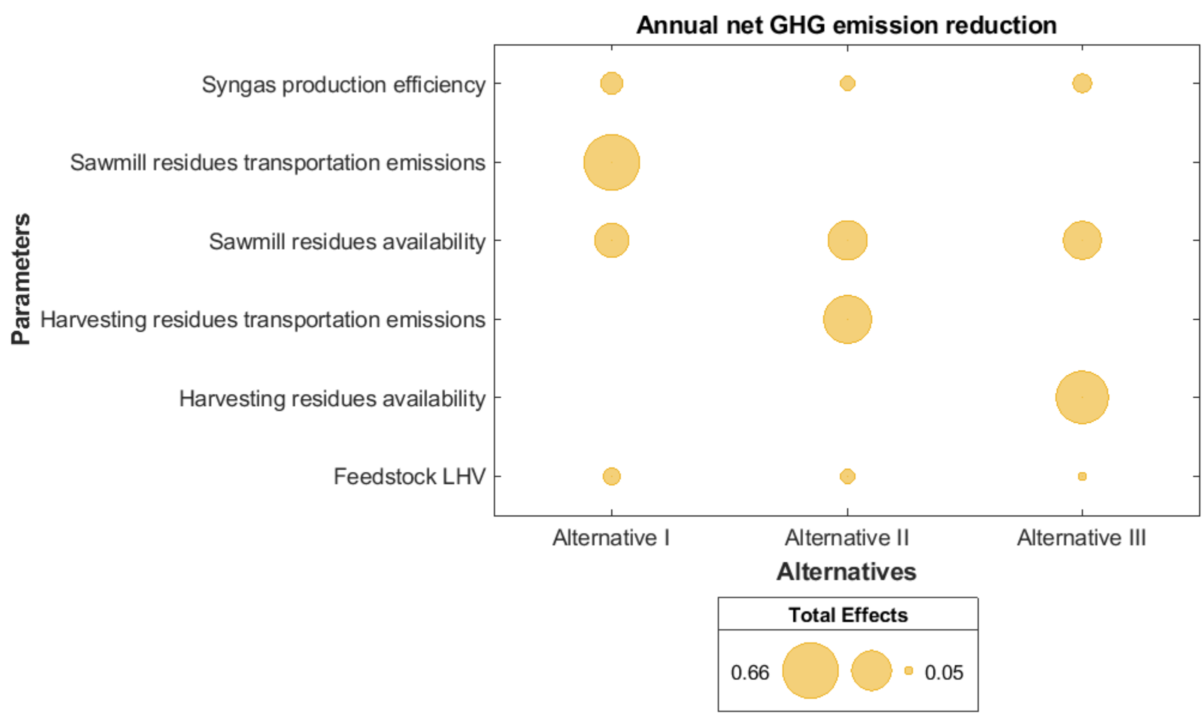


Figure 2.16 Global sensitivity analysis on annual net GHG emission reduction of alternatives

2.8.4 Multi-criteria decision making

Table 2.9 summarizes the mean NPV, mean annual net GHG emission reduction, and Value-at-Risk of alternatives. The values are normalized using Equation (2.5). According to Table 2.9, Alternative III has the highest NPV, and annual net GHG emission reduction, and the least risk of having low annual GHG emission reduction, followed by Alternative II and I. However, in terms of NPV-at-Risk, the order is reversed; the lowest NPV-at-Risk belongs to Alternative I, followed by Alternatives II and III. Since no alternative can outweigh other alternatives in all the above-mentioned criteria, multi-criteria evaluation is performed to select the best alternative considering different weights (i.e., importance) for the four criteria given in Table 2.9.

Table 2.9 Summary of mean NPV, mean annual net GHG emission reduction, and Value-at-Risk of alternatives (The values in bolded show the first rank alternative in each criterion)

Alternative	**I: 38MW Syngas**		**II: 38MW Syngas & 40MW RNG**		**III: 38MW Syngas & 62MW RNG**	
Criteria	Value	Normalized value	Value	Normalized value	Value	Normalized value
Mean NPV (Million $)	3.75	0.00	55.87	0.42	128.01	**1.00**
NPV at risk (Million $)	-75.04	**1.00**	-139.36	0.22	-157.92	0.00
Mean annual net GHG emissions savings (thousand t of CO2 eq.)	55.34	0.00	105.28	0.69	127.77	**1.00**
Annual net GHG emissions savings at risk (thousand t of CO2 eq.)	54.67	0.00	102.14	0.87	109.33	**1.00**

Since sensitivity analysis on the criteria weights helps to reveal the ranking of the alternatives when the priority of the criteria changes, it would provide decision makers with useful insights into which alternative is the best option for investment under a particular circumstance. For instance, the decision makers might be conservative and consider higher importance for the risks associated with the project's economics and emissions rather than the mean value of NPV and annual net GHG emission reduction. Thus, the criteria should be weighed according to their importance. The weighted sum score and rank of each alternative under different weights for the criteria are summarized in Table 2.10.

Table 2.10 The ranking of the alternatives based on different criteria weights

	(A) NPV + GHG emission reduction		**(B) Mean values**		**(C) Only GHG emission reduction**		**(D) Only NPV**		**(E) Risk values**	
Weight[a]	*(0.25, 0.25, 0.25, 0.25)*		*(0.5, 0, 0.5, 0)*		*(0, 0, 0.5, 0.5)*		*(0.5, 0.5, 0, 0)*		*(0, 0.5, 0, 0.5)*	
Alternative	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
I	0.250	3	0.000	3	0.000	3	0.500	1	0.500	2
II	0.550	2	0.554	2	0.779	2	0.322	2	0.546	1
III	0.750	1	1.000	1	1.000	1	0.500	1	0.500	2
Weight	*(0.12, 0.12, 0.37, 0.37)*		*(0.25, 0, 0.75, 0)*		*(0, 0, 0.25, 0.75)*		*(0.25, 0.75, 0, 0)*		*(0, 0.25, 0, 0.75)*	
Alternative	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
I	0.125	3	0.000	3	0.000	3	0.750	1	0.250	3
II	0.665	2	0.622	2	0.824	2	0.273	2	0.707	2
III	0.875	1	1.000	1	1.000	1	0.250	3	0.750	1
Weight	*(0.37, 0.37, 0.12, 0.12)*		*(0.75, 0, 0.25, 0)*		*(0, 0, 0.75, 0.25)*		*(0.75, 0.25, 0, 0)*		*(0, 0.75, 0, 0.25)*	
Alternative	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
I	0.375	3	0.000	3	0.000	3	0.250	3	0.750	1
II	0.436	2	0.487	2	0.734	2	0.371	2	0.385	2
III	0.625	1	1.000	1	1.000	1	0.750	1	0.250	3

a) Criteria weight (weight for mean NPV, weight for NPV-at-Risk, weight for mean annual net GHG emission reduction, weight for annual net GHG emission reduction-at-Risk)

The alternatives' ranks in column (A) of Table 2.10 indicate that when all criteria are considered simultaneously and their weights vary in the weighted-sum model, Alternative III is ranked in the first position, followed by Alternatives II and I. The same order of ranking is observed when either only mean values for NPV and annual net GHG emission reduction are important for decision makers, and risk measures get zero weight (column B) or only mean value and Value-at-Risk of annual net GHG emission reduction are important for decision makers and mean NPV and NPV-at-Risk get zero weight (column C). When the mean NPV and NPV-at-Risk are important for the decision makers and they disregard the importance of the annual net GHG emission reduction (column D), either Alternative I, Alternative III, or both can be selected as the best option. Finally, the results in column (E) shows when decision makers are risk-averse and are only concerned about the Value-at-Risk of NPV and GHG emission reduction, all three alternatives can be ranked in the first position depending on the weights assigned to the Value-at-Risk of NPV and annual net GHG emission reduction.

According to the sensitivity analysis on the weights of criteria, it can be interpreted that when decision makers (i.e., the pulp mill) consider the importance of either all criteria, only GHG emission reduction, or only mean values of NPV and emission reduction, the large-scale gasification with syngas and RNG production capability is the best alternative to invest. Investment in small and large-scale gasification can both suit decision makers prioritizing only the mean value of NPV and its risk measure. Finally, investment in all three gasification capacities can be recommended for risk-averse decision makers depending on how much weight they allocate to the risk associated with the NPV and GHG emission reduction.

In order to assist the pulp mill to make decision on the most suitable gasification alternative for investment, their preferences over the given criteria were obtained through asking them to weigh the criteria. Table 2.11 shows their preferences and the corresponding score and ranking of the alternatives. As it be seen from the weights, the pulp mill prefers risk-averse approach on the economic aspect of investment in biomass gasification, as such Alternative I appears to be the most suitable option.

Table 2.11 Weights assigned by the pulp mill to the criteria and rank of alternatives

Criteria	**Weight**	**Alternative**	**Score**	**Ranking**
Mean NPV	0.2	**I**	**0.600**	**1**
NPV-at-Risk	0.6	II	0.374	3
Mean annual net GHG emission reduction	0.1	III	0.400	2
Annual net GHG emission reduction-at-Risk	0.1			

2.9 Discussion and conclusions

In previous works that assessed the economics and GHG emissions of biomass gasification for syngas and RNG production, the uncertainty analysis was limited to the local sensitivity analysis. In addition, when several alternatives were assessed for investment in biomass gasification, previous studies did not perform multi-criteria decision making for identifying the best alternative under uncertain conditions. The first objective of the thesis was to perform multi-criteria decision making on biomass gasification investment considering uncertain conditions. The economic and environmental analysis models were developed for a case study of a Kraft pulp mill in British Columbia, Canada. In this case study, syngas was utilized to replace natural gas consumption of the pulp mill's lime kiln, and RNG was to substitute natural gas content of the gas pipeline. Three different alternatives were assumed for investment in the gasification plant. Alternative I was defined to produce 38MW syngas to only meet the lime kiln heat demand. In Alternatives II and III, in addition to the 38MW syngas for heating the lime kiln, 40MW and 62MW of RNG was assumed to be produced, respectively, to be injected to the gas pipeline.

The results of the economic analysis indicated that Alternative I benefited from having the lowest initial investment of $16 million, whereas Alternatives II and III required $195 million and $246 million to be initially invested. The higher initial investment cost of Alternatives II and III was attributed to the requirement of investment in a more advanced gasifier (i.e., DFD gasifier) as well as gas cleanup and conversion technologies required for simultaneous production of syngas and RNG. Contrarily, Alternative I only needed investment in a commercialized CFB gasifier with significantly lower purchase cost. Due to lower initial investment cost, Alternative I obtained shorter payback period of 3 years compared to Alternatives II and III with payback periods of 7 and 6 years, respectively. Despite the short payback period and low initial investment, the annual net cashflow of Alternative I experienced a steady decrease, becoming negative from year 12 and afterwards. This occurred because the pulp mills that decide to sign a contract with FortisBC to sell their syngas, still have to pay the cost of natural gas and its carbon tax, even though they do not factually combust any natural gas in their lime kilns. Since Canada's government rises carbon tax annually from $45/t of CO_2 in 2021 to $170/t of CO_2 until 2030 (Government of Canada, 2021d), the pulp mill's annual payment for carbon tax increases constantly, leading to gradual decrease in the annual net cashflow. For the same reason, Alternatives II and III experienced a similar downward trend in their annual net cashflow. However, the annual revenue from RNG sale in these two alternatives compensated for the reduction in the net income from syngas sale; therefore, the annual net cashflow of Alternatives II and III remained positive throughout the project's lifetime. Regarding other economic factors, i.e., NPV, AW, and ROR, all alternatives were economically feasible for investment, however Alternatives II and III generated a significantly greater NPV and AW compared to Alternative I because these two alternatives produced RNG in addition to syngas.

According to the environmental analysis, transportation of sawmill and harvesting residues were the main contributor to the GHG emissions of the alternatives, accounting for well over 60% of total GHG emissions in all alternatives. The annual net GHG emission reduction obtained by replacing natural gas with syngas and RNG in all alternatives outweighed the GHG emissions released to produce RNG and syngas and Alternative III achieved the highest level of GHG emission reduction due to having the largest gasification capacity.

To capture the impact of simultaneous uncertainty in the input parameters on the economic feasibility and emission reduction of the alternatives, Monte-Carlo simulation was applied to the economic and environmental analysis models to calculate the probability distribution, mean value and value-at-risk of alternatives' NPV and GHG emission reduction. In the presence of uncertainty, the mean value of the outputs decreased in all three alternatives compared to the deterministic model. However, Alternative III with the largest gasification capacity still had the greatest mean NPV and GHG emission reduction due to additional revenue and reduction in NG consumption obtained by the RNG production. Moreover, the risk of having low emission reduction in alternative III was less compared to the other two alternatives. Despite all the benefits associated with Alternative III, it was exposed to higher risk of having a large negative NPV under uncertain conditions.

To identify the impact of single and simultaneous variations in the input parameters on the NPV and GHG emission reduction of alternatives, local and global sensitivity analyses were performed. According to both analyses, NPV of the alternatives was mainly sensitive to the syngas and RNG offtake prices as well as the fixed capital investment.

Since none of the alternatives could achieve the best performance in terms of the mean value and risk associated with the NPV and emission reduction, multi-criteria decision making was conducted to rank the alternatives under uncertain conditions. According to the multi-criteria decision making results, when the decision makers allocate the highest weight to the Value-at-Risk of NPV, the smallest gasification capacity with only syngas production capability (Alternative I) was recommended for establishment, while when they allocated equal weights to the Value-at-Risk of GHG emission reduction and NPV, the medium gasification capacity with syngas/RNG production capability (Alternative II) was ranked as the best alternative for establishment. In other cases, the largest syngas/RNG production capacity (Alternative III) achieved the best performance. To identify the best investment alternative for the pulp mill considering the mean and risk values of NPV and GHG emission reduction, the pulp mill's preferred weights over the criteria were considered. Since the pulp mill had a conservative approach toward economics of the project and highly weighed the risk posed to the NPV of the alternatives, Alternative I with the lowest NPV-at-Risk was ranked first.

In summary, Alternative I appeared to be the best investment option for pulp mills to minimize the risk of having negative NPV. Moreover, according to personal communication with the pulp mill and (Taillon et al., 2018), short payback period was one of the determining factors for the pulp mills to invest in biomass gasification. As a result, when the payback period of the alternatives was considered, Alternative I with 3 years payback period would be the most suitable option to invest in. Moreover, CFB gasification technology utilized in Alternative I was readily installed at commercial scales in pulp mills across the world. Therefore, the technology could be commissioned without any risk of having disrupted operation. On the other hand, Alternative II and III were exposed to risk of having greater negative NPV under uncertainty. In addition, these two alternatives required installing a DFB gasifier and downstream technologies for syngas clean up and conversion for RNG production. These equipment pieces not only increased the investment cost but also were not as mature as a CFB gasifier (which is utilized in Alternative I) in terms of readiness for operation at a commercial scale. Considering the above-mentioned factors, Alternative I outranked other two alternatives. Nonetheless, Alternatives II and III generated greater NPV, AW, and GHG emission reduction either in the deterministic conditions or under the uncertainty. For this reason, they could maximize both profitability as well as environmental benefits generated by biomass gasification. In addition, their annual net cashflow was always positive throughout their service life, while that of Alternative I became negative from year 12 due to annual increase in the carbon tax.

