SUPPLY CHAIN PLANNING FOR BIOENERGY AND BIOFUEL PRODUCTION FROM FOREST-BASED RESIDUES IN INTERIOR BRITISH COLUMBIA: A SIMULATION STUDY

by

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B.Sc Industrial Engineering, Universidad de Monterrey, 2010

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF SCIENCE

in

The Faculty of Graduate and Postdoctoral Studies
(Forestry)

THE UNIVERSITY OF BRITISH COLUMBIA
(Vancouver)

April 2016

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ABSTRACT

This thesis analyzes a forest-based biomass supply chain network considering uncertainties and variations. It is based on the Williams Lake Timber Supply Area (TSA) located in British Columbia, Canada. The network includes: five conversion facilities distributed in three locations, two types of forest-based biomass, sourced from 337 cutblocks, and two types of sawmill residues sourced from three local sawmills. The main objective of this research is to evaluate the supply chain of forest-based residues for bioenergy and biofuel production considering uncertainties and variations. The specific objectives of this research are to: 1) Develop a simulation model to evaluate a forest-based biomass supply chain for bioenergy and biofuel production considering uncertainties and variations; and 2) apply the simulation model to a case study. To achieve the objectives, a discrete-event simulation model is developed using the commercial software Anylogic 7® (Anylogic 7, 2000). Evaluating a network with various supply and demand points, with various biomass types, and a hybrid push-pull biomass flow management distinguishes this work from previous research. The results show the demand is fulfilled to at least 95%, requiring 23 to 24 trucks during the peak season. Furthermore, the cost and CO₂ equivalent emissions vary per location, from $56.52 to $87.36 and from 19.66 to 72.61 (kg/odt), respectively. Long transportation distances and transportation cycle times greatly affected the number of required resources, and consequently the final cost per oven dry tonne. This results in higher costs than similar studies performed in less remote areas. Finally, a sensitivity analysis is performed to evaluate the effect of changes in moisture content and in supply and demand. Extreme changes in biomass supply and demand affected dramatically the demand fulfillment. By increasing the biomass demand 20% while simultaneously decreasing the biomass supply 20%, reduced the demand fulfillment by
23.18%. Finally, this model can be improved in several ways, one of them being by including the possibility of routing between different cutblocks to consolidate biomass pick-ups, therefore increasing the demand fulfillment of the supply chain and possibly reducing costs.
PREFACE

This dissertation presents the work of the author Diana Gabriela Siller Benitez. The literature review, data gathering, simulation model development, and results analysis were performed by the author, with guidance from the research supervisor Dr. Taraneh Sowlati and committee members Dr. Dominik Roser and Dr. Julie Cool.
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ACKNOWLEDGEMENTS

I wish to thank my supervisor, Dr. Taraneh Sowlati for the direction and advice provided to attain my academic goals. I also wish to thank the members of my supervisory committee, Drs. Dominic Röser and Julie Cool for enriching my research with their comments and guidance. Furthermore, I wish to thank Charles Friesen, from FPInnovations, for his direction and helping me in data gathering. I would like to thank some previous and current members of the Industrial Engineering Research Group Dr. Mahdi Mobini, Shaghaygh Akhtari, Claudia Cambero, and Krishna Teja Malladi for their support and comments during the preparation of this research. Finally, I would like to thank my sister Viviana Siller Benitez for developing some graphics used in this thesis.
DEDICATION

“When it is dark enough, you can see the stars”

By Ralph Waldo Emerson (1803-1882)
Chapter 1. INTRODUCTION

1.1. BACKGROUND

Biomass is the organic matter resulting from living or recently living organisms such as plants and animals (Biomass Energy Centre, 2008). Biomass is considered as the fourth largest energy source in the world, after coal, oil, and natural gas (Mafakheri and Nasiri, 2014; Rentizelas et al., 2009; Spellman, 2012). Currently, it accounts for 14% of the global primary energy sources; and the trends show its contribution would continue to increase (Mafakheri and Nasiri, 2014; Rentizelas et al., 2009; Sharma et al., 2015; Spellman, 2012). In fact in the U.S. alone, biomass has already become the largest source of renewable energy, providing 3% of the total energy consumption (Spellman, 2012). In the European Union (EU), biomass accounted for 4% of the total energy demand in 2008 (Uslu et al., 2008). In addition, the EU governments have favoured the use of biomass as an energy source, having the target to substitute 10% of transportation fossil fuels by biofuels in 2020 (Uslu et al., 2008). In Canada, biomass contributes to approximately 6% of the total energy supply, and a recent study led by FPInnovations and FPAC, called the Bio-pathways Projects, indicated huge potential for forest-based biomass as feedstock for bioenergy production (FPAC, 2010; “Bio-pathways Project,” 2015; “Forest bioeconomy, bioenergy and bioproducts,” 2015;).

The increased popularity of biomass is due to two unique characteristics: 1) it is the only renewable energy source which can be transported and stored as a fuel; and 2) it is a versatile energy source with a wide variety of potential feedstocks that could supply a variety of bioconversion facilities (Spellman, 2012). These characteristics, along with the environmental and sustainability benefits inherent to all renewable energies, has made biomass a great candidate
to increase fuel security and reduce greenhouse gas emissions (Spellman, 2012). In the present study, biomass will be used to refer to plant-based biomass.

Over the past few decades, there have been different trends regarding the type of biomass feedstock used for energy and fuel production. Each of these feedstock types, commonly known as “feedstock generations”, have unique limitations and strengths. First generation feedstocks are made from biomass high in sugar, starch, and vegetable oils, such as grains, sugar beet, sugarcane, soybeans, etc. (Sims et al., 2008; Spellman, 2012). There are several mature markets for first generation biofuels like sugarcane ethanol in Brazil, corn ethanol in the US, and rapeseed oil biodiesel in Germany (Gold and Seuring, 2011; Lee and Lavoie, 2013; Sharma et al., 2013; Sims et al., 2008). Between 2000 and 2007, the global demand for liquid biofuels produced from first generation feedstocks tripled, and potential future investments indicated a strong growth in the near future (Sims et al., 2008). However, the increased use of first generation feedstock has proven to cause negative effects on society and the environment. It has caused an increase in food prices and indirect and direct deforestation by competing with food and fibre producers for land and water (Mafakheri and Nasiri, 2014; Sharma et al., 2013; Sims et al., 2008). Furthermore, first generation biofuels did not meet the expected environmental benefits which initially triggered their production (Mafakheri and Nasiri, 2014; Sharma et al., 2013; Sims et al., 2008). Second generation feedstocks are non-food biomass which range from grass and trees, also known as lignosellulosic biomass, to municipal wastes (Antizar-Ladislao and Turrion-Gomez, 2008; Lee and Lavoie, 2013; Sims et al., 2008). Lignosellulosic biomass, is usually divided into agricultural and forest-based biomass (Sims et al., 2008). Agricultural biomass refers to non-food agricultural products, like corn-stover (stalks, leaves, and cobs), wheat straw, energy crops
(amaranth, bamboo, eucalyptus, and grass etc.), and trees grown specifically for the production of bioenergy (switchgrass, hybrid poplar, willow, etc.) (Antizar-Ladislao and Turrion-Gomez, 2008). Forest-based biomass refers to biomass which can be obtained from the forest management activities or from forest by-products. It is comprised of all parts of a tree, including the trunk, branches, bark, and needles or leaves (Natural Resources Canada, 2015c). Some of the benefits of second over first generation feedstock are: 1) the higher annual energy yields (GJ/ha/yr), 2) the use of wastes, which would otherwise be landfilled, for energy production, and 3) the decrease in competition for prime land and water, since this biomass type can be grown in land not suitable for food crops (Sims et al., 2008). However, the production of energy from second generation feedstocks entails high cost for infrastructure and operation, which has greatly challenged the development of large scale bioenergy projects (Antizar-Ladislao and Turrion-Gomez, 2008; Buckley, 2014). Third generation feedstock uses the lipid content found in algae to produce energy. This feedstock has the benefits, compared to second generation, of higher growth yields and lower total resource inputs required for the generation of energy (Demirbas, 2011; Lee and Lavoie, 2013). However, there are a couple of challenges present in the use of this type of biomass. Large volumes of water are required for large scale production, which poses a problem for countries where temperatures reach below freezing point, since this would require large amounts of energy to keep the water from freezing. Furthermore, the extraction of lipids requires high levels of technicality due to the high moisture content of the algae (Demirbas, 2011; Lee and Lavoie, 2013; Sharma et al., 2013). Finally, fourth generation feedstock refers to crops which have been genetically modified to produce higher energy yields and which can be easily transformed into usable energy while not competing with food crops (Biopact Team, 2007; Demirbas, 2011).
This research study focuses on the use of second generation feedstock for energy production, specifically forest-based biomass. Forest-based biomass can be divided into three types: forest residues, mill residues, and urban wood wastes (Spellman, 2012; Yemshanov et al., 2014). Forest residues are the result of sawlog harvesting and forest conservation activities, such as thinning. In regions such as British Columbia, Canada, where forestry operations are of great importance, using forest residues represents an advantage because of the already available harvesting and collecting infrastructure that could be extended to recover forest residues (EPA, 2007; Yemshanov et al., 2014). Forest residues are commonly grouped into the following categories: 1) logging residues, 2) rough, rotten and salvageable dead wood, 3) small pole trees and 4) forest thinnings. Logging residues are the unused fraction of merchantable logs, such as tops and branches (EPA, 2007). These residues are either left in the forest to improve soil conditions or are disposed of by open burning (EPA, 2007). Rough, rotten, and salvageable wood refers to those trees which are not merchantable species, or which do not contain sawlog because of rot, or because their diameter at breast height (DBH) is less than 4.9 inches. Small pole trees are those with a DBH greater than 5 inches yet smaller than merchantable trees (EPA, 2007). Forest thinning is the result of attempts to decrease the risk of forest losses by fire, insects and disease (Spellman, 2012). Forest thinning usually refers to removing underbrush, saplings smaller than 2 inches in diameter and fallen or standing dead trees (EPA, 2007; Spellman, 2012). Currently, the high costs of harvesting, collecting, processing, and transporting forest thinning have made it more cost effective to practice controlled burnings instead (EPA, 2007). Mill residues are the by-products from the processing of merchantable logs or engineered wood products, such as bark, chips, sawdust, shavings, wood trims, etc. (Spellman, 2012). Mill residues have been preferred for bioenergy conversion because of their homogeneity, and
relatively low amount of contaminants (EPA, 2007). Urban waste wood refers to household and industry wood waste, yard trimmings, and wood construction and demolition waste that is generally disposed of at landfills (Spellman, 2012). A major issue with urban waste is the high level of impurities contained in the wood, mostly in the form of chemicals which are meant to extend its life. This would require extra filtration to reduce the possible emission of fumes when burnt or an effective separation of contaminants prior to burning the biomass (Spellman, 2012).

Different operations/processes are needed to convert forest-based biomass to bioenergy. These processes that compose the forest-based biomass supply chain include harvesting and collection, pre-processing, storage, transport, and biomass conversion (Awudu and Zhang, 2012; Correll et al., 2014; Gold and Seuring, 2011; Mafakheri and Nasiri, 2014; Rentizelas et al., 2009; Sharma et al., 2013; Wolfsmayr and Rauch, 2014; Yue et al., 2014). Figure 1.1 presents the various possible supply chain configuration (Sharma et al., 2013). As it can be observed, the supply chain starts with the harvesting and collection of biomass and may end at the conversion facility or the final customer. However, the processes in between can occur in different sequences and at different locations (i.e. forest landing, forest roadside, terminals, or conversion facility). The sequence of these operations and their location depend on the feedstock type and its sourcing point, location and capacity of conversion facility, and the desired final product (Sharma et al., 2013).
Each stage of the forest-based biomass supply chain has specific objectives and involves multiple complex decisions. The harvesting and collection of biomass could occur in one or several locations, such as different forest cutblocks and sawmills, or both. Additionally, one or several feedstock types may be used to supply one conversion facility (Gold and Seuring, 2011). The main concerns at this stage are: land allocation or supplier selection, and appropriate harvesting machinery selection and scheduling to meet the biomass demand (Mafakheri and Nasiri, 2014). The storage tends to be an optional step in biomass supply chains. However, it is a common approach to ensure consistent biomass supply to the conversion facility despite harvesting seasonality (Gold and Seuring, 2011; Rentizelas et al., 2009; Wolfsmayr and Rauch, 2014). Yet, there are high costs involved in the use of storage, which are highly dependent on the location, type, duration of storage, and the amount of biomass to be stored (Gold and Seuring, 2011; Rentizelas et al., 2009). The storage can be located at the harvesting site, conversion facility, or a terminal in between (Gold and Seuring, 2011; Rentizelas et al., 2009). The pre-processing or densification of biomass is meant to improve the handling, transportation, and conversion efficiency (Gold and Seuring, 2011; Uslu et al., 2008). The selection of the pre-
processing option greatly depends on the type of feedstock, conversion process, the desired final product and the market where it will be sold (Gold and Seuring, 2011; Uslu et al., 2008). A proper pre-processing selection can drastically improve the economic feasibility of bioenergy projects. Transportation is greatly affected by the available road infrastructure and travel distances (Gold and Seuring, 2011). Because forest-based biomass resources are usually dispersed over large and remote areas, road infrastructure pose a restriction on both the speed and transportation mode selection (Wolfsmayr and Rauch, 2014). Indeed, there are different transportation modes which could be used for transporting biomass. However, even though several studies have given recommendations on transportation mode selection based on distances (Gold and Seuring, 2011; Rentizelas et al., 2009; Sharma et al., 2013; Wolfsmayr and Rauch, 2014), the selection of the transportation mode depends on the location of the biomass, available road infrastructure, characteristics of biomass, and the location and size of the conversion facility (Wolfsmayr and Rauch, 2014). Additionally, due to the low energy and bulk density of biomass, compared to those of fossil fuels, transportation and logistics costs account for the highest proportion (20%-50%) of the total delivered biomass cost (Rentizelas et al., 2009; Sharma et al., 2013; Spellman, 2012). Therefore, it is important to enhance the utilization and allocation of vehicle payload, personnel, and vehicle scheduling in order to reduce transportation costs and environmental emissions (Gold and Seuring, 2011). Finally, the decisions concerning the conversion process are: the type of technology and final products, the capacity and number of conversion facilities, and their location (Gold and Seuring, 2011).

These complex decisions are highly influenced by uncertain and variable parameters (Rentizelas et al., 2009; Sharma et al., 2013; Wolfsmayr and Rauch, 2014). Awudu et al. (2012) classified the uncertain parameters into four categories: 1) raw material supply, 2) transportation
and logistics, 3) production and operation, and 4) final product demand and price. In the raw material supply category, the uncertain parameters which affect the supply chain are: the biomass type, its yield and quality, and the reliability of its supply (Awudu and Zhang, 2012). These includes the physical and chemical properties of biomass, supplier selection, and unforeseen circumstances which would affect the reliable and steady biomass supply from the source to the conversion facilities (Rentizelas et al., 2009; Sharma et al., 2013; Wolfsmayr and Rauch, 2014). In the transportation and logistics category, the main uncertain parameters are: unforeseen delays in transportation, transportation and warehousing costs, vehicle type and characteristics, and level of coordination (Awudu and Zhang, 2012). In the production and operation category, the main uncertain parameters are: delays in biomass supply, production yields, unforeseen machine breakdowns, lead time and inventory levels (Awudu and Zhang, 2012). In the final product demand and price category, the main uncertain parameters are: unpredictable variations in demand quantity and timing, and in price (Awudu and Zhang, 2012). The fluctuations in these two parameters seem to be related to fluctuations in the energy, forestry, and food industry, as well as governmental policies (Awudu and Zhang, 2012; Mafakheri and Nasiri, 2014).

Since bioenergy projects are capital intensive, it is importance to guarantee its economic, environmental, and social feasibility and resiliency throughout their planning and execution process (Mafakheri and Nasiri, 2014). To achieve this, decisions at all planning levels (i.e. strategic, tactical, and operational) and at all supply chain stages have to consider the effects of uncertain and variable parameters appropriate to the situation (Spellman, 2012; Yue et al., 2014). However, the integration of uncertain and variable parameters in the decision making will increase the complexity of the decision making process (Haartveit et al., 2004). According
to Awudu et al. (2012) uncertainties can be integrated in supply chain planning by either mathematical or simulation methods, the latter being the most appropriate for dynamic systems with high level of machine interactions, such as those found in supply chains.

Simulation models have been used to analyze the effect that different harvesting practices and natural disturbances would have in timber yield, and future forest structure and composition (He et al., 2002; Phillips et al., 2004; Radeloff et al., 2006; Rüger et al., 2007; Cordonnier et al., 2008; Thorpe et al., 2010 Lucas et al., 2014; Bose et al., 2015; Luo et al., 2015;). In these models, trees exhibit specific behaviour such as growth, reproduction, death, or disease in response to resource availability (i.e. sunlight and soil nutrients), and their environment, (i.e. spread of disease, forest fires, or the harvest of a neighbouring tree). Bose et al. (2015) explains, that simulation modelling is the best approach to perform this type of analysis since most of the relationships and behaviours exhibited by trees tend to be either non-linear or stochastic, which would make it almost impossible to perform an analysis using the traditional growth and yield tables. Furthermore, simulation has also been used to assess the economic and environmental performance of not only harvesting and logistics operations but also the entire supply chains (Asikainen, 2001; Talbot and Suadicani, 2005; Vaatainen et al., 2006; Mahmoudi et al., 2009; Asikainen, 2010; Mobini et al., 2011; Karttunen et al., 2012; Zhang et al., 2012; Mobini et al., 2013; Windisch et al., 2015). In these simulation studies, resource constraints and allocation are evaluated to improve the performance of the system. They consider uncertain parameters such as machinery productivity and breakdown frequencies and intensity; biomass characteristics, availability, and demand; seasonality of operations; and transportation distances and speeds. Specifically, when evaluating biomass supply chains, most of the models consider a single demand and single supply source (Talbot and Suadicani, 2005;
Mahmoudi et al., 2009; Asikainen, 2010; Mobini et al., 2011; Karttunen et al., 2012; Zhang et al., 2012; Windisch et al., 2015). Additionally, most of the models also consider a single biomass type (Talbot and Suadicani, 2005; Mahmoudi et al., 2009; Asikainen, 2010; Mobini et al., 2011; Karttunen et al., 2012; Zhang et al., 2012; Windisch et al., 2015) and all of them considered unlimited number of trucks for biomass transportation. There is a gap in the literature in which multiple demand and supply points (i.e. a network), different conversion technologies, multiple biomass types, and a mixed push-pull biomass flow are evaluated.

1.2. RESEARCH OBJECTIVES

The overall goal of this research is to evaluate the supply chain of a forest-based biomass for bioenergy and biofuels production considering uncertainties and variations at the operational level. The characteristics of this supply chain are: multiple supply and demand points (i.e. network), various biomass feedstock types, different conversion technologies, and biomass flow managed by a hybrid push-pull flow.

The following activities will aid in achieving this main goal:

- Develop a simulation model for a forest-based biomass supply chain with the characteristics mentioned above which will account for uncertainties and variations.
- Apply the simulation model to a case study:
  - Estimate the critical parameters related to inventory of each biomass type at each conversion facility to ensure a year-round reliable supply of biomass. These parameters are reorder point, initial inventory, and maximum inventory.
  - Determine the required number of trucks that would ensure the timely delivery of biomass from the forest to the conversion facilities.
- Evaluate the demand fulfillment of biomass at different conversion facilities.

- Assess the cost (C$ per odt) and the CO2 equivalent emissions (kg per odt) associated with the logistic operations.

- Perform sensitivity analysis to evaluate the effect of changes in the parameters on the results.

1.3. CASE STUDY

The case study considered in this thesis is based on the results obtained from an optimization model developed by another member of our research group (Cambero et al. 2014). This model looked into the strategic design of a bioenergy and biofuel supply chain. The optimization model’s objective was to maximize the net present value of the supply chain and determine:

- The amount of biofuel and bioenergy to produce.

- The location, type, and size of the conversion facilities to install and when to install them.

- The aggregated cutblocks which would supply each location per period.

- The type and amount of logging residues to collect from each aggregated cutblock per period.

- The type and amount of sawmill residues to use and transport to each location.

- The amount of final product to produce and transport from conversion facilities to markets.

This model was bound by several constraints which limit the amount of biomass available per aggregated cutblock and the amount of biomass delivered to the conversion
facilities at any given period. Furthermore, it was also bound by constraints which control the yield of each technology and the distribution of biofuels to different markets. Finally, it was also bound by demand constraints (the minimum and maximum demand) for each bioenergy or biofuel product.

The optimization model was applied to the Williams Lake Timber Supply Area (TSA), which is located in the central part of the Cariboo Region in British Columbia. The Williams Lake TSA is one of the largest TSAs in the province with approximately 4.93 million hectares, of which 1.8 million hectares are available for harvesting (BC Ministry of Forests, Lands, and Natural Resources Operations, 2013). This region, however, has been greatly affected by the mountain pine beetle infestation (Government of British Columbia, 2012). Therefore, most of the harvesting operations in the area are focused on salvaging killed or infested trees. The average harvest, in this area, during the years 2001 to 2010 was 3.4 million m³, of which 74% was infested pine. The communities in this area are highly dependent on the forest sector, which employs 32% of the population. In 2012, there were five lumber mills, one chip mill, one pellet mill, one veneer and plywood mill and one bioenergy power plant located in this area.

There are several communities in this TSA, however, studies performed by FPInnovations identified Williams Lake, Hanceville, and Anahim Lake as potential locations to install biomass conversion facilities. Williams Lake is the largest community in this TSA, located in the intersection between highway 20, which goes to Bella Coola, and highway 97, which goes to Alaska. This community has approximately 12,000 inhabitants and is home to the bioenergy power plant and most of the mills in the area. Hanceville is a small remote community 92 km west from Williams Lake on highway 20 with approximately 100 inhabitants involved in ranching and forestry activities. There is one sawmill in Hanceville which is
operated by four First Nations Bands. Because of its remoteness, both the sawmill and the community’s electricity needs are powered by diesel generators. This has triggered the interest in installing a power plant to supply enough power for the sawmill’s operations. Finally, Anahim Lake is located on highway 20 approximately 200 km west of Williams Lake and 135 km east from Bella Coola. It is a small remote community of 300 inhabitants with forestry as their main activity. It is home to one of the sawmills in the area which, similar to Hanceville, is run based on a diesel generator. To increase the economic benefits from the forest in the area while increasing the power security, these communities are interested in establishing conversion facilities in their sawmills. Furthermore, the high transportation and logistics costs, due to their remoteness and limited road infrastructure, have made their forest and sawmill residues unaffordable for the existing pellet mills in the area, thus forcing the mills to dispose their residues by burning or landfilling.

Two types of forest residues: logging residues and Mountain Pine Beetle (MPB) logs; and two types of sawmill residues, wood chips and hog fuel, are considered in the optimization model. Logging residues are mostly tops and branches of both lodgepole pine merchantable logs and MPB trees. MPB logs are lodgepole pine logs deemed non-merchantable due to high level of infestation. Both, logging residues and MPB logs, are considered to be left at the roadside. Finally, hog fuel is composed of bark and sawdust and wood chips are considered to be clean wood chips. Both hog fuel and wood chips are by-products of sawmilling operations. Table 1.1 shows the biomass characteristics considered for this case study.
Table 1.1 Biomass Characteristics

<table>
<thead>
<tr>
<th>Biomass Type</th>
<th>Moisture Content (% WB)</th>
<th>Bulk Density (kg/m³)</th>
<th>Ash Content</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sawmill Residues</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wood Chips</td>
<td>33.17\textsuperscript{a}</td>
<td>206.74\textsuperscript{a}</td>
<td>0.52\textsuperscript{a}</td>
</tr>
<tr>
<td>Hog Fuel</td>
<td>44.89\textsuperscript{a}</td>
<td>142.85\textsuperscript{a}</td>
<td>4.75\textsuperscript{a}</td>
</tr>
<tr>
<td><strong>Forest Residues</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Logging Residues</td>
<td>25</td>
<td>483.108</td>
<td>1.00\textsuperscript{b}</td>
</tr>
<tr>
<td>MPB Logs</td>
<td>25</td>
<td>483.108</td>
<td>1.92\textsuperscript{c}</td>
</tr>
</tbody>
</table>

Source: \textsuperscript{a} (Kehbila, 2010); \textsuperscript{b} (Badger, 2002); \textsuperscript{c} Sample W6 (Lehtikangas, 2001)

The availability of forest residues in Williams Lake TSA was obtained from FPInnovations using the FPInterface Software (FPInnovations, 2014). The information was for four 5-year harvesting periods for a total of 1592 aggregated blocks distributed over 904,551 hectares. These aggregated cutblocks are composed of several smaller cutblocks located at a proximity of 10 km radius. The available biomass is based on the AAC limit, and the yearly available biomass is calculated using the 5-year period availability. Table 1.2 shows the yearly available forest-based biomass for each 5-year harvesting period in all the Williams Lake TSA. The units used are oven-dry tonnes (odt), which is the metric measurement of weight at 0% moisture content. It is important to note that the yearly availability of both MPB logs and logging residues tend to decrease at almost every harvesting period. This is due to the decrease in mountain pine beetle infestation in the area.
Table 1.2 Williams Lake TSA Yearly Available Forest Residues

<table>
<thead>
<tr>
<th>Harvesting Period</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MPB Logs (odt)</strong></td>
<td>539,729</td>
<td>494,329</td>
<td>429,473</td>
<td>211,280</td>
</tr>
<tr>
<td><strong>Logging Residues (odt)</strong></td>
<td>978,888</td>
<td>1,568,652</td>
<td>1,239,993</td>
<td>625,305</td>
</tr>
</tbody>
</table>

Source: (FPInnovations, 2014)

From the 1592 aggregated cutblocks, the optimization model only selected 337 to supply biomass to the bioenergy and biofuel conversion facilities. Furthermore, different bioenergy and biofuels conversion technologies and capacities were prescribed for each location. Table 1.3 shows the results of technologies, capacities, years of operations, and total required biomass, for the lifespan of 20 years, for each of the conversion facilities. Note that the production of the pyrolysis plant in Hanceville will reduce to 50% of its capacity for the last ten years. A second pyrolysis plant, located in Williams Lake, will produce the remaining bio-oil during this period. This is due to the high costs involved in collecting the available biomass during those harvesting periods in Hanceville and the increase in biomass availability closer to town at Williams Lake. Furthermore, Table 1.4 contrasts the total yearly biomass availability and demand for each 5-year harvesting period for the selected cutblocks.
Table 1.3 Optimal Technology Selection per Location

<table>
<thead>
<tr>
<th>Locations</th>
<th>Technology</th>
<th>Capacity</th>
<th>Periods of Operation (each period = 5 years)</th>
<th>Total Biomass Demand (odt)</th>
<th>Yearly Average Biomass Demand (odt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anahim Lake</td>
<td>Biomass boiler + steam turbine (power only)</td>
<td>5 MW</td>
<td>1-4</td>
<td>Logging Residue: 146,250</td>
<td>41,288</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>MPB Logs: 185,510</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Wood Chips: 323,000</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Hog Fuel: 171,000</td>
<td></td>
</tr>
<tr>
<td>Hanceville</td>
<td>Biomass boiler + steam turbine (power only)</td>
<td>0.5 MW</td>
<td>1-4</td>
<td>Logging Residue: 49,902</td>
<td>99,890</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Hog Fuel: 32,000</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pyrolysis plant</td>
<td>400 odmt day$^1$</td>
<td>1-4</td>
<td>Logging Residue: 344,808</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>MPB Logs: 1,442,140</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Wood Chips: 127,110</td>
<td></td>
</tr>
<tr>
<td>Williams Lake</td>
<td>Biomass boiler</td>
<td>2MW</td>
<td>1-4</td>
<td>Logging Residue: 25,582</td>
<td>34,417</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>MPB Logs: 13,209</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Wood Chips: 7,111</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Hog Fuel: 21,460</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pyrolysis plant</td>
<td>200 odmt day$^1$</td>
<td>3-4</td>
<td>Logging Residue: 185,177</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>MPB Logs: 421,101</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Wood Chips: 14,225</td>
<td></td>
</tr>
</tbody>
</table>

Source: (Cambero et al., 2015; FPInnovations, 2014)
<table>
<thead>
<tr>
<th>Location</th>
<th>Harvesting Periods</th>
<th>MPB Logs (otd)</th>
<th>Logging Residues (otd)</th>
<th>Hog Fuel (otd)</th>
<th>Wood Chips (otd)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Available</td>
<td>Demand</td>
<td>Available</td>
<td>Demand</td>
</tr>
<tr>
<td>Anahim Lake</td>
<td>1</td>
<td>7,775</td>
<td>6,079</td>
<td>10,556</td>
<td>10,509</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>15,252</td>
<td>15,002</td>
<td>39,316</td>
<td>1,586</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>7,990</td>
<td>7,358</td>
<td>17,413</td>
<td>9,230</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>9,230</td>
<td>8,663</td>
<td>24,955</td>
<td>7,925</td>
</tr>
<tr>
<td>Hanceville</td>
<td>1</td>
<td>118,875</td>
<td>116,214</td>
<td>206,210</td>
<td>2,959</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>119,141</td>
<td>118,100</td>
<td>290,551</td>
<td>2,495</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>27,365</td>
<td>26,381</td>
<td>74,206</td>
<td>37,605</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>29,346</td>
<td>27,733</td>
<td>91,382</td>
<td>36,253</td>
</tr>
<tr>
<td>Williams Lake</td>
<td>1</td>
<td>1,967</td>
<td>1,860</td>
<td>2,077</td>
<td>507</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>963</td>
<td>782</td>
<td>1,800</td>
<td>163</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>47,539</td>
<td>45,830</td>
<td>62,620</td>
<td>17,069</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>38,470</td>
<td>38,390</td>
<td>85,510</td>
<td>24,509</td>
</tr>
</tbody>
</table>

Sources: (Cambero et al., 2015; FPInnovations, 2014)
It is assumed that the extraction of sawlogs is the main purpose of the harvesting operations from which the forest residues were extracted from. Therefore, the harvesting system considered in this study is the conventional roadside harvesting system (MacDonald, 2006, 1999). In this system, trees are felled by a feller-buncher and transported to the roadside by a grapple skidder. Once at the roadside, whole trees are delimbed, topped, and sorted by log diameters using two dangle-head processors. The tops and branches, along with rejected logs will become logging residues and MPB logs, respectively. As required by the conversion facilities, the logging residues (tops and branches) and MPB logs will then be ground by a grinder directly into a chip van, which will transport the chips to the conversion facilities.

1.4. THESIS STRUCTURE

The structure of this thesis is as follows:

- Chapter 2 presents a review of literature relevant to the research. The use of simulation modelling in the forest products industry and forest management are discussed and classified based on their field of application.

- Chapter 3 presents the structure and logic of the model, input data, assumptions, and equations used for the development of the simulation model.

- Chapter 4 presents, discusses, and analyzes the results of the base case scenario and sensitivity analysis.

- Chapter 5 presents the conclusions, limitations, and suggested future work.
Chapter 2. LITERATURE REVIEW

This chapter is divided into two sections. Section 2.1 describes the different conversion processes for obtaining bioenergy and biofuels from lignocellulosic biomass. Section 2.2 discusses the different trends in the use of simulation modelling for decision making in the forest industry when faced with uncertainties.

2.1 LIGNOCELLULOSIC BIOMASS CONVERSION PROCESSES

Lignocellulosic biomass is composed of cellulose, hemicellulose, and lignin as it can be observed in Figure 2.1. The proportions of each of these components present in lignocellulosic biomass depends primarily on its source. Table 2.1 shows the proportions of the above mentioned component on a dry basis for different types of biomass. Note that there are minor amounts of proteins, minerals, and other components which are also found within lignocellulosic biomass.

![Lignocellulosic Biomass Structure](image)

Figure 2.1 Lignocellulosic Biomass Structure
Table 2.1 Proportion of Lignocellulose Components by Source

<table>
<thead>
<tr>
<th>Lignocellulosic materials</th>
<th>Cellulose (%)</th>
<th>Hemicellulose (%)</th>
<th>Lignin (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Harwood stems</td>
<td>40-55</td>
<td>24-40</td>
<td>18-25</td>
</tr>
<tr>
<td>Softwood stems</td>
<td>45-50</td>
<td>25-35</td>
<td>25-35</td>
</tr>
<tr>
<td>Grasses</td>
<td>25-40</td>
<td>35-50</td>
<td>10-30</td>
</tr>
<tr>
<td>Leaves</td>
<td>15-20</td>
<td>80-85</td>
<td>0</td>
</tr>
<tr>
<td>Wheat straw</td>
<td>30</td>
<td>50</td>
<td>15</td>
</tr>
<tr>
<td>Switchgrass</td>
<td>45</td>
<td>31.4</td>
<td>12</td>
</tr>
</tbody>
</table>

Excerpt of: (Sun and Cheng, 2002)

Cellulose is a pure polymer generated from solar energy during the process of photosynthesis (Sun and Cheng, 2002). It serves as a structural component which provides mechanical and chemical stability to plants (Sun and Cheng, 2002). Hemicellulose is a mixed polymer which also functions as a supporting material of the cell wall (Sun and Cheng, 2002). Lignin is an aromatic polymer which forms a protective layer on the plant walls that regulates the transport of water and nutrients into the plant cell (Sun and Cheng, 2002). It acts as a binder between cells, and has a noteworthy resistance to impact, compression and bending (Sun and Cheng, 2002).

Figure 2.2 shows how lignin, cellulose, and hemicellulose can be used in different conversion processes in order to obtain different bioenergy or biofuel products. Biomass may undergo pre-processing or densification processes before going through any of the conversion processes in order to reduce handling and transportation costs (Spellman, 2012). Pre-processing options could include the grinding, drying, and torrefaction of biomass (Clarke and Preto, 2011). Densification involves applying pressure to increase the density of the material, obtaining
products such as bales, pellets, cubes, briquettes, and pucks (Clarke and Preto, 2011). At this stage of the process, biomass can be sold as solid fuel or it can continue to one of the different conversion processes (Sharma et al., 2015).

Figure 2.2 Lignocellulosic Biomass Pre-processing, Densification, and Conversion Processes
Modified from: (Chung, 2013)

The conversion processes can be categorized into: thermochemical and biochemical (Lee and Lavoie, 2013; Mafakheri and Nasiri, 2014; Natural Resources Canada, 2013; Sharma et al., 2015, 2013). In the thermochemical conversion processes, the biomass is heated with or without the presence of oxygen (Lee and Lavoie, 2013; Natural Resources Canada, 2013; Sharma et al., 2015). There are three different thermochemical conversion processes: pyrolysis,
gasification, and combustion. These conversion processes vary mainly based on the temperature and the amount of oxygen present in the reaction (Lee and Lavoie, 2013; Natural Resources Canada, 2013; Sharma et al., 2015). Pyrolysis is used to convert biomass into liquid, solid, and gaseous fuels, at temperatures between 550°C and 750°C without the presence of oxygen (Lee and Lavoie, 2013; Sharma et al., 2015; Uslu et al., 2008). The produced liquid, called bio-oil, can be used as feedstock in bio refineries; however, its poor thermal stability and high corrosivity poses big challenges (Lee and Lavoie, 2013; McKendry, 2002; Sharma et al., 2015). The produced solid, called char or bio-char, is rich in carbon and highly flammable (Sharma et al., 2015; Uslu et al., 2008). Finally, the hot gases emitted are generally used to provide heat to the pyrolysis reactor (Sharma et al., 2015). Gasification is the partial oxidation of biomass into a mixture of gases called syngas (McKendry, 2002). This process occurs at temperatures between 750°C and 1200°C and with limited amount of oxygen (Lee and Lavoie, 2013; McKendry, 2002). Syngas can be used to produce methanol and hydrogen, both of which could be used for transportation fuels (McKendry, 2002). Furthermore, when combined with a gas turbine, it could produce heat and electricity (McKendry, 2002). This integration called biomass integrated gasification combined cycle (BIGCC) ensures a high conversion efficiency (40%-50%) for plants with 30-60 MW capacity (Balu et al., 2015; McKendry, 2002). Finally, combustion is the most common conversion process, in which biomass burns in the presence of excess oxygen (McKendry, 2002). This process is commonly used in stoves, furnaces, boilers, steam turbines etc. and its primary product is thermal energy which can be used to generate electricity or combined heat and power (CHP) (McKendry, 2002; Sharma et al., 2015). The temperature at which combustion produces hot gases is between 800°C and 1000°C (McKendry, 2002). For combustion to take place, the moisture content of the biomass should be less than
50% (McKendry, 2002). The efficiencies of conversion facilities with sizes smaller than 100MW ranges between 20%-40% (McKendry, 2002). Higher efficiencies could be reached in either larger systems or in co-firing with coal (McKendry, 2002).