It can be concluded that each alternative came with its own benefits and challenges. Since short payback period, low investment risk, and commercial readiness of biomass gasification were the primary factors for the pulp mill of this study to decide on biomass gasification investment, they could meet these criteria by investment in Alternative I that only met the energy demand of the lime kiln. To solve the low NPV and negative annual net cashflow of Alternative I, the pulp mill is well advised to negotiate with FortisBC to increase the syngas price or modify the policy related to mandatory payment of natural gas cost and carbon tax because the adjustment of these parameters can effectively solve the negative cashflow as well as low NPV of Alternative I. The negotiation is possible as without the pulp mills' agreement to investment in gasification, FortisBC and BC province will most likely fail to achieve the GHG emission commitment. Thus, negotiation on syngas pricing, natural gas price and carbon tax accounting would be needed to find a common denominator. In the next step, the pulp mill can decide on extending gasification capacity for RNG production in addition to syngas based on the commercial success of DFB gasifiers and downstream technologies required for RNG production. In such stepwise transition, the pulp mill is able to minimize the economic risk and technological failure of biomass gasification in the present time and maximize its revenue by RNG production in the future by waiting to see the financial viability and technology readiness of RNG production.

Chapter 3: Tactical biomass supply chain planning considering minimization of costs and GHG emissions

3.1 Synopsis

In Section 2.8.4, it was concluded that when the mill's preferences over the mean and value-at-Risk of NPV and GHG emission reduction of alternatives were considered, the most suitable option for the pulp mill to invest in gasification technology was to produce syngas to meet the energy demand of the lime kiln. In this chapter, the goal is to determine the optimal monthly plan for forest-based biomass transportation, storage, and preprocessing such that the total supply chain cost and GHG emissions take place at the minimum possible value. In this regard, the supply chain activities, the required equipment pieces, and possible options for delivery and storage of forest-based biomass are first explained. Then, the mathematical formulation of the bi-objective model, which is developed to optimize the biomass supply chain, is provided. Thereafter, the data on the input parameters of the mathematical model and the solution method to solve to model are presented. Finally, the outputs of the model are discussed.

3.2 Supply chain activities for forest-based biomass gasification at the pulp mill

The supply chain for biomass gasification at the pulp mill starts from the supply sources and ends at the gasifier plant. Along the way, biomass has to undergo a sequence of processes that make up the biomass supply chain. The most common processes in a forest-based biomass supply chain include collection, transportation, storage, pre-processing, conversion, and distribution (Sowlati, 2016). The processes connecting the start and endpoint of the supply chain can occur in different sequences, at different locations and costs. These processes are briefly explained in the following sections.

3.2.1 Supply and transportation

Three sources of forest-based biomass available to the pulp mill are harvesting residues from forest cut blocks, sawmill residues from three nearby sawmills, and mill residues generated onsite at the pulp mill and at nearby satellite yard owned by the pulp mill. Hereinafter, the mill residues available at the pulp mill, satellite yard, and sawmills are referred to as sawmill residues, while residues available at forest cut blocks is referred to as harvesting residues. Since the mill and its potential biomass suppliers are located inland, residues are transported from forest roadside or sawmills to the gasification facility or an intermediate facility using self-unloading trucks. Self-unloading trucks are the most economical mode of transportation as they do not require investment in a truck dumper or any other unloading equipment (Charles Friesen, Senior Scientist at FPInnovations, personal communication, November 3, 2020)**.**

3.2.2 Storage and handling

Storage of residues is necessary for continuous supply of biomass to the gasifier throughout the entire year despite the fluctuation in monthly availability of residues. The type of storage depends on the properties of residues and size of the facility. In the case of small facilities with limited space for storage, intermediate facilities can be used for storage. Open pile storage, closed storage, and silo are the most common types of storage systems used in gasifier plants (Badger 2002). At the pulp mill considered in this work, an open pile system is used for the storage of both types of residues at the gasifier plant and the potential terminal storage. In an open pile storage system, the only incurred cost is the pile management cost. The pulp mill employs front-end loaders for pile management. They move the residues from the unloading zone at the mill to the storage area.

3.2.3 Preprocessing

The required pre-processing steps are determined by the quality characteristics of the biomass and the requirement of the gasifier. Biomass quality characteristics, such as its moisture content, particle size and contamination level, may vary by seasons, storage conditions, supply origins, species, and tree parts (Shabani & Sowlati, 2016a, 2016b; Sharma et al., 2013). The characteristics of the wood residues supply have to match the feedstock requirements of the gasifier technology. Contamination (salt content) is not a concern for gasification of wood residues at the pulp mill under study since the mill and its potential suppliers are located inland. However, particle size of sawmill residues and moisture content of both types of residues differ from the requirements of the intended gasifier technology. Therefore, residues need to undergo the following processes before being fed to the gasifier.

As per feedstock demand of the gasifier, residues are first moved from the piles and are placed on the conveyors by a reclaimer. The reclaiming method depends on the method of storage, the volume that has to be moved, the cost of the retrieval systems, and operating and maintenance requirements (Paul Janzé, 2016). In this project, an underground screw feeder is considered to move the harvesting residues to the gasifier and sawmill residues to the screener.

Bush grinding contractors comminute the harvesting residues to the gasifier's specification using horizontal mobile grinders at roadsides. This improves the efficiency of transportation and handling activities (Sowlati, 2016). Sawmill residues, on the other hand, are not received in a uniform size that is compatible with the requirement of the gasifier technology since sawmill residues are a mixture of particles of different sizes with a high percentage falling in the acceptable size range (Badger 2002). Performing size reduction for all particles can increase the energy consumption and wear on the comminution equipment. Therefore, it is important to screen the sawmill residues before grinding to remove particles with acceptable size. In this study, scalping is considered as the screening equipment with a screen size of 45 mm. It is a type of disk screen and is used to remove oversized particles from the particle flow. The oversized particles pass over the end of the screen, and the acceptable-sized material passes through the screen (Paul Janzé, 2014).

According to the personal communication with the pulp mill, it was recommended to consider a drop feed hog as a suitable stationary grinder to comminute sawmill residues. The reason for this recommendation was that sawmill residues have to be screened with a scalping screener prior to grinding, and drop feed hogs, compared to other grinder types, are easier to be tied into scalping screeners. In addition, they are single machines requiring a custom infeed system and an outfeed system. Finally, all residues have to be dried to a moisture content of 10% or less to meet the gasifier design requirement. The intended gasifier technology comes with a separate belt dryer that reduces the moisture content to the desired level. Since the gasifier package includes the drying equipment and all residues are required to be dried regardless of their type, the drying was not included in the biomass supply chain optimization model. Details on the cost, and GHG emission intensity of preprocessing equipment pieces are explained in Section 3.4.

3.2.4 Determination of supply chain options

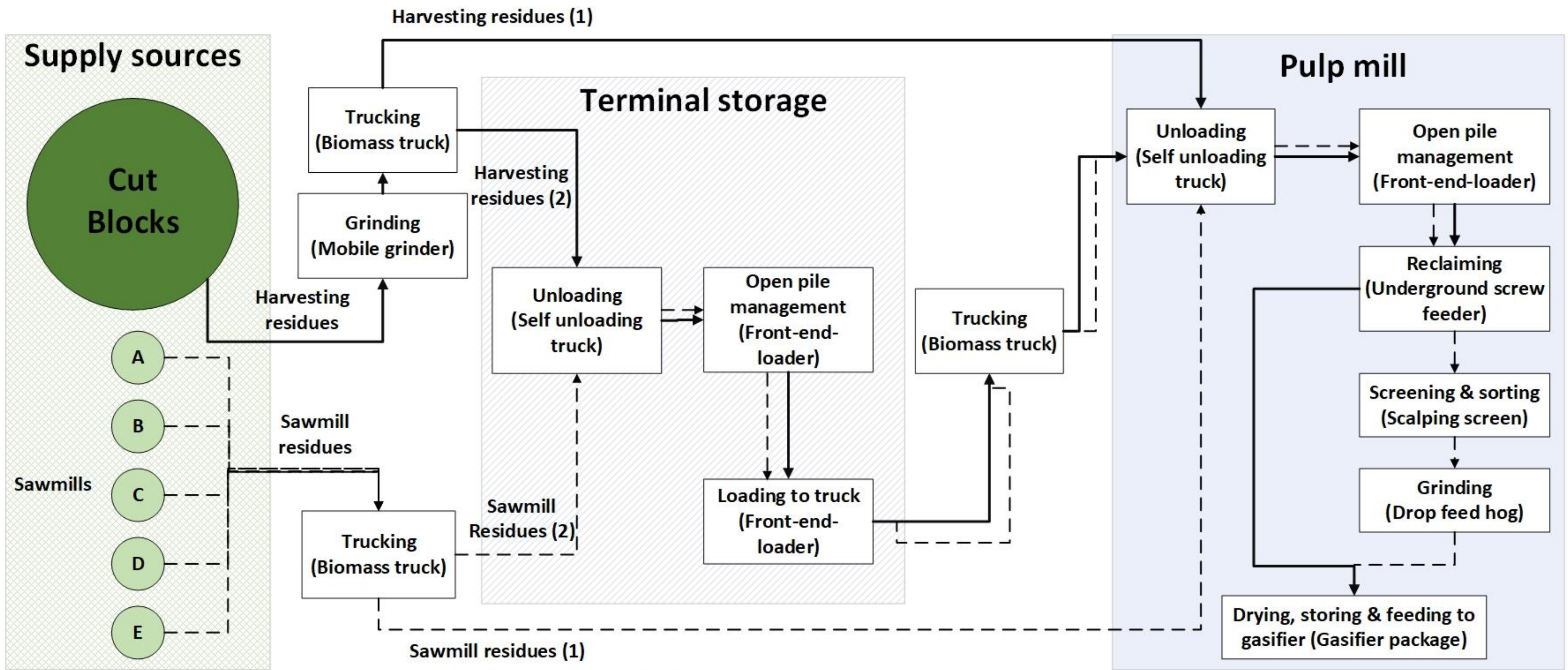
Supply chain design is determined by the number of supply chain nodes and sequence of the processes. In this project, supply chain design varies depending on whether a terminal storage is established or not. In case of establishing a terminal storage, the residues can be sent to the gasifier via the terminal. In the absence of the terminal storage, all residues are directly sent to the gasifier. Both supply chain options are shown in Figure 3.1 and explained in the rest of this section.

3.2.4.1 Direct delivery of residues to the gasifier plant

In this supply chain option, the harvesting and sawmill residues are sent directly to the gasifier plant. Harvesting residues are ground to trucks at cut blocks using mobile grinders, and sawmill residues are loaded into trucks at sawmill sites. Both residues are transported to the gasifier plant by self-unloading dump trucks. After unloading at the gasifier plant, the residues are moved to the open pile storage by front-end loaders. From the storage, residues are discharged to the conveyor system by underground screw reclaimers. The conveyor system moves sawmill residues to the screener to separate acceptable and oversized particles. The acceptable size particles are sent to the drier, whereas oversized particles are sent to the drop feed hog for sizing. After the reduction in the size of particles, the sized residues are fed to the dryer. Harvesting residues are directly reclaimed and conveyed from the storage to the gasifier as they are ground as per the gasifier's requirement at the cut blocks and do not require any pre-processing at the pulp mill.

3.2.4.2 Delivery of residues via the terminal storage

In this supply chain option, the harvesting and sawmill residues are sent to the gasification plant via a terminal storage. The residues are sent from cut blocks and sawmills to the terminal storage by self-unloading dump trucks. At the terminal storage, the residues are moved to the open pile storage by front-end loaders. The residues are transported from the terminal storage to the gasifier plant when needed by self-unloading dump trucks. Loading to dump trucks is performed by front-end loaders at the terminal storage. At the gasifier plant, all activities remain the same, as in the case of the direct delivery of residues to the gasifier plant.



Harvesting residues (1): ODT of harvesting residues that are directly sent to the mill
Harvesting residues (2): ODT of harvesting residues that are sent to terminal storage

Sawmill residues (1): ODT of sawmill residues that are directly sent to the mill
Sawmill residues (2): ODT of sawmill residues that are sent to the terminal storage

Figure 3.1 Supply chain for forest-based biomass gasification at the pulp mill

3.3 Mathematical formulation

In order to optimize the biomass supply chain and minimize its cost and GHG emissions, a bi-objective optimization is developed. The sets, decision variables, and parameters of the model are presented in Table 3.1. The developed model is in a generic form that consists of multiple gasification plants and terminal storages.

Table 3.1. Indices, decision variables, and parameters of the bi-objective optimization model

Sets	
$i \in I$	Set of supply sources including sawmills and forest cut blocks
$j \in J$	Set of terminal storages
$k \in K$	Set of gasification plants
$t \in T$	Set of time periods
Decision variables	
xs_{ikt}	Flow (ODT) of sawmill residues from supply source i to gasification plant k at time t
xh_{ikt}	Flow (ODT) of harvesting residues from supply source i to gasification plant k at time t
ys_{ijt}	Flow (ODT) of sawmill residues from supply source i to terminal storage j at time t
yh_{ijt}	Flow (ODT) of harvesting residues from supply source i to terminal storage j at time t
zs_{jkt}	Flow (ODT) of sawmill residues from terminal storage j to gasification plant k at time t
zh_{jkt}	Flow (ODT) of harvesting residues from terminal storage j to gasification plant k at time t
ws_{jt}	Amount (ODT) of sawmill residues stored at terminal storage j at time t
wh_{jt}	Amount (ODT) of harvesting residues stored at terminal storage j at time t

vs_{kt}	Amount (ODT) of sawmill residues stored at gasification plant *k* at time *t*
vh_{kt}	Amount (ODT) of harvesting residues stored at gasification plant *k* at time *t*
us_{kt}	Amount (ODT) of sawmill residues ground, and fed to the dryer of gasification plant *k* at time *t*
uh_{kt}	Amount (ODT) of harvesting residues fed to the dryer of gasification plant *k* at time *t*
r_j	Binary variable= $\begin{cases} 1 & \text{if treminal storage } j \text{ is established} \\ 0 & \text{otherwise} \end{cases}$
Parameters	
α_{ik}	Unit cost (including purchase, grinding, loading, round trip transportation, and unloading) of delivered residues from supply source i to gasification plant *k* in $/ODT (purchase is only applied to sawmill residues, and grinding is only applied to harvesting residues)
β_{ij}	Unit cost (including purchase, grinding, loading, round trip transportation, and unloading) of delivered residues from supply source i to terminal storage *j* in $/ODT (purchase is only applied to sawmill residues, and grinding is only applied to harvesting residues)
γ_{jk}	Unit cost (including loading, round trip transportation and unloading) of residues from terminal storage *j* to gasification plant *k* in $/ODT
σ_j	Unit handling cost of residues at terminal storage *j* in $/ODT
ρ_k	Unit handling cost of residues at gasification plant *k* in $/ODT
μ_k	Cost of screening, reclaiming, and grinding one ODT of sawmill residues at gasification plant *k* in $/ODT
τ_k	Cost of reclaiming one ODT of harvesting residues at gasification plant *k* in $/ODT
α'_{ik}	Unit GHG emissions of grinding and round trip transportation of delivered residues from supply source i to gasification plant *k* in kg CO2 eq./ODT (grinding is only applied to harvesting residues)
β'_{ij}	Unit GHG emissions of grinding, and transportation of delivered residues from supply source i to terminal storage *j* in kg CO_2 eq./ODT (grinding is only applied to harvesting residues)

γ'_{jk}	Unit GHG emissions of transportation (including loading, and unloading) of residues from terminal storage *j* to gasification plant *k* in kg CO_2 eq./ODT
σ'_j	Unit GHG emissions of residue handling at terminal storage *j* in kg CO_2 eq./ODT
ρ'_k	Unit GHG emissions of residue handling at gasification plant *k* in kg CO_2 eq./ODT
μ'_k	Unit GHG emissions of screening, reclaiming, and grinding one ODT of sawmill residues at gasification plant *k* in kg CO_2 eq./ODT
τ'_k	Unit GHG emissions of reclaiming one ODT of harvesting residues at gasification plant *k* in kg CO_2 eq./ODT
ε_j^{max}	Maximum storage capacity in ODT at terminal storage *j*
π_k^{max}	Maximum storage capacity in ODT at gasification plant *k*
π_k^{min}	Safety stock in ODT at gasification plant *k* in ODT
η_k	Screening and grinding capacity in ODT at gasification plant *k*
ψ_k	Reclaiming capacity in ODT at gasification plant *k*
λ_{it}	Maximum availability of sawmill residues in ODT at supply source *i* at time *t*
ω_{it}	Maximum availability of harvesting residues in ODT at supply source *i* at time *t*
δ_{kt}	Feedstock demand of the gasification plant *k* in ODT at time *t*
θ_j	Annualized investment cost of establishing the terminal storage *j*
M	A very large number used in the accessory constraint(s) for establishment of terminal storage(s)
L	Dry matter loss (%) per period during storage at terminal storage(s) and gasification plant(s)

The mathematical formulation of the model including the objective function and constraints are explained in the following sections.