In biochemical conversion processes, enzymes and other organisms produce ethanol by fermenting sugars obtained from cellulose and hemicellulose contained in the feedstock (McKendry, 2002; Natural Resources Canada, 2013; Sharma et al., 2015; Sims et al., 2008). There are two main biochemical conversion processes: fermentation and anaerobic digestion. Fermentation is widely used for large commercial ethanol production (McKendry, 2002). In this process, the starch found in biomass is converted into sugar using enzymes, which is later converted to ethanol by adding yeast (McKendry, 2002). Once ethanol is obtained, it has to be purified by distilling (McKendry, 2002). Anaerobic digestion is the process by which biomass is converted into gas, mainly methane and CO2 using bacteria in an environment free of oxygen (McKendry, 2002). The obtained gas can be used directly as fuel to produce electricity (McKendry, 2002). This process is widely used in commercial projects for the conversion of biomass with high moisture content (80%-90%), i.e. wastes (McKendry, 2002).
2.2 SIMULATION IN THE FOREST INDUSTRY

For more than 40 years, Operations Research (OR) techniques have been used to deal with complex decisions related to forest management and the forest product industry. These techniques can be divided into three categories: mathematical models, multi-criteria decision making (MCDM), and simulation (Power and Sharda, 2007; Segura et al., 2014). Each of these techniques has its own strengths and weaknesses; the appropriate technique to use depends on the particular characteristics of the problem at hand (Segura et al., 2014). Mathematical models provide an optimum solution to a problem based on specific decision variables, objective functions, and constraints (Hillier and Lieberman, 2010; Power and Sharda, 2007). Multi-criteria decision making consists of quantifiable evaluations of multiple possible alternatives based on multiple criteria (Power and Sharda, 2007). Finally, simulation models are built to understand how a system behaves under different circumstances (Power and Sharda, 2007; Tako and Robinson, 2012). They imitate its behavior in a series of experiments where the results obtained are then aggregated, manipulated, and analyzed (Power and Sharda, 2007; Tako and Robinson, 2012). Mathematical models have been successfully used in the forest industry, yet the integration of uncertain parameters and interdependencies poses a challenge (Weintraub and Romero, 2006; Mobini, 2015). Stochastic optimization, scenario-based optimization, and robust optimization are methods to incorporate uncertainties in mathematical models (Awudu and Zhang, 2012; Mobini, 2015). However, even though some of these approaches have proven to give good results in the past, these models can become too complex to be solved (Mobini, 2015). In these situations, simulation modelling is the recommended alternative (Segura et al., 2014; Mobini, 2015).
There are different simulation approaches (e.g., Monte Carlo, agent-based, system dynamics, and discrete-event) each with its unique modelling characteristics to solve specific problems (Brailsford and Hilton 2001). Monte Carlo simulation was first developed and used in the midst of World War II by the U.S. government (Harrison, 2010). It uses random sampling and probability distributions to obtain mathematical functions that would explain the operations of a static system (Harrison, 2010; Awudu and Zhang, 2012). System dynamic simulation is used to model situations in which a higher abstraction level is required that can be represented by causal diagrams (Tako and Robinson, 2012). These causal diagrams will then be modelled as a stock and flow diagram, where the effect of changes over time in a system can be observed based on specific relationships (Tako and Robinson, 2012). This type of simulation is mostly deterministic, using average values for different parameters (Tako and Robinson, 2012). According to several users, system dynamics is used to model situations at a strategic level; therefore, it requires fewer data to develop (Tako and Robinson, 2012). Discrete-event simulation is modelled as a network of queues and activities, where the characteristics of each of the entities change in discrete time periods (Tako and Robinson, 2012). This type of simulation is usually stochastic, using statistical distributions to represent certain events (Tako and Robinson, 2012). Compared to system dynamics, this type of simulation is developed to analyze situations at tactical and operational levels; therefore, it requires more detailed data than system dynamic models (Tako and Robinson, 2012). Finally, agent-based simulation, developed in the early 1990’s, is used to model systems in which agents have certain autonomy in their actions and an adaptive behavior to other individuals or spatial conditions (Siebers et al., 2010). Unlike discrete-event simulation, there is no concept of queues, solely the adaptive behavior of each individual agent (Siebers et al., 2010).
In this section, a non-exhaustive literature review, describing the use of simulation modelling in the forest products industry and forest management after the year 2000, is presented. The papers under study are initially categorized into their area of study: 1) Forest Management, and 2) Supply Chain and Logistics.

2.2.1 SIMULATION STUDIES IN FOREST MANAGEMENT

This category refers to the evaluation of different harvesting systems, and the effect that other anthropogenic and natural disturbances have on timber yield, forest landscape composition, soil quality, and wildlife sustainability. Table 2.2 shows a summary of the reviewed literature relevant to this category. The information contained in this table includes the objectives of the simulation model, the considered uncertainties in the model, the main findings, and the simulation type.

He et al. (2002) developed an agent-based simulation model, using LANDIS, to evaluate the effects of forest harvesting operations and increasing forest fires, due to global warming, on landscape tree composition after 300 years, simulated in a 10-year time step. The model included several uncertain parameters such as fire and wind disturbances, temperature, precipitation, and seed dispersal. Historical data for temperatures and precipitations were used. To incorporate the effect of global warming, a linear annual temperature increase of 5°C for the first 100 years was used. The results showed that changes in forest composition were evident under warming conditions, with many boreal and northern hardwood species disappearing from the landscape and southern species slowly taking over. In general, there was a decrease in the total percent of forest cover.
Phillips et al. (2004) used SYMFOR to build an agent-based simulation model to evaluate the effects of harvesting operations on forest composition, profits, and timber yield. The model included the following stochastic ecological processes for each individual tree in a total of 10 plots: growth rate, mortality rate, and reproduction rate (appearance of new trees of diameter minimum of 5cm). These processes were closely related to a resource competition index and the diameter at breast height of each tree. Finally, logging operations were assumed to occur in year 4 and every 30 years thereafter for a total of 160 years using yearly time-steps. The trees deemed of commercial value, by a combination of a “stem quality” parameter, which value is randomly assigned between 0 and 1, and other tree characteristics, were harvested up to a limit of 40m$^3$ per plot. The results showed that, even though, the required harvested volume was met on the first three harvests, the cost continuously increased. This was due to a reduction in tree diameter after every harvest, requiring to harvest more trees to attain the required volumes. As a result of these harvesting operations, the forest composition dramatically changed with a significant decrease in hardwood species. It was therefore suggested to reduce the removal per plot, or to increase the time between harvests to allow the forests to fully recover.

After years of successful fire suppression efforts in northern Wisconsin, it was evident that some wildlife species were not thriving because of the reduction in open areas within the forest. Radeloff et al. (2006) simulated the current forest management practices and fire disturbances to understand the effect of varying 1) target tree species to be managed, 2) cut unit size for clear-cut, and 3) the minimum tree harvest age, on the forest composition and open forest areas necessary for the survival of wildlife. The main tree species considered for management was jack pine, however, the possibility of additionally managing 50% of the red pine was modelled. The considered cut unit sizes were 4, 16, 65, or 259 hectares, and the minimum tree harvest age
evaluated for jack pine was 40 and 60 years. Seedling establishment and fire frequency and size were uncertain parameters in this simulation model. The model was built using LANDIS. It was run for 500 years in 10-year time steps. The results showed that all three parameters affected the forest composition and landscape. Cut unit size had the strongest effect on landscape patterns, increasing the size and amount of open areas as the parameter increased. In contrast, openings decreased in size up to two-thirds when jack pine harvest was combined with a 50% red pine harvest.
<table>
<thead>
<tr>
<th>Reference/Provenance</th>
<th>Model Description</th>
<th>Simulation Type</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>(He et al., 2002)</strong> Wisconsin, USA</td>
<td><strong>Objectives:</strong> Investigate the effect of harvesting and fire and wind disturbances, due to climate warming, on future forest composition and landscape.</td>
<td>Agent-based</td>
</tr>
<tr>
<td><strong>Uncertainties:</strong></td>
<td>- Temperature - Precipitation</td>
<td>- Seed dispersal - Fire and wind disturbance frequency and size</td>
</tr>
<tr>
<td><strong>Main Findings:</strong></td>
<td>Significant changes on forest landscape and composition would occur after 200-250 years. The original predominant tree species would disappear and other more resistance tree or grass species would take their place.</td>
<td></td>
</tr>
<tr>
<td><strong>(Phillips et al., 2004)</strong> Brazil</td>
<td><strong>Objectives:</strong> Investigate the effects of current forest management practices on forest composition and timber yield.</td>
<td>Agent-based</td>
</tr>
<tr>
<td><strong>Uncertainties:</strong></td>
<td>- Growth rate - Mortality rate</td>
<td>- Reproduction rate (appearance of new trees with a diameter greater or equal to 5 cm) - Stem quality</td>
</tr>
<tr>
<td><strong>Main Findings:</strong></td>
<td>Timber yields would only be sustained for four harvest periods. The composition of the forest would slowly transit from hardwood to softwood species, decreasing the size of trees and requiring an increased number of trees to sustain yields, thus decreasing the profitability of logging companies.</td>
<td></td>
</tr>
<tr>
<td><strong>(Radeloff et al., 2006)</strong> Wisconsin, USA</td>
<td><strong>Objectives:</strong> Investigate the effects of different forest management practices on forest composition and landscape patterns.</td>
<td>Agent-based</td>
</tr>
<tr>
<td><strong>Uncertainties:</strong></td>
<td>- Seed dispersal - Fire disturbance frequency and size</td>
<td></td>
</tr>
<tr>
<td><strong>Main Findings:</strong></td>
<td>All management practices had a strong effect on forest composition and patterns. The best combination of this management practices to increase the open areas was identified.</td>
<td></td>
</tr>
<tr>
<td><strong>(Rüger et al., 2007)</strong> Chile</td>
<td><strong>Objectives:</strong> Investigate the effects of three logging practices on timber yields, and forest structure and composition.</td>
<td>Agent-based</td>
</tr>
<tr>
<td><strong>Uncertainties:</strong></td>
<td>- Average light irradiance above canopy - Tree geometry parameters - Biomass production parameters - Seed dispersal parameters</td>
<td>- Mortality parameters - Climatic variables. - Soil nutrient availability - Disturbance frequencies and intensities</td>
</tr>
<tr>
<td><strong>Main Findings:</strong></td>
<td>The forest practice with the highest timber yields dramatically altered the forest structure and composition.</td>
<td></td>
</tr>
<tr>
<td>Reference/Provenance</td>
<td>Model Description</td>
<td>Simulation Type</td>
</tr>
<tr>
<td>----------------------</td>
<td>-------------------</td>
<td>-----------------</td>
</tr>
<tr>
<td><strong>Table 2.2. Continued.</strong>&lt;br&gt;<strong>Objectives:</strong></td>
<td>Determine the best forest management practice that would increase the protection against rock-falls and avalanches and the stand resilience.</td>
<td><strong>Uncertainties:</strong>&lt;br&gt;− Growth, mortality and regeneration rate of Norway spruce&lt;br&gt;− Seedling establishment</td>
</tr>
<tr>
<td>(Cordonnier et al., 2008) Norway</td>
<td><strong>Main Findings:</strong> Low thinning intensities increase the resilience and protection against rock-fall, however not the protection against avalanches. There should be a compromise between the two objectives based on local hazards.</td>
<td><strong>Objectives:</strong> Evaluate the effects of three partial harvesting parameters on post-harvest stand development.</td>
</tr>
<tr>
<td>(Thorpe et al., 2010) Ontario, Canada</td>
<td><strong>Main Findings:</strong> A reduction in mortality-rates of residual trees was observed in scenarios with reduced skidding trail widths and high level of tree retention.</td>
<td><strong>Objectives:</strong> Evaluate the effects of different forest management scenarios on levels of calcium, magnesium, potassium and sodium (base cations) pools in forest mineral soils.</td>
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<td>(Lucas et al., 2014) Sweden</td>
<td><strong>Main Findings:</strong> The scenario for maximum tree growth management resulted in the greatest base cation removals. The removal of tree tops, branches, and stumps increased the base cation removal rates 50%-100% more than business as usual scenario and 3 to 4 times more than scenario promoting natural conservation.</td>
<td><strong>Objectives:</strong> Evaluate the reliability of forest landscape simulation models including the effects of succession, fire and harvest.</td>
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<td>(Luo et al., 2015) China</td>
<td><strong>Main Findings:</strong> The simulated result of the forest landscape closely represented the actual density and basal area observed in reality.</td>
<td><strong>Uncertainties:</strong>&lt;br&gt;− Species establishment probability&lt;br&gt;− Solar energy distribution&lt;br&gt;− Water availability</td>
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Table 2.2. Continued.

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<th>Reference/Provenance</th>
<th>Model Description</th>
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<tr>
<td>(Bose et al., 2015) Quebec, Canada</td>
<td>Assess the reliability of simulation results. Identify the parameters of partial treatments which accelerates the development of complex stands; and assess the effects of specific treatments on pure and mixed aspen stand development after 100 years.</td>
<td>Agent-based</td>
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<td><strong>Objectives:</strong></td>
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<tr>
<td><strong>Uncertainties:</strong></td>
<td>Light availability</td>
<td>Tree physical characteristics and spatial location</td>
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<tr>
<td></td>
<td>Tree growth and regeneration rates by species</td>
<td>Budworm outbreak frequency, intensity, and spread</td>
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<td></td>
<td>Tree mortality by tree life-stage, species, and reason (budworm, competition)</td>
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<td><strong>Main Findings:</strong></td>
<td>Species composition and size distribution in short-term simulation results were similar to empirical values. Long-term simulations showed more unexpected trends. Stand structure and timber production rates are affected by retention levels of partial harvesting and spatial configuration of residual trees.</td>
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To assess the effects of three different harvesting practices on timber yield, and forest structure and composition, Rüger et al. (2007) developed an agent-based simulation model. This model included the carbon balance for photosynthesis and respiration of each individual tree, tree mortality due to large falling trees or strong winds, and tree regeneration. The three evaluated logging treatments were: selective logging with and without retention of large old trees and strip-cutting. Selective logging refers to logging of trees with a DBH between 50 and 100 cm. In the scenario with retention of old trees, trees with a DBH greater than 1m will be left standing. In the scenario without retention of old trees, trees with a DBH greater than 1m will be felled before the logging operations and will be left in the forest. In both selective logging scenarios, the logging cycle was varied from 10 to 50 years and the harvest target from 1 to 10 m$^3$ per hectare every year. Strip-cutting refers to clear-cutting an area of 20 m wide per hectare. The return time to each strip was varied from 50 to 150 years. The results showed the harvest target was met by all logging scenarios up to a 4 m$^3$ per hectare per year. Selective logging without tree retention was able to harvest 8 m$^3$ per hectare per year for a logging cycle of 20 years. Furthermore, strip-cutting was able to harvest from a 6 m$^3$ per hectare per year at a logging cycle of 150 years to a 13.4 m$^3$ per hectare per year at a logging cycle of 60 years. However, strip-cutting seemed to alter the forest structure and composition, while the selective logging maintained the structural complexity of the forest. The simulation was developed in FORMIND software and was run for 1500 years in a yearly time-step. The uncertain parameters included in this model were related to the light and nutrients availability, tree geometry and mortality, biomass production and seed dispersion, and climatic variables.

In mountainous conditions, trees have been used as protection against rock-fall and avalanches in the past. Cordonnier et al. (2008) developed an agent-based simulation model to
assess the effect of two different silvicultural strategies, at various thinning intensities, on protection against rock-fall and avalanches, and forest resilience. In the first strategy, randomly selected trees with a DBH greater than 12.5 cm were harvested regardless of their location. The percentage of trees removed varied from 5% to 30%, in 5% increments. In the second strategy, every tree with a DBH greater than 12.5 cm located within predetermined circles of 10 m radius were harvested. The intensities increased by increasing the number of circles or gaps per hectare. For both strategies, harvesting operations were simulated every 20 years. It was assumed that risk of avalanches would increase with gap size, a maximum gap size of 400 m$^2$ was consider effective against snow avalanches. In the case of rock-falls, rock size and basal area of trees are the main parameters which could stop a falling rock. A basal area higher than 30 m$^2$ per hectare are considered effective against rock-falls. Resilience measures the ability of a forest to rapidly mature after a disturbance. For this metric, sapling stages are crucial. A sapling cover higher than 500 m$^2$ per hectare is the indicator for a resilient forest. The results of the model showed the increase of saplings with the increase of harvesting intensities. The objective of continuously maintaining the basal area at levels higher than 30 m$^2$ per hectare were obtained for random tree selection at intermediate intensities. However, a low protection critical period of 12 years would have to be tolerated. For group selection, permanent protection was obtained at thinning intensities between 1 and 4 gaps per hectare. The objective of maintaining a maximum gap size below 400 m$^2$ was obtained without a critical period only in the randomly tree selection at 15% intensity. Otherwise, critical periods of low protection longer than 10 years would have to be tolerated for all other intensities. The objective of continuously maintaining a sapling cover higher than 500 m$^2$ per hectare was obtained at an intensity of 30% for random tree selection and at two circles per hectare in the second strategy. Therefore, it was concluded that attaining permanent protection against
snow avalanches was not compatible with forest resilience and permanent protection against rock-falls. A compromise between objectives and the evaluation of mixed silvicultural strategies based on local hazards was suggested.

A successful partial harvesting depends, to a certain level, on the survival of residual trees. However, previous studies have shown that there was an increase in mortality rate amongst residual trees. Thorpe et al. (2010) developed a short term (12 years) and a long term (120 years) simulation model with the following objectives: 1) understand the effects of different partial harvesting prescriptions on growth and mortality dynamics on residual trees; 2) understand how high mortality rates affect short and long term stand development; and 3) understand how different partial harvest prescriptions affect the time required for the forest to recover. There were a total of 27 different scenarios in which the following parameters were varied individually to meet specific standard partial harvesting prescriptions: 1) diameter limit (cm), 2) skidding trail width (m), and 3) leave strip width (m). These simulations modelled each tree individually. The short simulations were modelled over yearly time-steps and the long simulations on time-steps of 5 years. The results showed there was an increased mortality rate after partial harvesting prescriptions, and depending on the prescription applied, the forest could take anywhere from 25 to 115 years to recover. Reduced mortality rates were observed in areas with decreased harvesting intensity, yet, this could mean a significant decrease in timber yield. Based on the results, an alternative for forest managers was suggested in which timber yield might not be compromised. The alternative was to increase the amount of residual trees by decreasing the width of skid trails and increasing the leave strip width.

Intensive forest harvesting rapidly reduces the soil quality by decreasing its levels of calcium, magnesium, potassium, and sodium, also known as base cations. Base cations are slowly
produced by the breakdown of organic matter. However, by means of harvesting, a fast reduction in base cations would acidify the soil and water threatening plants and animals. Lucas et al. (2014) developed an agent-based model which assessed different forest management strategies based on the sustainability of base cations’ removal. The simulation model included single tree growth, regeneration, and mortality for 100 years. It evaluated four different scenarios. Scenario 1) “MaxGrow”: Intensive forest management to increase tree volume production. It included loosening of soil surface, soil fertilization, planting of non-native yet fast growing lodgepole pine and minimum thinning. This scenario allowed whole-tree and stump removal. Scenario 2) “NatCons”: Few management activities aiming to conserve natural resources and increase carbon storage. In this scenario, only tree stems were removed during harvesting operations and a minimum of 25 large trees were to be left uncut for regeneration. Furthermore, no harvesting was allowed close to water sources and Norway spruce was managed by selective cutting and Scots pine by long rotations and thinning. Scenario 3) “Reindeer”: Increase lichen production and reindeer habitat. This scenario included long rotations and heavy thinning, promoting the regeneration of Scots pine. Scenario 4) “Business as usual”: Management varied depending on site index and site index species. It determined whether to plant or to allow natural regeneration of scots pine. All Norway spruce were planted. Thinning removed 30% of the basal area 2-3 times during the rotation, and rotation lengths were longer than the lowest allowed by the Swedish Forestry Act. The results showed that “MaxGrow” scenario decreased the base cation’s pools approximately 50%-100% more than the “business as usual” scenario; and 3 to 4 times more than “NatCons” scenario. Potassium was the most sensitive base cation to intensive forest harvesting. Forest management strategies should include the increase of potassium levels by fertilization.
However, the precision of the results seemed to be affected by the uncertainty on base cations’ weathering rates.

Attempting to quantify the reliability of simulation model results, Luo et al. (2015) developed an agent-based simulation model and compared the results obtained to forest inventory data. In this model, forest disturbances, such as, forest harvest and fires were considered independently. It included three different forest harvesting areas: harvest restricted, harvest permitted, and no harvesting area. Furthermore, it considered natural and human-caused fires with different frequencies and intensities based on regions. It evaluated three scenarios: 1) forest succession without disturbances, 2) forest succession including fire, and 3) forest succession including harvesting. The model simulated 300 years, in 5-year time-steps. By obtaining the resulted density (tree per hectare) and basal area (m² per hectare) for each tree species and for each landscape type and comparing it to the inventory data, it was concluded that the model successfully predicted forest succession and disturbances.

Bose et al. (2015) developed a short-term (12 years) and a long-term (100 years) agent-based simulation model using yearly time steps. The main objectives of these models were to: 1) assess the reliability of the simulation by comparing the results with the empirical data; 2) identify the parameters of partial treatments which accelerated the development of complex stands; and 3) assess how specific treatments applied to pure aspen and mixed aspen could affect stand development after 100 years. Two different stands were modelled: pure aspen and mixed aspen stands. Six different harvesting treatment scenarios were modelled, all of them including the effect of spruce budworm: 1) partial cut 33% removal, 2) partial cut 61% removal, 3) partial cut 80% removal, 4) aggregated cut 400m² gaps, 5) aggregated cut 900m² gaps, and 6) aggregated cut 1600m² gaps. For these last three scenarios a 15 m wide band should be kept unharvested. The
results showed the short-term simulations were closer to empirical values than long-term simulation when evaluating species composition and size distribution. The source of discrepancy between the simulation models and the empirical data were assumed to be caused by mortality sources not considered in the model such as: damage by harvesting machinery, wind throw, and dry summers. Furthermore, the parameters which appeared to promote the development of complex stands and which the authors suggest should be considered in harvest prescriptions were: 1) spatial configuration of residual overstory, 2) number of residual conifer seed trees, 3) conifer mortality by spruce worm, and 4) presence of woody shrubs like mountain maple. Finally, aspen regeneration and growth were favoured by large gaps, and spruce and fir (conifers) thrived with small gaps and a varied range of intensities, at the expense of aspen.

All the analyzed simulation models had the objective of understanding the effect of various disturbances on forest composition and landscape. Additionally, various scenarios were run in which the authors attempted to find the best forest management practice which would: 1) meet timber yield targets while reducing the effect on forest composition and landscape (He et al., 2002; Phillips et al., 2004; Radeloff et al., 2006; Rüger et al., 2007), 2) meet timber yield targets while decreasing the mortality-rates of residual trees (Thorpe et al., 2010), 3) meet timber yield targets while reducing the effect on soil nutrient depletion (calcium, magnesium, potassium, and sodium) (Lucas et al., 2014), 4) ensure the development of complex forest stands (Bose et al., 2015), and 5) ensure the protection against rock-falls and avalanches while ensuring the forest resiliency (Cordonnier et al., 2008).

All the simulation models explained in this section explored the complex forest and tree dynamics over space and time, especially when exposed to natural (i.e. fires, rock-fall, avalanches, wind, infestations) and anthropogenic (i.e. fire and harvesting practices) disturbances. It is
important to understand the short and long-term effects of different forest management practices on forest stands to ensure forest ecological and economical sustainability. Growth and yield tables could be used to partially achieve this objective, however, these cannot be used for understanding the dynamics in mixed stands or introducing the effect of disturbances. As Bose et al. (2015) explains, most of the relationships and behaviours exhibited by trees tend to be either non-linear or stochastic, which would make it almost impossible to perform an analysis without the use of simulation. Furthermore, in these models trees are required to exhibit specific behaviour (e.g. growth, reproduce, death, diseased) in response to other trees, such as competition for sunlight and soil nutrients, and their environment, such as the spread of disease, forest fires, or the harvest of a neighbouring tree. Therefore, agent-based simulation is the best approach for this type of analysis. Both Bose et al. (2015) and Luo et al. (2015) proved it by building their agent-based simulation models from past historical forest inventory data and incorporating the effects of historical disturbances to finally validate their models by comparing the results with the current forest state. They both found their results were consistent with the observed forest composition and structure.

2.2.2 SIMULATION STUDIES IN FOREST SUPPLY CHAINS AND LOGISTICS

This category refers to the use of simulation for the performance evaluation of different supply chain and logistics configurations in the forest product industry. All the reviewed models in this section measure performance based on cost and productivity of operations. Additionally, the most recent models include environmental performance measures, such as CO2 emissions or energy consumption by the operations understudy. Table 2.3 shows a summary of the reviewed literature relevant to this category. The information contained in this table includes the objectives
of the simulation model, the considered uncertainties in the model, the main findings and the simulation type.
Table 2.3 Literature on Simulation for Supply Chain and Logistics

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<th>Reference/Provenance</th>
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<th>Simulation Type</th>
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<tr>
<td>(Asikainen, 2001) Finland</td>
<td><strong>Objectives:</strong> Investigate the effects of using interchangeable barges and direct loading by forwarder on the cost of delivered logs. <strong>Uncertainties:</strong> - Machine failures and other delays - Transportation and forwarding distance - Stem volume - Distance between islands - Stand size - Machinery productivities</td>
<td>Discrete-Event</td>
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<td></td>
<td><strong>Main Findings:</strong> A system of one pusher boat and three barges was the most competitive. Loading of logs into the barges should be done by a forwarder instead of a hydraulic crane.</td>
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<td>(Talbot and Suadicani, 2005) Denmark</td>
<td><strong>Objectives:</strong> Investigate the effects on efficiency and cost of changing chipping productivity, extraction and transportation distances, bin size and system interferences. <strong>Uncertainties:</strong> - Machine productivities - Stand Size - Transportation and forwarding distance - Road conditions - Machine failures and other delays</td>
<td>Discrete-Event</td>
</tr>
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<td></td>
<td><strong>Main Findings:</strong> A chip harvester working on its own was the best option when turnaround time was low and bin size increased. As the chipper productivity increased, the two-machine system became the best option regardless of the bin size.</td>
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<td>(Vaatainen et al., 2006) Finland</td>
<td><strong>Objectives:</strong> Identify profitable working patterns for hardwarders under different logging structures and conditions. <strong>Uncertainties:</strong> - All productivities including interruptions and breakdowns.</td>
<td>Discrete-Event</td>
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<td><strong>Main Findings:</strong> Harwarders were more efficient than traditional harvesting machines on sites with low removal per stand.</td>
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<td>(Mahmoudi et al., 2009) Canada</td>
<td><strong>Objectives:</strong> Analyze the feasibility of installing a 300MW power plant. <strong>Uncertainties:</strong> - Seasonality of harvesting operations - Machinary productivity - Weather conditions and temperature - Moisture Content</td>
<td>Discrete-Event</td>
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<td></td>
<td><strong>Main Findings:</strong> The available biomass could meet 30% of the demand of the power plant, therefore, another biomass source had to be considered. The cost of biomass delivered at the plant was $45 per oven-dry tonne.</td>
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Table 2.3. Continued.

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<th>Reference/Provenance</th>
<th>Model Description</th>
<th>Simulation Type</th>
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| **(Asikainen, 2010)** Finland | **Objectives:** Identify the ideal number of trucks for a crushing-at-landing truck transportation system for different distances.  
- Crusher productivity  
- Stump storage size  
- Distance between storages  
- Truck delays | **Uncertainties:**  
- Truck loading and unloading times  
- Driving speeds (loaded/unloaded)  
- Crusher and truck costs (working/idle) | **Main Findings:** The crushing costs increased as transportation distance increased due to the crusher’s idle time, when using one truck. The productivity of the crusher became the constraint as the number of trucks increased. Two trucks had to be used when distance was less than 40km. Three trucks had to be used when distances were between 40km and 100km. A fourth truck had to be used for longer distances than 100km. |
| **(Mobini et al., 2011)** Canada | **Objectives:** Evaluate the feasibility of a 300MW power plant for 20 years using a combination of different harvesting systems based on fuel/sawlog content.  
- Seasonality of harvesting operations  
- Machinery productivity  
- Biomass availability  
- Fuelwood/sawlog content | **Uncertainties:**  
- Weather conditions and temperature  
- Moisture content of wood | **Main Findings:** During the years 1-3 and 6-9, the plant’s biomass demand was not fulfilled, due to low fuelwood content in stands. |
| **(Zhang et al., 2012)** USA | **Objectives:** Identify the best location and size of a biofuel facility by assessing the performance of a biofuel supply chain.  
- Stand characteristics  
- Biomass availability  
- Machinery productivity  
- Transportation distances | **Uncertainties:**  
- Energy consumption and GHG emissions  
- Spring breakup data  
- Biofuel conversion efficiency | **Main Findings:** The best location and size for the biofuel plant was identified. In all possible locations for biofuel plant, the lowest capacity always seemed the best option. |
Table 2.3. Continued.

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<th>Reference/Provenance</th>
<th>Objectives</th>
<th>Uncertainties</th>
<th>Main Findings</th>
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| (Karttunen et al., 2012) Finland | Evaluate different barge transportation and harbour loading/unloading systems for the transportation of wood chips and compare with truck transportation. | - Distances between loading and unloading terminals  
- Biomass demand and consumption rate  
- Shipping routes characteristics  
- Speeds (loaded/unloaded) | Barge transportation was found to be 25% higher on energy density due to heaped loads. Water transportation was more cost-effective than truck transportation at distances above 150km. Loading and unloading at the harbour had to be done with a wheeled loader since it was not constrained to a specific shift which would reduce the costs and idle times. |
| (Mobini et al., 2013) Canada | Investigate the effects of different pellet supply chain designs. on cost, emissions, and energy consumption | - Biomass feedstock characteristics  
- Biomass production rate  
- Equipment failure rates and repair time | The highest costs of the supply chain were due to raw material procurement and transportation (29.16%) and production (40.19%). There was a reduction of 1.5% in costs by changing the fuel used to dry the biomass. There was a reduction of 4.75% in costs by blending 10% bark into the biomass feedstock and using bark as drying fuel, yet energy consumption and CO₂ emissions increased drastically. |
| (Windisch et al., 2015) Finland | Analyze the effect on cost of varying the importance of different criteria to plan biomass sourcing. | - Biomass characteristics and pile sizes  
- Transportation distances  
- Machine productivity  
- Machinery breakdowns and other delays | All scenarios showed an improvement in productivity and costs from the base case scenario where only First-In-First-Out policy was applied. |
A typical harvesting system, while logging on islands in Finland, is composed of a single-grip harvester, a forwarder, a raft, and a powered barge. The raft serves a double purpose. It is mainly used for the transportation of machines and personnel between islands; and is also used as a wood buffer between forwarding and water transportation, while logging is being performed. The loading of logs into the powered barges is done by a hydraulic crane mounted on the barge. Logs can be loaded to the barge from the buffer raft or from piles on the banks, yet loading from raft is favoured for ease of operation. These systems tend to be costly because of high idle times due to machine interactions. Asikainen (2001) developed three discrete-event simulation models to assess the performance of an island logging supply chain. The models simulated the operation from logging to unloading of barges at the mill. There were a total of five different scenarios modelled, aiming to improve the cost of delivered logs and reduce machine idle times. In these scenarios, the loading and unloading practices, and the number of barges in the system varied. All scenarios were run for 600 hours. The obtained results showed the current system had the lowest productivity and the highest costs due to high idle times. The system appeared to be constrained by the raft size and the number of barges being used. Furthermore, it was observed that the longer the distances, the more competitive the three barge systems were over any other analyzed scenario, with direct loading by a forwarder being the preferred loading option in all scenarios.

In-field chipping of whole trees is a common practice for biomass collection in Denmark. In this system, whole trees are felled and bunched by a feller-buncher; they are then left to dry and then chipping is performed with a chip harvester which had its own bin. The chips are then extracted to the landing by a bin forwarder and finally the chips are loaded into container trucks which transport the chips either to a storage or the conversion facilities. However, the option of using the chip harvester independently to extract the chips to the landing exists. In this type of
systems, machines have to be well synchronized in terms of throughput to reduce machine idle times and therefore increase production and reduce costs. Talbot et al. (2005) developed a simulation model with the objective of analyzing the effects that changes in: 1) chipper productivity, 2) extraction distance, 3) transportation distance, 4) bin size and 5) system interference would have on efficiency and economic feasibility. Two scenarios were analyzed: 1) “SOLO”: chip harvester working on its own and 2) “DUO” a chip harvester working with a bin forwarder in a two-machine system. The simulation model was limited to the chipping and extraction operations. The results showed that the chip harvester was the main constraint in the “DUO” system, with the system productivity decreasing as the bin size increased. However, bin size increase seemed to improve both system’s performance during poor road conditions and long distances. The “SOLO” system was more cost-competitive at shorter distances. Finally, the average cost per system was 73€ h\(^{-1}\) for “SOLO” and 105 € h\(^{-1}\) for “DUO”.

To compare the economic feasibility of different cut-to-length (CTL) logging machine concepts, under different logging conditions, Vaatainen et al. (2006) developed four discrete-event simulation models using the software Witness. Special interest was set in identifying the best working conditions in which hardwarder, machine which combines the work of one-grip harvester and a forwarder, would represent an economic advantage over regular machinery. Each simulation model evaluated a specific machine concept: 1) harwarder Ponse Dual, 2) harwarder Valmet Combi fix, 3) harwarder Valmet Combi rotating load space, and 4) harvester-forwarder chain. The Ponse Dual has two interchangeable heads, a forwarder and a harvester, where each transformation takes 20 minutes. It will first cut all available logs, undergo a transformation into a forwarder, and will then forward all the logs to the road side. There are two transformations per logging site, before cutting and before forwarding. The Valmet Combi is able to cut and forward at any time
without undergoing transformations. It has a turning cabin and either a fixed or rotating loading space. In the Valmet Combi fix model, the amount of logs cut will be equal the size of the loading space. Once the load space is full, it will forward the logs to the roadside and return to continue cutting logs. There were three types of sites evaluated, each with its own specific characteristics: 1) normally distributed logging site, 2) first thinning, and 3) logging site with less than 100m³ removal. All the time elements used for the simulation models were obtained from different time studies and used as probability distributions. The resulting logging costs compared to other publications proved to have similarities, specifically the costs obtained for the Ponse Dual. The Valmet Combi’s models appeared to be cost-efficient due to their simultaneous cut and forward capabilities and the possibility of direct loading. Finally, it was recommended to use harwarder for logging sites with less than 100m³ removals and long translocation (transportation between sites) distance, especially when the translocations costs were particularly high.

In Canada, the Mountain Pine Beetle (MPB) epidemic has increased the interest in using dead wood or logging residues as feedstock for bioenergy. Mahmoudi et al. (2009) developed a simulation model using ExtendSim, in which the feasibility of installing a 300 MW power plant, using MPB residues, was evaluated. The simulation ran for 1 year in hourly-time steps, modelling the flow of forest stands from the forest through a conventional harvesting system. In this system, trees are felled by a feller-buncher, moved to the roadside by a skidder, delimbed by a processor, chipped by a grinder or chipper, and finally transported to the conversion facility. The simulation model accounted for seasonality of harvesting operations due to spring breakup and increased delays caused by weather conditions such as rain, snow, or extreme temperatures. Furthermore, the model used relative humidity data to dynamically calculate the moisture content of biomass, and therefore, its bulk density, using the equilibrium moisture content equation from Kumar et al.
The model obtained results for feedstock availability, moisture content, average cost per oven dry tonne, and total carbon emissions. The results of this model showed only 30% of the biomass demand could be fulfilled by this system. The moisture content fluctuated between 7% and 25%. The average cost was $45 per oven dry tonne and the total emissions were 45,000 tonnes. Finally, a sensitivity analysis was performed by varying the AAC level, weather, and hourly cost data separately. The results showed that biomass availability was the main concern, a reduction of plant size or increased procurement from an alternate biomass source was suggested.