3.3.1 Objective functions

The first objective function is to minimize the total supply chain costs. It is the summation of all cost components and can be written as Equation (3.1).

$$Minimize\ Z_1 = CF + CD + CT + CH + CP \tag{3.1}$$

where CF is the annualized fixed cost of establishing terminal storage(s) (see Equation (3.2)), CD is the cost of purchasing, grinding (only in case of harvesting residues), loading, unloading, and transporting of residues from supply sources to terminal storage(s) and plant(s) (see Equation (3.3)), CT is the cost of loading, unloading, and transporting of residues from terminal storage(s) to the plant(s) (see Equation (3.4)), CH is the cost of residue handling at terminal storage(s) and plant(s) (see Equation (3.5)), and CP is the cost of preprocessing at plant(s) (see Equation (3.6)).

$$CF = \sum_j \theta_j \times r_j \tag{3.2}$$

$$CD = \sum_t [\sum_i \sum_k \alpha_{ik} \times (xs_{ikt} + xh_{ikt}) + \sum_i \sum_j \beta_{ij} \times (ys_{ijt} + yh_{ijt})] \tag{3.3}$$

$$CT = \sum_t \sum_j \sum_k \gamma_{jk} \times (zs_{jkt} + zh_{jkt}) \tag{3.4}$$

$$\begin{aligned} CH = \sum_t [\sum_i \sum_j \sigma_j \times (ys_{ijt} + yh_{ijt}) + \sum_j \sum_k \rho_k \times \left(zs_{jkt} + zh_{jkt}\right) \\ + \sum_i \sum_k \rho_k \times (xs_{ikt} + xh_{ikt})] \end{aligned} \tag{3.5}$$

$$CP = \sum_{t}\sum_{k}(\mu_k \times us_{kt} + \tau_k \times uh_{kt}) \tag{3.6}$$

The second objective function is to minimize the total GHG emissions of the supply chain. It is the summation of all GHG emissions components and can be written as Equation (3.7).

$$Minimize\ Z_2 = ED + ET + EH + EP \tag{3.7}$$

where *ED* is the GHG emissions released due to loading, grinding (only in case of harvesting residues), transporting, and unloading of residues from supply sources to terminal storage(s) and plant(s) (see Equation (3.8)), *ET* is the GHG emissions released due to loading, unloading, and transporting of residues from terminal storage(s) to the plant(s) (see Equation (3.9)), *EH* is the GHG emissions released due to residue handling at terminal storage(s) and plant(s) (see Equation (3.10)), and *EP* is the GHG emissions released due to preprocessing at plant(s) (see Equation (3.11)).

$$ED = \sum_{t}[\sum_{i}\sum_{k}\alpha'_{ik} \times (xs_{ikt} + xh_{ikt}) + \sum_{i}\sum_{j}\beta'_{ij} \times (ys_{ijt} + yh_{ijt})] \tag{3.8}$$

$$ET = \sum_{t}\sum_{j}\sum_{k}\gamma'_{jk} \times (zs_{jkt} + zh_{jkt}) \tag{3.9}$$

$$\begin{aligned} EH = \sum_{t}[\sum_{i}\sum_{j}\sigma'_{j} \times (ys_{ijt} + yh_{ijt}) + \sum_{j}\sum_{k}\rho'_{k} \times \left(zs_{jkt} + zh_{jkt}\right) \\ + \sum_{i}\sum_{k}\rho'_{k} \times (xs_{ikt} + xh_{ikt})] \end{aligned} \tag{3.10}$$

$$EP = \sum_{t} \sum_{k} (\mu_k^{'} \times us_{kt} + \tau_k^{'} \times uh_{kt}) \tag{3.11}$$

3.3.2 Constraints

In this section, constraints of the model are explained and represented by Equations (3.12)-(3.24).

Availability of sawmill residues: Each month, the total amount of residues delivered to gasification plant(s) and terminal storage(s) from each sawmill should be less than or equal to the maximum availability of residues at that sawmill.

$$\sum_j ys_{ijt} + \sum_k xs_{ikt} \leq \lambda_{it} \ \forall i \in I, \forall t \in T \tag{3.12}$$

Availability of harvesting residues: Each month, the total amount of residues delivered to the gasification plant(s) and terminal storage(s) from each cut block should be less than or equal to the maximum availability of residues at that cut block.

$$\sum_j yh_{ijt} + \sum_k xh_{ikt} \leq \omega_{it} \ \forall i \in I, \forall t \in T \tag{3.13}$$

Balancing constraint for sawmill residues at gasification plant(s): Each month, the total amount of sawmill residues stored at the plant(s) is equal to the amount remained from last month plus any new amount delivered to plant(s), plus any amount received from terminal storage(s), minus the amount that is screened, ground, and fed to the dryer of gasification plant(s) in that month.

$$vs_{kt} = (1 - L) \times vs_{kt-1} + \sum_i xs_{ikt} + \sum_j zs_{jkt} - us_{kt} \ \forall \ k \in K, t \in T \tag{3.14}$$

Balancing constraint for harvesting residues at gasification plant(s): Each month, the total amount of harvesting residues stored at the plant(s) is equal to the amount remained from last month plus any new amount purchased and sent to the plant(s), plus any amount received from terminal storage, minus the amount that is dried and fed to the gasifier(s) in that month.

$$vh_{kt} = (1 - L) \times vh_{kt-1} + \sum_i xh_{ikt} + \sum_j zh_{jkt} - uh_{kt} \ \forall\ k \in K, t \in T \tag{3.15}$$

Balancing constraint for sawmill residues at terminal storage(s): Each month, the total amount of sawmill residues stored at the terminal storage(s) is equal to the amount remained from last month plus any new amount purchased and sent to the terminal storage(s), minus the amount that is sent to the gasification plant(s).

$$ws_{jt} = (1 - L) \times ws_{jt-1} + \sum_i ys_{ijt} - \sum_k zs_{jkt} \ \forall\ j \in J, t \in T \tag{3.16}$$

Balancing constraint for harvesting residues at terminal storage(s): Each month, the total amount of harvesting residues stored at the terminal storage(s) is equal to the amount remained from last month plus any new amount purchased and sent to the terminal storage(s), minus the amount that is sent to the gasification plant(s).

$$wh_{jt} = (1 - L) \times wh_{jt-1} + \sum_i yh_{ijt} - \sum_k zh_{jkt} \ \forall\ j \in J, t \in T \tag{3.17}$$

Screening and grinding capacity (minimum of the two): Each month the amount of sawmill residues that is screened and ground should be less than the maximum monthly operating capacity of screening and grinding equipment pieces.

$$us_{kt} \leq \eta_k \ \forall\ k \in K, t \in T \tag{3.18}$$

Reclaiming capacity: Each month, the amount of residues that is reclaimed should be less than the maximum operating capacity of screw feeder equipment at gasification plant(s).

$$us_{kt} + uh_{kt} \leq \psi_k \; \forall \, k \in K, t \in T \tag{3.19}$$

Storage capacity at terminal storage(s): Each month the amount of sawmill and harvesting residues that are stored at each facility should be between the minimum required inventory and maximum storage capacity of the facility.

$$\varepsilon_j^{min} \times r_j \leq ws_{jt} + wh_{jt} \leq \varepsilon_j^{max} \times r_j \;\; \forall \, j \in J, t \in T \tag{3.20}$$

Maximum storage capacity at gasification plant(s): Each month the amount of sawmill and harvesting residues that are stored at each facility should be less than or equal to the maximum storage capacity of the facility.

$$vs_{kt} + vh_{kt} \leq \pi_k^{max} \;\; \forall \, k \in K, t \in T \tag{3.21}$$

Safety stock at gasification plant(s): Each month the amount of sawmill and harvesting residues that are stored at the gasification plant should be greater than or equal to the minimum storage capacity of the facility.

$$vs_{kt} + vh_{kt} \geq \pi_k^{min} \; \forall \, k \in K, t \in T \tag{3.22}$$

Gasifier feedstock demand: In each month, the amount of sawmill and harvesting residues that are fed to the dryer should be greater than or equal to the fuel demand of the lime kiln.

$$us_{kt} + uh_{kt} \geq \delta_{kt} \; \forall \, k \in K, t \in T \tag{3.23}$$

Logical (accessory) constraint for establishment of terminal storage(s) that ensures residues are sent to terminal storage only if it is established.

$$\sum_{t}\sum_{i}(ys_{ijt} + yh_{ijt}) \leq M \times r_j \; \forall\, j \in J \tag{3.24}$$

Sign restriction for decision variables:

$$xs_{ikt}, xh_{ikt}, ys_{ijt}, yh_{ijt}, zs_{jkt}, zh_{jkt}, ws_{jt}, wh_{jt}, vs_{kt}, vh_{kt}, us_{kt}, uh_{kt} \geq 0 \; and \; r_j \in \{1,0\} \;\; i \in I, j \in J, k \in K, t \in T$$

3.4 Input data and parameters

3.4.1 Biomass availability

The maximum monthly availability of residues at each sawmill and harvesting cut block *i* is shown by λ_{it} and ω_{it}, respectively, in the model formulation. An annual 81,625 ODT of sawmill residues could be procured from five sawmills that are on average 55 km away from the mill. The monthly supply from these sawmills is assumed to be constant throughout the year, except in the months of May, June, July, and August for Sawmills B, C, and E, respectively. Their supply is reduced by half in these months due to a two-week maintenance period. Average unit delivery cost of sawmill residues to the pulp mill is $30 per ODT. This cost includes purchase, trucking, loading, and unloading costs.

The availability and cost of harvesting residues from 1041 cut blocks in three TSAs of Arrow, Boundary, and Kootenay Lake during a 10-year simulated period are obtained from FPInnovations (Blackburn, 2019). The 10-year period, which consists of two 5-year cut periods, are assumed to start from 2019. Out of 1041 cut blocks, 505 are harvested during the first cut period (Charles Friesen, Senior Scientist at FPInnovations, personal communication, October 26, 2020) and therefore, are considered in this study. The average distance of these cut blocks to the mill is about

129 km. The average cost of harvesting residues delivered to the mill is $133 per ODT. This includes grinding, trucking, loading, unloading, and road maintenance costs.

The annual supply from these cut blocks totals to about 148,899 odt. The yearly availability of residues from each cut block are estimated by the block's average cut period availability over five years. To estimate the monthly availability of residues, the monthly harvest ratios are calculated based on the Harvest Billing System (HBS) data for three TSAs of Arrow, Boundary, and Kootenay Lake. For each TSA, the monthly volume of logs harvested for five years (2015-2019) are obtained from the HBS dataset (Ministry of Forests Lands Natural Resource Operations and Rural Development, 2021). The TSA associated with each cut block is not specified in the original data obtained from FPInnovations. Therefore, the average of three TSAs are used to calculate the monthly ratios for all cut blocks. Ratios for each month are multiplied by the yearly availabilities to obtain the monthly availability of residues from each cut block. Due to the thawing of frozen soil and heavy rains mainly in the months of April, May, and June, the forest roads become inaccessible, and consequently the amount of harvesting declines (Sowlati, 2016). As a result, the availability of harvesting residues decreases over these months. All residues are assumed to have a moisture content of 60% as they are received. They have to be dried to 10% moisture content or less to meet the gasifier's design requirement.

3.4.2 Feedstock demand

The average annual natural gas consumption of the lime kiln burner has been 1,187,974 GJ over seven years. Assuming an 86.7% biomass to syngas conversion efficiency, $\eta_{Syngas}[\%LHV_{daf}]$, for the gasifier (Mackėla, 2017) and a Lower Heating Value (LHV) of 18.97 (MJ kg^{-1}) for the feedstock (Stromberg, 2006), the monthly feedstock demand of the gasifier, shown as $\delta_{k=1,t}$ in the model formulation (See Table 3.1) is calculated using Equation (3.25).

$$Feedstock\ demand\ (ODT) = \frac{Monthly\ energy\ consumption\ of\ the\ lime\ kiln\ (GJ) \times 1000\ (\frac{MJ}{GJ})}{\eta_{Syngas}[\%LHV_{daf}] \times LHV_{Biomass\ (daf)}(MJ.Kg^{-1}) \times 1000\ (\frac{kg}{ODT})} \quad (3.25)$$

The annual feedstock demand of the gasifier is calculated at 57,784 ODT.

3.4.3 Residues handling cost and capacity

Handling of residues, which is carried out by a front-end loader, is required when residues first arrive at the terminal storage or at the mill. Front-end loaders move the residues to temporary piles after being unloaded from trucks. Residues that are stored at storage require additional handling. In this paper, the handling of residues is referred to as pile management when it is carried out at the storage site. Handling of residues has a cost which is applicable to both types of residues. In the mathematical formulation, $\sigma_{j=1}$ and $\rho_{k=1}$ represent the handling cost at the terminal storage and the gasifier plant, respectively.

Handling cost includes operating and maintenance cost of a front-end loader. Operating cost consists of the fuel cost and the operator's wage. The capital cost of front-end loaders at the mill is excluded from the calculations because the mill already owns as many of them as required. Therefore, handling capacity is assumed to be unlimited, and the capital cost does not incur.

The bucket capacity of the front-end loader is assumed to be 3.5 m^3. Each cubic meter of residues, on average, corresponds to 0.39 ODT. This is the average basic density of 13 wood species used in FPInterface (Charles Friesen, Senior Scientist at FPInnovations, personal communication, October 26, 2020). Thus, the mass of residues moved by the loader in one trip can be estimated as 1.365 ODT. The loader is assumed to require an average of 5 minutes for each trip, which is a conservative assumption accounting for breakdowns and setup of the area. The throughput of the loader is calculated using Equation (3.26).

$$\begin{aligned}&Amount\ of\ residues\ handled\ in\ one\ hour\ by\ the\ front-end\ loader\\&=\frac{Bucket\ capacity\ (odt)}{Trip\ time\ (h)}=\frac{1.365\ (odt)}{5\ (min)/60(\frac{min}{h})}=16.38\ (\frac{odt}{h})\end{aligned} \quad (3.26)$$

At the pulp mill, each front-end loader consumes 30.1 liter of diesel per hour. Assuming a diesel cost of $1 per liter, a maintenance cost of $36 per hour, and an operator's wage of $55 per hour according to the pulp mill's recorded data, the total operating and maintenance cost of each front-end loader would be $121.1 per hour (Project Manager at the mill, personal communication, September 25, 2020). Dividing this cost by 16.38 (ODT h^{-1}) results in a handling cost of $7.39 per ODT.

3.4.4 Preprocessing cost and capacity at the gasification plant

The total annual cost of all preprocessing equipment is used to determine the unitary preprocessing cost of residues at the gasification plant. The total annual preprocessing cost is the sum of annual capital, insurance, and operating and maintenance costs.

The annual capital cost of equipment is calculated using Equation (3.27) (Akhtari, 2012).

$$Annual\ capital\ cost\ of\ equipment = Capital\ cost\ * \frac{i(1+i)^n}{(1+i)^n-1} - SV * \frac{i}{(1+i)^n-1} \qquad (3.27)$$

where i is the interest rate, n is the operating life and SV is the salvage value of equipment. In Equation (3.27), the $Capital\ cost$ of each preprocessing equipment is adjusted according to its capacity using the order of magnitude method that was explained in Section 2.4 (See Equation (2.2)). The original capital cost data of preprocessing equipment pieces are shown in Table A.1 in the Appendix. The annual operating and maintenance cost of the preprocessing equipment pieces is the summation of maintenance cost estimated at 25% of the capital cost, and the costs of power, oil, and lubricant consumption (Charles Friesen, Senior Scientist at FPInnovations, personal communication, November 3, 2020). The components of operating and maintenance cost of each preprocessing equipment are provided in Table A.1 in the Appendix. The costs and other details that are used to calculate the unit preprocessing cost of the underground screw feeder, scalping screen and drop feed hog are shown in Table 3.2, Table 3.3, and Table 3.4, respectively. Lastly, the monthly required capacity of each preprocessing equipment is calculated based on the annual feedstock demand of the gasifier.

Table 3.2. Details of the reclaiming equipment (Underground screw feeder)

Capacity (ODT/month)	7,179
Capital cost	\$469,668 CAD[a]
Delivery cost (10% of capital cost)[b]	\$46,967 CAD
Salvage value (10% of capital cost)[b]	\$46,967 CAD
Operating life	20 years[a]
Interest rate	8%[d]
Annual capital cost	\$51,594 CAD

Annual insurance cost (2.5% of annual cost)	$11,742 CAD[d]
Annual operating and maintenance cost	$159,453 CAD
Total annual cost	**$222,789 CAD**
Annual feedstock demand of the gasifier	**57,784 ODT**
Unit cost	**3.86 (CAD $/ODT)**

a) (U.S. Environmental Protection Agency, 2007)
b) (Sales Manager at TerraSource, personal communication, December 1, 2020)
c) (Akhtari, 2012)
d) (BC Bioenergy Network, 2020)

Table 3.3. Details of the screening equipment (Acrowood Model 636 Disc Scalper)

Capacity (ODT/month)	7,179
Capital cost	$87,874 CAD[a]
Delivery cost (10% of capital cost)[b]	$8,787 CAD
Installation cost (2.6*Capital cost)[c]	$228,473 CAD
Salvage value (10% of capital cost)[b]	$8,787 CAD
Operating life	20 years[a]
Interest rate	8%[d]
Annualized capital cost	$32,924 CAD
Annual insurance cost (2.5% of annual cost)[e]	$2,197 CAD
Annual operating and maintenance cost	$25,728 CAD
Total annual cost	**$60,849 CAD**
Annual feedstock demand of the gasifier	**57,784 ODT**
Unit cost	**1.05 (CAD $/ODT)**

a) (Sales Head at Acrowood, personal communication, December 2, 2020)
b) (Sales Manager at TerraSource, personal communication, December 1, 2020)
c) (Project Manager at the mill, personal communication, September 25, 2020)
d) (BC Bioenergy Network, 2020)
e) (Akhtari, 2012)

Table 3.4. Details of the grinding equipment (Drop feed hog)

Capacity (ODT/month)	7,179
Capital cost	$199,976 CAD[a]

Delivery cost (10% of capital cost)[a]	$19,998 CAD
Installation cost (2.6*Capital cost)[b]	$519,938 CAD
Salvage value (10% of capital cost)[a]	$19,998 CAD
Operating life	20 years[a]
Interest rate	8%[c]
Annualized capital cost	$74,925 CAD
Annual insurance cost (2.5% of annual cost)[d]	$4,999 CAD
Annual operating and maintenance cost	$160,837 CAD
Total annual cost	**$240,761 CAD**
Annual feedstock demand of the gasifier	**57,784 ODT**
Unit cost	**4.17 (CAD $/ODT)**

a) (Sales Manager at TerraSource, personal communication, December 1, 2020)
b) (Project Manager at the mill, personal communication, September 25, 2020)
c) (BC Bioenergy Network, 2020)
d) (Akhtari, 2012)

3.4.5 Capacity and cost of storage at the gasifier plant (mill)

The storage capacity of the gasifier plant ($\pi_{k=1}^{max}$) at the mill is estimated at 12,870 ODT. This capacity is associated with almost 5,500 m^2 of land requirement. The safety stock ($\pi_{k=1}^{min}$) is assumed to be 30 times the maximum average daily feedstock demand of the gasifier. The average daily demand of the gasifier is highest in April and is equal to 175 ODT. Therefore, this makes the safety stock equal to 5,255 ODT. In an open pile storage system, the only incurred cost is the pile management cost. The pile management cost at the mill is similar to the residues' handling cost calculated in Section 3.4.3.

3.4.6 Capacity and cost of storage at terminal storage

The assumption is that the terminal storage capacity ($\varepsilon_{j=1}^{max}$) is identical to that of the mill storage. The storage cost at the terminal is comprised of: (a) fixed land investment cost, (b) capital cost of a front-end loader, and (c) the pile management cost. An online search was conducted to find commercial and industrial land listings in the pulp mill's region. The average land price of $105 per m^2 was calculated based on the listings' prices and land area. Following this estimation, the land investment cost for terminal storage was approximated at $577,500. Assuming an interest rate (i) of 8% and a service life of 20 years (n) for storage, the annualized investment cost of the open pile storage can be calculated using Equation (3.28) (Akhtari, 2012). The land is assumed to be owned by the pulp mill after the end of 20 years, and thus zero salvage value was assumed for the land.

$$Annualized\ investment\ cost = Land\ investment\ cost * \frac{i(1+i)^n}{(1+i)^n - 1} = \$\ 58{,}820 \qquad (3.28)$$

Given a capital cost of $650,000, a 10% delivery cost, a salvage value (SV) of 30% of the purchase price, and a service life (n) of 5 years, the annualized capital cost for the front-end loader can be calculated as $145,837 using Equation (3.27). The pile management cost at terminal storage is equal to the residues' handling cost calculated in Section 3.4.3 (i.e., $7.39 per ODT).

3.4.7 GHG emissions of the supply chain

In this study, the supply chain activities contributing to the GHG emissions are biomass transportation, off-site comminution (i.e., grinding of harvesting residues at the forest roadside), biomass handling, and preprocessing. The GHG emission intensity of biomass transportation was assumed to be the same as per ODT GHG emissions reported by (Cambero et al., 2016) for 1 km trucking of sawmill and harvesting residues in BC. For other activities, the per ODT GHG emissions was estimated based the productivity and fuel consumption of the involved equipment piece, and emissions intensity of the consumed fuel. Table 3.5 shows the data that are used to estimate the GHG emissions of the supply chain activities.

Table 3.5 Data used to estimate the GHG emissions of the supply chain activities

Supply chain activity	**Off-site comminution**	**Handling**	**Preprocessing**		
Equipment piece	Mobile grinder	Front-end loader	Drop feed hog	Scalping screener	Reclaim feeder
Fuel type	Diesel	Diesel	Electricity	Electricity	Electricity
Fuel consumption (L/PMH) or (kWh/PMH)	135.00[a]	30.10[b]	247.91[c]	3.73[d]	75.00[e]
Productivity (ODT/PMH)	24.70[a]	16.38[b]	19.91[c]	13.06[d]	11.33[f]
Fuel consumption (L/ODT) or (kWh/ODT)	5.47	1.84	12.45	0.29	6.62
Fuel GHG emissions (g CO_2 eq./L) or (g CO_2 eq./kWh)	3,007.00[g]	3,007.00	9.00[h]	9.00	9.00
GHG emissions (g CO_2 eq./ODT)	16,435.02	5,525.68	112.06	2.57	59.58
Transportation					
GHGs emitted from trucking of harvesting residues (g CO_2 eq./ODT-km)	320[i]				
GHGs emitted from trucking of sawmill residues (g CO_2 eq./ODT-km)	280[i]				

a) (Charles Friesen, Senior Scientist at FPInnovations, personal communication, November 3, 2020)
b) (Project Manager at the pulp mill, personal communication, December 10, 2020)
c) (Sales Manager at TerraSource, personal communication, December 1, 2020)
d) (Sales Head at Acrowood, personal communication, December 2, 2020) e) (Prakoso, 2018)
f) (U.S. Environmental Protection Agency, 2007), g) (Akhtari et al., 2021), h) (BC Hydro, 2020), i) (Cambero et al., 2016)

3.4.8 Dry matter loss

During storage, a fraction of residues are lost due to microbial activity, commonly fungal attacks (Anerud et al., 2019). This fraction is referred to as dry matter loss and is shown by L in the

Equations (3.14)-(3.17). According to Rentizelas et al. (2009), dry matter loss is 1% per month in ambient (open) piles. Anerud et al. (2019) approximated the monthly loss at 1.56% in dry basis in their literature review. For the sake of conservativity, the same value was applied to the monthly inventory of residues at the terminal storage and at the mill's storage.

3.5 Solution approach and model execution

The approaches for solving multi-objective optimization problems fall into three categories depending on the phase in which decision makers express their preferences for each objective. These include "a priori", "interactive", and "a posteriori" or generation methods. A priori method requires the decision makers to express their preferences before the solution process (Hwang & Masud, 1979). Goal programming is one of the widely used "a priori" methods for solving multi-objective optimization models (Hwang & Masud, 1979). It was recently applied to multi-objective biomass supply chain optimization problems for example in (Juan et al., 2019) and (Mahjoub & Sahebi, 2020). In goal programming, decision makers have to set weights and goals for each objective prior to solving the problem. Next, a preferred solution is found based on minimizing the weighted sum of deviations of objective functions from their goals. Setting goals and their importance may not be an easy task for the decision makers (Deb, 2005). Another drawback of "a priori" methods is that it only generates one solution, while decision makers might be interested in having a set of Pareto optimal solutions (Mavrotas, 2009). Pareto optimal solutions are solutions for which one objective cannot be improved without compromising at least one of the other objectives. In the "interactive" method, decision makers' inputs are given during the modeling process iteratively. This still requires the decision makers to define their preferences in order to obtain the results and this method is not able to provide the decision makers with the whole range of Pareto optimal solutions (Deb, 2005; Mavrotas, 2009).

Contrary to the two mentioned methods, “a posteriori” method divides the solution process into two independent phases. First, the whole set of all preferred solutions are generated and then they are presented to the decision makers. Therefore, the decision maker’s preferences are not needed in advance (Mavrotas, 2009). Two of the popular generation methods are weighted sum method and the ε-constraint method. Decision makers are able to see a representative subset of the Pareto front by implementing these methods. However, there are criticisms in performance of these two methods. The weighted sum method is only capable of generating efficient extreme solutions, and requires normalizing of the objective function values, which strongly influences the generated results. The ε-constraint method is free from these drawbacks. In this method, if the problem has N objectives, one objective is optimized, while the other (N-1) objectives are constrained by the epsilons (Ngatchou et al., 2005). However, this method has a weakness in computing the range of each objective. Also, there is no guarantee in the efficiency of the obtained solution when the ε-constraint is implemented (Mavrotas, 2009). A solution is guaranteed to be an efficient solution only if all the (N-1) objective functions’ constraints become binding.

The augmented version of the ε-constraint method (AUGMECON) was developed by Mavrotas (2009) to address the pitfalls associated with the ε-constraint method. AUGMECON is an “a posteriori” method that is similar to the conventional ε-constraint method in basics. It optimizes one objective, while the other objective(s) are constrained by the epsilon(s) (Ngatchou et al., 2005). AUGMECON addresses the problem of ε-constraint method in finding the range of each objective by using lexicographic optimization. It guarantees efficiency of all obtained solutions by ensuring that the slack and surplus variables of all (N-1) objective functions' constraints are zero; so that all (N-1) objective functions' constraints become binding. It also accelerates the computation process by exiting early from the iterations that lead to infeasible solution (Mavrotas, 2009). Readers are referred to (Mavrotas, 2009) to find thorough explanation about the mathematical formulation and the Pareto set generation procedure of the AUGMECON method.

In the present study, pulp mill managers were more interested in having a set of solutions rather than a single solution in order to see the possible trade-offs between the two objectives. For this reason, the category of "a posteriori" methods that can provide multiple solutions and reveal the possible trade-off between the objective was selected. Among a posteriori methods, the AUGMECON method was ultimately chosen as the most appropriate solution approach because it does not suffer from the pitfalls of other "a posteriori" methods including the weighted and ε-constraint methods. AUGMECON has been frequently used for solving multi-objective biomass supply chain optimization problems in recent studies (e.g. in Abdali et al., 2021; Rabbani et al., 2018, 2020; Rahemi et al., 2020; Razm et al., 2019; Vafaeenezhad et al., 2019).

A set of 31 Pareto optimal solutions were generated by executing the bi-objective model on AIMMS 4.77 software (AIMMS, 2021). The model was executed on a computer with Intel ® core ™ i7-6700 CPU @ 3.41 GHz processor and 16.0 GB RAM. The CPLEX 20.1 Solver was used to solve the model (IBM, 2021).