The practice of using stumps for bioenergy production is rapidly increasing in countries like Finland, Sweden, and the UK. Previously, stumps would be crushed at the conversion facilities or terminals; however, with the recent introduction of more suitable mobile crushers, stumps can now be crushed at the landing. Asikainen (2010) developed a discrete-event simulation to obtain the ideal number of trucks at different transport distances. The simulation modelled the stump crushing and the transportation of wood chips in 24 scenarios. The scenarios were represented by the combinations obtained by varying the number of trucks (1, 2, 3 and 4) and the transportation distances (20, 40, 60, 80, 100, and 120 km). The model ran for a total of 120 hours, corresponding to 3 shifts for 5 working days. The simulation obtained the cost per MWh generated for each of the scenarios. The highest crushing costs were obtained with a single truck scenario since the crusher’s idle time was at its maximum. Furthermore, as the distance increased so did the crushing costs. However, the transportation cost was at its lowest in the one truck scenarios, since there was no queuing and therefore no wait costs for the trucks. Moreover, the more trucks were introduced into the system the more the crusher became a constraint for the system. Finally, it was suggested to use two trucks for the shortest transportation distance, a third truck to be introduced at 40km, and the fourth truck to be introduced after 100km.
Looking to assess the feasibility of a 300 MW power plant in Quesnel, BC. Mobini et al. (2011) developed a simulation model expanding Mahmoudi et al.’s (2009) research by assessing 20 years of the power plant’s lifetime. Additionally, three different harvesting systems were used depending on the proportions of sawlog and fuelwood contained in each stand. Stands with less than 50% fuel wood would require the conventional harvesting system. The stands with fuelwood proportions between 50% and 95%, would require the satellite harvesting system. Finally, the stands with fuelwood proportions with more than 95% would require the whole tree harvesting system. The simulation included all the harvesting operations, and the grinding and transportation of wood chips to the conversion facility. To account for the availability of biomass throughout the 20 years as the degree of MPB infestation advanced, the authors integrated the FERIC’s shelf life model into the simulation. The model would generate the results in terms of delivered biomass, moisture content, average cost, and greenhouse gas emissions. Even though the available biomass increased by using the three different harvesting systems, the biomass delivered was not enough to cover the conversion facility’s demand due to low fuelwood volumes during the first few years. The 20-year average for the weighted average cost per oven dry tonne, including road management, administration, and silviculture costs, was C$90. The moisture content of biomass fluctuated between 7% and 25%, with a 20-year average of 13%. The carbon emissions per oven dry tonne for the conventional, satellite, and full-tree chipping harvesting systems were 12.86 kg, 13.04 kg, and 14.50 kg, respectively. The use of alternate biomass sources or the reduction of the power plant’s capacity was suggested.

Zhang et al. (2012) developed a discrete-event simulation model using GIS layers. The objective was to select the best location and size for a biofuel facility by evaluating the supply chain’s performance. The supply chain’s performance measures were the biomass cost, energy
consumption, and GHG emissions. The model included the harvesting operations, transportation to a terminal and to the conversion facility, and finally the chipping and storage at the conversion facility. Furthermore, the simulation model kept track of the inventory levels at the conversion facility at all times and was capable of selecting the preferred harvesting sites based on needs. This simulation was modelled as a “pull” system. As the inventory levels at the conversion facility depleted, biomass would be used from the onsite storage; and as the onsite storage’s inventory was reduced, logs would be transported from the terminal to the conversion facility. Finally, as the log inventory was reduced, it would trigger the harvesting operations. There were nine predetermined possible locations for the biofuel facility: 1) Manton, 2) Roscommon, 3) Kingsley, 4) Kalkaska, 5) Gaylord, 6) Clare, 7) West Branch, 8) Traverse, and 9) Boyne. Additionally, there were three possible biofuel facility sizes: 1) 30 MGY, 40 MGY and 50 MGY. The total possible combinations of locations and plant sizes were considered to be the scenarios for this model. The simulation ran for 20 years using a 1-day time-step. All performance measures indicated that Gaylord was the best location regardless of plant size with average costs of 6.51, 7.24, and 7.85 ($/ton) for the 30 MGY, 40 MGY and 50 MGY, respectively; energy use of: 59,845, 75,546, and 88,659 (Btu/ton) for 30 MGY, 40 MGY and 50 MGY, respectively; and GHG emissions of 14.17, 17.89, and 20.99 (lb/ton) for 30 MGY, 40 MGY and 50 MGY, respectively. By comparing the three different plant sizes, the 30 MGY was the best size by having the lowest cost, energy use and GHG emissions.

Karttunen et al. (2012) developed a discrete-event simulation model using the commercial package Witness. The objective of the model was to determine the logistics of a cost-effective biomass supply using waterway transportation and then compare it to a scenario using truck transportation. In the model, there were three biomass supply areas and three conversion facilities with varying sizes and therefore demand. There were a total of 16 different scenarios, in which
two different tugboat sizes, two different barge types, and two different unloading and loading practices were evaluated. The obtained results showed that the most economical transportation option (€1.25 MWh) was a small tugboat with a fixed hopper barge with shift-independent loading and unloading at the harbours. Furthermore, the wheeled loader and conveyor belt was the preferred loading and unloading method since it substantially decreased the wait times and therefore the costs. Finally, compared to road transportation, waterway transportation was more cost-effective when distances are above 150 km.

Mobini et al. (2013) developed a discrete-event and discrete-rate simulation model for pellet supply chain. It incorporated all activities from the raw material sourcing to the delivery of pellets to the end customers, including the pellet production. The operations inside the pellet plant model included: raw material storage, drying, size reduction, pelletizing, cooling, and pellet storage. The sequence of these stages would vary depending on the biomass type and its quality. There were five raw material suppliers in the considered case study which provided two types of biomass, sawdust and shavings, with different quality levels. Since two suppliers were close to the pellet mill, the biomass was conveyed by a pipe. The remaining three suppliers would use trucks to transport the biomass to the pellet mill. Ninety percent of the pellets produced were shipped to Europe in 90 tonne railcars which were loaded into ocean vessels. The remaining 10%, were sold locally by distributing them in 18kg bags to two local distribution centers. The simulation model was run for 1 year, where a total of 156.87 kt of pellets were produced. The resulted average production costs per oven dry tonne was $101.33, with average exporting costs per delivered tonne of $97.27, and domestic costs per delivered tonne of $97.40 and $112.80 for each of the two distribution centers. The resulting total energy consumption and CO2 emissions of the supply chain were 89,248,402.14 kWh and 21,477.95 tonnes, respectively. Three scenarios were
evaluated 1) changing drying fuel from sawdust to bark and hogfuel, 2) changing drying fuel from shavings to bark and hogfuel and 3) producing lower quality pellets for international markets. The results of scenarios 1 and 2 showed the costs were reduced 1%-1.5% from the base case scenario. Furthermore, the CO2 emissions and energy consumption results did not vary from the results obtained in the base case scenario. Finally, 4.75% savings could be obtained by combining either scenario 1 or 2 with scenario 3. However, the CO2 emissions and energy consumption results were 34% and 27.38% higher, respectively.

Windisch et al. (2015) developed a discrete-event model in which the transportation of logging residues from the roadside storage to a large-scale CHP plant was simulated. This model used a one truck-mounted mobile chipper and two-truck trailer combinations, with the maximum transportation distance of 110 km. The objective of the model was to evaluate the difference between the “business as usual” biomass sourcing strategy and using a biomass sourcing process which would use a ranking system based on different criteria. The business as usual would follow these steps: logging residues would remain at the landing for a month to dry before going into the storage. Once in the storage, biomass would be considered as ready for chipping. To reduce relocation times, the chipping would be done at storages located in the vicinity in a first in first out policy. In the new ranking system, the criteria evaluated were: 1) transportation distance to plant, 2) average volume per storage, and 3) estimated moisture content. The model incorporated drying curves to calculate the moisture content of biomass in each month during the storage. In this model the sequence in which roadside storages would be selected to supply biomass would vary depending on a ranking of a weighted index. The simulation model was run for 1 year. There were several scenarios in which the weights for each of the criteria varied. The results showed that all
the scenarios had higher annual energy content at the end of the year. Furthermore, all the scenarios had a lower supply cost than the base case scenario, varying between 1% to 7%.

Some of the simulation models reviewed in this section looked at the logistics of loading, transportation, and unloading of either logs (Asikainen, 2001) or chips (Asikainen, 2010; Karttunen et al., 2012; Talbot and Suadicani, 2005; Windisch et al., 2015). The studies considering the logistics of wood chips, included the chipping, or grinding of forest residues and the dynamics between the different machines involved. Two of these studies used different barge configurations as their main transportation mode (Asikainen, 2001; Karttunen et al., 2012), while the rest considered truck transportation. The rest of the papers modelled the supply chain from the harvesting operations to the delivery to either the mill or conversion facility, and in one case to the final customer (Mobini et al., 2013).

The models can be categorized in two main groups based on their overall objective: feasibility assessments and supply chain or operations design. In the feasibility assessment category, simulation models focused on a specific supply chain design with the objective of proving its viability. Both Mahmoudi et al (2009) and Mobini et al. (2011) modelled the supply chain for a 300MW power plant in Quesnel, British Columbia, for 1 and 20 years, respectively. Their models were based on previous studies which suggested the design of the supply chain (Kumar et al., 2005; MacDonald, 2006). The results of both models suggested there was not enough biomass available in the area to sustain a power plant of that capacity. In the supply chain or operations design category, models attempt to determine, based on different scenarios, the best logistical arrangement which would improve the overall operations. These studies vary in terms of the considered operations: loading and unloading arrangements (Asikainen, 2001; Karttunen et al., 2012); transportation configurations (Asikainen, 2010; Karttunen et al., 2012); harvesting,
extraction, and chipping configurations (Talbot and Suadicani, 2005; Vaatainen et al., 2006), location and capacity of conversion facility (Zhang et al., 2012), and feedstock sourcing policies (Mobini et al., 2013; Windisch et al., 2015).

All the models reviewed were assessed according to economic and productivity performance measures such as total cost and delivered or extracted volume. Additionally, the most recent models have included environmental performance measures such as carbon or GHG emissions or energy consumption. The uncertain parameters in the models reviewed under this category were mainly related to machinery productivity and breakdown frequencies and intensity; biomass characteristics, availability, and demand; seasonality of operations; and transportation distances and speeds. In all cases, the results showed there were unavoidable delays within the system due to machine interactions. These machine interactions are the cause of queueing or idling, which would be difficult to quantify and analyse without a simulation model, specifically discrete-event simulation (Asikainen, 2001).

2.2.3 DISCUSSION

Simulation modelling in the forest industry has been used to solve forest management and supply chain problems for decades. Both, discrete-event and agent-based simulation seem to be the preferred simulation types. Discrete-event simulation has been used mostly for the analysis of supply chains and logistics operations which involve machine interactions. This simulation type is ideal for evaluating resource constraints and allocation to improve the performance of the system. Furthermore, in these models, the entities used are either forest stands, trees, logs, or biomass which pass through different set of activities as the resources become available. It is the resources that adapt their performance to the entity’s characteristics, if needed. However, the level of
communication between resources or entities is in most cases non-existent. Agent-based simulation has been mostly used for the analysis of forest management practices and forest disturbances. In all the reviewed cases, the entities or agents require to either communicate with other entities or to react to specific environment situations. In most cases, the use of agent-based simulation is used to provide the flexibility and the effect of an adaptive behaviour.

Given that the present research is based on the assessment of a bioenergy supply chain including uncertainties and machine interactions. Discrete-event simulation is the simulation approach which will be used in this research.

Except for Mobini et al. (2013) which models a supply chain with two demand points, local and European; the rest of the reviewed literature related to supply chains, has been mostly focused on modelling single demand supply chains. Furthermore, except for Mobini et al. (2013) in which two types of biomass and various biomass supply points are modelled; the rest, model a single source and biomass type. Moreover, except for both Zhang et al. (2012) and Mobini et al. (2013) in which the flow of biomass and pellets are modelled as a “pull” system based on demand; the rest of the models are based on a push system in which all the biomass harvested or available is transported to the conversion facility or final costumer. This is evident since part of the models’ objective is to assess the availability of biomass. Finally, all of these models assume an unlimited number of trucks. This research will include multiple demand and supply points, a network, multiple biomass types, a hybrid push and pull management system, and it will determine the number of required trucks to fulfill the required demand.
Chapter 3. THE SIMULATION MODEL

This chapter describes the simulation model built for this research study. Section 3.1 describes the simulation model structure and its different modules, and section 3.2 describes the input data used to build the model, as well as the assumptions made.

3.1 MODEL STRUCTURE

The developed simulation model is composed of five modules for each location: 1) cutblock generator, 2) harvesting operations, 3) grinding, hauling, and unloading, 4) sawmill operations, hauling, and unloading, and 5) inventory management. These modules are connected to a spreadsheet where all the input data are contained. Likewise, the “inventory management”, “grinding, hauling, and unloading” and “sawmill hauling and unloading” modules are connected to another spreadsheet where all the results are stored at the end of each run. Figure 3.1 shows the structure of the model, in which the connections between the different modules and data files are shown. As it can be seen, there is a flow of biomass and a flow of information between the modules. The flow of biomass depicts the route the entities take once the model is running. In the case of the forest residues, they are generated in the “cutblock generator”, then they flow through the “harvesting operations”, and finally into the “grinding, hauling, and unloading” module, where the entities are finally destroyed once they reach the conversion facility. In the case of the sawmill residues, entities only flow within the “sawmill hauling and unloading” module, where they are also created and destroyed.
The flow of information for the forest residues occurs in three stages. In the first stage, the initialization, all the modules receive information directly from the input file. The second stage, the inventory flow, occurs between the “harvesting operations”, “inventory management”, and “grinding, hauling and unloading” modules. At this stage information regarding inventory levels at all stages of the supply chain are communicated between the modules. This information flow manages the movement of entities into the “grinding, hauling and unloading” module. In the third stage, at end of each run, the results generated by the “inventory management”, and the “grinding, hauling, and unloading” modules are stored in a spreadsheet. In the case of the sawmill residues, the information flow also occurs in three stages. The first stage, the initialization, occurs between the input file and the “sawmill hauling, and unloading” module. The second stage, the inventory flow, occurs between the “sawmill hauling, and unloading” and the “inventory management”
module. Finally, in the last stage, the results obtained from the “sawmill hauling, and unloading” and the “inventory management” modules, are stored in a spreadsheet.

The input file, which is an Excel spreadsheet, includes data relevant to each of the aggregated cutblocks. The data contained in the spreadsheet include: the area in hectares, the amount of biomass available, transportation distance and cycle time to the conversion facilities, and the average stem volume. The input data relevant to the harvesting, grinding, and transportation operations such as the productivity curves and other delays, are assigned to each resource within the simulation model.

The output file, which is an Excel spreadsheet, collects information for each conversion facility and biomass type. The data collected include the daily number of truckloads generated with the amount of biomass contained, and the daily amount of biomass delivered to the conversion facilities. The total costs and emissions per operations, and the idle times were calculated within the simulation model.
Figure 3.2 Cutblock Generator Module

Figure 3.2 shows the detailed logic of the “cutblock generator” module. The “cutblock generator” module releases entities called cutblocks for each location (i.e. Williams Lake, Anahim Lake and Hanceville), every first day of the month. These entities contain the monthly proportion of forest to be harvested, based on the monthly seasonality. The number of entities to be generated for each location remains constant during the 5-year period. In other words, every 5-year period the number of cutblocks that will be simultaneously harvested, will vary. This is determined by the optimization model results. These cutblocks are then assigned a “cutblock number” based on the harvesting schedule determined by the optimization model results. Based on this “cutblock number”, the entities are then assigned specific stand attributes relative to their cutblock number. “Cutblocks” will then be subdivided into smaller 30 hectares “cutblocks”, this is done to improve
the flow through the model, and to better simulate the lag between the different harvesting operations. If the “cutblocks” are smaller than 30 hectares, they will not be subdivided and will flow through the model as such. It is important to note that once the agent “cutblock” is subdivided, some of its attributes will be recalculated based on the number of subdivisions or smaller “cutblocks” generated. Finally, the agent “cutblock” is released into the harvesting operations module.

Figure 3.3 shows the “harvesting operations” module in detail. In this module, the “cutblocks” will go through the felling, skidding, and processing operations sequentially. It is important to note that the flow of “cutblocks” through these operations will be based on the equipment’s availability, which is given by their productivity curves, capacity, and work schedule; and the total monthly harvested wood, which represents the total merchantable wood (m3) plus the total available biomass (m3). If a “cutblock” arrives at one of these operations and the machinery is not available, it will go into a queue. Data relevant to the machinery considered in this research are described in section 3.2. Once the “cutblocks” have gone through the harvesting operations, the entity “cutblock” will be subdivided into two entities: “logging residues” and “MPB logs” based on the parameter total available biomass. The amount of biomass contained in the ‘logging residue” entity is calculated by multiplying the total available biomass from the original “cutblock” entity by a random number which varies from 0.6 to 0.7. This random number represents the percentage of logging residues from the total available biomass. It was obtained from data provided by FPInnovations. The amount of biomass contained in the “MPB logs” is calculated by multiplying the total available biomass from the original “cutblock” entity by the complementary percentage of the random number. Once the entity has been divided, the variable “total available biomass”, for each biomass type, will be updated by adding the biomass contained
in the entities. Note that this variable manages the available biomass at each cutblock independently. The entities will then be on hold in a queue. There is a queue for each biomass type until there is an order from the conversion facility or until they have waited for a year.
**Figure 3.3 Harvesting Operations Module**

1. **Felling**
2. **Skidding**
3. **Processing**

- **Calculate biomass proportion for Logging Residues and MPB Logs.**
- **Divide entity into two:** Logging Residues and MPB Logs

Update the "total biomass available" per cutblock by adding the biomass amount contained in the entity.