3.6 Results

3.6.1 Pareto optimal solutions

The Pareto optimal set generated by the AUGMECON method is shown in Figure 3.2. The Pareto frontier displays the trade-off between the annual cost and GHG emissions of the upstream supply chain. As such, the Pareto optimal solutions shown in Figure 3.2 only account for the costs and GHG emissions of the supply chain activities occurring up to feeding biomass to the gasifier and the emissions released during downstream activities, including biomass gasification are not considered in the optimization model. In Solution A, the GHG emissions of the supply chain over a one-year planning horizon is at minimum, equal to 899 t of CO_2 eq. This is achieved in Solution A at the expense of having the highest total cost ($2,578,056) among all Pareto optimal solutions. On the other hand, Solution C has the lowest cost ($2,545,322). However, in this solution, the annual supply chain GHG emissions has the highest value, 1,116 t of CO_2 eq., among the Pareto optimal solutions. The slope of the Pareto curve indicates that when moving from Solution C to Solution A, the cost increases by $32,734 (1.3%), while the supply chain GHG emissions considerably decreases by 217 t of CO_2 eq. (24.2%). To find an idea about the amount of changes in the emission reduction, this amount of reduction in GHG emissions is equivalent to avoiding GHG emissions released due to natural gas consumption of around 59 residential houses in BC (Canada Energy Regulator, 2021). The reason behind the compromises between the two objectives can be traced back to the delivery cost and emission intensity of biomass procurement from sawmills and forest cut blocks, that is explained in the following Section 3.6.2.

The trade-off between the objectives can be compared with the numbers reported in (Malladi & Sowlati, 2020a). The authors developed a bi-objective optimization model for operational planning of a biomass supply chain in BC to minimize its costs and emissions. The model's decisions included the amount of wood residues, wood pellet, briquettes, and NG to be used to meet the energy demand of the heating plant. The results indicated that the annual supply chain cost varied between $2.37 million CAD and $2.54 million CAD and the supply chain emissions varied between 1,200 and 3,951 t of CO_2 eq. In other words, in their case study, the supply chain GHG emissions could be reduced by 70% at the expense of 7% increase in the supply chain cost. Similar to (Malladi & Sowlati, 2020a), the percentage of changes in the supply chain GHG emissions in the present work is greater than that of the supply chain cost. However, the supply chain cost and emissions experienced greater changes in (Malladi & Sowlati, 2020a) because their optimization model had the flexibility to also use NG to meet the energy demand of the heating plant. Due to the fact that NG has higher emission intensity than biomass but at a lower cost, considering NG as a fuel in the feedstock mixture increases the ranges of changes in the costs and GHG emissions of the supply chain.

Analysis of the trade-off between the cost and GHG emissions of the supply chain in Figure 3.2 reveals that the ratio of changes in the supply chain costs to the changes in the supply chain GHG emissions when we move from Solution C to Solution A is equal to $150.68/t of CO_2 eq. This ratio means that the pulp mill has to pay $150.68 to reduce every t of CO_2 eq. GHG emissions released from the supply chain activities. Therefore, if the government of British Columbia provides the industry with the same $/t of CO_2 eq. incentive to decline the industrial fossil GHG emissions, the pulp mill would be able to move from choosing Solution C with the minimum cost (which is the most preferable solution for the pulp mill due to having the minimum cost) to Solution A with the minimum GHG emissions. This is because the emission incentives can offset the increase in the supply chain costs.

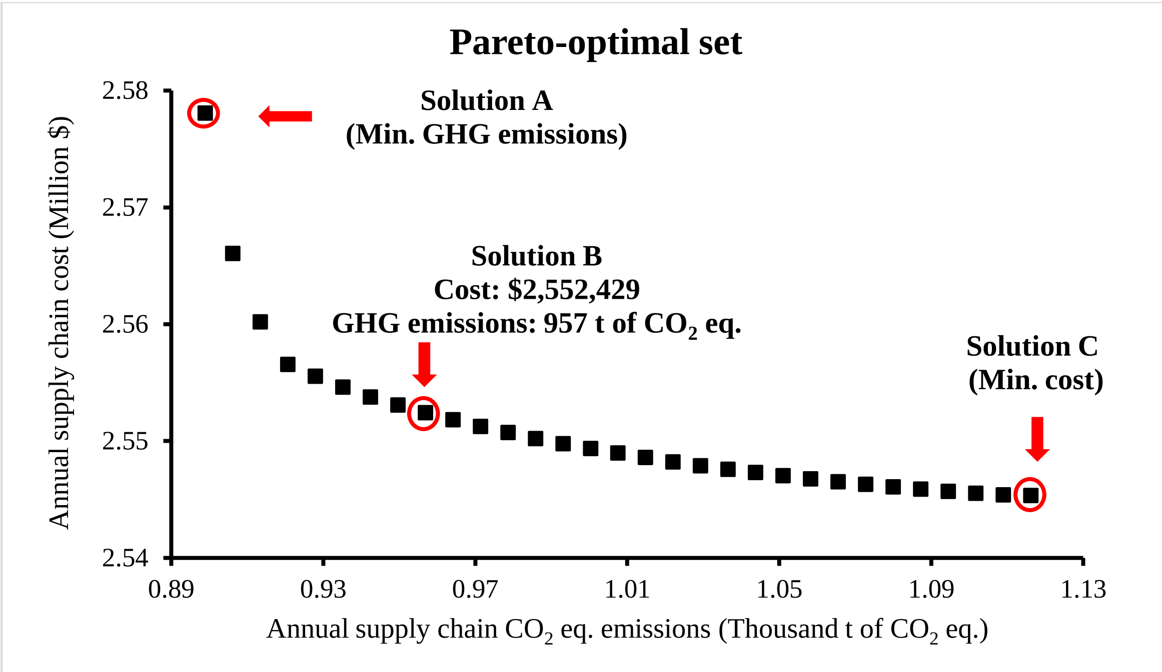


Figure 3.2. Pareto frontier

In 2021, the carbon tax was $45/t of CO_2 eq. in BC (Province of BC, 2021). The government of BC would direct a portion of revenue from the carbon tax into incentives for investment in projects that aim to reduce the industrial emissions (through CleanBC Industry Fund) and payment for cleaner industrial operations that meet a world-leading low-carbon emission benchmark (through CleanBC Industrial Incentive). The incentives are designed for regulated large industrial operations including pulp and paper mills (Province of BC, 2021). Since investment projects are eligible to receive CleanBC Industry Fund, the available funding from this resource is considered as a part of the available incentive for investment in biomass gasification in Section 2.4.

Regarding CleanBC Industrial Incentive, Kraft pulp mills that have CO_2 emissions intensity below 0.0506 t of CO_2 eq. / t of Kraft pulp are eligible to receive an incentive payment for their cleaner operation (CleanBC, 2021). The method for calculating the incentive amount is explained in (CleanBC, 2021). Calculating CO_2 emission intensity of the pulp mill in this study and evaluating whether it is eligible to receive CleanBC Industrial Incentive are out of the scope of this work. Nonetheless, it is beneficial for the pulp mill to know the trade-off between the cost and GHG emissions of the biomass supply chain because they can evaluate in case they decide to switch from an optimal solution with higher emissions to one with lower GHG emissions, if the increase in their supply chain costs would be offset by the incentives provided by the government of BC. For instance, in case that the government incentivizes GHG emissions avoided by the industry for \$45 per t of CO_2 eq. (i.e., carbon tax rate in 2021), the pulp mill in this study is able to move from Solution C with minimum cost to Solution B. This is because \$44.61/t of CO_2 eq. would cost the pulp mill to move from choosing the Solution C for planning its supply chain to the Solution B.

Although the results for all Pareto optimal solutions are obtained, for brevity, only the results obtained for the two extreme points of the Pareto frontier, i.e., Solutions A and C are presented and discussed in the following subsections. Solutions A and C represent the maximum possible trade-off between the objectives, as such comparing their results can provide more insight into the bi-objective model's outputs and performance across the Pareto optimal frontier as compared to any other points.

3.6.2 Flow of residues from supply sources to the gasification plant

In all the Pareto optimal solutions including Solutions A and C, the binary variable for the establishment of the terminal storage becomes zero. Opening the terminal storage is not economical in any of the solutions because the storage capacity at the mill is sufficient to maintain the monthly inventory level prescribed by the optimization model. In addition, the high establishment costs and additional costs associated with transporting biomass from the terminal storage to the plant does not favor biomass storage at the terminal. Therefore, there is no flow of residues from supply sources to the terminal storage, and all residues are sent directly to the gasifier plant.

Figure 3.3 shows the annual cumulative flow of residues from each sawmill and collective cut blocks for Solutions A and C. The annual procured biomass for Solution A totals 63,984 ODT, while this value is 63,978 ODT for Solution C. There is a slight increase of 6 ODT in annual biomass procurement when moving from Solutions C to A, which is attributed to higher dry matter losses in Solution A that occur due to maintaining higher inventory levels of biomass in Solution A. In both optimal solutions, the annual flow from Sawmills A, B, C, and D are identical. The maximum monthly available residues at Sawmills A, B, and C are utilized throughout the year in both solutions because of the lower cost of procured residues from these sawmills compared to Sawmill E. On the other hand, only all available residues of the first month are utilized from Sawmill D and the residues flow from Sawmill D becomes zero in other months. Flow of residues in the first month from Sawmill D is to meet the residue amount required for fulfilling the safety stock. The zero flow of residues from Sawmill D in other months is due to the fact that the total of cost as well as emission intensity of procuring one ODT of wood residues from this sawmill is greater than the other sawmills and cut blocks selected in Solutions A and C.

There is 3,958 ODT flow of wood residues from Sawmill E to the plant in Solution C, whereas the flow from this sawmill to the plant drops to zero in Solution A. This indicates that the total biomass flow from the sawmills decreases by 3,958 ODT in Solution A in comparison with Solution C. The decline in the sawmill residue flow in Solution A is compensated by bringing more harvesting residues from the cut blocks to the plant. As it can be seen in Figure 3.3, the flow of harvesting residue increases by 3,964 ODT in Solution A. The reason behind procuring more harvesting residues in Solution A is that the total average GHG emissions released to grind, transport, pile, and preprocess the 3,964 ODT extra biomass collected from the cut blocks is low and equal to 32.62 kg CO_2 eq./ODT, which favors minimization of the supply chain GHG emissions. If this amount was supplied from Sawmill E in Solution A, GHG emissions released to transport, pile, and preprocess the wood residues would rise to 87.57 kg CO_2 eq./ODT, which is not favorable for emission minimization. The increase in the emission intensity of biomass procurement from Sawmill E is due to having longer distance from the pulp mill compared to a number of cut blocks.

On the other hand, since the total cost associated with the biomass purchase, transportation, handling, and preprocessing from Sawmill E is \$55.66/ODT, which is comparatively less than the average \$63.83/ODT unit cost of extra harvesting residues procured in Solution A, this sawmill was selected for biomass procurement in Solution C to keep the supply chain cost at minimum.

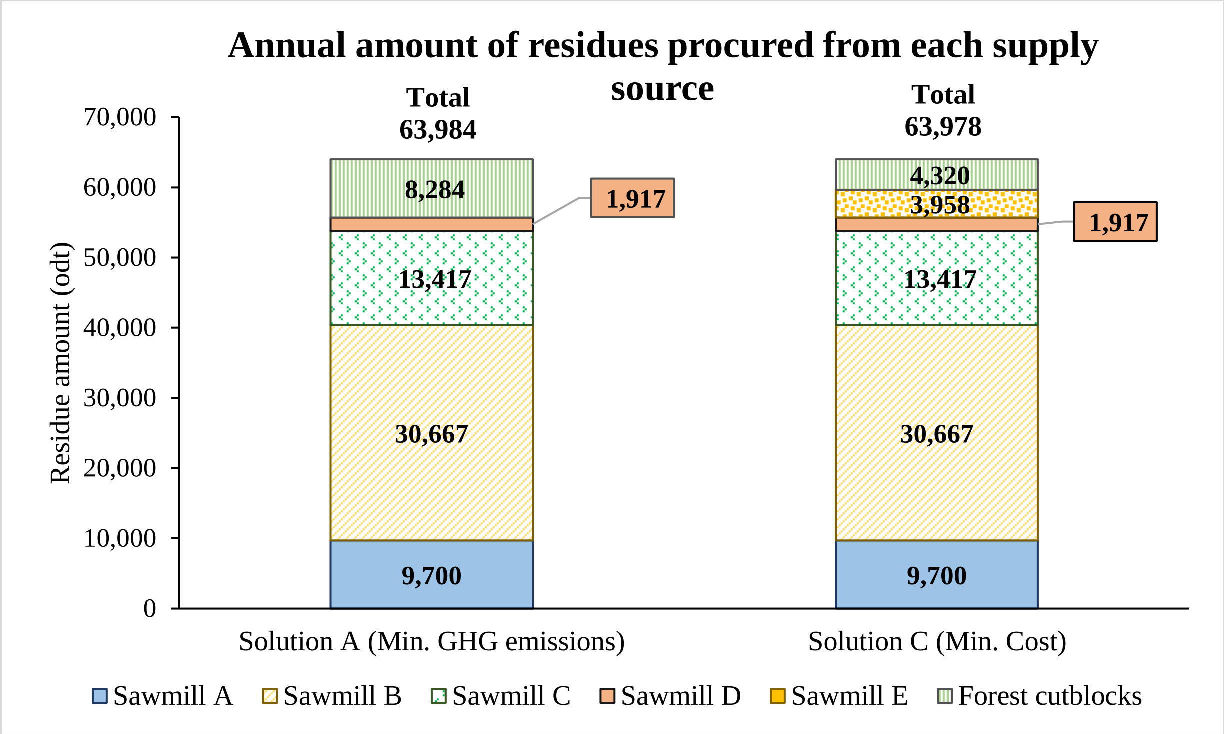


Figure 3.3. Annual flow of residues from sawmills and cut blocks to the gasifier plant in Solutions A and C

3.6.3 Monthly flow of residues from supply sources

Figure 3.4 depicts monthly collective flow of wood residues from the sawmills and forest cut blocks to the plant. Since the mathematical model is to optimize the supply chain for the first operation year of the gasification plant, no initial safety stock is available at the mill. Consequently, flow of biomass to the plant in the first period is almost doubled to procure the biomass amount required for fulfilling the safety stock equal to one month feedstock demand of the gasifier. To evaluate the model outputs for the next fiscal years when the safety stock is available from the previous year, the model with assuming initial inventory as the safety stock was run and the main changes in the results are discussed in Section 3.6.7.

In all months, except for the first month, the same amount of wood residues is delivered to the plant throughout the year. The slight fluctuation in monthly flows is attributed to the monthly fluctuations in the gasifier's feedstock demand as well as fluctuation in the monthly availability of wood residues. Overall, the model prescribes wood residue supply from sawmills due to their relative proximity to the mill compared to the cut blocks. Nonetheless, the supply of harvesting residues slightly rises in Solution A with the minimum GHG emissions because the GHG emission intensity of biomass delivery from some of the forest cut blocks is less than that of far located Sawmills D and E.

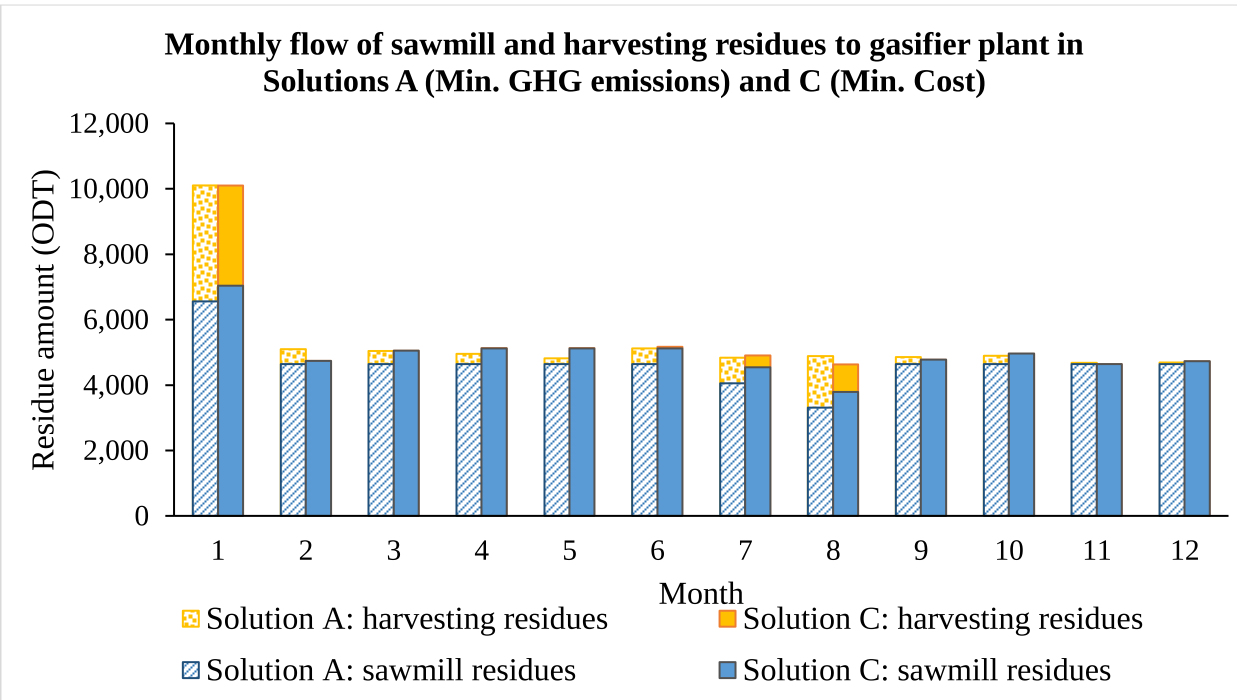


Figure 3.4 Monthly amount of sawmill and harvesting residues delivered to the plant in Solutions A and C

3.6.4 Inventory of residues at the gasification plant

The monthly inventory of sawmill and harvesting residues maintained at the gasifier plant in Solutions A and C are depicted in Figure 3.5. As it can be seen from this figure, in both solutions, the monthly inventory level always meets the safety stock. The inventory level in some months including May, June, and July exceeds the safety stock in both solutions because of an increase in the gasifier's feedstock demand in August coupled with a reduction in the availability of cheap sawmill residues in June and July. Thus, the model prescribes keeping an inventory of lower-cost residues in the prior months to prevent the shortage and increased costs. In both solutions, the optimization model prescribes maintaining sawmill residues as the inventory instead of harvesting residues because sawmill residues delivery cost on average is less than that of harvesting residues.

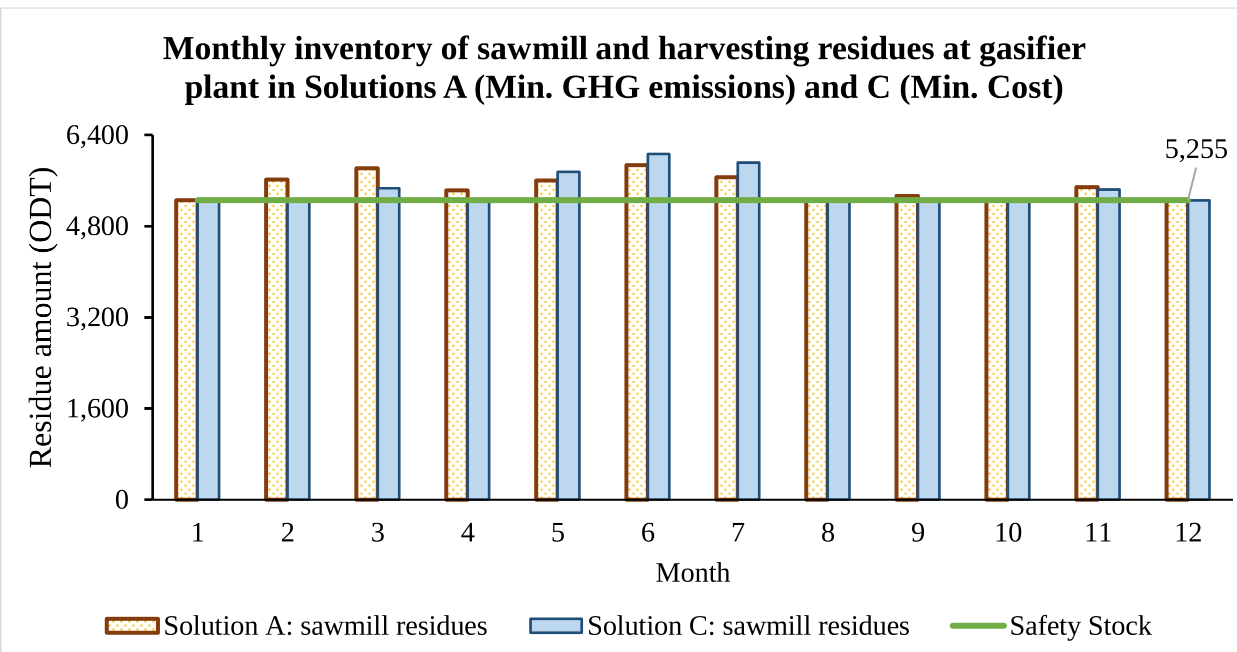


Figure 3.5 Inventory of wood residues maintained at the gasifier plant in Solutions A and C

3.6.5 Supply chain cost

The cost components of Solutions A and C are compared in Figure 3.6. Purchase cost of sawmill residues is the main cost component in both solutions accounting for about 36% of the total supply chain cost. The cost associated with the biomass transportation, preprocessing and handling at the mill are the following components of the supply chain cost, each contributing to about 20% of the total cost. Lastly, the contribution of pre-processing cost of the harvesting residues at the forest roadside is the least, ranging between 5% and 9% of the supply chain cost.

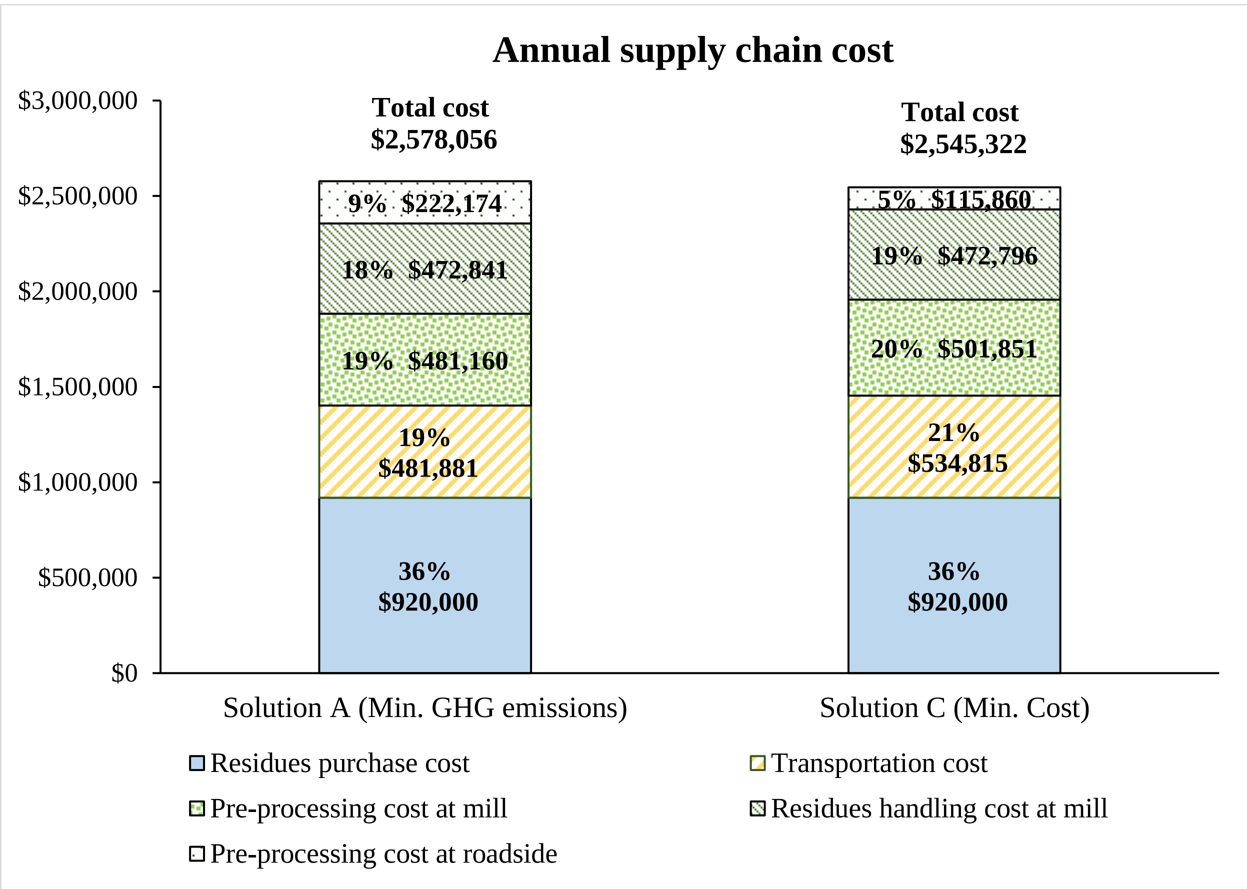


Figure 3.6 Components of the optimum annual total cost in Solutions A and C

The total supply chain cost over a one-year planning horizon is $2,587,056 and $2,545,322 in Solutions A and C, respectively. Solution A with minimum GHG emissions has $32,734 higher cost in comparison with Solution C. According to Figure 3.6., this increase mainly happens because of procuring more harvesting residues in Solution A compared to Solution C, which leads to an increase in the preprocessing cost at the roadside (i.e., grinding of harvesting residues to the trucks). Preprocessing cost at the mill and biomass transportation cost both experience decrease in Solution A compared to Solution C because supplying the gasifier's feedstock demand by harvesting residues available at the nearby cut blocks in Solution A eliminates the need for onsite preprocessing at the mill and reduces the transportation cost due to vicinity of these cut blocks to the mill. The supplied biomass from all cut blocks as well as Sawmill E is free of charge. Since Solutions A only has a shift from using wood residues available at Sawmill E to using more harvesting residues, the purchase cost remains unchanged. The handling cost almost remains the same in both solutions since the total amount of sawmill and harvesting residues procured is approximately the same in both solutions and all residues require handling at the mill regardless of their type.

3.6.6 Supply chain emissions

The amount and contribution of each activity to the supply chain GHG emissions are shown in Figure 3.7. Biomass transportation leads to over 40% of the GHG emissions in both solutions. Biomass handing and preprocessing at the mill are the following contributors to the supply chain GHG emissions. Biomass preprocessing at the mill has a negligible impact on the supply chain emissions (up to 1%) since preprocessing activities operate with electricity and GHG emission intensity of electricity is very low in BC. Moving from Solution A to Solution C, the amount of

GHG emissions from biomass transportation increases due to procuring biomass from far-located Sawmill E in Solution C, whereas the GHG emissions from preprocessing at the roadside declines because of using less harvesting residues in Solution C. The amount of GHG emissions released by biomass handling at the mill is not changed because the total volume of biomass delivered to the mill remains almost the same in both solutions. GHG emissions of biomass preprocessing at the mill is almost the same in both solutions because of its negligible contribution to the total GHG emissions.

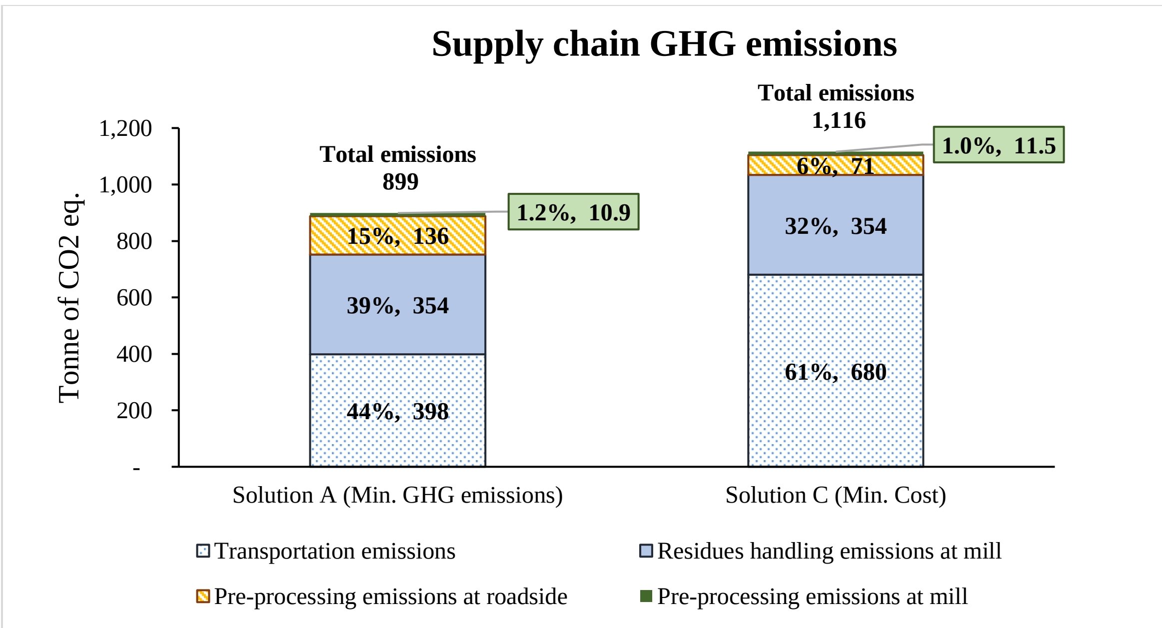


Figure 3.7 Components of the optimum annual supply chain GHG emissions in Solutions A and C

3.6.7 Model outputs with assuming initial inventory as a safety stock

To present and analyze the outputs of the bi-objective optimization model in the previous sections, zero initial inventory of biomass at the mill's storage at the beginning of the first month was assumed to be the case. This assumption was made to provide the pulp mill with the optimal plan for the biomass procurement in the first operation year of the gasifier when no biomass would initially be stored. In the next fiscal years, however, the ending biomass inventory from the previous year would be available as the initial inventory. To analyze the results under this new consideration, the optimization model was run assuming an initial inventory for the first month. The initial inventory is assumed to be equal to the ending inventory of the last year, i.e., inventory in period 12 shown in Figure 3.5. In all Pareto optimal solutions, the costs and GHG emissions of the supply chain decrease because in the first month, biomass is procured to just fulfill the gasifier's feedstock demand and no biomass is needed within this period to meet the safety stock. In other periods than the first month, the decision on the biomass quantity procured from each supplier remains unchanged. For brevity, only the changes in the results of Solution C (with the minimum supply chain cost) are reported.