Orders available for this biomass type?
- Yes
- No

Hold entity in a queue until orders are available or until entity has waited for one year.
- Yes
- No

Enough biomass for 1/2 a truckload?
- Yes
- No

Hold entity in a queue until there is enough biomass and orders available or until entity has waited for one year.
- Yes
- No

Enough biomass and orders available for this biomass type?
- Yes
- No

Destroy entity

**INPUT DATA**

- Productivity curves Schedule
- \( U(0.6, 0.7) \)
If there is an order, but the amount of biomass available at a specific cutblock number is less than half a truck load, the biomass will stay on hold, for a maximum of 1 year, until enough biomass to complete at least half a truckload is available. If after a year the agents are still on hold, agents are destroyed assuming a controlled burning occurred. If there is an order and there is enough biomass for at least half a truckload, the agent, either logging residues or/and MPB logs, will then be released into the grinding, hauling, and unloading module.

Figure 3.4 shows the “grinding, hauling, and unloading” module in detail. As entities come in to this module, they will be subdivided into “biomass truckloads”. This will be done using the chip van’s capacity, the biomass bulk density, and a compacted volumetric expansion given by a random number between 2.5 and 3. This volumetric expansion refers to the increase in volume of wood chips compared to the volume of a solid log or forest residue (Briggs, 1994). Furthermore, this volumetric expansion is considered to be compacted since it is assumed the chips would have settled due to gravity (Briggs, 1994). At this stage, the newly formed “biomass truckloads” will merge with another entity generated by the inventory management called “order truckload”. They will then trigger the order of a chip van. Chip vans are moving resources which will accompany truckloads through the grinding, hauling, and unloading operations. If there are no chip vans available, the truckloads will enter into a queue arranged in the ascending order of transportation cycle time, this is to maintain the transportation costs as low as possible. As a chip van becomes available, it will attach itself to the truckload agent. At this point, the variables “available biomass” and “in transit inventory” are updated in the inventory management module by subtracting and adding the biomass contained in the truckload agent, respectively. Hereon, the chip van will accompany the truckload entity through grinding, hauling, and unloading operations sequentially.
Figure 3.4 Grinding, hauling, and unloading module
It is important to note that the flow of truckloads through these operations will be based on the equipment’s availability which is given by their productivity, capacity, work schedule, and other delays. If a truckload arrives at one of these operations and the machinery is not available, the truckload will go into a queue. Data relevant to the machinery considered in this research are described in section 3.2. Once the unloading operation is done, the inventory management module will be updated by subtracting the biomass amount contained in the agent truckload from “in transit inventory” and adding it into the “on hand inventory”. Finally, the chip van will be released and the truckload entity will be destroyed.

Figure 3.5 shows the inventory management module in detail. This module was built using system’s dynamics simulation. This module continuously keeps track of the inventory levels for each biomass type at each conversion facility. Whenever the “on hand inventory” plus the “in transit inventory” reaches the reorder point or below, it will first verify there are no pending orders to be fulfilled for that specific biomass type and conversion facility. If there are “orders” awaiting to be fulfilled, nothing will occur; however, if there are no pending orders, it will release an entity into the system called “order”. This entity will contain an attribute called “order quantity” which equals the required amount for the inventory to reach the maximum inventory level for the specific biomass type at the conversion facility. The entity “order” will then be subdivided into “order truckloads”. This will be done using the chip van’s capacity, the biomass bulk density, and a compacted volumetric expansion given by a random number between 2.5 and 3. The “order truckloads” will then enter a queue where they will wait until there is biomass available for pick up in the form of “biomass truckloads”. These two truckloads, order and biomass, will merge and will continue the flow through the grinding, hauling and unloading module maintaining the attributes of the “biomass truckload”.

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Figure 3.5 Inventory Management Module
Figure 3.6 shows the sawmill hauling, and unloading module in detail. This module will release an entity every day with the amount of hog fuel and wood chips produced. If the biomass is to be used in the conversion facilities installed in the same sawmill where the biomass was produced, the amounts of biomass generated will automatically update the “on hand inventory” in the inventory management module. If the biomass is to be used in a conversion facility located at another sawmill, biomass will be divided into truckloads using the chip van’s capacity, and the biomass bulk density. The truckloads will then trigger the order of a chip van, which upon availability, will deliver the biomass to the specific conversion facility.

At each conversion facility, there is only one dumper to unload all the different biomass types. Chip vans will be unloaded based on a priority determined by the inventory level for the biomass type they carry. The lower the inventory level is, the higher the priority for those chip vans to be unloaded will be.

The model was run for 20 years with 30 replications. The results on daily inventory, truckloads generated, costs, demand fulfilment, and emissions were exported into an Excel file. Following the end of the simulation, the average for the 30 replications was calculated. The results are presented and analyzed in Chapter 4.
Figure 3.6 Sawmill Hauling, and Unloading

INPUT DATA
- Generate entities: "hog fuel" and "wood chips"
- Assign biomass amount
- Biomass to be used in another location?
  - Yes: Divide into truckload entities
  - No: Add biomass amount into "on hand inventory"

OUTPUT DATA
- Number of truckloads per day
- Volume and weight of biomass
- Cost
- Emissions
- Demand fulfillment

INPUT DATA
- Biomass amount
- Bulk density
- Truck capacity

OUTPUT DATA
- Biomass amount
- Volumetric Expansion U(2.5, 3)
- Truck capacity
- Number of truckloads per day
- Volume and weight of biomass
- Cost
- Emissions
- Demand fulfillment

End
3.2 INPUT DATA AND ASSUMPTIONS

As can be seen in Figure 3.7, the case study considers the use of four biomass feedstock types (i.e. wood chips, hog fuel, logging residues and MPB logs) from two different sources: small privately owned sawmills and forest cutblocks. For each location under study, there is one sawmill where the conversion facilities are assumed to be located. Daily, each sawmill produces wood chips and hog fuel which are assumed to be readily available for the conversion facilities once produced. It is assumed that all the biomass produced by the sawmills is allocated, and therefore the total demand of sawmill residues will equal the supply. In most of the cases, the sawmill residues will be used in the conversion facilities located at the sawmill where the residues were produced. In these cases, it is assumed that no transportation or handling is required. The only case where transportation would be required for sawmill residues is only during first 5-year period, where Williams Lake will send 1,422 odt wood chips per year to Hanceville.

Figure 3.7 Supply Chain Structure
In the case of the forest residues, they would be obtained as a result of a conventional harvesting system, being its main objective the extraction of sawlogs (MacDonald, 2006). Figure 3.7 shows the different stages of a conventional harvesting system and which were modelled in the simulation. Harvesting operations tend to be seasonal, since most of the roads become inaccessible to trucks and most machinery during the spring breakup season. In order to account for the seasonality of the harvesting operations, a monthly distribution of available biomass was developed. To develop this distribution, the Monthly Scaling History Report was obtained from the Harvesting Billing System for the Cariboo-Chilcotin region for the years of 2012, 2013 and 2014 (Government of British Columbia, 2014). The percentage of harvesting volume per month was obtained for each of the three years and an average for each month was calculated. Figure 3.8 shows the monthly harvesting distribution for the three years and their average. As it can be observed, even though there are some slight differences from year to year, the shape of the distribution is similar, which confirms a seasonal trend. This monthly harvesting distribution was used to manage the flow of total yearly biomass in a monthly basis.

![Figure 3.8 Monthly Harvesting Distribution](image-url)
From the original 1592 aggregated cutblocks provided by FPInnovations, the economic optimization selected 337 which would satisfy the conversion facilities’ biomass demand (Cambero et al., 2015). As previously mentioned, each of these cutblocks were assigned to a specific location by the optimization model in order to maximize the economic benefits of the project. Multiple aggregated cutblocks can and will be harvested simultaneously per location, in order to comply with the sawlog demand. Table 3.1 shows the distribution of stand characteristics of the aggregated cutblocks assigned for each of the locations. These were obtained from FPInnovations and were directly used in the model.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Anahim Lake</th>
<th>Hanceville</th>
<th>Williams Lake</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Area (ha)</strong></td>
<td>Min (1)</td>
<td>Max (843)</td>
<td>Mean (180.33)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Min (1)</td>
<td>Max (814)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Min (1)</td>
<td>Max (320)</td>
</tr>
<tr>
<td><strong>Mean stem volume (m³)</strong></td>
<td>0.07</td>
<td>0.18</td>
<td>0.12</td>
</tr>
<tr>
<td><strong>Total available biomass (odt)</strong></td>
<td>135</td>
<td>156,440</td>
<td>28,975</td>
</tr>
</tbody>
</table>

As it can be observed, the number of hectares per cutblock varies considerably. In the simulation model, this characteristic is used to divide the initial aggregated cutblocks into entities of 30 hectares or less to ease the flow of the harvesting operations and increase the veracity of the simulation model. The average stem volume is a measure of tree growth, which in this case represents the size of the tree population at each aggregated cutblock. In the simulation model, the average stem volume is used for the productivities of feller buncher and dangle head processor, since these seem to be affected by this factor when harvesting in a mountain pine beetle infested sites (Dyson and McMorland, 2008). Finally, the total available biomass represents the total
biomass a cutblock would have available for bioenergy purposes after five years of harvesting. This includes both logging residues and MPB logs.

The details of the machinery considered for the harvesting operations, grinding, hauling and unloading of biomass can be seen in Table 3.2. All equipment is scheduled to work 6 days a week, 9 hours a day, except for the semi-trailer chip van and the dumpers. The semi-trailer chip van is scheduled for 7 days a week, 13 hours a day. The dumper is scheduled to receive incoming chip vans 24/7.

Table 3.2 Machinery Characteristics

<table>
<thead>
<tr>
<th>Type of Equipment</th>
<th>Power (kW)</th>
<th>Productivity/payload (m$^3$h$^{-1}$)</th>
<th>Assigned per cutblock</th>
<th>Cost ($ h^{-1}$)</th>
<th>Fuel Consumption (L h$^{-1}$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Feller-buncher</td>
<td>149$^a$</td>
<td>See Eq. 3.1</td>
<td>1</td>
<td>171.94$^a$</td>
<td>30 - 47 $^c$</td>
</tr>
<tr>
<td>Grapple skidder</td>
<td>95$^a$</td>
<td>See Eq. 3.2</td>
<td>1</td>
<td>116.48$^a$</td>
<td>20 - 30 $^e$</td>
</tr>
<tr>
<td>Dangle-head processor</td>
<td>126$^a$</td>
<td>See Eq. 3.3</td>
<td>2</td>
<td>144.21$^a$</td>
<td>22 - 25 $^e$</td>
</tr>
<tr>
<td>Loader</td>
<td>146$^a$</td>
<td>120 - 170 $^a$</td>
<td>1</td>
<td>105.54 $^g$</td>
<td>13 $^g$</td>
</tr>
<tr>
<td>Horizontal grinder</td>
<td>600$^b$</td>
<td>24.7 (odt PMH$^{-1}$)$^g$</td>
<td>1</td>
<td>409.49 $^g$</td>
<td>135 $^g$</td>
</tr>
<tr>
<td>Semi-trailer chip van</td>
<td>352$^a$</td>
<td>113m$^3$$^c$</td>
<td>-</td>
<td>124.28$^d$</td>
<td>0.68 L km$^{-1}$ $^e$</td>
</tr>
<tr>
<td>Dumper</td>
<td>-</td>
<td>15 min per truck</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Sources: $^a$ (MacDonald, 2006); $^b$ (Vermeer, 2015); $^c$ (Akhtari, 2012); $^d$ (Akhtari et al., 2014); $^e$ (Cambero et al., 2014); $^f$ (Dyson and McMorland, 2008); $^g$ calculated from (Friesen, 2015a)

The productivities for feller-buncher, grapple skidder, and dangle-head processor are regression models obtained from Dyson et al. (2008). These productivity curves consider the effect of working under mountain pine beetle conditions (Dyson and McMorland, 2008). The productivity of the feller-buncher (y), which is valid on terrains with slopes less than 20°, is dependent on the stem volume (X). The grapple skidder’s productivity (y) is dependent on the skidding distance (X) which in this case is consider to be fixed at 250 m. Finally, the dangle-head
processor’s productivity \((y)\) is also dependent on the stem volume \((X)\), and it assumes trees are of different lengths. For these operations, it is assumed that all delays such as maintenance, machinery breakdowns, and weather delays are accounted for by the use of the monthly harvesting distribution.

\[
\text{Feller-buncher: } y = 173.02X^{0.7464} \quad R^2 = 0.6686 \quad \text{Eq. 3.1}
\]

\[
\text{Grapple skidder: } y = -48.05\ln(X) + 312.91 \quad R^2=0.9955 \quad \text{Eq. 3.2}
\]

\[
\text{Dangle-head processor: } y = 85.131X^{0.737} \quad R^2 = 0.7947 \quad \text{Eq. 3.3}
\]

The horizontal grinder’s productivity shown in Table 3.2 is the standard productivity. In reality, the grinder has an operational efficiency of 60\%. Its actual productivity, calculated using Eq. 3.4, would be 14.82 odt PMH\(^{-1}\).

\[
\text{Horizontal grinder: } \text{Efficiency (\%)} = \frac{\text{Actual Productivity}}{\text{Standard Productivity}} \quad \text{Eq. 3.4}
\]

Furthermore, the transportation distance and cycle time distributions for the aggregated cutblocks of each location are shown in Table 3.3. The transportation cycle time, obtained from GIS layers of the area, takes into consideration the different road types and infrastructure currently available, plus the logging roads required to be built in the 20-year lifespan of the project. In the model, the transportation cycle time is used as the transportation time to the conversion facility from the landing, and vice-versa, which ultimately is used to calculate the costs. The transportation distance, in kilometers, measures the two-way distance between the landing of the aggregated cutblock to the corresponding conversion facility. In the model the transportation distance is used to calculate the CO\(_2\) equivalent emissions. The distance between the different cutblocks was not
available, and therefore biomass consolidation from different cutblocks is not considered in this case study.

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Anahim Lake</th>
<th>Hanceville</th>
<th>Williams Lake</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>1.4</td>
<td>1.4</td>
<td>1.6</td>
</tr>
<tr>
<td>Max</td>
<td>3.3</td>
<td>8.1</td>
<td>4.3</td>
</tr>
<tr>
<td>Mean</td>
<td>1.9</td>
<td>3.5</td>
<td>2.8</td>
</tr>
<tr>
<td>Transport cycle time (hrs)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>4.4</td>
<td>187.6</td>
<td>350.1</td>
</tr>
<tr>
<td>Max</td>
<td>31.3</td>
<td>333.7</td>
<td>421.4</td>
</tr>
<tr>
<td>Mean</td>
<td>17.9</td>
<td>275.0</td>
<td>384.9</td>
</tr>
<tr>
<td>Two-way transp. distance (km)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The semi-trailer chip vans are assumed to be owner-operated from local inhabitants of each location. Therefore, it is assumed that the semi-trailer chip vans will start the day at each of the sawmills. Furthermore, it is assumed that chip vans will not be dispatched to pick up biomass if the remaining available working hours are less than the transportation cycle time to a specific cutblock. This is due to the restrictions imposed by the government of British Columbia, in which truck drivers are only allowed to drive for 13 hours straight. All work is pre-empted by work schedule.

As previously mentioned, once the agent cutblock enters the grinding, hauling, and unloading module it will be subdivided into truckloads. Eq. 3.5 is used to calculate the number of truckloads into which each agent cutblock will be subdivided. It is important to mention that each truckload is assumed to contain only one type of biomass, either logging residues or MPB logs.

\[
\text{Number of truckloads} = \frac{\text{Total Amount of biomass in cutblock (odt)}}{\text{Truck capacity (odt)}} \quad \text{Eq. 3.5}
\]

\[
\text{Truck Capacity} = \text{Truck Volume} \times \frac{\text{Bulk Density}}{1000 \times \text{volumetric exp factor}} \times \left(1 - \frac{\text{MC}\%}{100}\right) \quad \text{Eq. 3.6}
\]
To calculate the truck capacity (odt), which is required to calculate the number of truckloads, Eq. 3.6 was used. The semi-trailer chip van has a volumetric and a weight limiting capacity. According to MacDonald (2011), the semi-trailer chip van is weight restricted to 17.7 odt when the moisture content of the biomass is greater than 38%, and volume restricted to 113m³ when moisture content is below that threshold. In this research, it is assumed that moisture content (MC) of both logging residues and MPB logs is 25%, since mountain pine beetle infested wood does not absorb as much moisture as healthy wood does. Therefore, we assume the trucks to be volume restricted. The bulk density of biomass is required to calculate the truck capacity (odt). Bulk density, $\rho_{MC}$ (kg m$^{-3}$), describes the mass (including water) per unit of volume. The following equations are required to calculate the bulk density (Bergman et al., 2010):

$$\rho_{MC} = 1000 \times G_{MC} \left( 1 + \frac{MC\%}{100} \right) \quad \text{Eq. 3.7}$$

$$G_{MC} = \frac{G_b}{\left( 1 - 0.265 \times G_b \left( 1 - \frac{MC}{MC_{fs}} \right) \right)}, \quad MC < MC_{fs} \quad \text{Eq. 3.8}$$

$G_{MC}$ is the specific gravity which represents the ratio of wood’s density compared to that of water. This measurement varies greatly depending on moisture content (MC). $G_b$, is the basic specific gravity, which represents the ratio of oven dry mass per green volume (m$^3$). This measure is species dependent, and for lodgepole pine it is assumed to be 0.38 (Bergman et al., 2010). $MC_{fs}$ represents the fiber saturation point. This is the moisture content at which all the wood cell walls are fully saturated with water (Washington State University, 2000). When the moisture content of wood is below $MC_{fs}$, as the moisture content changes, both mechanical and physical properties of wood change (Washington State University, 2000). However, when the moisture content of wood is above the $MC_{fs}$, both mechanical and physical properties of wood will remain the same with
changes in moisture content (Washington State University, 2000). It is assumed to be 30% (Bergman et al., 2010).