The annual supply chain costs and GHG emissions in Solution C decrease by 13% and 25% when initial inventory was assumed for the first month. The comparison shows that monthly biomass inventory at the mill remains unchanged throughout the year. The monthly biomass flow from the sources to the mill, and monthly biomass quantity fed to the gasifiers also do not change during the year, except in the first month. In period 1, 2,111 ODT and 3,062 ODT less sawmill and harvesting residues are required to be transported to the mill since the 5,255 ODT safety stock requirement is met by the initial inventory. When initial inventory was not assumed, the feedstock demand of the gasifier in period 1 was fulfilled by 1,787 ODT and 3,062 ODT of sawmill and harvesting residues, respectively. Whereas, assuming initial inventory leads to meeting the gasifier's feedstock demand by only 4,849 ODT of sawmill residues.

3.7 Sensitivity analysis

The results of the bi-objective optimization model presented the trade-off between the cost and GHG emissions of the supply chain. By analyzing the trend in solutions of the Pareto frontier, one could understand how the two objectives perform with respect to each other. It is also important to analyze the sensitivity of model results to the changes in key parameters of the supply chain. In this study, local sensitivity analysis is carried out to examine the impact of variations in the biomass availability, biomass delivery cost, GHG emissions of biomass delivery, and feedstock demand of the gasifier on the changes in the costs and GHG emissions of the Pareto optimal solutions. The mentioned parameters are varied by ±20% to analyze the results. Since a set of 31 Pareto-optimal solutions was generated in this study, it is not possible to report the result of local sensitivity analysis on the cost and GHG emissions of each single solution. Instead, the average of changes in the costs and emissions of these solutions is reported here to illustrate the outputs of the local sensitivity analysis.

Figure 3.8 and Figure 3.9 illustrate the results of local sensitivity analysis on the cost and GHG emissions of the supply chain, respectively. The supply chain cost exhibits sensitivity mainly to the changes in the gasifiers' feedstock demand because when the feedstock demand of the gasifier changes by 20% and -20% the supply chain cost varies by 26% and -32%, respectively. Changes in the availability of sawmill residues as well as delivery cost of sawmill residues and harvesting residues impact the supply chain cost by less than 20%. The impact of variations in the harvesting residue availability, and GHG emissions released to deliver sawmill and harvesting residues on the total cost is negligible and close to zero.

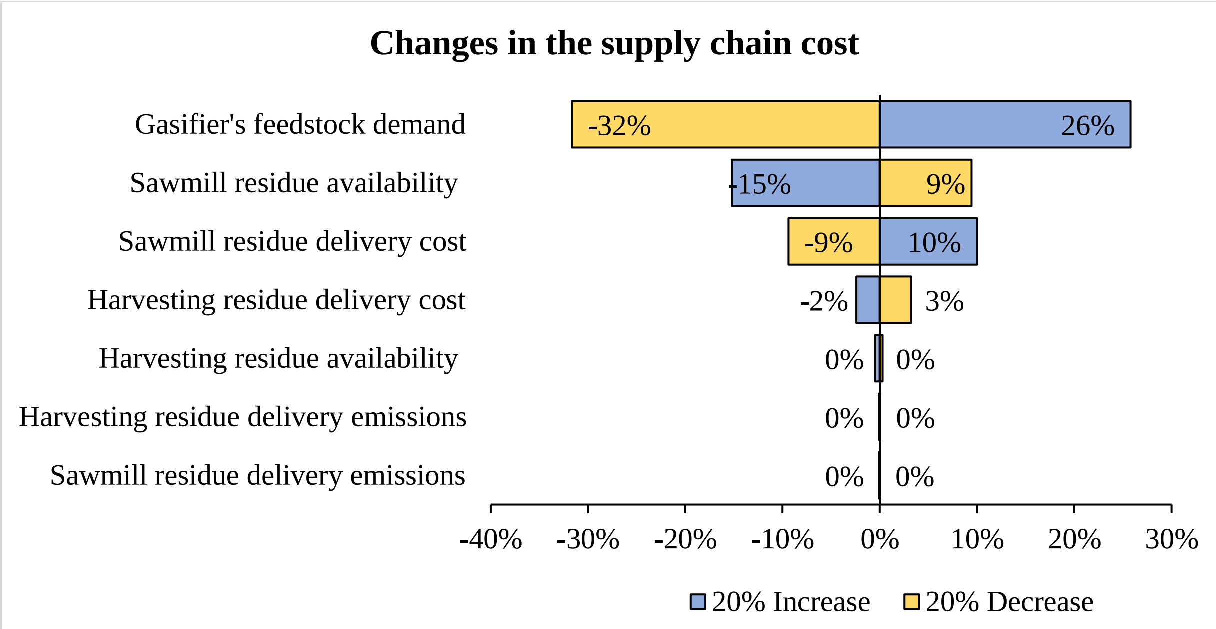


Figure 3.8 Local sensitivity analysis on the supply chain cost

According to Figure **3.9**, the supply chain GHG emissions has mainly sensitivity to the gasifier's feedstock demand and sawmill residues availability because ±20% changes in their value impacts the supply chain GHG emissions by over 30%. The impact of variation in other parameters on the supply chain GHG emissions is less than or equal to 10%.

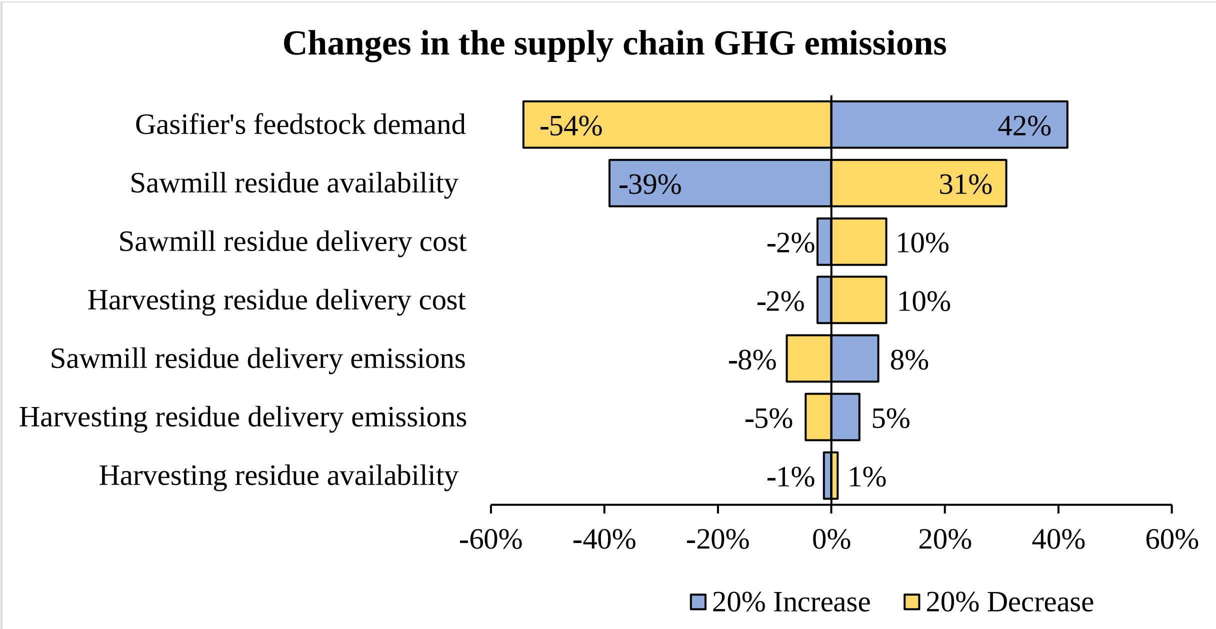


Figure 3.9 Local sensitivity analysis on the supply chain GHG emissions

3.8 Discussion and conclusions

Biomass supply chain costs can hinder the economic viability of the bioenergy projects due to their considerable contribution to the fuel production costs and GHG emissions of biomass supply chains can also reduce the GHG emissions avoided by replacing fossil fuels with bioenergy and biofuels. In addition, supply chain activities including biomass transportation, storage, and preprocessing are interdependent tasks, requiring to be managed all together to ensure their optimal operation. For this reason, in this chapter, a bi-objective optimization model is developed for the tactical planning of a forest-based biomass gasification supply chain. The cost and GHG emissions of the supply chain were formulated to be minimized as two separate objectives. The model outputs provided the pulp mill manager with the monthly amount of biomass to be (1) procured from each supplier, (2) stored at the mill and terminal storage, and (3) preprocessed and fed to the gasifier plant.

Unlike the previous studies, which minimized the cost and GHG emissions of the supply chain at tactical level as a single objective function and reported a single optimal solution, this study aimed to generate a set of Pareto-optimal solution using AUGMECON method. This set of solutions gives a clear picture about the trade-off between the objectives and allows the decision makers to involve their qualitative, non-technical, and experience-driven preferences in choosing the best solution. The analysis of the Pareto front indicated GHG emissions could be decreased by 24.2% from 1,116 t of CO_2 eq. in Solution C (the extreme Pareto solution with minimum cost) to 899 t of CO_2 eq. in Solution A (the extreme Pareto solution with minimum GHG emissions), when the supply chain cost increased by %1.3 from \$2.55 M to \$2.58 M. In this case study, the trade-off between the costs and GHG emissions was due to higher GHG emission intensity of biomass delivery from one of the far-located sawmills (i.e., Sawmill E) than some of the nearby forest cut blocks. For this reason, in Solution A, to minimize GHG emissions of the supply chain, no biomass procured from Sawmill E and instead biomass delivery from forest cut blocks was increased. On the other hand, in Solution C, to minimize the supply chain costs, biomass procurement from forest cut blocks decreased and replaced by bringing residues from Sawmill E because this mill has a lower delivered unit cost compared to that of majority of the harvesting cut blocks.

In both solutions, costs associated with biomass purchase and transportation were the major cost components, followed by biomass preprocessing and handling costs. Regarding GHG emissions, biomass transportation and handling were the main contributors to the GHG emissions of the supply chain, followed by biomass handling and preprocessing. The model did not prescribe establishing the terminal storage in any of the solutions as the mill storage capacity was sufficient to maintain the monthly inventories prescribed by the optimization model.

Sensitivity analysis was conducted on the key parameters of the model. To do so, the average changes in the costs and GHG emissions of the Pareto-optimal solutions was calculated by varying the key input parameters of the model by ±20%. The results of this analysis revealed that the feedstock demand and sawmill residue availability are the most impactful parameters on the costs as well as GHG emissions of the supply chain.

The main research implication of this chapter is that there is a trade-off between minimization of the costs and GHG emissions of the supply chain for biomass gasification in this study. Solution C with minimum cost favors the pulp mill because this solution helps them to minimize the supply chain cost of syngas production and thus maximize the profit generated by selling syngas. It was concluded that depending on the incentives provided by the province of BC for the pulp mill to reduce every tonne of the GHG emissions of the upstream supply chain, the pulp mill would be able to switch from Solution C with minimum cost toward Solution A with minimum GHG emissions. The pareto front can be used to find the most appropriate solution based on the given incentives and the optimization model can be run again to generate the optimal annual supply chain plan for that particular solution.

Chapter 4: Conclusions

4.1 Conclusions

Gasification is a thermochemical process through which forest-based biomass can be converted to heat and power or more advanced biofuels including RNG. The bioenergy and biofuels produced from biomass gasification can replace fossil fuels to reduce the release of fossil greenhouse gases. However, prior to investing in a gasification technology, it is essential to analyze its economic feasibility. In the literature, previous works analyzed the economics as well as GHG emission reduction of biomass gasification for syngas and RNG production. It was concluded that the biofuel offtake prices, government incentives, and fixed capital cost were among the most impactful parameters on the NPV of the investment. Although these parameters and other key input parameters of the models may experience variations, previous works limited their uncertainty analysis to local sensitivity analysis to identify the impact of changes in one parameter at a time on the economics of the project.

To address the above-mentioned limitation, the second chapter of this thesis was to evaluate different alternatives for investment in biomass gasification under uncertain conditions. To achieve this goal, economic and GHG emission analysis models were developed for investment in biomass gasification at three different capacities to produce syngas and RNG in case of a Canadian Kraft pulp mill in British Columbia. In Alternative I, only 38 MW syngas was produced to meet heat demand of the lime kiln, while in Alternatives II and III, 40 MW and 62 MW RNG was assumed to be produced in addition to 38 MW syngas. Economic analysis model showed that under deterministic conditions, Alternative I benefited from a lower fixed capital investment, shorter payback period compared to the other two alternatives; however, it suffered from generating negative net annual cashflows from year 12 onwards. Alternatives II and III always had positive annual net cashflow throughout their service life and generated greater NPV, AW, and ROR. To calculate the mean and Value-at-risk of the NPV and GHG emission reduction of the alternatives, Monte-Carlo simulation was applied to the deterministic models. The results of Monte-Carlo simulation showed that the mean NPV and mean GHG emission reduction increased in large scale gasification alternative; and the mean NPVs of all alternatives were lower than the deterministic value under uncertainty. Large scale gasification also decreased the risk of having low GHG emission reduction. Despite all these advantages associated with large scale gasification, it was exposed to risk of having greater negative NPV in the worst cases.

Since no alternative could outrank other alternatives in all criteria, multi-criteria decision making was performed to select the best alternative considering different weights for the criteria. Risk-averse investors, who highly prefer to minimize the NPV-at-Risk of the project, were recommended to invest in Alternative I. Investment in Alternative II was the most suitable option for the risk averse investors who consider equal weights for the risk values of the NPV and GHG emission reduction of the alternatives. In other cases, Alternative III with the greatest gasification capacity was the most appropriate option. When the pulp mill's preferences were applied to the weights of criteria, Alternative I was ranked first as the pulp mill highly weighed the NPV-at-Risk of the project due to having conservative viewpoint toward investment in biomass gasification.

Through local and global sensitivity analyses, the impact of single and simultaneous variation in the key input parameters of the models on the changes in the NPV and GHG emission reduction of alternatives was evaluated. According to both analyses, the offtake price of syngas/RNG and fixed capital investment were the primary impactful parameters on the NPV of the alternatives.

Since the pulp mill preferred to invest in a gasification project with short payback period, low economic risk, readily available technology, it was concluded that Alternative I seemed the best option. To combat low NPV, and negative cashflow of Alternative I, the pulp mill and FortisBC need to make new developments on the syngas offtake price, natural gas cost, and carbon tax accounting as these factors are among the main parameters affecting the profitability of this alternative. The negotiation on these factors could be possible because FortisBC and the BC province require the GHG emission reduction credits obtained by gasification at pulp mills to reach their emission reduction targets. Otherwise, they would fail to meet their goals. Alternatives II and III with RNG production capacity did not appear to be suitable for investment in the present time due to exposure to longer payback period, higher risk of having negative NPV under uncertainty, higher fixed capital cost and lower technological readiness compared to Alternative I. Therefore, the pulp mill is better off to wait and see how the RNG production technologies will become more mature in the future, then they can decide on extending biomass gasification from only syngas production to coproduction of syngas and RNG.