Furthermore, the volumetric expansion of wood due to grinding also plays an important role in determining the truck capacity (odt). Volumetric expansion refers to the ratio of volume of solid wood to the volume of ground wood (Briggs, 1994). There are two types of volumetric expansion factors: loose and compacted (Briggs, 1994). Loose expansion factor refers to the ratio of volume of wood chips directly after comminution (Briggs, 1994). Compact expansion factor refers to the ratio of volume of wood chips after some time has passed and the chips have settled due to gravity or other mechanical compaction (Briggs, 1994). This characteristic is also species dependent. A compacted expansion factor between 2.5 and 3 is assumed in this case study (Briggs, 1994). In the simulation model, this number is generated randomly using a uniform distribution.

To calculate the total cost of delivered biomass, Eq. 3.9 was used. In the scope of this research study, it is assumed that the final delivered cost of biomass is not affected by the costs associated with the felling, skidding, and processing activities, since these are fully covered by the logging contractors, being the main purpose of the harvesting operations the extraction of sawlog.

\[
\text{Total Cost} = \text{stumpage cost} + \text{loading cost} + \text{grinding cost} + \text{transp. cost} \\
\text{Eq. 3.9}
\]

The stumpage cost considered in this study is $0.25/m^3 (Ministry of Forests, 2015). It was obtained from the timber pricing branch, where it can be found under wood chips of all tree species from post-harvest material. The loading and grinding costs can be calculated using Eq. 3.10 and Eq. 3.11. The loading and grinding hourly rate, based on scheduled machine hours, can be found
in Table 3.2. The transportation cost is calculated using Eq. 3.12, where the hourly rate can be found in Table 3.2. The unloading and loading times are a result of machine interactions gathered for each truckload agent by the simulation model. Finally, the transportation cycle time is an attribute of each truckload agent-based on the aggregated cutblock of origin.

\[
\text{Loading cost} = \text{Rate} \times \text{Scheduled machine hours} \quad \text{Eq. 3.10}
\]

\[
\text{Grinding cost} = \text{Rate} \times \text{Scheduled machine hours} \quad \text{Eq. 3.11}
\]

\[
\text{Transportation cost} = \text{Rate} \times (\text{loading time + transp. Cycle time + unloading time}) \quad \text{Eq. 3.12}
\]

The CO\textsubscript{2} equivalent emissions consider the emissions of carbon dioxide (CO\textsubscript{2}), methane (CH\textsubscript{4}), and nitrous oxide (N\textsubscript{2}O). To calculate the total CO\textsubscript{2} equivalent emissions Eq. 3.13 was used. In this equation, only the emissions generated by the diesel consumption of the loading, grinding, and transportation activities are considered. Eq. 3.14 and Eq. 3.15 were used to calculate the CO\textsubscript{2} equivalent emissions for each of the machines. Furthermore, Table 3.4 shows the CO\textsubscript{2} equivalent emission rates per liter of diesel consumed. It is important to note that the chip van’s diesel consumption is based on kilometers traveled, while the loader’s and grinder’s is based on their productive machine hours.

\[
\text{Total CO}_2\text{eq. emissions} = \text{Chip van CO}_2\text{eq. emissions} + \text{Loader CO}_2\text{eq. emissions} + \text{Grinder CO}_2\text{eq. emissions} \quad \text{Eq. 3.13}
\]

\[
\text{Chip van CO}_2\text{eq. emissions} = \text{distance traveled} \times \text{fuel consumption rate} \times \text{CO}_2\text{eq. emission rate} \quad \text{Eq. 3.14}
\]
Loader/Grinder CO₂ eq. emissions = Productive machine hours * fuel consumption rate * CO₂ eq emission rate

\[
\text{Eq. 3.15}
\]

<table>
<thead>
<tr>
<th>CO₂ (kg L⁻¹)</th>
<th>CH₄ CO₂eq (kg L⁻¹)</th>
<th>N₂O CO₂eq (kg L⁻¹)</th>
<th>Total CO₂eq Emission Rate (kg L⁻¹)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.7ᵃ</td>
<td>0.00325ᵃ</td>
<td>0.1788ᵃ</td>
<td>2.88205ᵃ</td>
</tr>
</tbody>
</table>

Source: ᵃ (United States Environmental Protection Agency, 2015)

Prior to running the simulation model to obtain the desired results, it was run several times to determine, via trial and error, the inventory initial parameters for each conversion facility’s biomass types. The inventory initial parameters are: maximum inventory, reorder point and initial inventory. The maximum inventory was initially estimated via a personal conversation with Charles Friesen (Friesen, 2015b). It was estimated based on space availability. The maximum inventory for Anahim Lake and Hanceville could be up to 6 months of demand and for Williams Lake 3 months of demand. Starting with a maximum inventory of ½ a month, several runs in which the maximum inventory was increased by ½ a month, were performed. Additionally, a reorder point of half the maximum inventory was used during the runs. The maximum inventory and reorder point which allowed for the highest percentage of demand fulfillment were selected. The initial inventory is meant to supply enough biomass to last for the start-up lead time (1 to 2 weeks) for the first delivery of logging residues. This will trigger the inventory management module to continuously monitor the inventory levels. Table 3.5 to Table 3.11 show the selected inventory parameters for each of the locations and each of the biomass types which are managed by the pull system.
Table 3.5 Inventory Parameters for Anahim Lake MPB Logs

<table>
<thead>
<tr>
<th>Harvesting Period</th>
<th>Initial Inventory (odt)</th>
<th>Reorder Point (odt)</th>
<th>Maximum Inventory (odt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>117</td>
<td>760</td>
<td>1520</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>1900</td>
<td>3800</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>920</td>
<td>1840</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>1100</td>
<td>2200</td>
</tr>
</tbody>
</table>

Table 3.6 Inventory Parameters for Anahim Lake Logging Residues

<table>
<thead>
<tr>
<th>Harvesting Period</th>
<th>Initial Inventory (odt)</th>
<th>Reorder Point (odt)</th>
<th>Maximum Inventory (odt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>200</td>
<td>1300</td>
<td>2600</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>200</td>
<td>400</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>1200</td>
<td>2400</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>990</td>
<td>1980</td>
</tr>
</tbody>
</table>

Table 3.7 Inventory Parameters for Hanceville MPB Logs

<table>
<thead>
<tr>
<th>Harvesting Period</th>
<th>Initial Inventory (odt)</th>
<th>Reorder Point (odt)</th>
<th>Maximum Inventory (odt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2230</td>
<td>14530</td>
<td>29060</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>14760</td>
<td>29520</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>3300</td>
<td>6600</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>3500</td>
<td>7000</td>
</tr>
</tbody>
</table>
Table 3.8 Inventory Parameters for Hanceville Logging Residues

<table>
<thead>
<tr>
<th>Harvesting Period</th>
<th>Initial Inventory (odt)</th>
<th>Reorder Point (odt)</th>
<th>Maximum Inventory (odt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>120</td>
<td>370</td>
<td>740</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>311</td>
<td>622</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>4700</td>
<td>9400</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>4530</td>
<td>9060</td>
</tr>
</tbody>
</table>

Table 3.9 Inventory Parameters for Hanceville Wood Chips

<table>
<thead>
<tr>
<th>Harvesting Period</th>
<th>Initial Inventory (odt)</th>
<th>Reorder Point (odt)</th>
<th>Maximum Inventory (odt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>55</td>
<td>180</td>
<td>360</td>
</tr>
</tbody>
</table>

Table 3.10 Inventory Parameters for Williams Lake MPB Logs

<table>
<thead>
<tr>
<th>Harvesting Period</th>
<th>Initial Inventory (odt)</th>
<th>Reorder Point (odt)</th>
<th>Maximum Inventory (odt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>70</td>
<td>155</td>
<td>310</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>65</td>
<td>130</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>3820</td>
<td>7640</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>3200</td>
<td>6400</td>
</tr>
</tbody>
</table>

Table 3.11 Inventory Parameters for Williams Lake Logging Residues

<table>
<thead>
<tr>
<th>Harvesting Period</th>
<th>Initial Inventory (odt)</th>
<th>Reorder Point (odt)</th>
<th>Maximum Inventory (odt)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20</td>
<td>40</td>
<td>80</td>
</tr>
<tr>
<td>2</td>
<td>-</td>
<td>15</td>
<td>30</td>
</tr>
<tr>
<td>3</td>
<td>-</td>
<td>1422</td>
<td>2844</td>
</tr>
<tr>
<td>4</td>
<td>-</td>
<td>2040</td>
<td>4080</td>
</tr>
</tbody>
</table>
Whenever the inventory level plus the biomass in transit reaches the reorder point or below, a new order is placed. The amount to order is calculated using Eq. 3.16.

Order quantity = Maximum inventory − On hand inventory − In transit inventory Eq. 3.16
Chapter 4. RESULTS AND SENSITIVITY ANALYSIS

In this chapter, the results of the simulation model and sensitivity analysis are presented and analyzed. This chapter is divided into different sections according to the results obtained from the model. Section 4.1 will discuss the demand fulfillment; Section 4.2 will discuss the amount of truckloads per year and total number of trucks required; Section 4.3 will discuss the cost of delivered biomass; Section 4.4 will discuss the CO\(_2\) equivalent emissions resulted from the logistics operations; Section 4.5 will discuss the idle and wait times experienced in the system, and finally, Section 4.6 will discuss the sensitivity analysis.

The results presented in this chapter are the averages from the 30 replications executed which ensures a confidence level of 95%. It is important to note, that the model was verified throughout its building process by debugging after each change was performed. This was done using input values with known results and by using visualization techniques.

4.1 DEMAND FULFILLMENT

The demand fulfillment percentage represents the percentage to which the total yearly demand was met. It was calculated, for each conversion facility, based on the total delivered biomass per year and the total yearly demand for each biomass type.

The results obtained for Anahim Lake’s biomass boiler and steam turbine (5MW), showed the demand was met 100% for hog fuel, wood chips, and logging residues throughout the 20-year lifespan. In the case of the MPB logs, the demand was fulfilled up to 99% except for the years 6 to 15, where the demand fulfillment fluctuated around 96%. According to Table 1.4 in which the yearly available biomass during the different harvesting periods is shown, the yearly demand for
logging residues during the first harvesting period almost reaches the total yearly available biomass. Although there is enough available biomass per year to fulfill the demand, a certain percentage could have been lost due to rounding, when subdividing the cutblocks into different agents, or to incomplete truckloads at different cutblocks, which means biomass was destroyed.

The results obtained for Hanceville’s biomass boiler and steam turbine (0.5 MW) showed the demand was fulfilled at 100% throughout the 20-year lifespan. This is not a surprise since this conversion facility only uses logging residues and hog fuel, from its own sawmill. When looking at Table 1.4 which describes the yearly available biomass during the different harvesting periods, it is evident that the demand of logging residues compared to its availability is quite low. This will reduce the effects of loss of biomass due to rounding and incomplete truckloads, explaining the consistent 100% of demand fulfillment.

The demand fulfillment result obtained for Hanceville’s pyrolysis plant (400 odt/per day) was maintained between 99% and 100% throughout the 20-year lifespan. When observing Table 1.4 it is evident there is enough biomass to supply the conversion facility, and to buffer the effects of loss of biomass due to rounding and incomplete truckloads left at the different cutblocks.

The demand fulfillment obtained for the Williams Lake’s biomass stoker boiler (2 MW) fluctuated between 96% and 100%. The MPB logs are responsible for the low demand fulfillment due to the effects of loss of biomass due to rounding and incomplete truckloads. When observing Table 1.4 it is evident there is enough biomass available to fulfill the demand and also to mitigate the effects of biomass loss due to rounding and incomplete truckloads, in the case of the logging residues. In contrast, the demand fulfillment of the MPB logs seems to be affected by these two factors.
Finally, the demand fulfillment for the Williams Lake’s pyrolysis plant (200 odt/day) was maintained at 100% for the first 10 years; yet, during the last 5 years, the demand fulfillment fluctuated around 97%. The decrease in demand fulfillment is due to the effects of biomass loss due to rounding and incomplete truckloads.

4.2 TRUCKLOADS AND TRUCKS REQUIRED PER YEAR

The viability of this supply chain depends on the steady supply of biomass throughout its lifetime. For this to be possible, it is not only required to have enough biomass available at a specific time, but also to have enough resources to deliver the biomass as is required by the conversion facilities. Table 4.1 shows the average number of truckloads required per year to deliver the total amount of biomass to the three different locations. In this table, the truckloads are shown per location, where the truckloads of different biomass types are included. The slight variations from year to year is due to the variations in biomass delivered and the effect of the random number used for the compacted volumetric expansion factor. As it can be observed, the total number of truckloads per year appears to have a slight increase in the second half of the supply chain’s life time. This is due to the shift in capacity in the pyrolysis plants between Hanceville and Williams Lake, and the increase use of forest residues over sawmill residues.
Table 4.1 Total Number of Truckloads per Year

<table>
<thead>
<tr>
<th>Harvesting Period</th>
<th>Year</th>
<th>Williams Lake</th>
<th>Hanceville</th>
<th>Anahim Lake</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>133</td>
<td>7872</td>
<td>1106</td>
<td>9111</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>147</td>
<td>8065</td>
<td>1106</td>
<td>9318</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>159</td>
<td>7898</td>
<td>1088</td>
<td>9145</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>153</td>
<td>7989</td>
<td>1148</td>
<td>9290</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>167</td>
<td>7856</td>
<td>1051</td>
<td>9074</td>
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<tr>
<td>2</td>
<td>6</td>
<td>69</td>
<td>7885</td>
<td>1129</td>
<td>9083</td>
</tr>
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<td>8988</td>
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<tr>
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<td>11</td>
<td>3917</td>
<td>4299</td>
<td>1090</td>
<td>9306</td>
</tr>
<tr>
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<td>12</td>
<td>3921</td>
<td>4241</td>
<td>1082</td>
<td>9244</td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>3809</td>
<td>4401</td>
<td>1012</td>
<td>9222</td>
</tr>
<tr>
<td></td>
<td>14</td>
<td>4288</td>
<td>3993</td>
<td>1100</td>
<td>9381</td>
</tr>
<tr>
<td></td>
<td>15</td>
<td>4198</td>
<td>4174</td>
<td>1010</td>
<td>9382</td>
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<tr>
<td>4</td>
<td>16</td>
<td>4100</td>
<td>4038</td>
<td>1168</td>
<td>9306</td>
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<td>17</td>
<td>4250</td>
<td>4028</td>
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<td>9398</td>
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<td>4040</td>
<td>4061</td>
<td>1105</td>
<td>9306</td>
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<td>19</td>
<td>4074</td>
<td>4116</td>
<td>1128</td>
<td>9318</td>
</tr>
<tr>
<td></td>
<td>20</td>
<td>4077</td>
<td>4222</td>
<td>1108</td>
<td>9407</td>
</tr>
</tbody>
</table>
Using the average transportation cycle time for each of the locations, and assuming a maximum of 13 hours per day, the total number of trucks were calculated. Table 4.2 shows the distribution of the trucks between the different locations, in which the shift in biomass flow in the last ten years is evident. Throughout the lifetime of the supply chain, the required number of trucks only varies by 1 truck in the second half of the supply chain’s lifetime, this might be due to the high transportation cycle times in Hanceville and the increase in demand of forest residues over sawmill residues.

<table>
<thead>
<tr>
<th>Years</th>
<th>Williams Lake</th>
<th>Hanceville</th>
<th>Anahim Lake</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>1-10</td>
<td>1</td>
<td>21</td>
<td>1</td>
<td>23</td>
</tr>
<tr>
<td>11-20</td>
<td>10</td>
<td>13</td>
<td>1</td>
<td>24</td>
</tr>
</tbody>
</table>

4.3 COST

Table 4.3 shows the cost per oven-dry tonne at each location. This cost varies, per location, from $56.52 to $87.36. In the case of the loading and grinding cost, the variation between locations is quite low, the maximum variation is $1.63 per odt. This cost seemed to increase as the average yearly biomass demand decreased. On the other hand, the transportation costs seemed to increase due to the increase in both the yearly biomass demand and the transportation cycle times. Hanceville has the highest average yearly biomass demand and the highest transportation cost, therefore it is expected for it to have the highest transportation cost per oven dry tonne.
Table 4.3 Total Cost per Location

<table>
<thead>
<tr>
<th>Activity</th>
<th>Anahim Lake</th>
<th>Hanceville</th>
<th>Williams Lake</th>
</tr>
</thead>
<tbody>
<tr>
<td>Loading/Grinding</td>
<td>32.66</td>
<td>31.03</td>
<td>31.25</td>
</tr>
<tr>
<td>Transportation</td>
<td>22.70</td>
<td>55.17</td>
<td>41.42</td>
</tr>
<tr>
<td>Sub Total</td>
<td>55.36</td>
<td>86.20</td>
<td>72.67</td>
</tr>
<tr>
<td>+ Stumpage cost</td>
<td>1.16</td>
<td>1.16</td>
<td>1.16</td>
</tr>
<tr>
<td>Total</td>
<td>56.52</td>
<td>87.36</td>
<td>73.83</td>
</tr>
</tbody>
</table>

4.4 EMISSIONS

Table 4.4 shows the CO₂ equivalent emissions for each location. These are the result of diesel consumption from the loading, grinding, and transportation activities in the supply chain. As it is shown, the emissions from the loader and grinder present no variation between the locations because the diesel consumption is directly related to the machines’ productivities which are maintained stable throughout the simulation. On the other hand, the CO₂ emissions derived from transportation are calculated using transportation distance (km). Table 3.3 shows the transportation distance between the different locations which explains the great difference between the transportation emissions in the three locations.

Table 4.4 Carbon Dioxide Equivalent Emissions per Location

<table>
<thead>
<tr>
<th>Activity</th>
<th>Anahim Lake</th>
<th>Williams Lake</th>
<th>Hanceville</th>
</tr>
</thead>
<tbody>
<tr>
<td>CO₂ Emissions</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(kg/odt)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Loading/Grinding</td>
<td>17.57</td>
<td>17.57</td>
<td>17.57</td>
</tr>
<tr>
<td>Transportation</td>
<td>2.09</td>
<td>55.04</td>
<td>39.43</td>
</tr>
<tr>
<td>Total</td>
<td>19.66</td>
<td>72.61</td>
<td>57.00</td>
</tr>
</tbody>
</table>
4.5 IDLE AND WAIT TIMES

Throughout the simulation runs, the grinders and dumpers observed significant idle times caused by machine interdependencies. In the case of the grinders, because it was assumed there would be one grinder available at each cutblock, their idle times were significantly higher than that of the dumper. The grinders’ idle times varied between each cutblock, and was directly related to the amount of biomass to be ground.