Due to considerable contribution of the supply chain cost to the bioenergy/biofuel production cost and the negative impact of the supply chain GHG emissions on the GHG emissions reduction of replacing fossil fuels with bioenergy/biofuels, the third chapter of this thesis aimed to minimize the cost and GHG emissions of the biomass supply chain for transportation, storage, and preprocessing of biomass at the tactical level planning. In previous studies, authors optimized the economic and environmental aspects of the supply chain at tactical level as a single objective model and reported a single optimal solution for their problems. However, decision makers prefer to have a set of optimal solutions rather than a single solution in multi-objective problems. The optimal solution set helps them to understand the trade-off between the objectives and incorporate their experience-driven, qualitative, and non-technical preferences in their decision making. To address this limitation, the AUMECON method was employed to solve the developed bi-objective model. To analyze the results of the model, it was applied to optimize the supply chain for biomass gasification in Alternative I.

The trade-off between the objectives indicated that the pulp mill would be able to reduce the GHG emissions of the supply chain by 24.2% by allowing the supply chain cost to be increased by 1.3%. To analyze other outputs of the model, the results of two extreme solutions of the optimal solution set, namely Solution A with minimum GHG emissions and Solutions C with minimum cost, were compared. The optimization model prescribed to meet 93% and 87% of the gasifier's feedstock demand from sawmill residues in Solutions A and C, respectively, and the rest from harvesting residues because the cost and GHG emissions of sawmill residues delivered to the pulp mill was on average lower than those of harvesting residues. Nonetheless, about 3,964 ODT more harvesting residues was prescribed for procurement in Solution A (with minimum emissions) than Solution C (with minimum cost) because the GHG emission intensity of delivering harvesting residues to the pulp mill was lower than one of the far located sawmills. This fact was the reason behind the trade-off between the cost and emissions of the supply chain. In both solutions, the transportation and purchase of biomass were the main cost components, while biomass transportation and handling were the main contributors to the GHG emissions of the supply chain.

Finally, the local sensitivity analysis revealed that the cost and emission objectives were both primarily sensitive to the feedstock demand of the gasifier and sawmill residues availability.

From the Pareto-front, it was concluded that the best solution from the pulp mill's viewpoint was Solution C with minimum cost, whereas Solution A would result in the minimum emissions from the upstream supply chain activities, which is in line with the province interest in emission reduction. Therefore, the Pareto optimal solutions could be used to identify a common optimal solution based on the incentives considered by the province for the whole supply chain to reduce every tonne of CO_2 eq. emissions.

Although in the second chapter, the best alternative was evaluated under uncertainty for the case of syngas and RNG production at a pulp mill, the same approach can be taken for other investment projects to rank the alternatives under uncertain conditions. Likewise, the bi-objective optimization model in the third chapter with some modification can be applied to other cases of forest-based biomass gasification for production of other biofuels and bioenergy.

4.2 Limitations

According to (Thunman et al., 2019), the heat generated in GoBiGas project during biomass gasification, syngas clean-up, and upgrade to RNG are additional to the heat demand of the RNG plant. Therefore, the RNG plant is self-sufficient in terms of supplying its internal thermal energy demand. Likewise, according to personal communication with the pulp mill, the heat demand of the dryer and gasifier in the case of only syngas production (i.e., Alternative I) is met by the secondary heat from the pulp mill and available low-pressure steam. Due to these facts, in chapter 2, it was assumed that the heat demand of the gasification plant in all alternatives would be met by the excess low-pressure steam and excess heat available from the gasification plant or the pulp mill. In addition, the data available from similar gasification plants were used to calculate the electricity consumption of the plant. Consideration of mass and energy balances would enhance the accuracy of estimating the thermal and power consumption of the gasification plant. This consideration also enables evaluation of the heat integration potential of the gasification plant with the pulp mill, and investigation of the possibility for green power generation from the excess heat.

In chapter 2, only the economic and emission criteria were considered to evaluate the gasification alternatives. However, other criteria including (1) the maturity level of the gasifier and RNG production technologies, (2) the number of new jobs created by commissioning of each alternative and (3) quantity of sawmill and harvesting residues that are not utilized can be considered as other important criteria in the multi-criteria decision making. Consideration of maturity level of the fuel processing technologies can reflect the decision maker’s concern about the commercial readiness of the gasification process because the steam-blown DFB gasifiers and syngas upgrading processes required to produce RNG still has less maturity than the air-blown CFB gasifiers that has been installed widely for syngas production (Hofbauer & Materazzi, 2019). Involving the number of job created by each alternative helps to incorporate the social sustainability aspects of biomass gasification. Lastly, unutilized sawmill and harvesting residues end up being disposed at landfills and being incinerated to prevent wildfires, respectively. These actions lead to occupying landfills or releasing the biomass carbon content directly to the atmosphere. Therefore, it sounds reasonable to incorporate the amount of unutilized sawmill and harvesting residues as a criterion in the decision making to account for the consequences of leaving wood residues at landfills or at forest cut blocks.

To evaluate the environmental aspects of the biomass gasification, in chapters 2 and 3, only the CO_2 eq. of GHG emissions released from combustion of fossil fuels were considered. In addition to the GHG emissions of fossil fuels, the environmental analysis model can be extended to account for other environmental pollutants such as particulate matters and NO_x emissions released by the input material that are consumed to produce syngas and RNG. This analysis is meaningful as the level of environmental pollutants can be increased considerably by scaling up the biomass gasification from only syngas production to coproduction of syngas and RNG. Therefore, Alternatives II and III may generate significantly more environmental pollutants as compared to Alternative I despite having higher annual net GHG emission reduction. Furthermore, the environmental analysis model would become more comprehensive by involving the biogenic GHG emissions that would be released to the atmosphere due to either incineration or decay of the sawmill residues and harvesting residues that are not gasified and left at the landfills and forest roadsides, respectively.

In chapter 3, the transportation cost of the sawmill and harvesting residues were provided by the pulp mill and were given in the oven-dry basis. The pulp mill did not have any data on the moisture content of wood residues supplied from each source. As such, the maximum moisture content of 60% (wet basis) was assumed for the wood residues. Since the moisture content of the residues may experience monthly variation, it is suitable to gather data on the monthly moisture content of the residues and adjust the models developed in this thesis to account for variation in the moisture content.

One of the limitations of the bi-objective model developed in Chapter 3 for optimizing forest-based biomass supply chain at the tactical level is related to the assumption that biomass supply and demand quantities were known with certainty. However, the pulp mill, whose data were used to evaluate the optimization model, had a general idea about the biomass supply and demand quantities based on their prior experience. As a result, in reality, the amount of supply and demand are prone to variations over the year. Moreover, limited accessibility to forest cut blocks due to summer wildfires and spring break-up or temporary mill shutdowns due to unprofitable market conditions would be among possible disruptions in the biomass supply chains. The current optimization model was deterministic and did not consider for any unforeseeable interruptions nor variations in the biomass demand and supply quantities. Consideration of variations in the biomass supply and demand amounts and disruptions in the supply chain would require additional information about these parameters and would require modifications to the optimization model.

4.3 Future work directions

The following directions are suggested for the future work:

(1) Incorporating a thermodynamic model in addition to the economic and emission models developed in chapter 2 to calculate the mass and energy balance of the gasification plant to increase the accuracy of estimating the power and thermal consumption of the plant. Moreover, the potential heat integration of the gasification plant with the pulp mill can be evaluated using pinch analysis. Based on the output of the pinch analysis, the possibility of power production from the excess heat in each alternative can be further investigated.

(2) In chapters 2 and 3, only the fossil GHG emissions were calculated. In the future work, life cycle impact assessment (LCIA) can be performed to calculate other emissions such as particulate matters and NO_x released to produce syngas and RNG. In addition to fossil GHG

emissions, the biogenic greenhouse gases, which are emitted by incineration or decay of wood residues left at the landfills or the forest roadsides, can be considered in the future study.

(3) In addition to economic and environmental criteria, other important criteria can be incorporated in evaluating the alternatives for investment. The maturity level of the gasifier technology, the cost and environmental impacts associated with disposing wood residues that are not unutilized for gasification, and social benefits of biomass gasification (e.g., creation of new jobs) are among the other important criteria to be considered.

(4) Due to existence of variation in biomass supply and demand quantities and biomass moisture content, one of the suitable future avenues for this bi-objective optimization model illustrated in Chapter 3 is to develop a stochastic bi-objective optimization model to accounts for variation in the above-mentioned parameters. The stochastic optimization model can be developed such that it would also account for the common disruptions in the biomass supply chains including the sawmill curtailments and limited accessibility to forest cut blocks due to summer wildfires and spring break-up.

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Appendix

Table A.1 shows the data used for calculating the purchase cost of equipment pieces in Sections 2.4 and 3.4.4. Table A.2 displays the data used to calculate the operating and maintenance costs of equipment pieces in Sections 2.4 and 3.4.4.

Table A.3 shows the data used to calculate the annual net GHG emission reduction in Section 2.5.

Table A.1 Data for calculating purchase cost of equipment pieces

Equipment	**Original purchase cost**	**Scale factor**	**Currency, original capacity, and original year**	**Data source**
Purchase cost of equipment for syngas production (Alternatives I)				
Fuel handling and feeding system (conveyors and lock hoppers)	14,787,000	0.67	EUR, 38MW syngas, 2018	a
Belt dryer				
Air-blown CFB gasifier				
Primary gas cleaning (filters)				
Auxiliary equipment				
Lime kiln multi-fuel burner				
Purchase cost of equipment for syngas and RNG production (Alternatives II and III)				
Fuel handling and feeding system (conveyors and lock hoppers)	50,400	0.55	Thousand SEK, 20MW RNG, 2014	(Thunman et al., 2019)
Belt dryer	16,557	0.80		
Steam-blown atmospheric DFB gasifier (reactors, refractory, condensate treatment and steam generation)	29,490	0.65		
Primary gas cleaning (filters, coolers, scrubbers and analyzers)	23,780	0.63		
Flue gas and ash handling system (coolers, filters, fans and ash handling)	18,930	0.77		
Tar removal (filters, activated carbon beds, and regeneration system)	10,620	0.70		
Compressor	34,590	0.70		
Olefin hydrogenation	9,060	0.70		
H2S scrubber	9,150	0.70		
Water-Gas Shift reaction	5,290	0.70		
Premethanation	5,150	0.70		

CO_2 scrubber	17,570	0.70		
Methanation	19,410	0.70		
Drying and odorization	4,970	0.70		
Auxiliary equipment	146,520	0.50		
Lime kiln multi-fuel Burner	333,333	0.67	EUR, 40MW syngas, 2017	(Mackėla, 2017)
Purchase cost of equipment for biomass handling and preprocessing				
Biomass handling[b] (front-end loader 250HP)	650,000	0.77	CAD, 43.05 ODT/PMH, 2020	a
Reclaiming (underground screw feeder)	415,345		CAD, 680 t/day, 2007	(U.S. Environmental Protection Agency, 2007)
Screening (scalping screener)	74,879		CAD, 13.06 ODT/PMH, 2020	c
Biomass grinding at pulp mill (drop feed hogger)	213,975		CAD, 19.91 ODT/PMH[e], 2020	d

a) (Project Manager at the pulp mill, personal communication, March 08, 2021)
b) Service life of front-end loader was assumed to be 5 years. (other equipment pieces were assumed to be 20 years.)
c) (Sales Manager at TerraSource, personal communication, December 1, 2020)
d) (Sales Head at Acrowood, personal communication, December 2, 2020)
e) PMH: Productive Machine Hours

Table A.2 Data for calculating operating and maintenance cost

O&M cost	**Original cost**	**Currency, original capacity, and original year**	**Data source**
Personnel	30,408	thousand SEK/year, 20MW RNG, 2014	(Thunman et al., 2019)
Maintenance (gasifier)	5,981		
Maintenance (gas cleaning and upgrading)	8,971		
Electricity (gasification plant)	6,317		
Consumables (except electricity)	9,257		
Overheads	4,452		
Make-up lime[a]	350	USD $/tonne of lime, NA, 2017	(Kuparinen & Vakkilainen, 2017)
Ash disposal cost	100	CAD $/tonne of ash, NA, 2018	(Petrov, 2018)
Maintenance of preprocessing equipment	25% of purchase cost	NA	c
Electricity (drop feed hogger)	88,557[b]	CAD $/year, 248 kw, 2020	d
Electricity (scalping screener)	1,332[b]	CAD $/year, 3.7 kw, 2020	e
Electricity (screw feeder)	26,791[b]	CAD $/year, 75 kw, 2020	(Prakoso, 2018)
Oils & lubricants (drop feed hogger)	24,696	CAD $/year, 248 kw, 2020	c
Front-end loader's operator, fuel, and maintenance cost	121.1	CAD $/hour, 250 HP, 2020	f

a) Make-up lime increase due to presence of none-processed elements in syngas was assumed at 2kg/air-dried tonne of pulp (Kuparinen & Vakkilainen, 2017)
b) At electricity rate of $0.0567 (www.energyrates.ca)
c) (Charles Friesen, Senior Scientist at FPInnovations, personal communication, October 26, 2020)
d) (Sales Manager at TerraSource, personal communication, December 1, 2020)
e) (Sales Head at Acrowood, personal communication, December 2, 2020)
f) (Project Manager at the pulp mill, personal communication, March 08, 2021)

Table A.3 Data for calculating the annual net GHG emission reduction

Equipment piece	**Fuel type**	**GHG emissions intensity ($g\ CO_2$ eq./ODT)**
Biomass grinding at roadside (horizontal mobile grinder)	Diesel	16,435.02[a]
Biomass handling (middle-size front-end loader)	Diesel	2,802.88[a]
Biomass handling (large-size front-end loader)	Diesel	4,077.97[a]
Biomass grinding at pulp mill (drop feed hogger)	Electricity	112.06[b]
Screening (scalping screener)	Electricity	2.57[b]
Reclaiming (underground screw feeder)	Electricity	59.58[b]
Syngas production (gasifier air fans)	Electricity	831.6[b] (kg CO_2 eq./MW Syngas)
RNG production (gas compression)	Electricity	4,131.96[b] (kg CO_2 eq./MW RNG)
Trucking of harvesting residues	Diesel	320[c] (g CO_2 eq./ODT-km)
Trucking of sawmill residues	Diesel	280[c] (g CO_2 eq./ODT-km)
Trucking of ash to landfill	Diesel	110.80[d] (g CO_2 eq./tonne-km)
Natural gas combustion[f]	-	49,870[e] (g CO_2 eq./GJ)

a) GHG emission intensity of diesel equipment was calculated assuming 3kg CO_2 eq./L emission intensity for diesel
b) GHG emission intensity of electrical equipment was calculated assuming 9g CO_2 eq./kWh emission intensity for power in BC
c) (Cambero et al., 2016), d (Mathers et al., 2019)
e) (Ministry of Environment & Climate Change Strategy, 2019)
f) GHG emission intensity of natural gas was used to calculate the emission reduction obtained by replacing natural gas with syngas and RNG