Table 4.5 shows the average percentage of scheduled machine hours which the grinder spent idle. This was obtained by averaging the percent idle time of the grinders per location throughout the 30 replications. In some cases, particularly in the weeks following the spring breakup season, some grinders would experience a surge in the amount of biomass to grind which caused trucks to queue. The wait times derived from these queues are negligible when averaged with the remainder of the time the grinder was idle.

<table>
<thead>
<tr>
<th>Table 4.5 Grinder Idle Times</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anahim Lake</td>
</tr>
<tr>
<td>Grinder Average Idle Time (%)</td>
</tr>
</tbody>
</table>

Anahim Lake was the location with the highest grinder idle times. This was caused by the low amount of biomass to be ground, and the fact that there was only one truck serving the different cutblocks in this location. During the first ten years, Williams Lake experienced similar idle times to those experienced by Anahim Lake; yet once the pyrolysis plant was installed, the idle times decreased. Finally, the idle times experienced by the grinders in Hanceville, appeared to increase during the last ten years of the simulations, evidently due to the decrease in biomass demand in the area.
In the case of the dumpers, each location experienced different machine interactions. Table 4.6 shows the average percent idle times of the dumpers in each location. Anahim Lake experienced high idle times due to one truck serving the area and the low number of loads transported daily. The lack of wait times or queuing in this location is therefore evident. During the first ten years, Hanceville experienced some queuing especially during the weeks following the spring breakup season. However, the wait times were not significant enough to be reported. The dumper mainly experienced idle times, especially during the spring break-up months. Evidently, during the last ten years, the idle time increased due to the reduction in capacity of the pyrolysis plant. Finally, in the case of Williams Lake, the first ten years the dumper appeared to be idle over 90% of the time. However, in the last ten years, once the pyrolysis plant was installed, the idle time was significantly reduced and it even experienced brief queuing in the weeks following the spring breakup season. The wait times experienced by the trucks in Williams Lake were not significant to be reported.

<table>
<thead>
<tr>
<th>Dumper Average Idle Time (%)</th>
<th>Anahim Lake</th>
<th>Hanceville</th>
<th>Williams Lake</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>85</td>
<td>57</td>
<td>63</td>
</tr>
</tbody>
</table>
A sensitivity analysis was performed to understand the effects that parameters such as moisture content and supply and demand have on the performance of the supply chain. Initially, it was also intended to evaluate the impact of varying grinder performance, yet since the results showed high idle rates of the grinders, this idea was not pursued.

The scenarios evaluated are the following: 1) ±5% change in moisture content, and 2) two extreme biomass supply and demand combinations. Similar to the base case scenario, 30 replications were run for each of the parameters and the results obtained, for all locations, were then aggregated and analyzed.

### 4.6.1 MOISTURE CONTENT VARIATIONS

A sensitivity analysis was performed to understand the effect that changes in moisture content have on demand fulfillment, yearly number of truckloads, total number of trucks required, cost per oven-dry tonne of biomass, and CO₂ equivalent emissions. As previously mentioned, the logging residues used in this supply chain are assumed to be all infected by mountain pine beetle. Therefore, it is also assumed that it cannot absorb as much moisture as healthy wood can. Consequently, this sensitivity analysis only considers an increase and decrease of 5% from the base case scenario of 25% moisture content. The results of this analysis are shown in Figure 4.1.
The number of truckloads per year is the performance measure the most affected by these changes. By increasing the moisture content by 5% the total number of truckloads per year seemed to increase by 8.8%. In contrast, by decreasing the moisture content by 5%, the number of truckloads per year decreases by 7.5%. These results are evident since the moisture content is directly related to the amount of biomass a semi-trailer chip van can carry as is explained in Eq. 3.6. As it is expected, the change in yearly truckloads translates into a change in number of trucks required to deliver the biomass to the conversion facilities. However, this change is lower in intensity than that of the number of yearly truckloads. This could be because by increasing the amount of trucks by 1 it would already represent few hundred truckloads per year, this evidently depends on the transportation cycle times.

A change in moisture content ultimately translates into a change in costs of delivered biomass. Analyzing the results obtained, it appeared the changes in cost are principally affected
by the transportation costs. This is easily explained by the fact that the loading and grinding costing is based on the equipment’s productive hours, which is directly related to the machines productivity that remain unchanged. Even though the percentage change in cost is not too high, this could seriously affect the economic feasibility of capital intensive projects such as bioenergy generation. Therefore, it is of great importance to assess the moisture content of the biomass to be used and the possible variations in this parameter. The CO₂ equivalent emissions are also affected by changes in moisture content, almost as much as the costs are. In the same way as the costs were impacted by changes in the moisture content, the change in emissions is caused exclusively by the change in transportation activities; emission from loading and grinding remained unchanged. Finally, demand fulfillment is the output the least affected by the change in moisture content. It appears that a decrease of 5% moisture content does not affect demand fulfilment significantly, it increases by 0.10%. And an increase of 5% in moisture content decreases the demand fulfillment by 1.5%. This could be due to the amount of biomass the chip vans can carry, increasing or reducing the amount of biomass which is left at the roadside due to incomplete truckloads.

4.6.2 EXTREME DEMAND AND SUPPLY

A sensitivity analysis was performed to understand the effect that extreme biomass supply and demand patterns would have on demand fulfillment, yearly number of truckloads, total number of required trucks, cost per oven-dry tonne of biomass, and CO₂ equivalent emissions. The analyzed scenarios were: 1) 20% increase in demand and 20% decrease in supply of biomass and 2) 20% decrease in demand and 20% increase in supply of biomass. To easily identify these two scenarios, the following initialisms will be use henceforth: HDLS and LDHS, respectively.
The analysis of these scenarios is of great importance since it looks at the effects of extreme changes in market conditions on the supply chain’s performance which would help in order to plan for a more flexible and resilient bioenergy project. Figure 4.2 shows the results obtained from this analysis.

As it can be observed, the effects on the demand fulfillment are very drastic between the two scenarios. In the HDLS scenario, the percent change from the base case scenario is a decrease of 23.18%. It is important to emphasize, this demand fulfillment is measured against 20% higher biomass demand than that of the base case scenario. And even though the scenario also considers a 20% lower biomass supply, this decrease in demand fulfillment is mostly affected by the availability of MPB Logs. On the other hand, the LDHS scenario, remains almost constant, with an increase of 1.1%. This is evident since this would mean there would be enough biomass remaining at the roadside to mitigate the effects of loss of biomass due to rounding and due to
incomplete truckloads. Since the total amount of biomass transported in both scenarios is quite lower than the base case scenario, the yearly number of truckloads seems to decrease in both analyzed scenarios. In the HDLS scenario, the truckloads observe a decrease of 10%, while in the LDHS scenario, the results seem to vary proportional to the change of biomass supplied. Similar to the previous sensitivity analysis, the change in yearly truckloads translates into a change in costs of delivered biomass. Once more, the cost of biomass delivered is mostly affected by the transportation activities since the loading and grinding costing is based on the machines productive hours which remain unchanged. It is important to note that in the case of HDLS, the decrease of approximately 9.7% of the cost, showed in Figure 4.2, does not include the effect of having to acquire the remaining biomass to fulfill the inflated demand. This could necessitate having to procure biomass from other sources, which in turn can increase biomass prices up to $90 per oven-dry tonne (MacDonald, 2006). The price depends on the biomass type, its source, quality, and transportation cycle times to the conversion facilities. Thus, considering the location of the conversion facilities to be remote, it may appear the costs incurred would be on the higher end. The CO₂ equivalent emissions are also affected by changes in supply and demand patterns. In the same way as the costs, the change in emissions is caused exclusively by the change in transportation activities, the emissions caused by loading and grinding activities remained unchanged. Finally, in the case of the number of trucks required, both scenarios appear to be slightly less affected than the number of truckloads per year. This might be due to the high transportation cycle times in some aggregated cutblocks which would only allow for one or two loads per day, requiring extra trucks to handle the remaining biomass.
4.7 DISCUSSION

This chapter presented and discussed the results of a discrete-event and system dynamics simulation model built to evaluate a bioenergy and biofuel supply chain. Furthermore, the results of a sensitivity analysis were also presented.

The results of the model showed that once the appropriate storage size, reorder points, and initial inventories have been determined, most of the demand would be fulfilled by the pre-determined aggregated cutblocks.

Moreover, the cost per oven-dry tonne in this supply chain varied depending on the location and was mainly affected by the long transportation cycle times. In Anahim Lake, the delivered cost was of $56.52 odt\(^{-1}\), in Hanceville, $87.36 odt\(^{-1}\), and in Williams Lake, $73.83 odt\(^{-1}\). In a similar study, Mobini et al. (2011) obtained a cost per oven dry tonne of C$57.10. This seems to be close to the results obtained for Anahim Lake, yet too low when compared to those obtained for Hanceville and Williams Lake. When looking into the cost of each logistics operation in Mobini et al.’s (2011) research, the cost of chipping was $32.34 odt\(^{-1}\) and the cost of hauling was $21.97 odt\(^{-1}\). The cost of chipping is close to the one obtained by this research study which averages $31.98 (see Table 4.3). Yet, even though Mobini et al.’s (2011) hauling cost is very similar to the one obtained for Anahim Lake, $22.70, it seems too low when compared to the ones obtained for Hanceville and Williams Lake. As it can be seen in Table 3.3 the one way transportation distances in this case study vary from 8.95 to 193 km. MacDonald (2006) estimated that the processing and hauling costs for these distances could range from $40 odt\(^{-1}\) to $75 odt\(^{-1}\). These results seem to be very comparable to the ones obtained by the present study.
In a similar way, the CO₂ equivalent emissions varied between locations and were mainly affected by the transportation distance. The emissions were 19.66 kg odt⁻¹ in Anahim Lake, 57 kg odt⁻¹ in Hanceville, and 72.61 kg odt⁻¹ in Williams Lake. The results obtained for Anahim Lake seem to be close to those obtained by Mobini et al. (2011), 12.86 kg odt⁻¹. However, the results obtained for Williams Lake and Hanceville are too high. This could be due to the high transportation distances observed in these areas.

The number of generated truckloads appear to increase in the second half of the supply chain’s lifetime. This is because the shift in pyrolysis capacity from Hanceville to Williams lake triggered a change in the overall feedstock mix of the supply chain, which relied much more heavily on logging residues than on sawmill residues. However, this increase in number of truckloads was only translated into an increase of 1 extra truck.

In the sensitivity analysis, the number of truckloads and the number of trucks were the most affected factors by the change in the moisture content. Moisture content is thus a very important parameter to consider when designing a bioenergy supply chain. However, the combined changes in supply and demand parameters affected the results the most, specifically the demand fulfillment. This shows the importance of accurate and reliable supply and demand forecasts in the supply chain design.

Finally, extra logistical arrangements should be made to mitigate the loss of biomass due to incomplete truckloads, especially for the MPB logs. This logistical arrangements could be to allow the use of alternate biomass sources or to consolidate incomplete truckloads by including the routing between different cutblocks. These logistical arrangements were not evaluated due to the lack of data related to the transportation distance between cutblocks.
Chapter 5. CONCLUSIONS, LIMITATIONS, AND FUTURE RESEARCH

5.1 CONCLUSIONS

This thesis examined the performance of a biomass supply chain, considering uncertainties, originally designed by an economic optimization model. This supply chain was located in the Williams Lake TSA and was composed of five conversion facilities which were distributed in three locations: Williams Lake, Hanceville, and Anahim Lake. Each of these conversion facilities differed in their product type, capacity, biomass feedstock blend, and spatial distribution of biomass.

The main objective of this research was to evaluate the supply chain of a forest-based biomass for bioenergy and biofuels production considering uncertainties and variations. This would be achieve by following the specific objectives: 1) develop a simulation model which would accurately represent the supply chain; and 2) apply the simulation model to a case study. Using the Anylogic 7 (Anylogic 7, 2000) simulation software, a simulation model was developed and applied to the case under study. This simulation model used two different simulation approaches, discrete-event simulation and system dynamics. The discrete-event simulation modeled the process of harvesting (felling, skidding, and processing), grinding and hauling the biomass from the forest to the conversion facility. It is important to note that the grinding and hauling operations were managed based on a pull system approach using a reorder point. On the other hand, the system dynamics model was used to manage the inflows and outflows of each biomass feedstock at each of the conversion facilities, in order to keep track of the inventory and manage the biomass orders.
Although the delivery of the biomass to the conversion facilities was managed by a pull system, which aimed to reduce the inventory, there was a need to maintain a certain inventory at the conversion facilities in order to balance the seasonal supply and the constant demand. This inventory was based on a maximum inventory and a reorder point. The reorder point and the maximum inventory parameters were obtained by trial and error using the simulation model. Several maximum inventory levels were tested by increments of $\frac{1}{2}$ month worth of demand, for each biomass type, based on a personal communication with Charles Friesen (2015b). It was assumed the reorder point would be half the amount set by the maximum inventory. The amounts which resulted in the highest demand fulfillment were selected. For the conversion facilities in Anahim Lake and Hanceville, the maximum inventory and reorder points for each biomass type were 3 and 1.5 months of demand, respectively. In the case of Williams Lake, due to the lack of space for storage, the maximum inventory was 2 months of demand, and the reorder point was equal to 1 month of demand.

Furthermore, the total number of trucks required per year in order to maintain a steady supply of biomass was determined. The results showed 23 trucks would be required for the first 10 years of the supply chain, and then one extra truck should be added for the remaining years. The distribution of these trucks within the locations would vary depending on the biomass blend per conversion facility and the transportation cycle times due to governmental restrictions in maximum driving times. It is important to note that the number of trucks required was enough to maintain the supply during the peak harvesting season, yet during the low months fewer trucks would be required.

The results of the model showed at least 95% of the conversion facilities demand would be fulfilled. Although, Table 1.4 shows there is enough biomass to fulfill the demand, there were
two factors which seemed to affect the demand fulfillment. The first factor was an error caused by rounding, this occurred each time the agent “cutblock” was subdivided until it became an agent “truckload”. The second factor was caused by a policy established for reducing transportation costs. This policy stated that no biomass would be retrieved from the roadside unless it was at least enough to fill half a truckload. The biomass left at the roadside was destroyed after 1 year, assuming a controlled burning. The MPB logs seem to be the most affected by these two factors because of their low availability. The delivered cost of biomass was estimated, considering only the stumpage fee, loading and grinding, and transportation costs. The costs seemed to vary between the locations ($56.52 odt$ - $87.36 odt$), mainly driven by the transportation cycle times. Likewise, the CO₂ equivalent emissions obtained varied by each location (19.66 kg odt⁻¹ – 72.61 kg odt⁻¹), affected mainly by the transportation distance. Furthermore, the grinders appeared to experience high idle times which varied between locations (53%–75%), affected mainly by the allocation policy, biomass demand, and number of trucks.

A sensitivity analysis was performed to evaluate the effects that changes in moisture content, and supply and demand trends would have on demand fulfillment, trucks required per year, delivery cost, and CO₂ equivalent emissions. The changes in moisture content (± 5%) seem to affect the cost, emissions, and number of trucks required, since it directly affects the payload of the trucks. As the moisture content increased, the costs increased by 5.3%, the emissions by 4.3% and the number of trucks by 6.1%. As the moisture content decreased, the costs decreased by 3.6%, the emissions by 3.3%, and the number of trucks by 4.9%. The changes in demand and supply trends affected all of the parameters. However, the demand fulfillment in particular saw a reduction of 23.18% when the demand was high (+20%) and the supply was low (-20%). This shows how
sensitive the supply chain is to market fluctuations, and therefore, more attention should be paid on obtaining accurate and reliable supply and demand forecasts.

This model shows how important it is to precisely identify the best location for the conversion facilities. In this case, Anahim Lake and Hanceville, only 239 km apart from each other, present very different transportation distances and cycle times from their closest biomass sources. This not only affects the number of trucks required to supply the biomass, but it affects the final biomass costs jeopardizing the feasibility of the supply chain. Furthermore, it is essential for the supply chain to have access to the biomass year round. Therefore, since this supply chain is affected by seasonality, the use of storage of an appropriate capacity, either on site or between the cutblocks and the conversion facilities, is absolutely necessary. Moreover, the appropriate selection of equipment is essential for the success of the supply chain. In this study, the use of a more efficient grinder was not beneficial, since the flow of biomass was restricted, making it impossible to utilize the extra capacity. Finally, this supply chain was more sensitive to changes in extreme demand and supply patterns, than to changes in moisture content. It is necessary for biomass supply chains to have access to reliable supply and demand forecasts, since this could also drastically affect its feasibility.

5.2 LIMITATIONS

First, this model is limited to the decisions determined by the results of the economic optimization model, such as harvesting system, supply, flow and demand of biomass, and cutblock selection (Cambero and Sowlati, 2014). Second, the simulation model lacks flexibility in terms of biomass availability preference. In other words, the model will not use other available biomass type to make up for shortage in another biomass feedstock. Furthermore, operational details in the
harvesting and grinding operations were not considered, such as the movement between trees or between residue piles. Finally, the validity of the results obtained are highly dependent on the data gathered in the literature, the optimization model, and through personal communications. Therefore, its application is limited to the data available for this case study, and the assumptions previously discussed in Section 3.2, however, it could be adapted to other case studies provided the data were available.

5.3 FUTURE RESEARCH

To improve the current model, routing between different cutblocks could be researched, to consolidate biomass remaining at different cutblocks and therefore increase the demand fulfillment of the supply chain. Yet, to achieve this, data regarding distances and travel times between cutblocks would be required. Additionally, trucks could be modelled as agents in which they could communicate and adapt their routing policies based on the supply chain needs, increasing the supply chain’s flexibility. Furthermore, the movement of the grinder between cutblocks, to reduce the idle times, or the use of a smaller grinder could be researched. Finally, biomass substitutions in the model when there is a shortage of a specific biomass type would increase the supply chains performance.
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